



BIRMINGHAM CITY
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**Industry 4.0 Readiness Level and Operational Performance:
Empirical Evidence from the Indian Auto Components
Manufacturers**

By

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Declaration

This thesis is submitted in partial fulfilment of the University's requirement for the Degree of Doctor of Philosophy (PhD) at Birmingham City Business School in Birmingham City University, Birmingham, United Kingdom. I hereby declare that this thesis is the original of my work except for the quotations and citations that I have appropriately acknowledged. I also declare that this work has never been submitted either partially or in full to any universities or institutions.

Signed

Kokil Talan

May 2025

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Abstract

Industry 4.0 is significantly impacting the operations, processes and business models and has attracted attention among manufacturers of developed economies, where the adoption is more advanced as compared to emerging economies. However, challenges remain entailing the adoption of Industry 4.0 in emerging economies. To fully unfold Industry 4.0, manufacturers need to assess the readiness of their firms and identify the preconditions which can be manifested in the implementation of Industry 4.0. This study was motivated by the need to identify these preconditions and extended into evaluating how such preconditions contribute to operational performance, which has always been pivotal for managers before embracing any technological advancement. This research endeavours to fill the gap in the literature by integrating two subsets of Industry 4.0, encompassing Industry 4.0 readiness and operational performance. This study investigated the relationship between readiness level and operational performance within the context of the Indian auto component industry.

A mixed methodology was adopted to explore the current practices and operational performance through semi-structured interviews with 15 small and large-scale companies. Following a web survey on 217 Indian auto component firms, this study elucidates the Industry 4.0 readiness field by focusing on how readiness levels affect operational performance. Following exploratory factor analysis (EFA), four factors were used for structural equation modelling to test the number of hypotheses for determining the relationship between Industry 4.0 readiness level (independent construct) and operational performance (dependent construct).

The readiness level confirmed the assumption that companies still require several steps to scale to level 4 as 60.8% of firms are at the beginner and intermediate level. The research found that Industry 4.0 readiness levels have a significant positive relationship with production process efficiency and network integration. There is no significant relationship between Industry 4.0 readiness level and responsiveness towards OEM demand. Network integration is the key operational performance measure considering it makes the largest contribution to production process efficiency, while technology readiness level contributes more to network integration than production process efficiency and responsiveness towards OEM demand.

The thesis contributed to the existing research in the following ways. First, the study developed a progressive tool to measure the Industry 4.0 readiness for operational performance. Second, this research contributes to the existing literature by refining concepts such as network integration, production process efficiency and responsiveness in the context of Industry 4.0. These concepts were further tested with a quantitative study and attempts to provide a holistic framework for measuring performance with operational variables in the context of Industry 4.0. As a theoretical contribution, this study tested the relationship between Industry 4.0 readiness level and operational performance from a Resource-Based View perspective.

Keywords: Industry 4.0 Readiness; Auto Components Firms; Operational Performance, RBV

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List of Abbreviations

3DP	3-Dimensional Printing
ACMA	Automotive Component Manufacturers Association
AI	Artificial Intelligence
AVE	Average Variance Extracted
BDA	Big Data Analytics
BMC	Business Model Canvas
BMD	Business Model Design
BSR	Buyer-Supplier Relationship
CII	Confederation of Indian Industry
CB-SEM	Covariance-Based SEM
CEO	Chief Executive Officer
CFA	Confirmatory Factor Analysis
CIMO	Contexts, Intervention, Mechanisms, Outcomes
CNC	Computer Numerical Control
CPS	Cyber-Physical System
CR	Composite Reliability
CRM	Customer Relationship Management
CVPAT	Cross-Validated Predictive Ability Test
DCT	Dynamic Capability Theory
EFA	Exploratory Factor Analysis
e-Procurement	Electronic Procurement
ERP	Enterprise Resource Planning
EVs	Electronic Vehicles
FAME	Faster Adoption and Manufacturing of Hybrid and Electric Vehicles
GDP	Gross Domestic Product
GDPR	General Data Protection Regulation
GPS	Global Positioning System
HTMT	Heterotrait-Monotrait
IBEF	India Brand Equity Foundation
ICT	Information Communication Technologies
IOS	Inter-Organisational Systems
IoT	Internet of Things
IT	Information Technology
KMO	Kaiser-Meyer-Olkin

MGA	Multi-Group Analysis
MNC	Multi-National Corporation
MSMEs	Micro, small and medium enterprises
N	Number of Samples
NI	Network Integration
NCR	National Capital Region
OEMs	Original Equipment Manufacturers
PLCs	Programmable Logic Controllers
PP	Production Process
PLI	Production Linked Incentive
PLS-SEM	Partial Least Squares Structural Equation Modeling
PSS	Product Service System
QR	Quick Response
R&D	Research and Development
RBV	Resource-Based View
REP	Responsiveness
RFID	Radio Frequency Identification
RO	Research Objective
SAP	Systems, Applications & Products in Data Processing
SCADA	Supervisory Control and Data Acquisition
SCR	Supply Chain Resilience
SEM	Structural Equation Modelling
SIAM	Society of Indian Automobile Manufacturers
SLR	Systematic Literature Review
SmartPLS	Smart Partial Least Squares
SMEs	Small and Medium Enterprises
SPSS	Statistical Package for Social Sciences
SSCI	Sustainable Supply Chain Innovation
TAM	The Technology Acceptance Model
TOE	Technological-Organisational-Environmental Framework
TPM	Total Productive Maintenance
TQM	Total Quality Management
TRL	Technology Readiness Level
VIF	Variance Inflation Factor

Chapter 1: Introduction

This thesis aims to identify the Industry 4.0 readiness level of the auto component industry and the ways in which the operational performance of firms can be improved. These areas are examined through the study of manufacturing operations of Indian auto component manufacturers, which will characterise the level of technology usage and the existing technological infrastructure exhibited by Indian auto component firms, and ascertain the performance embedded in the current technological patterns. The findings of the study will suggest policy recommendations regarding the future of the Indian auto component industry in the context of ongoing Industry 4.0 developments (see below **sections 1.1 and 1.2**).

1.1 Background

The manufacturing sector has witnessed tremendous advancements since the 1960s through the introduction of automation using computer numerical control (CNC) and programmable logic controllers (PLCs) machine tools for automating production and improving precision as maintained by various commentators (Dilts, et al., 1991; Xu & Newman, 2006; Newman et al., 2008). Following automation, digitalisation within manufacturing began in the 1970s with the creation of digital designs for products within the manufacturing process (Stecke & Solberg, 1981; Yin, et al., 2017; Mourtzis, 2020). Building on the idea of manufacturing advancement, numerous manufacturing techniques, including lean manufacturing, total quality management, and just in time gained attention for process improvement to enhance productivity and efficiency (Boaden, 1997; Hellsten & Klefsjö, 2000; Anvari, et al., 2011; Dilanthi, 2015). This suggests that automation and digitalisation have been integral enablers of increasing efficiency and improved competitive advantage as highlighted by (Mourtzis, 2020). Moreover, according to Chryssolouris, et al., (2008); MacCarthy, (2013); Mourtzis, (2016), the evolution of manufacturing processes has been propelled by a rapidly changing business environment and to respond to market demand characterised by mass customisation. At this point, it can be inferred that the evolution across the manufacturing industry underscored three key themes which include competitive advantage, customer satisfaction and efficiency improvement. Building upon the trends of efficiency and customisation, the introduction of Industry 4.0 in 2011 characterised by its emphasis on automation and digitalisation marked the fourth industrial revolution, signifying a paradigm shift in manufacturing as emphasised by Kagermann, et al., (2011).

The term was coined in 2011, and it further evolved into the manufacturing arena in the year 2013 with new aspects of applications across operations, supply chains, customer experience, and business models (Orzes & Jia, 2019; Fatorachian & Kazemi, 2021; Marcon, et al., 2022). It involves incorporating advanced technologies such as blockchain technology, Internet of Things (IoT), Artificial Intelligence (AI), Cyber-Physical Systems (CPS), Digital Twin, and robotics to create a more efficient and flexible production process with real-time data collection, optimising the production process, supply chain

integration and informed decision-making (Zhong et al. 2017; Fatorachian & Kazemi, 2021; Unhelkar et al. 2022). It is maintained by various commentators (Zhou, et al., 2016; Mohamed, 2018; Machado, et al. 2021; Hughes, et al. 2022; Sigov, et al., 2022) that while the advent of Industry 4.0 is revolutionising the manufacturing industry, it presents a challenge for organisations to transform their technological infrastructure to incorporate digital models and intelligent manufacturing within existing processes.

Industry 4.0 has been understood from various perspectives in the literature. For instance, few commentators (Burmeister and Piller, 2016; Vinodh, et al., 2021; Marcon, et al. 2022) emphasise the role of Industry 4.0 in transforming business models. This involves shift from product-centric models to service-oriented which unlocks new dimensions of value creation as supported by Barquet, et al., (2013) and Capello and Lenzi, (2021) including customisation, supply chain integration, and collaborative partnerships for improving operational performance (Brettel, et al., 2014). However, due to the area being relatively new, there is a lack of comprehensive research on strategies or prerequisites for the adoption of Industry 4.0 technologies in restructuring manufacturing operations and business models for operational performance as pointed out by numerous commentators (Chen, et al., 2017; Raut, et al., 2020; Raj, et al., 2020; Akbari, et al., 2024).

On the other hand, the literature substantially covered the advantages linked with the integration of Industry 4.0 technologies by keeping large enterprises in context (Schaefer, et al., 2017; Elding and Morris, 2018; Truant, et al., 2021; Papanikolaou, et al., 2021; Hopkins, 2021). The benefits include flexible manufacturing and adaptability to changing production needs, increased efficiency through real-time process monitoring, and intelligent decision-making (Fragapane, et al., 2022). Several companies such as Bosch, Siemens, General Electric, BMW, and Airbus have already implemented industry 4.0 practices to restructure the manufacturing system for production process optimisation, efficiency enhancement, and quality control improvement (Rüßmann et al. 2015; Annanth, et al. 2021; Ray and Rao, 2019; GE Vernova, 2023).

From the preceding discussion, it can be inferred that Industry 4.0 has shown significant improvement in productivity and efficiency for manufacturing operations, particularly in large enterprises. These improvements, however, may not be directly transferable to small and medium-sized enterprises within developing economies like India due to contextual challenges as pointed out by Müller, et al., (2018) and Dalenogare, et al., (2018). The challenges faced by enterprises within developing countries stem from several factors including unclear strategies, in terms of adoption of Industry 4.0 technologies (Raj, et al., 2020 & Sayem, et al., 2022), lack of awareness regarding the value proposition associated with these technologies (Temur, et al., 2018; Khanzode, et al., 2021; Kumar, et al., 2022), and an underdeveloped information and communication technologies infrastructure (Herceg, et al., 2020; Kumar, et al., 2023) (see **section 2.5.1** and **2.6.1**).

Consequently, it can be inferred that research in the realm of Industry 4.0 has examined different aspects independently like manufacturing operations, business models, and adoption of Industry 4.0 technologies by large-scale enterprises in developed economies (Schaefer, et al., 2017; Crešnar, et al., 2020; Pozzi, et al., 2023). This focus overlooks the distinct challenges faced by companies within developing countries due to the distinct technological, and economic environment. Bogoviz, et al., (2018) & Loukil, (2019) observe that much of these dynamics behind the change in technological environment are influenced by developed economies. This underscores the imperative for enterprises in developing countries like India to consider the requirements of ever-evolving technological advancements (see **section 2.3.3**) and assess their readiness for Industry 4.0. As emphasised by Schumacher, et al., (2016), such readiness requires a thorough assessment of existing operational practices, internal activities and processes to align the same with new digital advancement.

Therefore, based on the foregoing arguments, the research presented in this thesis takes a deliberate focus on manufacturing operations transformation in the context of Industry 4.0 specifically within the Indian auto components industry. The research focuses on identifying the prerequisites for adopting Industry 4.0 within the auto components industry, with an emphasis on manufacturing operations that can leverage technological advancements to improve operational performance. By concentrating on the business practices at the industry level, practical insights for manufacturing firms can be gained to help auto component firms strategise the industry 4.0 adoption. These strategies would align better with their existing operational practices for enhancing their operational productivity and efficiency.

1.2 Problem statement

Manufacturing firms across emerging nations face unique challenges in keeping up with emerging technological advancements and maintaining competitiveness as pointed out by numerous commentators (Cezarino, et al., 2019; Chauhan, et al., 2021; Sharma, et al., 2022). This highlights the need for early monitoring of the internal and external environment to avoid the risk of strategic crisis (Olimova et al., 2022). The ongoing process of transformation that unfolds in response to a change in environmental conditions such as technological advancements, necessitates strategic change to remain competitive (Hanelt, et al., 2020 & Volberda, et al., 2021). Yuldasheva (2019) further argues that firms that do not adopt new technologies and innovative management practices within the production process to create new economic value tend to lose their competitiveness. Therefore, Wang, et al., (2022) stated that to remain viable in a fast-changing environment, firms must adopt strategic renewal processes. The strategic renewal process can allow firms to evaluate opportunities and threats present in their operating environment as triggered by technological advancements. According to Zeebroeck, et al., (2023), strategic renewal in terms of competitiveness and business model necessitates changes in corporate-level strategy. Therefore, firms should consider the potential benefits of achieving competitiveness by integrating Industry 4.0 technologies into their existing processes and operations. Industry 4.0 technologies offer a range of tools and capabilities that can help firms optimise their operations by

configuring their resources, and processes to meet the specific demands of their industry and market (Vial, 2019). As discussed by Johnson, (1998) gaining a fresh perspective on firm's current situation and leveraging the advantages of advanced technologies can prevent the risk of strategic drift, which arises due to an unstable and dynamic external environment.

Nevertheless, the introduction of Industry 4.0 is still challenging for firms due to a lack of prior knowledge and awareness of the application of Industry 4.0 technologies as discussed by Brunswicker and Vanhaverbeke, (2015) & Masood and Sonntag, (2020). This challenge, according to various commentators (Rikalovic, et al., 2022; Kamble, et al., 2018; Raj, et al., 2020) is further exacerbated by the non-compatibility of existing technological infrastructure and processes which is characterised by a limited volume of data, a lack of Information Technology (IT) infrastructure, and poor value chain integration with Industry 4.0 technologies. Masood and Sonntag, (2020) & Alsaadi, (2022) take a critical stance and argue that most firms struggle to understand the requirements of factors necessary for implementing Industry 4.0. These ideas are supported by Dixit and Thampi (2023) who argued that the difficulty in understanding the Industry 4.0 requirements has made it complicated for the widespread use of Industry 4.0. Therefore, there is a crucial requirement to understand the readiness level by evaluating the technological infrastructure of the current operations and thus devise any strategy as a road forward to Industry 4.0 adoption.

In the context of Indian manufacturing firms, many are following the processes from the Industry 2.0 phase. Iyer, (2018) pointed out that with the advent of Industry 4.0, these processes are becoming obsolete, and this highlights the major technological gaps in the existing business models. He further emphasised that the mechanical plants and production lines need a shift from the second phase of the industrial revolution to the fourth phase viz. Industry 4.0. Further, Horvat, et al., (2018) stated in their research focussing on emerging economies, that Industry 4.0 embraces smart processes including automation and human-machine interactions for managing production processes. This implies a shift from a centre-oriented perspective towards a network-oriented production process for creating value through product variety and customisation managed by the smart elements connecting the factory floor and cyber computational space (Horvat, et al., 2018). The processes necessitate a renewal across Indian auto component firms to create an alignment with 4.0 technologies which will be driven by the change in strategy.

According to Dhawan et al., (2018), within the Indian auto component industry, principal transformation in the demand and changing market dynamics (see **section 2.3.3**) have pushed original equipment manufacturers (OEMs) to be stricter towards adopting the international standards and best practices followed by foreign multinational corporations. Consequently, various commentators recognised the necessity of aligning domestic automakers' operations and supply chain practices with those of multinational firms to remain competitive and fulfil the market's increasing demands (Benton and Maloni, 2005; Kumar and Kaur, 2014; Miglani, 2019; Singh et al., 2020). A comprehensive report

by the Automotive Component Manufacturers Association (ACMA) presented three overarching themes, including product innovation, process innovation and business model innovation for achieving a competitive advantage within the Indian automotive landscape (Dhawan et al., 2018). The product portfolio focuses on adding customer value. Process innovation emphasises the renewal of processes, including procuring, manufacturing, and delivery processes. Business model innovation focuses on enhancing value creation and creating new dynamics for the value chain. Building on this, Mukhtyar, et al., (2021) observe that the key elements of survival of the auto component industry are digital transformation, enhanced capabilities, agility in the supply chain and stabilising manufacturing as per the demand. This can be observed through a strong alliance with customers and suppliers, which is recognised as a factor for success (Miglani, 2019). These conditions are the contextual backdrop (further discussed in **Chapter 2**) as to the conditions in which auto component manufacturers may have to adopt new dynamics (see **section 2.3.3**), thus necessitating a considerable change in the operations of auto component suppliers.

Prior studies have confirmed that restructuring the existing manufacturing system to prepare for Industry 4.0 is not a technology-related issue, rather it is a strategic issue (Ghobakhloo and Morteza, 2018 & Goswami & Daultani, 2021) (discussed in **section 3.4.2.2**). Jones et al., (2021) argue that digital transformation triggers the change in business processes more pervasively than integrating digital technology into the production line. Consequently, according to Sony and Naik, (2019); Stentoft, et al., (2021) digital readiness precedes the actual implementation of technology, where readiness is described as the degree of a company's ability to change existing processes in alignment with digital technologies (Botha, 2018 & Hizam-Hanafiah, et al., 2020). However, Govindarajan and Immelt, (2019) argued that the road towards digital readiness is treacherous as increasing complexity of the manufacturing system demands context-related strategies. There is a notable shortage within the literature (as discussed in **Chapter 3**) in terms of understanding what comprises readiness for manufacturing operations in the context of the auto component industry and the impact of the readiness level of Industry 4.0 on operational performance.

Few industry readiness models are developed in the literature serving two main purposes, encompassing practice applicability and finding users for the respective readiness model (Botha, 2018). However, Haddara and Elragala, (2015) noted that these models are developed from an academic perspective and lack applicability in the fast-changing industrial landscape. Nonetheless, in a practical setting, the increased level of readiness raises the likelihood of increasing performance. For instance Tasmin, et al., (2020) studied the relationship between Industry 4.0 readiness and quality performance where Industry 4.0 readiness comprised factors including Enterprise Resource Planning (ERP), the IoT, and applied technology, and quality performance was evaluated using productivity and delivery variables. The results confirmed a strong positive relationship between Industry 4.0 readiness and quality performance. A similar study conducted by Naeem and Garengo, (2022) assessed the strong interplay between the

‘as is’ state termed as the maturity of manufacturing processes for Industry 4.0 and performance measurement. To this end, this research investigates two areas within the literature combining the research on the adoption of Industry 4.0 technologies and manufacturing operations. Consequently, concerning the impact of readiness on the operational performance of auto component firms, the review of extant literature failed to find any study in this context (see **section 3.11**). This study will facilitate the understanding of the prerequisites (practices) adopted by the firms prior to the adoption of Industry 4.0 technologies and the impact of these practices on the operational performance of the auto component manufacturing firms.

1.3 Motivation for research

The auto component industry is undergoing a significant transformation to address various business challenges (Manners-Bell and Lyon, 2019) such as inventory reduction, customer value enhancement, supply chain visibility, order fluctuations, product innovation, and diverse customer requirements within the manufacturing sector (Christopher and Lee, 2004 & Panigrahi et al., 2021). The concept of Industry 4.0, which was introduced and escalated in developed economies to manage these needs concerning ever-increasing market volatility and shortening innovation cycles (Kagermann, et al., 2013) has provided an ideal context for the established enterprises within the developing economies. According to Lucas, et al., (2013), the concept of Industry 4.0 enables the evolution of the existing business processes and sets forth a transformative business model that can disrupt innovation in the entire manufacturing sector. The focus of the research is therefore to understand Industry 4.0 readiness factors within manufacturing operations, particularly in developed countries with advanced economies, compared to emerging economies such as India. Understanding these factors will help in contextualising readiness within the Indian auto component industry. Through the comprehensive review of the literature, the research seeks to identify the gap in the current literature concerning Industry 4.0 readiness within the auto component industry (see **section 4.3**).

Further, the key fundamental principles of Industry 4.0 including data integration, communication, transparency, and visibility into the supply chain, aim at reaching varied goals (Vogel-Heuser and Hess, 2016 & Dalenogare, et al., 2018). These goals identified by Shafiq, et al., (2016) include mass customisation, flexible adaptation to the production process, product tracking, and communication among different stakeholders in an organisation. Consequently, this research will further investigate how the current readiness level within the Indian auto components industry concerning Industry 4.0 impacts operational performance.

In the context of technology adoption, the scale of companies demonstrated varied readiness based on the existing resources and technological infrastructure. Small and medium manufacturing enterprises are characterised by processes, technology, and equipment that lack automation and integration of information and communication technology in the manufacturing system. On the other hand, large-

scale enterprise follows more advanced processes, for example, Frank et. al., (2019) revealed that large-scale enterprises are more advanced following an adaptable system with flexible production lines including machine-to-machine communication, supervisory control and data acquisition (SCADA), enterprise resource planning (ERP) and manufacturing execution system. Similarly, Hopkins, (2021), noted large-scale firms are highly adaptable and prepared to adopt robotics, virtual reality, and big data analytics. However, as observed by Ghobakhloo and Morteza, (2018), most manufacturers from small and medium enterprises lack strategies to align advanced technologies with their firm's objectives when compared to large-scale firms.

The motivation to create a framework for understanding the Industry 4.0 readiness factors that would facilitate the adoption of Industry 4.0 technologies emerged from the initial literature review. These initial reviews inspired a strong motivation to conduct a comprehensive evaluation of the operational landscape within the Indian auto component industry. This exploratory research will therefore investigate the current operational practices within the Indian auto component industry. The goal is to bridge the gap between the current scenario of operational practices, and Industry 4.0 preconditions adopted by the developed countries. Hence, this research studied the current operational practices of the Indian auto component manufacturing industry to assess their current position and design a way ahead for improvement in the context of Industry 4.0 requirements. The assessment will serve as a foundation for the framework refinement and will adopt a strategic approach to ensure successful integration and transformation. To establish the requirements of such a framework, the prerequisites adopted by developed countries will be studied to understand the Industry 4.0 readiness factors through a systematic literature review (discussed in **Chapter 4**). Consequently, the study expands knowledge of how the Industry 4.0 readiness factors affect operational performance.

1.4 Research aim

The study aims to assess the Industry 4.0 readiness level and its impact on the operational performance of the Indian auto component manufacturers.

1.5 Research Objectives

The research has therefore set out to achieve the following objectives:

1. To evaluate the readiness factors for implementation of Industry 4.0.
2. To measure the current operational practices of the Indian auto components industry in the context of Industry 4.0 within the horizontal and vertical value chain comprising suppliers and customers.
3. To examine the impact of the current practices on operational performance.
4. To measure the readiness level of the Indian auto components industry comprising SMEs and large-scale companies by designing a progressive readiness tool.

5. To empirically investigate the relationship between the readiness level and operational performance.

1.6 Research Approach

The study followed a methodological approach comprising three stages as presented in Figure 1.1. During the first stage, the literature was systematically reviewed to trace the availability of Industry 4.0 readiness factors or Industry 4.0 readiness framework within the manufacturing sector. The literature review consolidates the studies and theories regarding the evolution and developments within Industry 4.0 by considering the data published in national and international journals, international conferences, and scientific literature databases.

In the second stage, a qualitative approach was adopted to study the Industry 4.0 readiness factors identified from the systematic literature review findings. This stage involved conducting semi-structured interviews with fifteen Indian auto component firms (see **Chapter 6**) to understand readiness levels across Industry 4.0 readiness factors identified from the literature review (discussed in **Chapter 4**). The aim of conducting an exploratory study was to refine the research framework and unearth levels of technology usage that exist in the current practices of the auto component industry and to understand the resulting operational performance (discussed in **Chapter 6**). The newly identified levels and operational performance concepts were then affixed to the existing conceptual framework (discussed in **Chapter 7**), thus designing the progressive readiness tool. This framework was further validated using pilot surveys (see **sections 7.5 to 7.8**).

During the third stage, a quantitative study was conducted. 217 survey questionnaires were analysed to measure the readiness level of the Indian auto components industry comprising SMEs and large-scale companies using the progressive tool developed from the qualitative study (results discussed in **Chapter 8**). Additionally, the impact of readiness level on the operational performance of Indian auto component firms is empirically tested using structural equation modelling (SEM) (see **Chapter 9**). The justification for the choice of research methodology is presented in **Chapter 5**.

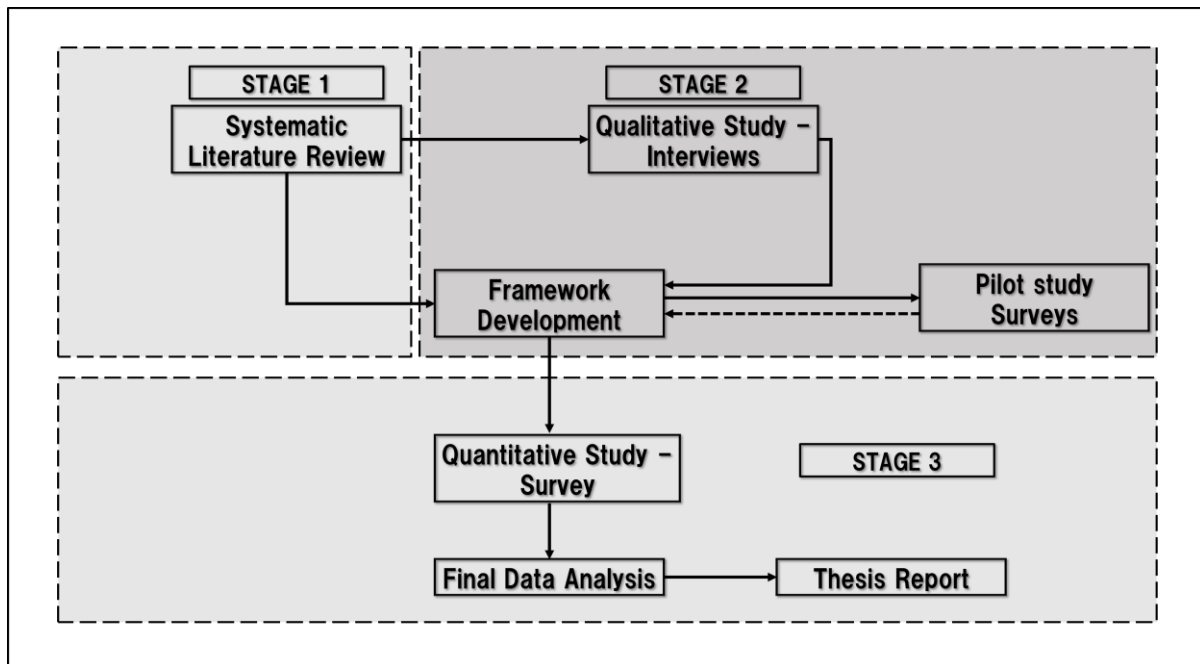


Figure 1.1 : Structure of Thesis

Source: Adopted from Shishank and Dekkers (2013)

1.7 Outline of the thesis

This section provides a summary of the thesis structure, consisting of ten chapters arranged below to contribute to the completion of this study.

Chapter 1: Introduction

This chapter provides an overview of the research motivation, outlining the requirements for undertaking this research by briefly examining the problem. Additionally, the chapter delves into the research background, aims and objectives to offer a comprehensive understanding of the study's context. The chapter concludes by providing a synopsis of the research methodology adopted to achieve the research objectives.

Chapter 2: Contextual overview of the Indian auto component industry

This chapter thoroughly examines the contextual background and describes in great detail the structural changes within which the debate surrounding the Indian component industry is currently situated. This chapter also provides the rationale for choosing the auto component cluster, which is studied during the qualitative phase of this study.

Chapter 3: Literature Review

This chapter presents the relevance of Industry 4.0 to manufacturing operations and supply chains. The chapter begins with a discussion of the theories underpinning this research. Further, this chapter explains the key Industry 4.0 terms, providing insight into digital transformation in the context of

Industry 4.0, challenges to digital transformation and maturity models developed to address the challenges and the value of Industry 4.0 in modern manufacturing.

Chapter 4: Research Framework – populating the framework

This chapter reviews the extant literature on the readiness factors for Industry 4.0 adoption. Further, empirical studies within the extant literature were classified according to the themes identified in Chapter 3 to determine the readiness factors. These include i) Manufacturing and operations; ii) Supply Chain; iii) Business Model; and iv) Strategy. The identified readiness factors across these themes lead to the design of a theoretical framework. The factors identified are discussed in this section. The chapter then concludes with the gaps found in the theories and literature of Industry 4.0 readiness factors following the preliminary research framework.

Chapter 5: Research Methodology

This section outlines the methodology employed to gather and analyse empirical data for meeting research aims and objectives. This chapter rationalises the choice of exploratory sequential design for collecting data utilising qualitative and quantitative research methods. The sampling techniques and research population for qualitative and quantitative research methods are discussed. Data analysis techniques, time horizon and ethical considerations are discussed at the end.

Chapter 6: Qualitative phase – Exploring the Indian Auto Component Industry

In this chapter, the exploratory process of the research is discussed comprising pilot and semi-structured interviews. The discussion is organised around Industry 4.0 factors identified in Chapter 4. The exploratory study seeks to understand the technology usage across the readiness factors and understand the resulting operational performance. The chapter concludes with an understanding of the impact of current practices on operational performance in the context of Industry 4.0. The research hypothesis for the quantitative phase is developed based on the findings from the exploratory study.

Chapter 7: Hypotheses Development

This chapter is instrumental in developing the research framework and research hypothesis derived from the exploratory study. This chapter reiterates the impact of technology readiness level on operational performance, thus establishing the need for the conceptual framework in understanding Industry 4.0 readiness level in the Indian auto component industry. The chapter discusses the research variables encompassing dependent, independent and control variables describing Industry 4.0 readiness factors and the measures of operational performance. Thereafter, the chapter discusses the results of the pilot study conducted, based on the survey questionnaire designed from the research framework. Additionally, the discussion includes the standpoints for employing exploratory factor analysis to validate the survey instruments. The chapter concludes by presenting the results of the reliability of the survey instrument.

Chapter 8: Survey Findings: Descriptive data analysis

This chapter presents the descriptive analysis of the survey data collected from 217 managers, owners and C-level executives of Indian auto component firms. The chapter discusses the overall readiness of the Indian auto component industry followed by the comparative analysis of readiness levels across SMEs and large-scale firms thus realising the objectives of the research.

Chapter 9: Empirical Analysis - Structural Equation Modelling

This chapter discusses the results of the statistical analysis. The chapter begins by examining data before inferential analysis to enhance the validity and reliability of the results. This includes normality test, non-response bias, and common method bias. Following this, SEM is discussed to test the hypothesis and establish the relationship between technology readiness level and operational performance to meet the research objectives.

Chapter 10: Discussion and Conclusion

This chapter interprets and discusses the results of the quantitative data analysis by comparing them with the prior studies. Subsequently, the research contribution to literature and implications for managers are discussed followed by the limitations of the study and recommendations for future research.

1.8 Chapter Summary

This chapter outlines the overall structure of the thesis. The chapter begins with the introduction and motivation for the research. Subsequently, the research background is provided, following the research aim, and objectives. The chapter concludes by providing a brief description of the research methodology.

Chapter 2: Contextual Overview of the Indian Auto Component Industry

2.1 Introduction

This chapter provides an overview of the world auto industry with a key focus on the Indian auto component industry, including a macro-overview of the industry and industry market, and describes the ecosystem within which the industry operates. It first outlines the Indian automotive industry's role in the Indian economy and the interplay of the automobile and auto component industry within the automotive industry before honing in on the auto component industry. Following this, it highlights the evolution and structural changes in the automotive industry that have shaped the present landscape of the auto component industry. Finally, it highlights the potential implications of technological advancements in the context of Industry 4.0 on the auto component industry.

This chapter aims to provide the significance of the issues around which this thesis is centred in the context of the Indian auto component industry to which this research aims to contribute.

2.2 World Auto Industry

The world auto industry is marked by a notable transformation, characterised by a shift in evolving economic patterns across the globe. The global automobile industry's shift from the mature markets such as the US and European markets to emerging countries like China, Malaysia and India has captured the attention of various commentators (Lung, 2000; Balcer & Reut, 2011; Nagy & Jámbo, 2018). These authors emphasise the recent rise of emerging countries in East Asia, attributing the growth to several economic factors. Factors including low production cost and a growing consumer market have prompted developed countries to shift their production base to emerging countries (Gereffi, 2019). Consequently, according to the OICA (2024) report, China became the leading passenger car producer in the global automobile market with 26.12 million units produced in 2023. Japan holds the second position with the production of 7.77 million units. India holds the third position with the production of 4.78 million units in 2023. This is closely followed by Germany, which produced 4.11 million units. South Korea holds the fifth position with the production of 3.1 million units of passenger cars. A comparative analysis of the economic factors and developments within the key players in the global auto industry is presented in Table 2.1. It is evident from the automobile industry's contribution to GDP that the automobile industry holds a strong multiplier effect on the economy of all countries and has acted as a driver of economic growth. Much of this, according to Chakraborty et al., (2020), is enacted through the increasing global trade and the associated contribution of the automobile industry to the economy. The interlinkage in the global automotive market which is evident from the export share of each of these countries (see Table 2.1), is considered by various commentators (Shioji, 2012; Nagy & Jámbo, 2018; Pla-Barber & Villar, 2019) as the driving force behind increased competition in the global automobile market.

According to Llopis-Albert et al. (2021), the evolving changes in the global automotive industry, comprising emission norms, electric vehicles and adherence to passenger safety requirements, have resulted in the increased requirement for technology integration across the global automotive industry. Consequently, it is maintained by various commentators (Rüßmann et al., 2015; Papanastassiou et al., 2020; Mulaj and Dedaj, 2022) that the global industry is now moving towards an attempt to increase innovation and research and development (R&D) expenditure to utilise advanced technologies for increasing production. For instance, Germany's automobile industry is characterised by high integration of advanced technologies, including robotics, cyber-physical systems and robotics. This can be witnessed from the country's significant investment in R&D amounting to USD 59.71 billion (ZEW, 2024). It is maintained by Nettekoven (2023) that Germany's automobile industry focuses on high-end luxury innovative cars, and the integration of autonomous driving technology has strengthened the country's position in the global automotive supply chain. Similarly, Japan's strong R&D investment amounting to USD 29.08 billion (see Table 2.1) has attained a significant position for its dominance with fuel-efficient and hybrid technologies. China, on the other hand, is aggressively investing in EV production to assume the global market share. According to a report of Niti Aayog (2025), India lacks significantly in R&D investment, with only 0.64 per cent of total GDP invested in R&D. It can be inferred that while most of the countries (Japan, China and Germany) have attained technological breakthroughs with their heavy emphasis on innovation activities. In contrast, while India has emerged as a strong player securing the third position in the global market as the highest producer, according to Chatterjee et al., (2018), the industry has primarily responded to the technological changes in the global market rather than driving its own technological breakthroughs. To summarise, the Indian automobile industry showcases differences from the world automobile industry in terms of technological advancements and readiness, export orientation and R&D intensity.

Table 2.1: Comparison of economic factors of major players in the Global automobile market

Economic Factors	India	China	Japan	Germany	South Korea
Contribution to GDP (Year 2023)	7.1%	10% of total GDP	2.9% of total GDP	6% of total GDP	14% of total GDP
Export share (Year 2023)	USD 6.7 billion	USD 77.6 billion	USD 110.13 billion	USD 177.2 billion	USD 68.2 billion
Global Ranking based on export share	Twenty third	Third	Second	First	Fourth

According to the data from the WTO (2024), in terms of export orientation, the world export for automotive products has increased from USD 1.5 trillion to USD 1.8 trillion in 2023. The export from India has also witnessed an upward trend during FY 2023 from USD 15.3 billion to USD 17.05 billion. However, India's share in global exports remained in the twenty-third position in comparison to other players as presented in Table 2.1. This may be due to the focus of the Indian automotive sector on the

production of combustion engines, with 26% of the engine components being supplied to OEMs by the auto component industry (see figure 2.7), as the world is moving to EVs. While the global automakers are characterised by a diverse portfolio that includes luxury cars and EVs, the Indian automobile industry is significantly inclined towards the manufacturing of affordable vehicles, with evidently low presence of EVs in the market (discussed in section 2.4.3.1).

Furthermore, while the supply chain within the global auto market is uniformly following advanced technologies. Indian auto component suppliers heavily relied on frugal ways of manufacturing, showcasing low integration of technologies in manufacturing activities (discussed in section 2.4.3.4). Nevertheless, the inclination of the global automotive market towards Asia, quality consciousness and manufacturing excellence among OEMs (end customers for auto component manufacturers), is pushing the Indian automotive industry to adopt advanced technologies for improved product quality and an integrated supply chain as highlighted by Dhawan et al., (2018). It can be inferred that, within the global auto industry landscape, the Indian auto industry exhibits the characteristics of a late adopter of advanced technologies. Several challenges, such as a lack of infrastructure and the inability of local suppliers to meet the quality requirements of MNCs, may challenge the sustainable growth of the industry. In such situations, the Indian automotive industry risk remained a peripheral player, which challenges the government of India's initiative to position the country as a manufacturing hub. To summarise, the Indian automobile industry showcases differences from the world automobile industry in terms of technological advancements and readiness, export orientation and R&D intensity. The following section discusses in detail the landscape of the Indian automobile industry and dynamics within the Indian auto component industry.

2.3 Indian Automotive Sector (Macro-Overview)

The Indian Automotive sector comprises two major industries, the automobile industry (Original equipment manufacturers) and the auto component industry, as shown in **Figure 2.1**. The Indian automobile industry has played a significant role in the macroeconomic growth, including GDP growth, contributing 7.1% to India's total GDP and accounting for 49% of Manufacturing GDP (Indian Brand Equity Foundation, 2024). India became the world's third-largest automobile market in the financial year (FY) 2023, significantly marking its dominance in global prominence. The IMF has acknowledged India as the fastest-growing automotive market with a growth projection of 0.70 percent in 2030 as against the global growth forecast of 3.70 percent. The growing middle class in India propels the demand for automobiles, with vehicle ownership of 400 per 1,000 vehicles demonstrating the potential of this industry. The Indian automobile industry is divided into five key categories (see **Figure 2.1**): passenger vehicles, commercial vehicles, two-wheelers, three-wheelers, and quadricycles. The manufacturing activities across these five key categories within the automobile industry are highly dependent on the auto component industry, which has also played a crucial role in the Indian economy.

The auto component industry accounts for 2.7% of India's Gross Domestic Product (GDP) (32% of Manufacturing GDP) and employs 1.5 million people (Indian Brand Equity Foundation, 2024). The auto component industry comprises several sub-sectors (see **Figure 2.1**), including engine components, suspension and braking, drive transmission and steering, body chassis, electrical, and electronics (ACMA, 2024). Original Equipment Manufacturers (OEMs) or automakers hold control of the automobile sector, while suppliers have taken over the market share of supplying auto components to OEMs.

The Government's automobile mission plan 2016 –26 envisions the auto industry to grow around four times by FY26, with approximately a 10% compound annual growth rate for vehicle sales volume. The same AMP 2026 policy projects the Indian auto component industry to touch US\$200 bn. Exports are estimated to reach US\$ 70 – 80 bn, roughly accounting for a 40 percent share in the total turnover, with key emphasis on technology and R&D development, collaboration and alliances to address capability gaps and positioning India as a preferred manufacturing destination for auto components globally. The evolution of OEMs and suppliers within the automotive sector is discussed in **section 2.3.1**.



Figure 2.1: Composition of the Indian automotive sector
(Source: Author)

2.4 Evolution and Structural Changes in the Indian Automotive Sector

1990s liberalisation policy significantly increased the role and contribution of the Indian automotive sector in the Indian economy, as shown in **Figure 2.2** and **Table 2.2**. The longitudinal analysis of SIAM indicated an increase in India's share in the global automotive sector in terms of production from 6% in 1995 to 32% in 2025 (see **Table 2.2**), showing an exponential growth of 433%. This change is attributed to the liberalisation policy of 1991. An increase in the share of the automobile industry in the global market has a direct bearing on the growth prospects of the Indian automobile sector, as shown in

Figure 2.2. Further, it is observed that the growth in the automobile industry is positively influencing the growth of the auto-component industry. Consequently, the growth in the production volume of the automobile industry resulted in a remarkable growth of 183% in auto component production turnover from USD 26.5 billion in 2008 to USD 74.9 billion in the year 2024, as shown in **Figure 2.4**. Additionally, liberalisation policy also enhanced the connectedness of the Indian automobile industry with the global industry in terms of scale and production, resulting in an integrated value chain system. In light of the above developments, it would therefore be instrumental to take a brief look at the evolution trajectories of the overall developments of the automotive sector, comprising the automobile and auto component industry.

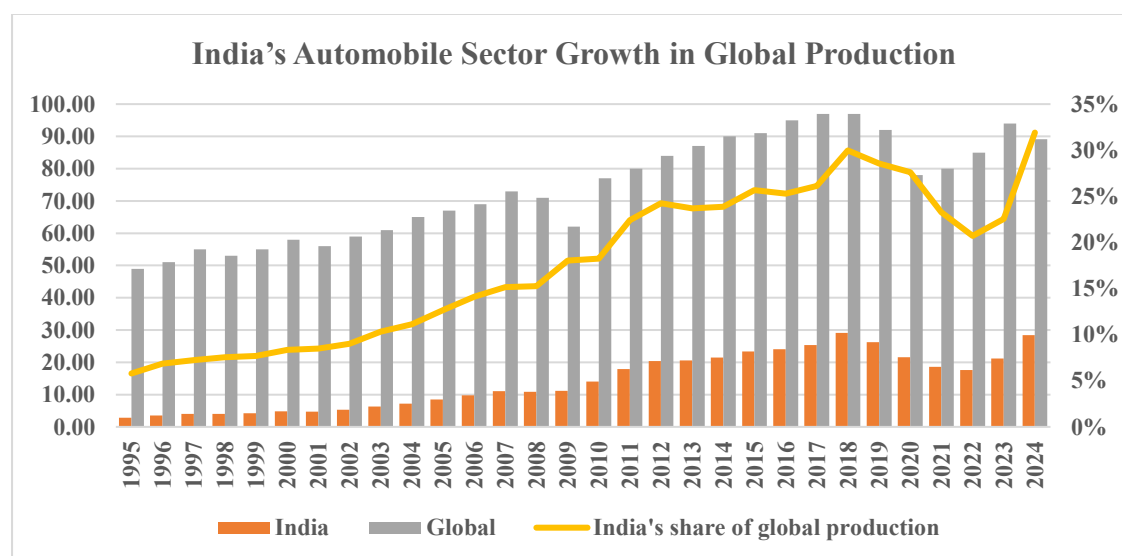


Figure 2.2: India's Automobile Sector analysis (1995 – 2024)
(Source: Compiled by author)

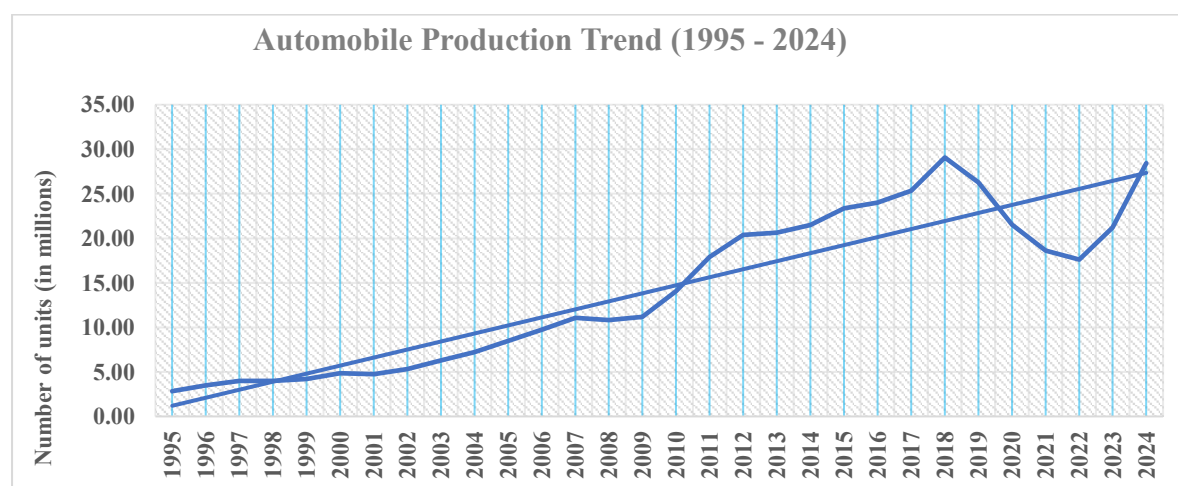


Figure 2.3: No. of vehicles produced in India (1995 – 2024)
(Source: Compiled by author from SIAM annual reports 1995-2024)

Table 2.2: India's Automobile Production in a Global Context

Year	India's production (units in million)	Total Global production (units in million)	India's share of global production
1995	2.84	49	6%
1996	3.50	51	7%
1997	3.99	55	7%
1998	4.00	53	8%
1999	4.22	55	8%
2000	4.84	58	8%
2001	4.76	56	8%
2002	5.32	59	9%
2003	6.30	61	10%
2004	7.23	65	11%
2005	8.47	67	13%
2006	9.74	69	14%
2007	11.07	73	15%
2008	10.83	71	15%
2009	11.18	62	18%
2010	14.05	77	18%
2011	17.92	80	22%
2012	20.37	84	24%
2013	20.63	87	24%
2014	21.48	90	24%
2015	23.37	91	26%
2016	24.02	95	25%
2017	25.33	97	26%
2018	29.08	97	30%
2019	26.27	92	29%
2020	21.55	78	28%
2021	18.62	80	23%
2022	17.62	85	21%
2023	21.20	94	23%
2024	28.43	89	32%

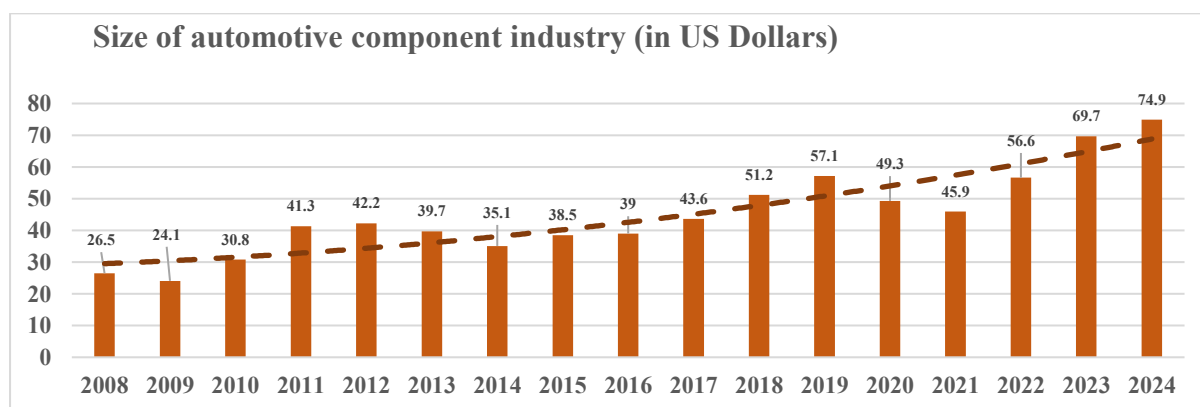


Figure 2.4: Auto component sales volume (2008 – 2024)
 (Source: Compiled by author from SIAM Annual Report 2008-2024)

Structural changes with regard to the manufacturing of automobiles and auto components since 1958 can be summarised as follows:

- The advancements and trends in the automotive industry influence the operations of auto component industries.
- Liberalisation and trade policy in 1991 shaped the present landscape of the Indian auto component industry.
- The industry is characterised by four regional clusters, which contribute to setting the trends in the industry.

The following section discusses the above trends in more detail.

2.4.1 Pre-Liberalisation Era

The period from 1977 – 1984 marked the pre-liberalisation era of the Indian automotive industry, which was characterised by a protectionist and strictly regulated environment. The automotive industry was prioritised during this period, leading to a limited market for auto components. The industry did not fully evolve and was largely rudimentary, owing to the significant focus given to automobile assembly and sales to meet the demand rather than developing the competency of auto component manufacturers. Consequently, to develop the local auto component sector, the government introduced the License Raj, which was aimed at fostering domestic production, indigenisation of auto components and self-reliance (Tiwari et al., 2011).

During this period, a dominant role was played by the government, by imposing restrictive licensing policies and high import tariffs for protecting the domestic manufacturers (Narayanan, 2001). The industry became dependent on the enterprises owned by the government, such as Premier Automobiles and Hindustan Motors. The sourcing of components was done from several state-supported small suppliers for premier automobiles and Hindustan Motors (Jacob and Jagannathan, 2007). While the government initiative was directed to create a strong domestic base for the auto component industry, it resulted in a decline in performance due to limited exposure to technological changes and low-quality standards (Das and Rao, 2004; Nag 2011).

Although significant efforts were made to promote the growth of industry, the slow growth of the Indian economy failed to support the vision of the government, marked by the limited domestic market demand that affected the scaling and expansion of the auto component industry. Further, the limited innovation and restricted market resulted in a stagnant market that further deteriorated the shape of the industry (Diebolt, 2016). The creation of a joint venture in 1982 between Maruti Udyog Limited (MUL) and Suzuki Motors of Japan was recognised as the first initiative taken by the government to deregulate the Indian automotive industry and revive the industry from the declining phase. Consequently, market liberalisation policies, which were introduced in early 1990, supported the revival of industry from the negative effects of the government's protectionist policies (Kumaraswamy et al., 2012). This transition

phase significantly emphasised the role of foreign firms and collaboration in shaping the catching-up strategies of domestic suppliers and auto manufacturers to compete on the global level (Kumaraswamy et al., 2012). The joint venture between MUL and the Japanese firm resulted in the development and collaboration of suppliers across the firms of both countries, which finally shaped the auto component industry, characterised by the pool of immediate suppliers of components to key players such as MUL and Suzuki.

2.4.2 Post Liberalisation

There have been significant transformations in the Indian automobile sector, particularly in the post-liberalisation phase that began in 1991. In the year 1991, economic reforms were introduced, which brought a new face to the Indian automotive industry. The Indian economy entered the global markets as a result of this phase, where the country assured Foreign Direct Investments, technological advancements and increased competition. As a result, global automakers such as Daewoo, Daimler, Ford, Honda and Toyota entered the Indian market, which led to a significant increase in foreign direct investment (Krishnaveni and Vaidya, 2015). This also contributed to the positive growth of the auto component industry as foreign companies encouraged Tier 1 suppliers to enter the Indian market. Following the positive changes, the government of India adopted the indigenisation policy as a strategic path to boost local manufacturing capabilities (Bowonder, 1998). The policy pushed the MNCs to invest in domestic production facilities to enhance the competitiveness of domestic auto component manufacturers. Thereupon, supplier development programmes were introduced, resulting in the formal structure of various suppliers characterised by a tier system (further discussed in **section 2.5.1**).

The key developments were witnessed in the year 1994 and early 2000 in the post-liberalisation era, with the launch of the Toyota Corolla in 1994. Toyota Corolla introduced quality standards and advanced technology to Indian consumers (Karunakar, 2017). More domestic players came into the market of auto component manufacturing, like Mahindra & Mahindra and Tata Motors, showcasing the growing capability of India in automobile manufacturing. As a result, 2.8 million units were produced in the year 1994-95, as shown in **Table 2.2**. The changing landscape and a boost in the economy due to liberal trade policies led to the rising demand. The production increased from 2.8 million in 1994-95 to 11.18 million in 2009, accounting for 294% growth in the production from the financial year 1995 to 2009 (see Table 2.2) (SIAM, 2010). Within the same period, sales, including exports, increased from 2.86 million in 1994 to 11.25 million in 2009, depicting a 293% increase in sales (see **Table 2.2**). This demonstrates the capability of the Indian automotive industry to cater for domestic and foreign demand for automobiles, marking its presence in the global market with a 200% growth rate in the global production share as shown in **Table 2.2** and **Figure 2.2**. The auto component industry consequently became more formalised as a result of the government's indigenisation policy that increased the quality of products to be supplied to OEMs.

2.4.3 Modernisation Era (Technological advancements and digital transformation)

The modern era in the automotive sector is characterised by rapid technological advancements, globally integrated supply chains and stricter environmental regulations (Parry and Kadakol, 2016). According to a report by Chouhan et al., (2017), Confederation of Indian Industry (CII) has recognised the transformation in the Indian auto component industry driven by digital technologies and growing attention to sustainability. These trends are discussed in the following sections.

2.4.3.1 Electrification

Within the Indian automotive sector, significant changes are marked by the adoption of electric vehicles, where the demand for lithium-ion batteries is increased along with lightweight materials and power electronics (Dhar et al., 2017). The government launched a scheme called Faster Adoption and Manufacturing of (hybrid &) electric vehicles (FAME) in 2015, which provides incentives for producing electric vehicles (EVs) by encouraging the manufacturers to invest more in new technologies (UDIT, 2024). However, Tarei (2021) pointed out the lack of infrastructure to adopt advanced technologies posing significant challenges in the growth of EVs. The development of charging stations in remote areas of India still remains a challenge, which requires robust infrastructure and crucial investments for developing and maintaining charging stations as stated by Tarei (2021). Rapid electric vehicle adoption is witnessed in urban centres of India, but the rural regions are showing slow transition to electric mobility. Ambitious goals are set for adopting electric vehicles by aiming for 30% of private cars and 80% of two-wheelers and three-wheelers to be electric by the year 2030. As reported by India Brand Equity Foundation (2024), 100,000 electric cars were produced in India in 2024, and 900,000 electric two-wheelers showed significant progress in the adoption of electric vehicles in India. However, the market is still dominated by internal combustion engine vehicles, showing the production of 5 million cars and 20 million two-wheelers. Still, there are only 8,700 public EV charging stations as of 2023, which shows the crucial difference in the predicted capacity. This shows that building capabilities in Li-ion battery manufacturing is still challenging for Indian auto component manufacturers due to a lack of technology advancements, resulting in increased imports to meet domestic demand. Consequently, the government is promoting the use of state-of-the-art technologies such as digital twins and Artificial Intelligence to improve product development and match global standards.

2.4.3.2 Industry 4.0

Besides, the industry is also embracing interconnected systems for optimising EV operations to facilitate machine-to-machine communications. Efficient data exchange and real-time monitoring play a crucial role in the operations of EVs, consequently impacting the manufacturing processes. While Industry 3.0 focus on the automation of individual machines, Industry 4.0 emphasises end-to-end digitisation for integrating physical assets with the digital ecosystem (Rana et al., 2025). The automobile industry shows readiness with its potential of progressively integrating digital and automated

technologies, which align with the principles of Industry 4.0 (Perody and Sudhakara, 2024). According to the report of Barooah (2016), Bajaj Auto is pioneering the integration of automation. The automation of manufacturing processes within Bajaj Auto initiated in 2010 and now significantly shifting towards the use of 100 to 120 collaborative robots known as Cobots in their production facilities. In the same vein, Maruti Suzuki also showed readiness for the changing industry landscape with Industry 4.0 by utilising 1700 robots across five assembly lines and seven process shops for enhancing their production precision and efficiency (Chouhan et al., 2017). Evidently, technological improvements in the form of electronic vehicles and Industry 4.0 are changing the landscape of the Indian automobile industry, consequently impacting the auto component industry as documented by Dhawan, et al., (2018). The changing landscape of the Indian auto component industry is reflected through constantly shifting market dynamics characterised by the localisation (made in India) policy of the government of India to make India the manufacturing hub.

From the preceding discussion, it is observable that the auto components industry is interlinked with the automobile industry in terms of demand within the industry. The growing international demand for Indian automobiles has impacted the auto component industry as well. This is also witnessed through the sharp increase in the Indian auto component turnover from INR 1.1 lakh crore in FY 2018 to INR 3.5 lakh crore in FY 2024. The increase in domestic vehicle sales of 12.5% in the year 2024, year-over-year growth of 49.90% in electronic vehicle sales as reported by IBEF, (2024) also indicates the evolving landscape of the industry. However, the technological advancements as propelled by Industry 4.0, the presence of international firms in India's commercial landscape due to the most preferred location for manufacturing and growing export is posing a significant impact on indigenous auto component suppliers as maintained by various commentators (Dhawan et al., 2018; A., et al., 2019; Indian Brand Equity Foundation, 2024). A synopsis of the evolution of the automotive sector from 1977 – 2024 is presented in **Figure 2.5**, highlighting the key triggering points that pushed the industry to adopt the global standards.

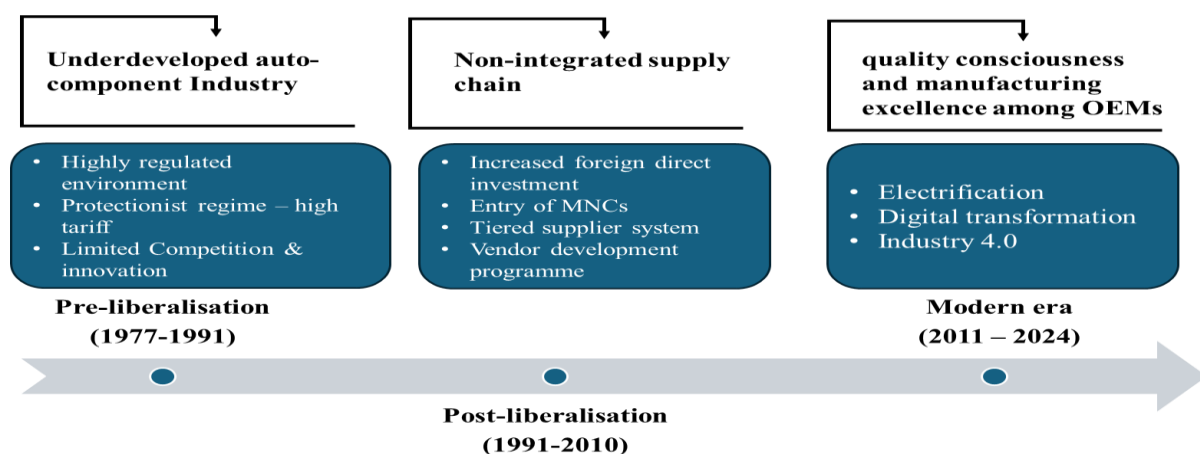


Figure 2.5: Evolution of the automotive sector from 1977 to 2024
(Source: Author)

2.4.3.3 Industry 5.0 and sustainability

The rapidly evolving global market's focus on reducing waste and eco-friendly manufacturing is significantly influencing the Indian government's approach towards sustainability. The concept of sustainability in the automotive sector strives to diminish the environmental impact of manufacturing activities by reducing the uncontrollable generation of waste, as discussed by Khalfallah and Leitão, (2024) and ever-increasing greenhouse gas emissions from internal combustion engine vehicles (Kumar et al., 2021). Additionally, according to Abbas and Tong, (2023), the increasing size and demand of the Indian automotive sector, comprising the automobile and auto component industry, are posing significant sustainability challenges in the form of increasing emissions and waste generation from manufacturing activities. India holds the third position (as shown in **Figure 2.6**) for emitting greenhouse gases (Crippa et al., 2022) within the global transportation sector. India's transport sector accounts for 12% of the carbon footprint (Utgikar, 2024). The emission from road transportation comprising passenger vehicles, two-vehicle and commercial vehicles has increased considerably and reached a record high of 340 GtCO₂ in 2023 (Crippa et al., 2022). India's GHG increased by 198.9% from 1990 to 2023.

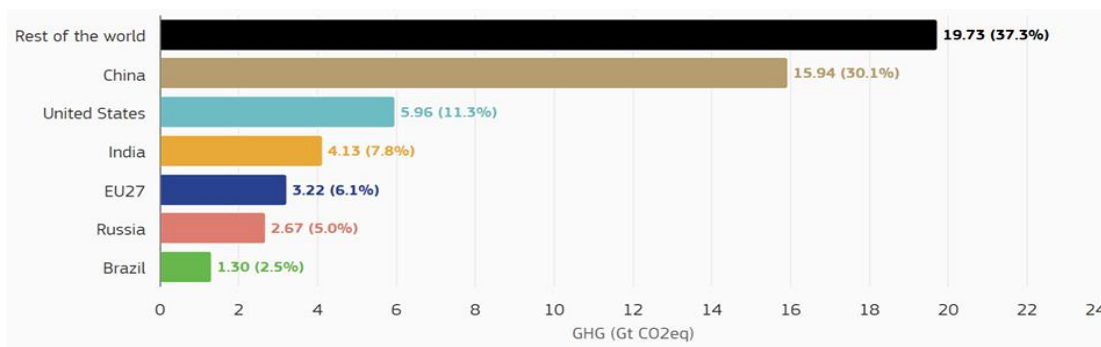


Figure 2.6: Global GHG emissions – Country ranking
(Source: JRC, 2024)

In response to the above trends, the government of India has committed to achieving carbon neutrality as announced during the COP26 climate summit at Glasgow, which has pressurised OEMs and auto component manufacturers to adopt sustainable practices. Additionally, ACMA recognised the efforts required by the auto component industry to expand the global market share by prioritising sustainability transition (Chhibber et al., 2024). As a result, auto component manufacturers are expected to ensure compliance with global sustainability standards such as the EU's Carbon Border Adjustment Mechanism (CBAM) and local market regulations on clean energy and recyclable material usage (Chhibber et al., 2024). However, according to Prasant (2024), technological advancement and innovation are observed as catalysts by the government for achieving social inclusion and sustainability. Recognising this, the government of India highlights the need for strategic alignment of policies with Industry 4.0 initiatives to attain the country's technological advancement and sustainable development agenda for realising the vision of "Viksit Bharat" (developed India) by 2047 (Dahiya, 2024).

2.4.3.4 Industry 4.0 transition to Industry 5.0

Industry 5.0, which shifts the focus from purely technological paradigm to environmental and social sustainability, can be recognised as a continued revolution of Industry 4.0 in the context of the Indian auto component industry to recognise the principles of sustainability (as discussed in **section 2.4.3.3**) in smart manufacturing as suggested by Kaswan et al., (2024). Therefore, it can be inferred that while Industry 4.0 focuses on achieving efficiency and automation, Industry 5.0 leverages these advancements to attain sustainable and resilient production. These ideas are supported by Payer et al., (2024), who argued that Industry 5.0 ensures the use of technological advancements for environmental sustainability. The technological advancements necessitate reuse/recycling to reduce manufacturing waste and achieve higher resource efficiency with the circular economy as discussed by Chishty (2023). Thus, Industry 5.0 supports the goal of sustainability, which is often overlooked in Industry 4.0 as argued by various commentators (Grabowska & Saniuk, 2022; Santhi and Muthuswamy, 2023).

While the world is moving to Industry 5.0, which seems to be a favourable solution for addressing growing sustainability concerns within the Indian automotive sector, Singh (2019) argued that India's economic infrastructure still heavily relies on achieving advancement in technology, particularly for micro, small and medium-sized firms. According to numerous commentators (Goswami and Daultani, 2022; Noor et al., 2024), the ongoing Industrial 4.0 revolution is considered in a continuing state of growth in the Indian economy. In the view of Kumar, (2023), companies are struggling to grasp the concepts and adjust the existing processes around the technology by understanding the preconditions for Industry 4.0 diversification, viz., awareness, knowledge, techniques, and tools. While the Indian auto component industry is experiencing a significant boom in terms of production volume (as presented in **Figure 2.4**), it lags in terms of technology adoption (Wankhede and Vinodh, 2021; Pulicherla, et al., 2022). Further, according to the Networked Readiness Index 2023, India ranked 58 out of 134 countries in terms of the adoption of future technologies. The trend highlights the level of progress towards digital readiness and network capabilities. India was ranked 72nd in 2019 (Dutta and Lanvin, 2019) and moved up by only 14 positions to 58th in the year 2023 (Dutta and Lanvin, 2023) on the scale of digital readiness. Over a period of five years, progress has highlighted a slow pace towards the adoption of future technologies. However, according to Kamble, et al., (2018) the statistics do not necessarily reflect a lack of infrastructure, but rather an indication towards insufficiency in the framework and strategic approaches needed for the successful implementation of future technologies.

In light of the above, Industry 4.0 assumes a significant role in laying the technological foundation, with further scope to evolve these in Industry 5.0 with a significant emphasis on sustainability. Therefore, the research on Industry 4.0 remains highly relevant in the purview of the increased emphasis on sustainability due to the challenges in the adoption of Industry 4.0 technologies in the Indian auto component industry. The transition of Industry 4.0, which focuses on integrating technologies to enhance competitiveness and innovation, provides the foundation for Industry 5.0 to evolve seamlessly

into a sustainable manufacturing ecosystem. Additionally, based on the current state of the Indian economy in terms of digital readiness rank and the challenges towards adoption of Industry 4.0, this research remains focused on the technological adoption in the context of Industry 4.0, with a scope to include the environmental aspects in a broader research framework in the future.

2.5 Indian Auto Components Manufacturers – Ecosystem

Business ecosystem has received significant attention from policymakers and practitioners due to its involvement in shaping technological advancement within organisations and the wider industry (Adomavicius et al., 2007; Senyo et al., 2019). According to Iansiti & Levien, (2004), ecosystem in the context of business and industry refers to a dynamic network of interconnected organisations that include customers, suppliers, intermediaries, and regulators, that collectively create value within a specific industry or a segment. Further, drawing on ecosystem theory (Moore, 1996), the auto component ecosystem is characterised by multiple levels comprising tiered suppliers, OEMs and regulatory bodies (SIAM, 2023). The role and functioning of these actors mark the complex interplay and hierarchies within the auto industry ecosystem, which is crucial to understanding the digital convergence in the Industry 4.0 era.

With respect to Indian auto component manufacturers, the Original Equipment Manufacturers (OEMs) assume the central position. These OEMs are characterised by the organised automobile manufacturing sector, including domestic and multinational corporations such as Maruti, Bajaj, Kia, Honda, Hyundai and Toyota (SIAM, 2023). These firms are highly involved in designing the product specifications and setting the quality standards for the final product. Their influence and practices shape the mechanisms and dictate the norms of the auto component suppliers' network represented by Tier-1, Tier-2 and Tier-3 suppliers (SIAM, 2023). Tier 1 suppliers often embody large domestic and foreign suppliers that works in close collaboration with OEMs in manufacturing and assembling auto component parts including engine components, braking systems, suspension and steering systems. Tier 2 and Tier 3 consist of micro, medium and small-scale firms catering to the demand of Tier 1 suppliers. Tier 2 suppliers specialise in the production of subcomponents as well as intermediate parts of vehicles comprising casting and forgings, gears, shafts, and pistons. Tier 3 provides raw materials like plastics, rubber and steel to the Tier 2 suppliers. Consequently, the auto component market comprises supply to OEMs, exports, aftermarket and imports (ACMA, 2024) as shown in Figure 2.7.

This tierisation within the supply chain is a result of the inherent power and resource ownership across the structure. It is supported by Jacobides et al., (2016) that while OEMs and Tier 1 are large-scale firms, this group exercise a disproportionate degree of control over pricing terms, pricing specification and technological patterns. In contrast, Tier 2 and Tier 3 firms have limited control over the process and activities and operate according to the directions of upstream actors. Consequently, their practices, particularly technology adoption, including automation on the shop floor and the use of PLC/CNC

machinery are largely dictated and shaped by OEMs and Tier 1. Notwithstanding, lower-tier suppliers' firms also face challenges in terms of resource constraint and their capabilities to adopt advanced technologies, as observed by Saripalle and Gupta (2024). Such resource limitation hinders their ability to meet evolving technological trends, particularly Industry 4.0 as noted by Kumar, (2023). This has resulted in resource heterogeneity across the Indian auto component industry as discussed by Riat (2018) (see **section 2.6.1**).

Further, the Indian auto component ecosystem is significantly shaped by the initiatives of the state, influencing the technological direction and manufacturing practices within the industry. Since the inception of the automotive sector, the government has played a key role through various policies such as Production Linked Incentive (PLI), the automotive mission plan and Make in India (Sodhi & Tang, 2021; Narayanan & Vashisht, 2018). The involvement of the government is often justified by the industry's substantial contribution to the country's GDP and its integrative role in meeting the demand of the automobile industry. This can be witnessed through the significant contribution of the auto component industry to the automobile industry, with a turnover of USD 62.4 billion out of a total of USD 74.9 billion largely consumed by OEMs (automobile industry) (see **Figure 2.7**). According to ACMA, (2024) report, domestic OEM supplies contributed 83% to the total industry's turnover, followed by the domestic aftermarket contributing 15% and trade surplus accounting for 2%. In the year 2024, auto component supplies to OEMs increased by 5.3% from 59.3 USD Billion in 2023 to 62.4 USD Billion in 2024, composed of different key segments as shown in **Figure 2.7**. The sales to OEMs include engine components (26%), steering and transmission components (13%), suspension and braking systems (15%), electronic and electrical components (12%), and body and chassis parts (14%) (see **Figure 2.7**). While the figures indicate an impressive and healthy demand side linkage, it magnifies the vulnerabilities within the industry as can be observed from the significant share of engine components accounting for 26% of sales to OEMs. Despite the increasing efforts of the government in promoting the integration of advanced technologies for manufacturing components such as EV parts and autonomous vehicles through PLI, the industry is significantly inclined towards the manufacturing of traditional components, including combustion engines.

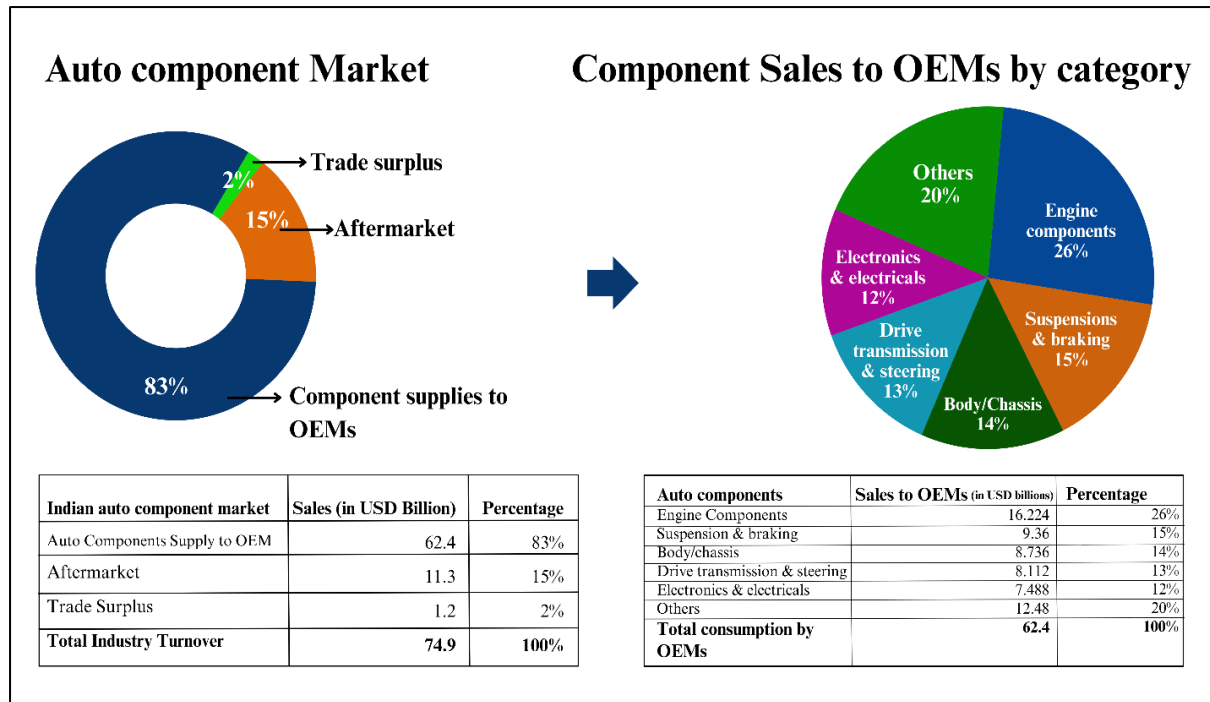


Figure 2.7: Composition and sales of the Indian auto component sector
(Source: Author)

2.5.1 Analysis of micro, small, medium & large auto components firms

Micro-enterprises play a significant role in the Indian auto component industry, especially as they are the supplier of specialised sub-components as well as raw materials. As per the SME Chamber of India (2020), micro-enterprises are defined as businesses having an investment of 1 crore in machinery and plants with an annual turnover of less than five crores (See **Table 2.2**). Micro enterprises are recognised as the backbone of the Indian economy due to their significant contribution to the growth within the rural areas and employment opportunities Ministry of MSMEs (2024). According to Beck & Demircug-Kunt, (2006), while micro enterprises are characterised by low investment with less than ten workers, they serve critical supplies within industrial ecosystems, enabling economic inclusivity. Despite their significant contribution to the Indian economy, micro firms face challenges in the form of limited capital. Mund (2020) highlighted that a lack of capital prevents their growth potential as opposed to the bigger firms having higher exposure to government incentives and bank loans. Maheshkar and Soni (2022) observe that limited financial capital and lack of robust technological infrastructure hinder micro-enterprises from adopting or upgrading machinery and modern production techniques resulting in outdated manufacturing processes and inefficiencies. It is maintained by Jain and Ajmera (2021) that the lack of technological infrastructure continues in the fourth industrial revolution within the manufacturing sector. The current infrastructure hinders the adoption of advanced technologies due to the high reliance of micro enterprises on the workforce-dependent model (Jain and Ajmera, 2021).

In contrast, small enterprises with investment ranging between 1-10 crores and turnover between 5-50 crores (SME Chamber of India, 2020) assume the same functionality as micro enterprises and are

engaged in manufacturing rubber seals, bushings and fasteners. The micro and small-scale are characterised by similar processes as they operate as tier three suppliers, providing sub-components and raw materials to tier one and tier two manufacturers. Further, a crucial role is played by medium-sized enterprises in the supply chain, where they are recognised as Tier-2 and Tier-1 suppliers. The manufacturing of intermediate components, such as forgings, castings, and precision machine parts, is undertaken by Tier-2 suppliers, who process the parts further for Tier-1 suppliers (SIAM, 2023). The definition of MSMEs based on turnover and capital investment is presented in Table 2.2.

According to the Ministry of MSMEs (2024), 51% of the total MSME enterprises are situated in rural areas providing employment to 22 million people in India's population. Additionally, the MSME sector accounted for 30% of India's gross domestic product in FY 2023, while its contribution to manufacturing output stands at 36%. However, Mukherjee, (2018) noted that despite the strong presence and significant contribution of MSMEs to the Indian economy, they are subject to certain challenges and constraints in terms of infrastructure, manpower and technological upgradation. It is maintained by Menon and Shah (2022) that the reliance of small enterprises on manual labour due to their limited capital makes them vulnerable to significant shifts caused by Industry 4.0 and automation.

The large-scale auto firms (capital and turnover exceeding 50 crores and 250 crores, respectively) are characterised by advanced manufacturing technologies and facilities, global supply chain integration and research and development capability. The prominent name in the category of large firms includes Bharat Forge, Motherson Sumi and Bosch India who dominate the market being tier-one suppliers (Miglani, 2019). The critical components of vehicles are supplied directly by tier-one suppliers to OEMs. These firms can maintain cost efficiency and scale production, which gives them competitive benefits in the international market. The definition of MSMEs and large-scale firms based on turnover and capital investment is presented in Table 2.2 below.

Table 2.3: Definition of MSMEs and large enterprises according to the SME Chamber of India (2020)

No	Category	Amount of capital invested (INR)	Amount of Turnover (INR)
1	Micro Enterprise	Up to 1 Crore	Up to 5 crores
2	Small Enterprise	1 – 10 Crores	5 – 50 crores
3	Medium Enterprise	10 – 50 Crores	50 – 250 Crores
4	Large Enterprise	50 Crores & Above	250 Crores & Above

All these firms differ in the scale of operations, invested capital, market reach and targeted segments, and supply chain integration (Acs et al., 2008). While the environmental and technological changes uniformly affect these firms owing to the interlinkages, the practices and capability of these firms to manage the changes vary across different tiers. The foregoing discussion in sections 2.3.1 and 2.3.2

revealed that the capability development efforts remain largely concentrated between OEMs and Tier 1 suppliers. This concentration of efforts, as discussed by Tambade et al., (2019) is largely attributable to the strong R&D, robust technological infrastructure, and globally integrated supply chain. Additionally, the recent policy initiatives including the PLI scheme, FAME, and the Automotive Mission Plan, highlight the strategic orientation of policies towards enhancing R&D and technological capabilities of industry for positioning India as a global manufacturing hub.

While Tier 1 suppliers are characterised by large firms with strong technological infrastructure, the government policies create extra pressure on Tier 2 and Tier 3 suppliers due to limited capital and resource constraints. However, OEM-led supplier development programmes may result in the spillover of technological capabilities to lower-tier suppliers; a systematic mechanism to realise the spillover is limited in the literature. Various reports (see Competition Commission of India, 2022; Saranga, 2011) discussed the strategic divide across the supply chain, indicating the limited engagement of Tier 2 and Tier 3 suppliers with OEMs. In such a scenario, these tiers are highly likely not to assume any advantages from the policies and technology spillovers due to their exclusion from the OEMs' supplier development programmes. Saranga (2011) demonstrates that Tier 1 firms enjoy greater opportunities and competitive advantage due to their immediate association with OEMs. This further magnifies the marginalisation of tier 2 and tier 3 suppliers within the auto component ecosystem. While policies in the context of the Indian auto component industry are designed to enhance competitiveness, the tierisation structure exposes the lack of cross-tier collaboration across the industry. Therefore, it can be inferred that the policy formulation in the Indian automotive sector is highly influenced by the tierisation structure, and the integration of policies is often operated in silos across different tiers of suppliers. According to Riat (2018), this tierisation has resulted in fragmented development across Indian auto component manufacturing firms.

2.6 Overview of Auto Components Clusters in India

While the auto component companies are distributed across all four regions in India, viz. North, West, South and East regions as shown in Figure 2.8, various commentators emphasise the significance of only three regions including North, South and East, in the formulation of auto component clusters (Okada and Siddharthan, 2007; Mittal et al., 2016; Diebolt, 2016). Additionally, according to IBEF (2025), the Indian auto component industry is strategically divided into three clusters, viz. north, south and west clusters. It is maintained by Okada and Siddharthan (2007) that the industry is shaped by similar characteristics driven by the principal automotive manufacturers, resulting in the demarcations of regions guided by cluster dynamics. Much of this, according to Ramaswamy (2021), is enacted through agglomeration economies that significantly steer the accumulation of suppliers in close proximity to automotive manufacturers. It is argued by Diebolt et al., (2016) that the structuring of these clusters facilitates cost efficiency and fosters collaboration within the supply chain across the manufacturers within the same cluster. At this point, it can be inferred that the aggregation of auto

component manufacturers across three clusters is driven by supply chain integration and similarities across operations and manufacturing practices.

Notably, the North cluster that spans Delhi, Gurugram, Faridabad and Manesar hosts big players from the automotive industry, including Maruti Suzuki and Hero MotoCorp. Both these OEMs work in close collaboration with Tier 1 suppliers which include Motherson Sumi, Bosch, and Lumax (IBEF, 2024). Western Cluster spans across cities like Pune, Chakan, Aurangabad, Sasand and Gujarat (IBEF, 2024). According to the report of Construction Week India, (2023), the Western cluster marks the high presence of global players like Mercedes–Benz and Volkswagen and plays a significant role in boosting the export infrastructure of the Indian auto component industry. Cluster in South spanning across cities like Chennai, Hosur, Bangalore and Coimbatore, also focuses on high export and depends heavily on the port infrastructure (Sourabh, 2025), showcasing less opportunity for understanding the supply integration and the supply chain dynamics within the country’s OEMs and suppliers.

2.6.1 Geographical distribution of auto component companies

Within the auto component industry, the organised sectors, including large-scale companies, comprise 402 companies (see **Table 2.3**) and account for 80% of the total market demand as Tier 1 suppliers and supplying components to OEMs. The majority of companies are in the Northern region, accounting for 40% of the total companies (See **Figure 2.10**). The geographical spread is as follows:

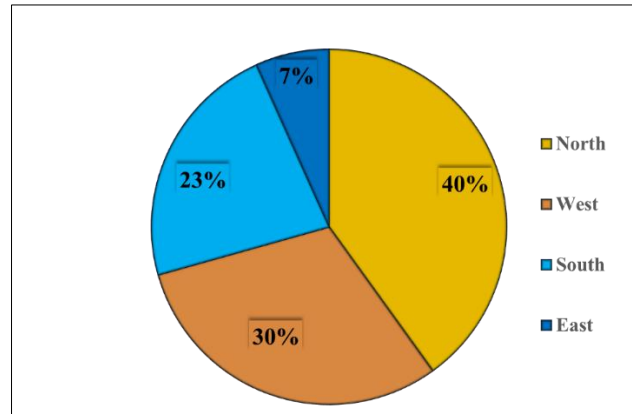


Figure 2.8: Distribution of medium and large-scale auto component companies across Indian regions
(Source: DSIR, 2025)

Table 2.4: Distribution of medium and large-scale auto component companies across Indian regions

Region	Number of medium and large companies
North region	161
Western region	123
Southern region	91
Eastern region	27
Total	402

The unorganised sectors comprise 5000 micro and small-scale companies and act as ancillaries to Tier 1 suppliers and serve the aftermarket (DSIR, 2025). The exact data in terms of the geographic spread is not available for small-scale companies. However, according to Ramaswamy (2021), the concentration of OEMS and medium and large-scale companies suggests a substantial number of auto component companies located in the Northern region due to agglomeration economies.

2.6.2 Industrial and Economic Significance of North Cluster

The Northern auto component cluster is predominantly characterised by OEM-driven dynamics. For instance, Maruti Suzuki, a key player in this region, has mandated the localisation of components and supporting suppliers to strategically set up facilities near manufacturing plants (Julka et al., 2014). In addition to geographical realignment, these suppliers are required to comply with strict quality and technological requirements established by Maruti Suzuki, in alignment with its total quality management approach (Sahoo, 2014). Regarding manufacturing, Maruti Suzuki outsources the majority of its manufacturing to suppliers and introduced the concept of Just in Time, necessitating the suppliers to be located near the assembly plant (Sudan, 2020). In addition to this, small-scale companies, which serve as ancillaries to Tier 1 suppliers, are incentivised through allocations of land in industrial estates at a subsidised cost. Correspondingly, several components are reserved to be manufactured by small-scale industries only, which has resulted in the growth of small-scale auto component firms near the location of Maruti Suzuki within the northern region (Sudan, 2020).

Similarly, Hero MotoCorp follows the same strategy with the strategic placement of its plant in Gurgaon to strengthen the linkage with its vendors, who are predominantly located in Faridabad, Delhi, Ghaziabad and Noida (Singh, 2016). It is maintained by Offenloch et al., (2025) that the spatial configuration of OEMs and their vendors leads to improved supply chain performance, reduces logistics costs and increases flexibility across the supply chain to streamline the production process. Therefore, the OEMs' need to streamline the supply chain set the benchmarks for the suppliers which are located in the North cluster. Further, the prominence of the Northern cluster in terms of the number of OEMs concentrated within the region is a result of the economic policy and geographic advantages (see **section 2.6**). The economic policy in terms of the production-linked incentive (PLI) and state incentives resulted in the emergence of the largest agglomeration in the North. It is maintained by Mukhopadhyay (2017) that government incentives like the Delhi-Mumbai Industrial Corridor (DMIC) highlight the strategic significance of the northern region as a manufacturing hub.

While the other clusters play a significant role in shaping the auto component industry, it is worth noting that the North Cluster currently rules in mass market vehicles, including four-wheelers and two-wheelers, with Maruti Suzuki as the major contributor (**Figure 2.9**). The manufacturing facilities of Maruti Suzuki, located in the Northern cities of India, particularly Gurugram and Manesar, largely drive the growth in the passenger car segment. Maruti Suzuki has not only dominated the market in the

northern cluster but also holds the largest market share of manufacturing passenger cars in India, accounting for 41.6%, as shown in **Figure 2.9**.

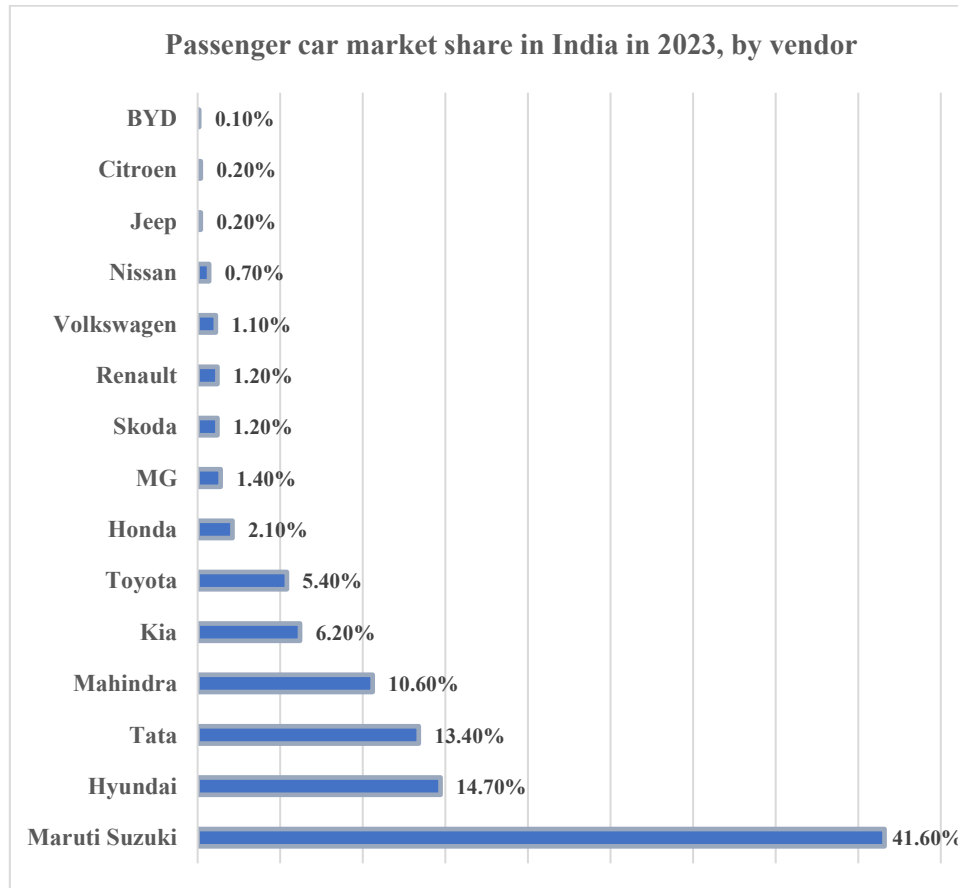


Figure 2.9: Market share of manufacturing passenger cars in India (OEMs' share)
(Source: SIAM, 2023)

2.6.3 The rationale for the choice of the North cluster

The decision to focus on the North cluster does not dismiss the significance of other clusters, but the choice is rooted in the analytical depth provided by this cluster. The concentration of OEMs in the North cluster provides an understanding of domestic-market-oriented supplier integration as evolved from the symbiotic relationship with OEMs like Maruti Suzuki and Hero MotoCorp. This ecosystem is distinct from the export-oriented South cluster and technologically oriented West cluster in Pune in terms of market orientations and innovation practices (Baporikar and Deshpande, 2015).

Specifically, according to Baporikar and Deshpande (2015) the West cluster, centred around Pune, focuses on manufacturing technologically advanced premium EVs. On the other hand, the South cluster's inclination is towards manufacturing export-oriented vehicles, including hybrids and EVs, supported by a supplier base that comprises Japanese and Korean-based Tier 1 suppliers (Dash & Chanda, 2017). The market orientations of West and South cluster stands in contrast to the North cluster, which predominantly caters the domestic market needs. In addition to market focus, the supplier base also varies as the North cluster heavily relies on domestic Tier 1, 2 and 3. On the other hand, the West

cluster's export orientation resulted in the emergence of a global Tier 1 supplier base (Dhingra, 2025). Following this, the South cluster's alignment with the international market resulted in a supplier ecosystem dominated by Japanese and Korean-based Tier 1 suppliers. The north cluster is characterised by the higher dominance of big players in the industry that shapes the suppliers' practices and auto component industry in terms of scale of operations and supply chain practices (Mittal et al., 2016).

Diebolt et al., (2016) highlighted the significance of geographic demarcation as found within the auto component clusters in shaping the OEMs-suppliers dynamics. Much of these dynamics, according to Humphrey (2000), are enacted through coordination in the supply chain where geographical proximity facilitates the sharing of standardised design specifications for automotive components. Given the dissimilarity of factors across auto component clusters in terms of market focus and suppliers, various commentators (Yin, 2009; Patton, 2013) suggest that the inclusion of dissimilar characteristics within a research framework may undermine the reliability of findings. Accordingly, the inclusion of other clusters (West and South) within the same study would likely result in a loss of generalisability due to the contextual variations. Moreover, Denzin & Lincoln (2011) argued that the inclusion of dissimilar characteristics spanning across all clusters may dilute the central argument concerning the industrial transition to Industry 4.0, with a key focus on supply chain dynamics. Therefore, narrowing the scope to a geographically concentrated cluster with consistent market orientation would facilitate capturing consistent and meaningful insights.

The selection of the northern auto component cluster, consisting of Haryana, Delhi, and Uttar Pradesh, as a focus for the qualitative study is grounded in the preceding discussion. These states are recognised as leading hubs in the development of auto component clusters (Mittal et al., 2016) due to the interplay of several factors. These factors, as discussed in section 2.6.2, highlight the proactive policy designing, significant concentration of suppliers within this region (see **Table 2.3**) and a close proximity of suppliers with major OEMs (discussed in **section 2.6.2**). Accordingly, the Northern cluster serves as a suitable backdrop for understanding current operational practices and supply chain dynamics within the auto component industry.

2.7 OEMs' Dominance and Challenges in the Indian Auto Component Industry

OEMs' constant effort to align with the Government of India's version of Industry 4.0 for manufacturing acts as a primary catalyst for transformation in the manufacturing process and value chain. The auto component is steered by these OEMs, who, despite being fewer in number (the snapshot of the market share of OEMs is presented in **Figure 2.10**) as compared to the auto component manufacturers, exert commanding influence over the supply chain network and practices (SIAM, 2023).

OEMs	Market Share (%) November 2023
Maruti Suzuki	41.60%
Tata Motors	14.85%
Hyundai	13.79%
Mahindra	10.80%
Kia	5.52%

Figure 2.10: Market share of OEMs
(Source: SIAM, 2023)

The market share of OEMs as presented in **Figure 2.10** underscores the oligopolistic market nature and the power of OEMs to dictate the operations of auto component manufacturers. Companies that would not be able to meet their requirements in terms of quality, transparency and visibility in operations risk would be excluded from the network (Dhawan et al., 2019). Smaller companies, particularly, face greater challenges in adapting to the evolving industry needs due to resource constraints (Srivastava et al., 2021). Further, with the current emphasis on supplier integration, technology upgrades and operational visibility, the industry is again under pressure to adopt advanced technology to meet these standards set by OEMs (Mukhtyar et al., 2021). These situations necessitate that they enhance their capabilities, optimise processes, and ensure compliance with quality and efficiency standards demanded by OEMs (Mukhtyar et al., 2021; Chaudhury et al., 2022).

Furthermore, the automotive industry's progressive dynamics and increasing expectations of domestic OEMs have ripple effects throughout the supply chain, reaching Indian SMEs that are a vital part of their extended network along with large enterprises. As major suppliers and partners to OEMs, SMEs are directly influenced to adapt to the OEM's increasing standards and requirements (Jacobides, et al., 2016). Irrespective of the size, the demand for high quality in design and manufacturing is the major driving force that necessitates each tier to consider the best supply chain strategy for achieving competitiveness. The frequent introduction of vehicle variants is another driving force behind the adoption of an agile supply chain. However, the Indian automotive industry is facing the biggest challenge in the form of a lack of visibility due to a lack of integration of the end-to-end supply chain (Kumar, et al., 2019). Close collaboration with the suppliers to improve visibility in the supply chain is acknowledged by Marwah et al., (2014) & Dubey et al., (2018). Significant bodies such as Ashok Leyland, Tata Motors, and Mahindra have already adopted best practices of the supply chain by integrating their suppliers (Khare, 2008; Bhat & Prabhudesai, 2022). Tata Motors and Ashok Leyland have entered the electric vehicle segment and are changing the landscape for auto component suppliers.

However, SMEs, major auto component suppliers within this ecosystem, have not taken any concrete steps towards aligning their operations with OEMs and thus lag in adopting integrated supply chain practices (Chandak 2018; Narkhede and Rajhans, 2019; Subburaj, et al., 2020). Today's supply chain

practices emphasise collaboration between parties and creating a network where suppliers are involved in all aspects of vehicle manufacturing. This means that to be part of a supply network, all firms will have to upgrade their capabilities of bringing transparency and visibility into their operations as pushed by OEMs (Patel, et al., 2021). The impetus is coming from the OEMs to enhance supplier-side integration because of stringent quality and delivery schedules. This indicates that a company lacking these capabilities will be driven out of the supply chain. Given these developments within the Indian automobile industry, auto components suppliers are forced to rethink and revamp their present supply chain strategies to make them more collaborative and digitally automated (Nag and De, 2019 & Mukhtyar et al., 2021).

2.7.1 Resource heterogeneity across suppliers

Some commentators suggest that in the context of the Indian auto component industry, homogenisation of resources across the industry is observed (Sattar et al., 2014; Fauzdar et al., 2022). For example, the automation of production lines and the use of CNC and PLC machinery across the industry suggest homogenisation in resource base across the auto component industry. By contrast, others argue that heterogeneity of resources across Tier 1, Tier 2 and Tier 3 suppliers results in different competitive advantages across the auto component industry (Thomé et al., 2014; Dubey et al., 2018). Tier 1, being large-scale and medium-sized companies, have access to capital and are investing in advanced technologies including Artificial Intelligence, Cyber-physical systems and robotics. As Tier 2 and Tier 3 are largely micro and small firms (discussed in **section 2.6**), it can be argued there is a lack of resources and strategies to adopt advanced technologies. This tierisation in terms of the size of the firm across the auto component firms was also confirmed by Kumaraswamy et al., (2012). These contrasting viewpoints are therefore associated with quite different operational performance outcomes rooted in the resource array across the Indian auto component industry (Riat, 2018).

From one perspective, it has been claimed that the government of India provides incentives and subsidies to small firms with the intent to reduce disparities in capital investments for increasing the operational efficiency of the firms (Hota and Dey, 2015; Gupta, 2023). A counterargument suggests that despite the policy efforts, the resource asymmetry across the industry is widening the gap in achieving the desirable operational performance across all tiers of the industry (Kumar, et al., 2019; Nag and De, 2019). According to Pradhan (2011) and Rehman (2016), MSMEs' lack of engagement in R&D activities underscores their limited innovation capacity. Moreover, OEMs tend to establish partnerships with suppliers that possess the capital for developing innovation capability and are successful in attaining the desired quality standards as set by OEMs (Dua, 2015; Joshi, 2017). These practices reinforce the divide between capital-constrained suppliers and well-capitalised suppliers. Therefore, to account for the heterogeneity of resources within the Indian auto component industry, the RBV needs to be contextually adapted based on the current resource base (as discussed in **section 3.3.2** and presented in **Table 3.1**) for transitioning to Industry 4.0.

2.7.2 Innovation & Technology diffusion

It is maintained by Tidd, (2023) that innovation is the process of developing new ideas and putting them into practice. An attempt to launch new products or redesign business models for the creation of value and achieving competitive advantage for the firm is inherently tied to innovation. According to Schumpeter and Swedberg (2021), innovation includes incremental change and radical redesign that transform industries and society. Building on the ideas of innovation, the evolution of Industry 4.0 within manufacturing industry emphasises redefining business models, processes and activities for enhanced production efficiency, personalisation of products and improved supply chain as discussed by Zhong et al., (2017); Fatorachian & Kazemi, (2021) and Unhelkar et al., (2022). However, much of this, according to Rogers et al., (2014), is enacted through the diffusion of technologies by which innovation spreads through industry or markets, or societies, over a period of time following S-curve adoption patterns. Various commentators (Pfohl et al., 2016; Sachdeva et al., 2017; Mohamed, 2018; Ghobakhloo et al., 2021; Kılıç & Atilla, 2023) discussed the key factors that impact diffusion rates in the context of Industry 4.0, encompassing perceived benefits of technology by the manufacturers, compatibility of new technology with existing systems, complexity and observability of new technology and innovation.

With the advent of Industry 4.0, dominated by cyber-physical systems, IoT, Artificial Intelligence, and automation, the Indian auto component Industry is experiencing a record transformation. Industry 4.0 integrates various technologies such as Internet of Things (IoT) for monitoring production lines on real time basis (Kagermann et al., 2013); deep machine learning and Artificial Intelligence for quality inspection and predictive maintenance (Lee et al., 2018); additive manufacturing and 3D Printing for rapid prototyping and personalisation of production (Weller et al., 2015); and Big Data Analytics for supply chain optimisation (Manyika et al., 2017). According to the ACMA-KPMG report released in 2022, these technologies offer cost savings, efficiency and global competitiveness to Indian auto component manufacturers. Nevertheless, technology diffusion and innovation pace vary significantly due to the structural, financial problems and unavailability of skills within the Indian auto component industry. Large Indian firms such as Bharat Forge and Motherson Sumi have adopted IoT and AI-driven automation (IBEF, 2024). According to Bharat Forge's (2021) sustainability report, the company has saved 20% of energy using smart grids and moved a step ahead by putting up automated forging lines with IoT integration. In the same direction, Motherson Sumi has utilised AI-based predictive maintenance for achieving a reduction in machine downtime while utilising digital twinning to simulate in real time.

While large-scale companies are making significant strides in digitally transforming their manufacturing processes, MSMEs face hurdles including high implementation costs and a lack of capital. According to the Ministry of MSMEs (2024), over 70% of the micro, small, and medium auto component enterprises exhibit slow technological integration, mainly due to insufficient funds. Kumar

et al., (2024) confirmed that the sluggish adoption of technology is further exacerbated by a lack of trained manpower in AI, data analytics and automation. In such a scenario, Singh (2019) suggested a technology innovation strategy to systematically adopt advanced technologies for performance improvement within MSMEs.

It can be inferred from the above discussion that the diffusion of innovation through which Industry 4.0 technologies can be adopted is not uniform within the Indian auto component industry. Consequently, the government of India is making continued efforts to address these challenges by undertaking initiatives to democratise innovation for MSMEs. For instance, Indian central government initiatives are facilitating digital transformation via Production Linked Incentive (PLI) programs for accelerating Industry 4.0-driven innovation (KPMG, 2024). The Economic Survey of India, (2023) has also outlined the policy recommendations regarding subsidy and tax relief for the purpose of SMEs' investment in automation. This initiative indicates the policy level shift for integrating SMEs in the technology upgradation driven by Industry 4.0. Additionally, the government's initiative for capability building with the support of academia through the IIT-NIT industrial-academic partnership is sparking innovation in the automotive component industry in India (Niti Aayog, 2025). While technological capabilities remained focal points across the government's initiative, various commentators have emphasised the role of effective leadership in the adoption and integration of technology-related innovation (Marci and Scandura, 2010; Li et al., 2018; Vlok et al., 2019). As discussed by Shamim (2022), leaders are identified as the key enablers for innovating the processes and products within an organisation, which also enhances the diffusion of innovation. Therefore, it is necessary to situate leadership as the core process of innovation that will later underpin how senior leaders facilitate digital transformation.

2.7.3 Role of leadership in innovation

As firms are navigating the adoption of advanced technologies in the context of Industry 4.0, the role of leadership has evolved as a critical factor to facilitate innovation and digital transformation. Leadership is identified as the stepping stone in any significant transformation by numerous commentators (Yansen et al., 2023; Phakamach et al., 2023; Ongena et al., 2024). Leaders comprising managers and business executives require the capability of embracing Industry 4.0 (Ö Akçay, 2018). Although Khin and Ho (2019) argued that firms with digital capabilities witness the adoption of digital technologies for product and business model innovation more readily. Hitt et al., (1998) take a critical stance on firm's capability and argue that while the firm's capabilities are segmented into dynamic and ordinary capabilities, a key catalyst to navigate these capabilities lies in the strategic leadership to keep the organisation competitive. However, Schoemaker et al. (2018) argued that dynamic capabilities, leadership and strategic reframing are interconnected elements rather than standalone drivers of innovation. Notwithstanding, according to Aldoseri et al., (2024), the adoption and integration of advanced technologies such as IoT, big data analytics, and artificial intelligence not only requires

strategic alignment but also requires the knowledge and mindset to foster innovation and digital transformation. Given that a significant number of suppliers within the Indian auto component industry are small and medium enterprises (as discussed in **section 2.6.1**), leadership must navigate an effective strategy for the adoption of Industry 4.0 technologies. However, according to Dixit and Thampi (2023), small and medium enterprises exhibit a lack of awareness towards the adoption of technologies. These challenges are further heightened by the overall low amount of R&D within the industry as documented in the report of Niti Aayog, (2022), necessitating the leaders to strategise resource allocation while leveraging knowledge as the preliminary resource. Apart from the internal challenges faced by firms, including R&D limitations and lack of technological infrastructure, the auto component industry is also facing rising cost pressure from OEMs and global competitors, compelling firms to balance innovation and cost pressures (Mukhtyar et al., 2021). This necessitates the leaders within auto component firms to balance short-term financial goals with long-term technological innovation. According to Weber et al., (2022), senior leadership is required to facilitate the process of digital transformation even before the actual implementation of technology. Therefore, leaders must establish a clear vision for the execution of Industry 4.0 adoption and strategically allocate resources for effective Industry 4.0 adoption. It can be understood that the motivation and strategic vision, therefore, are the key to innovation driven by Industry 4.0.

Whilst innovation provides the important contextual aspects, it is not directly studied in the current thesis due to the emphasis on current technological infrastructure across the core dimensions of manufacturing operations. Additionally, as this thesis is not focused on assessing the Industry 4.0 readiness by using innovation as an independent readiness factor, it is the discussions of innovation which are linked with the adoption of advanced technologies. Additionally, Lam et al., (2021) highlighted the link between leadership and collaboration practices to enhance innovation practices. Much of this according to Attah et al., (2024) is enacted through a culture of collaboration as facilitated by senior leaders across various domains within the manufacturing operations including engineers, managers and IT experts that eliminates the departmental silos and promotes diffusion of innovation across organisation. Therefore, innovation is not directly assessed in this thesis; its role is highlighted through other dimensions including leadership and collaboration as Industry 4.0 readiness factors in alignment with existing literature and readiness frameworks (See **section 4.3.4.1** and **4.3.4.2**).

2.8 Conclusion

This chapter indicates the importance of understanding the directions in which the Indian auto component industry is moving in terms of the fourth industrial revolution, which this study aims to capture. An understanding of the developments within this industry in terms of resource array and the influence of the resource on the operational performance may provide a significant contribution towards the current policy debate on leveraging Industry 4.0 for smart manufacturing.

Chapter 3: Literature Review

3.1 Introduction

This chapter considers the theoretical perspective applied within the studies of Industry 4.0 adoption in the manufacturing sector, including the automotive sector. The purpose is to establish a theoretical foundation for constructing a framework to understand the influence of Industry 4.0 readiness on operational performance within the Indian auto component industry and to further refine the research questions. Furthermore, this chapter provides an overview of the previous research in the field of Industry 4.0. The literature was investigated to find any preexisting model(s) that would encompass all the required characteristics viz. positioning of Industry 4.0 readiness factors in the auto component manufacturing industry for achieving operational performance. The literature review was conducted for the following reasons:

1. To present a broad, comprehensive representation of Industry 4.0 readiness factors by integrating the findings conducted on Industry 4.0 implementation strategies in developed countries so far (Webster & Watson, 2002; Snyder, 2019).
2. As the current research aims to develop a framework for assessing the impact of readiness level on operational performance, an SLR served as a significant tool for theory development by providing a basis for building a new conceptual model. Furthermore, an SLR assisted in evaluating theory and evidence in the field of Industry 4.0 specifically for investigating the relationship between two variables viz. Industry 4.0 readiness level and operational performance (Torraco, 2005).
3. The systematic literature review is conducted by several authors to highlight the research trend in Industry 4.0. For instance, Santana & Lopes (2020) present the learning methodologies and Industry 4.0 skills development. Further, Ghobakhloo, et al., (2021) conducted a systematic literature review on the concepts, definitions, and functionality of Industry 4.0. These studies indicate the existence of wealth and diversity of generic knowledge. This study is built upon these insights, tailoring them for a more integrated and focused approach to meet the specific needs of auto component manufacturing firms. This SLR reviewed the existing Industry 4.0 readiness framework's that focus on manufacturing operations and propose a framework. This framework was further studied and refined within the context of Indian auto component firms.

3.2 Theoretical Background

In the context of technology adoption, various theories have been used within the reviewed literature to understand the adoption of Industry 4.0. Studies have commonly used Resource Based View (Zheng, et al. 2021; Li et al., 2022, Schlecht et al., 2021); Network theory (Schlecht et al., 2021); Schumpeterian innovation (Schlecht et al., 2021); Socio-technical system theory (Perez-Lara et al., 2020); Technology Acceptance Model (TAM) (Chatterjee, et al., 2021); Technology-organization-environment (TOE)

framework (Lee et al., 2021; Chatterjee, et al., 2021) and Dynamic capability theory (DCT) (Li et al., 2022). Zheng, et al. (2021) used RBV to argue that business model design impacts product innovation. Within the same context, Li et al., (2022) studied the relationship between business model design on a firm's performance based on RBV and DCT. They conclude that supply chain agility mediates the relationship between business model design and firm performance. Perez-Lara et al., (2020) proposed a framework using socio-technical system theory to understand the interrelationship between three key elements, including technological system, organisational system and human operating system for vertical and horizontal integration. This framework offers insight into the significance of these three elements for digital transformation, but the framework has not been empirically tested. Chatterjee, et al., (2021) used the TOE-TAM framework to identify the determinants for the adoption of Artificial Intelligence using technological, organisational and environmental dimensions and the impact of perceived usefulness and perceived ease of use on the intention to adopt technology; significant for understanding the determinants of Industry 4.0 in the current study's context. Upon reviewing the theories, it is evident that no study was conducted to understand the impact of Industry 4.0 readiness on operational performance. Further, an integrative framework to understand what comprises Industry 4.0 readiness is not underpinned in any of the reviewed theories. To this end, this study utilises RBV to understand the relationship between Industry 4.0 readiness and operational performance.

3.3 Resource-Based View (RBV)

RBV of the firm focuses on the use of resources and capabilities, which include technologies and technological capability to achieve competitive advantage. A firm's resources including tangible (technology, equipment) and intangible (culture, knowledge, organisational structure) when combined with capabilities (skills, accumulated knowledge) are strategically aligned to fit with the firm's unique strategy, organisational processes, and business model contribute positively to performance (Galbreath, 2005 & Schroeder, et al., 2022). However, the descriptions of these resources are not similar in the literature. For example, Estensoro, et al., (2022) include products, innovation, internationalisation, alliances, strategy, leadership, and finances as the key resources regarding the transition to advanced stages of Industry 4.0; Sony and Aithal, (2020) proposed the use of variables including physical, human, organisational, technological, financial, and reputational resources for the implementation of Industry 4.0. Further, Ali and Johl, (2023) used leadership, training and learning, human resource management, teamwork, process management, and quality information and analysis as the key resources for Industry 4.0 readiness. These scholars focus broadly on the firm's transition to Industry 4.0, including human resource management, and finance areas and less explicitly on manufacturing areas, thus excluding supply chain, business model and manufacturing operations factors (Estensoro, et al., 2022 & Ali and Johl, 2023). This calls for further research to confirm the integrative model for Industry 4.0 implementation, focusing solely on transitioning manufacturing areas (Lee et al. 2021 & Trstenjak, et

al., 2022) for operational performance within the Indian auto component industry with a focused definition of resources in the context of Industry 4.0 readiness.

3.3.1 RBV and operational performance

With an emphasis on manufacturing operations, Zheng et al., (2021) argued that business model impacts performance outcomes by creating value for customers through consistently adapting to customer needs. Building upon these ideas Li et al., (2022) emphasise achieving firm performance by using firms' internal characteristics, arguing that supply chain performance can be achieved based on the existing resources and capabilities owned by the enterprise. For example, high visibility in terms of inventory, order status and production plans across parties in the supply chain allows agility in the supply chain and allows for immediate adjustment of production plans to meet customer needs (Christopher & Lee, 2004). Much of this, according to Grant, (1996), is enacted through visibility across the supply chain as facilitated by the communication and shared information among supply chain members. These studies align with RBV theory for establishing the relationship between existing resources and firm performance. A review of the literature and RBV showed the impact of technology adoption on achieving competitive advantage, where competitive advantage in the context of RBV is achieved in the form of operational performance that accrues due to resources that characterise Industry 4.0, as confirmed by Khanchanapong, et al., (2014). It is to be noted that competitive advantage, as defined by RBV, is realised through enhanced operational performance as asserted by Khanchanapong, et al., (2014); Weeks, et al., (2022); Zhu, et al., (2022). These authors have studied the impact of technologies on operational performance from an RBV perspective. This relationship is particularly looked upon in the context of the current research when considering Industry 4.0 readiness, as firms with resources that enable the adoption of Industry 4.0 are better positioned to improve operational performance, as asserted by Schroeder et al., (2022).

3.3.2 Resources for Industry 4.0 readiness in the context of the Indian auto component industry

RBV theory assumes a few premises. Firstly, organisations that belong to the same industry share a similar pool of resources. In terms of technological resources, the Indian auto component firms mainly employ automated production lines, PLC-CNC machinery, ERP systems and ICT (see **Table 3.1**). However, disparity of resources is observed amongst different tiers of suppliers as highlighted by Bhattacharya et al., (2014) and Khilari et al., (2022), resulting in varied competitive advantage across the industry. The second presumption is linked to the competitive advantage as explained by the company's strategic utilisation of resources. According to Bag et al., (2021), rapid technological changes challenge the competitive advantage of firms, requiring them to mobilise and reconfigure the existing resource base. With this considered, it can be argued that auto component firms are required to combine their resources and existing IT infrastructure to achieve a competitive advantage. Nevertheless, with the disparity of resource bases among different tiers (discussed in **section 2.6.1**), the integration of

resources may remain uneven across the industry. However, a clear strategic vision for the deployment of Industry 4.0 technologies will reduce the inequality of resources across all the tiers by providing a common pool of resources to enhance Industry 4.0 readiness across all tiers.

These ideas are supported by Prajapati et al., (2024) and Rana et al, (2025) who argued that the main challenges in adopting Industry 4.0 technologies within Indian auto component firms are inadequate IT infrastructure and a lack of frameworks to adopt Industry 4.0 technologies. Building on the ideas of existing IT infrastructure and capabilities, Industry 4.0 readiness indicates the preparedness level of firms to adopt Industry 4.0, which varies due to the non-uniformity of resources across the industry as noted by Wankhede and Vinodh (2023). RBV in this context emphasises the heterogeneity in resources possessed by firms, thus resulting in different competitive advantages across firms. Therefore, firms that lack these resources may struggle to gain a competitive advantage. Moreover, broadly Industry 4.0 readiness means firms already have those resources which prepare them to adopt Industry 4.0, giving them a competitive advantage (Schumacher et al., 2016; Chonsawat & Sopadang, 2020) as all firms are not on the same readiness level (Crešnar, et al., 2020) due to the variations in resources owned by them (Chonsawat and Sopadang, 2020 & Trstenjak, et al., 2022).

Industry 4.0 readiness has received substantial attention from researchers who have identified various Industry 4.0 readiness factors, which majorly include resources (Simetinger and Zhang, 2020; Bhatt and Kumar 2022; Schroderus et al., 2022). These resources have received further investigation by numerous commentators (Kagermann, 2014; Hermann et al., 2016; Miranda et al., 2017; Tasmin, et al., 2020; Herceg et al. 2020; Unhelkar et al., 2022) who argued that the existence of some preliminary technologies, including ERP, ICT, RFID, sensors, and cloud computing reflects the readiness of firms. In the context of Industry 4.0 readiness, and according to RBV, these are valuable resources that help firms gain a competitive advantage (Xu, et al., 2014 & Chae, et al., 2014) in the form of enhanced operational performance (Aydiner et al., 2019 & García-Alcaraz et al., 2020), and supply chain efficiency (Flynn, et al., 2010 & Chahal, et al., 2020).

Notably, however, it is maintained by Perody and Sudhakara (2024) that within the auto component industry, tangible assets, including automation, ICT and intangible resources such as data analytics capabilities, contribute to achieving operational efficiency and supplier competitiveness within the value chain. Within this industry, the pool of tangible resources, including automation in combination with machine and computer system integration, programmable logic controllers (PLCs) and ICT infrastructure, is increasingly used by suppliers to synchronise the production process with OEMs and enhance production process efficiency, which is critical for competitive advantage (Singh et al., 2007; Prajogo and Olhager 2012; Dubey et al., 2018). For instance, Motherson Sumi, known for being the most diversified component supplier in the Indian automotive industry, leverage the automated production lines, IoT and ICT for real-time monitoring of OEMs' production schedules. However,

according to Barney (1991) the data collected from all these devices, while identified as a crucial resource, it leads to operational performance only when it is utilised for the decision-making process. It is argued by Sathyan et al., (2021), that auto component firms which effectively utilise data are better positioned to respond to customer demands as manifested by Motherson Sumi. Nevertheless, according to Črešnar, et al., (2022) & Alcácer, et al., (2021), IT infrastructure is a key requirement for leveraging data to make informed decisions.

While RBV is used as a prominent theoretical tool to identify the resource base for achieving competitive advantage, its application across the manufacturing sector, especially across the Indian economy, needs contextual adaptation to align with the Industry 4.0 readiness based on the existing technological resources and infrastructure (the summary of resources base within Indian auto component industry and their relevance to Industry 4.0 transition is discussed in **Table 3.1**). As the Indian auto component industry is characterised by a tiered system (discussed in **section 2.5**), which is significantly controlled by OEMs capabilities and resources (see **section 2.6**). The auto component ecosystem is highly influenced by the resource allocation and utilisation practices of OEMs. Further, there is resource asymmetry within the tiers. It is maintained by Herbst (2021) that Tier 1 suppliers achieve the advantage from OEMs' resource spillovers, while Tier 2 and Tier 3 often struggle during the technology adoption process due to systemic exclusion from the network system. Small firms encompassing Tier 2 and Tier 3 lack the integrated ERP system, communication technologies, which are conducive to Industry 4.0 readiness. This is also observed in Indian auto component firms by Riat (2018) that Tier 1 firms have access to strong technological composition and manufacturing capacities as compared to Tier 2 and Tier 3 firms (as discussed previously in **sections 2.4.1 and 2.6.1**).

Table 3.1: RBV component in the context of the Indian auto component industry and its relevance to Industry 4.0 readiness

RBV component	Examples in the Indian auto component industry	Relevance to industry 4.0 readiness
Tangible resources	Automated Production lines, CNC/PLC, IoT	real-time decision-making through the interconnectivity of machines and monitoring systems (Miranda et al., 2017; Schlecht et al., 2021; Simões et al., 2021) (discussed further in sections 4.2.1.1 and 4.2.1.2).
Intangible resources	- Vision and leadership towards technology integration - Interdepartmental collaboration - Culture of organisations - Collaboration with external experts	- External technological experts accelerate the adoption of innovative technologies (Simões et al., 2021) (see section 4.2.3.3). - An organisational culture of sharing ideas and knowledge facilitates vertical integration (Kiraz et al., 2020) (see section 4.2.4.1). - top management identified as the necessary resource for adopting Industry 4.0 (Antony, et al., 202 and Sureshchandar, 2023) (discussed in section 4.2.4.2).
Network resources	- Access to R&D - Collaboration with OEMs	Partnership with OEMs facilitates tech transfer and standardisation

3.3.3 RBV role in innovation

According to Turner and Williams, (2005), the automotive manufacturing supply chain is widely recognised as one of the most complex supply chains, which is exacerbated by globalisation and interconnectivity among supply chain partners. Consequently, the global competition is changing the face of the Indian automotive industry, pushing companies to enhance competitiveness by adopting supply chain best practices, which are based on strong R&D, robust infrastructure and integration of advanced technologies (Dhawan et al., 2018). In such a scenario, RBV serves as a meaningful framework to understand the role of a firm's R&D and strong technological infrastructure in the innovation process for achieving competitive advantage. RBV argues that the firm's resources, which are valuable, rare, and difficult to imitate (Barney, 1991) improve the competitive position of the firm, including the cost (Porter, 1980) and efficiency (Ojha, et al., 2013; Peteraf, 1993) for differentiation (Barney, 1991; Newbert, 2008). For example, companies like Bharat Forge are making continuous efforts to leverage the engineering talent and advanced forging technology for designing and delivering high-value components such as crankshafts (Bharat Forge Limited, 2021). This has resulted in Bharat Forge becoming one of the world's largest forging companies (Indian Brand Equity Foundation, 2024). The strategic initiatives undertaken by Bharat Forge, encompassing the application of engineering expertise in the adoption of advanced technologies and investment in R&D, indicate that innovation is not always the result of external pressures, as previously discussed by various commentators (Zahra and Bogner 2000; Jansen et al., 2006). While Indian auto component firms have built capabilities in achieving cost-effective manufacturing while leveraging frugal innovation, RBV magnifies these resources for the creation of innovative products, as highlighted in the case of Bharat Forge. RBV can thus encourage auto component firms to identify the internal resources that can enhance the competitive advantage of the firms by creating innovative products (Lubis, 2022).

Furthermore, supply chain complexity within the auto component industry arises from the multifaceted interplay of the automobile and auto component industry, accompanied by multiple stakeholders including OEMs, Tier 1 suppliers, and Tier 2 suppliers (Bhattacharya et al., 2014 & Mutschler, 2023). The complexity across the supply chain is further amplified by a broad spectrum of physical resources, an array of data and numerous operational processes. All this information can be used to create a meaningful segment of customers by identifying differentiated product development based on the characteristics of each segment, resulting in further innovation or the creation of a new product or service (Liang, 2009; & Marzi, et al., 2021). This is an example of RBV application where internal resources in the form of data can be made available to the supplier related to new product development. Much of this, according to Arvidsson and Melander, (2020) & Reche, et al., (2020) is enacted through a shorter product development cycle as facilitated by consistent open communication between the manufacturer and supplier. The advantage is not only limited to product development, as information

resources result in enhancing the efficiency of operations and a reduction in costs due to the availability of the right data at the right time as highlighted by Fuchs, et al., (2018) & Pop, (2020).

However, for assuming the above-stated benefits and efficiencies across the supply chain, R&D is considered the enabler of technological development within the auto component industry, as noted by Tiwari and Kalogerakis (2017). For instance, Bosch's high investment in R&D centres within India has resulted in the development of automated safety systems and connected car solution for Indian automotive OEMs. Such resource-driven technological development advances the firm's competitiveness within the domestic and global markets. Despite the benefits witnessed by the OEMs, the overall R&D remains low in the Indian auto component sector, hampering the innovation capacity of the industry (Niti Aayog, 2022). SMEs which constitute a significant portion of the Indian auto component industry, are facing challenges in integrating advanced technologies due to a lack of R&D. It can be inferred that as the adoption of advanced technologies such as robotics, artificial intelligence continues to rise in the automobile industry, the high cost of investment, insufficient infrastructure and negligible R&D within the Tier 2 and Tier 3 suppliers across the auto component industry remain a roadblock for the industry's innovation drive as noted by Jain and Ajmera (2021). From RBV perspectives, it becomes essential for auto component firms to identify and leverage existing resources while developing internal capabilities in a resource-constrained environment. This strategic transformation is thus critical for transforming the existing resources into a competitive advantage (Lubis, 2022).

With the advent of Industry 4.0 readiness, which leverages the existing resources and capabilities (Schroeder et al., 2022), the RBV framework becomes particularly relevant to zoom in on the current resource base of Indian auto component firms. In the context of this study, Industry 4.0 readiness is argued to be a strategic capability of the firm that combines resources and capabilities through integrating and reconfiguring the existing internal resources into organisational processes (Caldeira and Ward, 2003) for operational performance. Operational performance is also linked with internal and external resources owned and controlled by an organisation. An organisation that combines these resources always holds an advantage over its competitors (Schroeder, et al., 2022). Internal resources such as technologies, management perspectives, structures, and relationships are available within the boundaries of the organisation. The efficiency with which these resources are managed determines the firm's potential to gain a competitive advantage (Dyer & Singh, 1998). However, according to Latunreng and Nasirin (2019) internal resources are not always sufficient to gain the competitive advantage; external resources play a significant role. These resources include relationships with suppliers, customers, and external experts (Fahy, 2002). It is noted by Latunreng and Nasirin (2019) that productivity also improves when organisations manage these relationships with external entities and combine the resources in a unique way that competitors would be unable to do. It can be understood that there is a lack of a standard definition of resources for RBV studies in the context of Industry 4.0

readiness (discussed in **section 3.3**). The inconsistency in definition as to what entails Industry 4.0 foundational resources has been an issue for using the RBV in Industry 4.0 readiness. This research seeks to identify internal and external resources that would enhance the Industry 4.0 readiness for achieving operational performance. These resources, while developed theoretically in the context of different studies (discussed in **sub-sections of section 4.2**), are rarely tested empirically in the context of Industry 4.0. In this study, Industry 4.0 readiness is conceptualised as a strategic capability of firms to combine and reconfigure internal and external resources for achieving competitive advantage (Caldeira and Ward, 2003). This research, therefore, examines the relationship between Industry 4.0 readiness and operational performance in the context of the Indian auto component industry by using RBV as a suitable framework. The framework enables an understanding of how firms that achieve Industry 4.0 readiness can gain an operational performance advantage in the digital environment.

3.4 Industry 4.0 adoption

This section provides an overview of the most researched areas within Industry 4.0 including a discussion on digital transformation in manufacturing. The literature then discusses the challenges and barriers to digital transformation. The literature in this section focuses on the challenges faced by firms in digitally transforming manufacturing operations, and the factors that can facilitate or hinder the adoption of Industry 4.0 technologies. These challenges laid the foundation for another theme that emerged in the literature encompassing the maturity and readiness model. The literature is reviewed to identify the gaps and derive the research questions in the context of the current study.

3.4.1 Understanding digital transformation in the context of Industry 4.0

Industry 4.0 is identified as a major driver in transforming the manufacturing industry via digitisation, which means the integration of real and virtual worlds to introduce the concept of smart manufacturing. Kiraz et al., (2020) suggested that the foremost step towards digitisation is identifying the right roadmap. This roadmap evaluates an organisation's digital transformation readiness and capability before making any investment decisions. Therefore, it is understood that Industry 4.0 is not merely confined to the implementation or adoption of technology; it also necessitates changes to business models, manufacturing processes and supply chains within companies (Pérez-Lara et al., 2020; Teixeira and Tavares-Lehmann, 2021; Konstantinidis, et al., 2022; Núñez-Merino, et al., 2022). This demands a paradigmatic shift, wherein the transformational process serves as a catalyst, ushering forth the development of a robust Industry 4.0 infrastructure within existing business models and processes (Bordeleau and Felden, 2019; G, et al., 2019; Giudice, et al., 2021; Paiola, et al., 2021; Cruzara, et al., 2021). It is within this context that literature is heavily concentrated on understanding elements of digital transformation including what entails digital transformation, challenges and barriers and strategic frameworks for realising digitisation leveraging Industry 4.0 technologies (Chonsawat &

Sopadang, 2020; Ericson, et al., 2020; Herceg et al., 2020; Lee, et al., 2021; Cruzara, et al., 2021; Ratte, et al., 2022; Khourshed, et al., 2023).

Industry 4.0 technologies are becoming driving factors of digital transformation in the present age. The debate concerning digital transformation within the context of Industry 4.0 is multifaceted due to the involvement of several terms such as digitisation, digitalisation and digital transformation which are often used interchangeably in the literature (Schallmo, et al., 2017 cited in Lee et al., 2021; Nambisan, et al., 2017 cited in Lee et al., 2021; Boffa and Maffei, 2023). This interchangeability creates ambiguity in understanding the conceptual definition of digital transformation in the context of Industry 4.0. According to Lee, et al., (2021), digitisation refers to the conversion of analog information to digital information; digitalisation utilises digital technology to improve business processes. Digital transformation on the other hand is widely understood as the integration of digital technologies to transform existing processes by Imbar et al., (2022) & Lasi et al., (2014) cited in Ratte et al., (2022). In contrast, Müller and Voigt, (2017) describes digital transformation as the concept of transforming an organisation's business model to capture value. Similarly, King & Grobbelaar, (2020) emphasised the creation of new value propositions like personalisation, and enhanced customer experience by transforming the value chain. Savastano et al., (2019) argue that for companies to remain viable in digital age, redesigning the business and operational processes is the preliminary step towards digital transformation. Hu et al., (2024) identified the digital transformation process as the overhaul of strategy, capabilities, and organisations to accommodate digital technologies such as IoT, and CPS.

The scholars' perspectives are divided into two distinct yet interconnected domains: one focuses on technology-centric research and the other delves into the strategic prerequisites for achieving digital transformation. This implies that digital transformation precedes the application of Industry 4.0 technologies. Therefore, digital transformation is not merely a technology upgrade, rather it encompasses the scope of transformation in terms of integrating the whole organisation (Schwab, 2017 cited in Ratte et al., 2022), technology adoption patterns, and associated benefits. According to Vial (2019: 2), digital transformation is “a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies”. According to Cruzara et al., (2021:122), “Digital transformation allows organisational actors to communicate promptly with one another, which takes decision-making to the next step in terms of collaborations and inter-organizational relationships, such as collaborative networks”.

Drawing on the perspectives provided by Vial (2019) and Cruzara et al., (2021), digital transformation in this research is understood as the capability of organisations to create a network of stakeholders for seamless communication and decision-making across manufacturing operations to improve organisational performance (Zhang, et al., 2021). This aligns with Hermann et al., (2016) perspective

of digital transformation considering the importance of connectivity, communication, and the creation of a network for an agile and efficient decision-making framework which is essential to achieve operational efficiency. This is further supported by Ivanov et al., (2022) indicating the necessity of connectivity and integration across the supply chain within manufacturing operations for enhanced efficiency.

Digital transformation is arguably triggering strategic changes including changes in processes, activities, and network structure. Such intricacy poses significant challenges for companies to navigate through the nuances of digital transformation effectively. These challenges range from technological hurdles to a lack of strategy (discussed in **section 3.4.2**). Delving into these challenges is imperative to identify the comprehensive solutions which would pave the way for the smooth transformation of these businesses and the adoption of Industry 4.0 technologies.

3.4.2 Challenges and barriers to digital transformation in manufacturing firms

A significant portion of studies on Industry 4.0 have addressed the challenges faced by firms in digitally transforming manufacturing operations (Herceg et al., 2020; Fernández-Miranda, et al., 2017; G, et al., 2019; Stornelli et al., 2021). The various aspects where companies are lacking in digitally transforming their businesses to adopt Industry 4.0 technologies gave a clear idea indication to focus on these specific areas. This includes a clear strategy and proper technology integration across various operations and departments in the organisation to enable digital transformation. Two key areas emerged from the reviewed literature, including technological integration challenges and organisational and structural barriers.

3.4.2.1 Organisation and structural challenges

Stornelli et al. (2021) have identified the integration of Industry 4.0 technologies into the operational processes of organisations as a significant challenge influenced by various internal (e.g., operational processes, communication etc.) and external factors (e.g., suppliers management, strategic partnerships etc.) that ultimately affect digital transformation. Further, the lack of changes in operational and workflow improvements poses a significant barrier to the successful adoption of these technologies (Szalavetz, 2019 cited in Stornelli et al., 2021). Organisations encounter several internal factors that can hinder the successful adoption of Industry 4.0 technologies, such as challenges related to Buyer-Supplier Relationships (BSR) (Patrucco et al., 2022), limited access to information, disruptions on the shop floor (Moica et al., 2018), and technology system issues. The summary of factors identified as key challenges for the adoption of Industry 4.0 is presented in **Table 3.2**.

Table 3.2 : Factors identified in the literature outlining the key challenges for the adoption of Industry 4.0

Study	Focus	Factors	Common factors across studies
Stornelli, et al. (2021)	Barriers and enablers in the adoption of Industry 4.0 technologies	Barrier - Technology integration and strategy Resistance to change Enablers – strategy to incorporate technology into organisational processes. Alignment between operations and strategy	• Lack of Technology Integration • Strategy
Herceg et al. (2020)	Opportunities and challenges relevant to the implementation of Industry 4.0	Driving force – attempt to reduce cost. Market competition Customer satisfaction Improving efficiency Barrier – Lack of management competencies Lack of integrated communication Lack of standard processes	• Lack of strategy • Lack of technology integration
Pozzi et al. (2021)	Success factors for the adoption of Industry 4.0 technologies	Success factor – top management involvement in Industry 4.0 initiative Training Competitive priority Organisational culture	• Success factor – Clear strategy
Črešnar et al. (2022)	Factors for implementing Industry 4.0 technologies.	Technological factors - manufacturing concepts and technologies IT concepts and technologies Non-technological factor - strategic and organisational feature; product and service; Supply chain; business model; law and policy; culture and openness; organisational structure	• IT infrastructure • Clear strategy • Technology integration
Arnold et al., (2018)	Relevant factors that influence the adoption of Industry 4.0	The company's top management and high level of competition positively influence Industry 4.0 adoption	Management support
Alcácer et al., (2021)	Barriers to the adoption of Industry 4.0 technologies	Barriers - lack of I4.0 adoption strategy Low usage of data for decision-making. Underdeveloped IT structure	• Lack of strategy • Lack of technology integration
Fernández-Miranda, et al., (2017)	Challenges of Integrating Industry 4.0	Challenges - investment in IT infrastructure Lack of knowledge	• Lack of IT infrastructure • Lack of technological integration

While these challenges are extensively discussed, there is no formal process to overcome these challenges in terms of how organisations must carefully plan their adoption of new technologies and develop strategies that effectively manage these factors. For example, Pozzi et al. (2021) emphasised the significance of aligning the organisational structure with the appropriate technologies for operational processes. Stornelli et al. (2021) further supported this notion by pointing out that operational changes pose significant constraints during the pre-adoption and adoption phases of Industry 4.0 technologies, which can persist in the post-adoption phase if not designed properly, hindering the organisation's ability to fully realise the potential benefits of such technologies.

Herceg, et al., (2020) highlighted the absence of an integrated communication protocol and inadequate organisational structure further indicating the lack of technological infrastructure demonstrating

insufficient use of information technology and ERP systems. The digital transformation in the context of Industry 4.0 presents a significant challenge for organisations arising from the lack of foundational IT infrastructure that can facilitate an automated environment on the production shop floor (Pérez et al., 2022). Müller et al. (2018) conducted a survey involving 68 small and medium-sized enterprises (SMEs), revealing challenges in establishing an IT-enabled automated ecosystem for seamless communication between suppliers and customers, with access to real-time information. Additionally, Pérez et al., (2022) highlight that low connectivity in production monitoring and control hinders the digital transformation process. Parente, et al., (2022) also found poor technological infrastructure as the key challenge for digital transformation. Notably, the absence of technological infrastructure is identified as a significant barrier to digital transformation across several studies (Fernández-Miranda, et al., 2017; Črešnar et al., 2022; Trstenjak, et al., 2022; Parente, et al., 2022).

3.4.2.2 Lack of strategic framework

Building upon the challenges discussed in **section 3.4.2.1**, the strategy to incorporate technology into organisational processes is identified as the key enabler (Pozzi, et al., 2021; Stornelli, et al., 2021). Consequently, Trstenjak et al., (2022); Črešnar et al., (2022); and Herceg, et al., (2020) have identified frameworks to address the issues presented in **Table 3.2**. Trstenjak et al.'s (2022) model for optimal strategic planning serves as a useful starting point for companies seeking to adopt Industry 4.0 technologies and digitising their processes. The model assesses the company's implementation priorities for Industry 4.0 elements, taking into account critical factors such as organisational and human resources, infrastructure, and smart process planning during the planning phase. It emphasises the importance of strategic organisational connectivity throughout the supply chain and decentralisation of the company to achieve successful implementation of Industry 4.0. Furthermore, the model evaluates the company's readiness level in terms of potential challenges such as worker innovativeness, collaboration, and mindset. However, the model does not include any specific framework or guidelines for transitioning manufacturing industry operations.

Companies require a well-thought-out strategy to integrate new technologies into their existing systems while addressing any challenges that may arise during the process. While the planning phase is critical, careful consideration and attention must also be given to the implementation phase as emphasised by Pozzi, et al., (2021). In conclusion, while Trstenjak et al.'s (2022) model is a valuable starting point for Industry 4.0 adoption and digitalisation, a more comprehensive framework is necessary to guide companies through the entire process, from planning to implementation in terms of measuring the readiness level (Alcácer et al., 2021).

Recent studies by Črešnar et al. (2020) have explored the relationship between Industry 4.0 (I4.0) readiness and traditional management tools, such as Six Sigma, Total Quality Management (TQM), Radio Frequency Identification (RFID), balance scorecard, rapid prototyping, customer segmentation,

and digital transformation. It was found that these traditional management tools have positive implications for Industry 4.0 readiness and can support the effectiveness of technological advancements. Furthermore, these models analysed an organisation's readiness for initiating the digitisation process and measuring readiness can be considered a foremost step in the transitional strategy by evaluating the current state. Evaluating the limitations inherent in the research, it is crucial to acknowledge the impact of readiness on operational efficiency. Further, the adoption of Industry 4.0 technologies can be challenging for organisations due to the need for adjustments in non-technological dimensions, such as organisational culture, leadership, and learning practices (Leso, et al., 2023).

In a further study Črešnar et al. (2022), highlight the importance of considering both technological and non-technological factors in achieving operational efficiency and improving performance in manufacturing processes. For adoption of Industry 4.0, a framework that integrates technological and non-technological factors including the production process, communication process, supply chain integration, and inventory control is proposed. This holistic approach considers the interrelationships between technological and non-technological dimensions and emphasises the need for a thorough analysis of an organisation's internal processes to identify the adjustments required for successful technology adoption. Herceg, et al., (2020) highlight non-technological dimensions, such as reducing costs, as the strongest driver for implementing Industry 4.0, along with other key drivers such as market competition, reducing error rates, meeting customer and partner demand, and improving efficiency to enhance customer satisfaction. These drivers are given more weightage compared to an increase in return on assets or enterprise profitability. Implementing Industry 4.0 can lead to improvement in flexibility, expenditure reduction, improvement in lead time, better market positioning, improvement in quality, full control of corporate processes, reliable operations, compliance with customer needs, and minimised stoppage in production (Herceg, et al., 2020). These elements represent a significant change in operational processes, aimed at achieving greater efficiency and improved productivity. Though the research is promising in highlighting the impact of transformation on operational efficiency, the study lacks any empirical evidence to establish the relationship between digital transformation and operational efficiency.

Overall, these studies provide valuable insights into the importance of considering both technological and non-technological factors in the adoption of Industry 4.0 technologies. By taking a holistic approach, organisations can better understand the challenges and opportunities presented by Industry 4.0 technologies and develop strategies to maximise their benefits. By comparing the findings across studies, it becomes evident that the literature offered two perspectives in terms of the challenges faced by businesses in Industry 4.0 implementation.

The first perspective as provided by the various studies in this cluster on Industry 4.0 adoption and digital transformation suggests that a comprehensive approach is necessary to fully realise the potential

benefits of these technologies. These studies emphasise the importance of careful planning, organisational alignment, and strategic thinking prior to the adoption and implementation of Industry 4.0 technologies which are also termed as the Industry 4.0 enablers in the reviewed literature (Pozzi et al., 2021; Črešnar et al., 2022; Arnold et al., 2018). Further, a lack of strategy is identified as the incapacity of the firm to identify the opportunity and devise the strategy to incorporate the opportunity into processes and organization (G, et al., 2019). Firms are struggling to understand the right strategy around Industry 4.0 technologies (Herceg, et al., 2020; Ericson, et al., 2020; Favoretto, et al., 2021). The second perspective offered by the studies emphasised the lack of technological integration (presented in **Table 3.2** above) and suggested that firms operate in silos and there is no connectivity between processes and functions which is the preliminary for the industry 4.0 adoption according to Moica et al., (2018). The need for the integration of digital technologies into the company's operations is also highlighted as a critical factor in creating value and improving the customer experience by Müller & Voigt, 2017). Similarly, Korner, et al., (2020) identified customisation as the key enabler of Industry 4.0 for enhancing responsiveness by satisfying individual customer needs. Furthermore, Moica et al., (2018) & Müller and Voigt, (2017) point out that operational changes pose significant constraints during the adoption phase, which can persist in the post-adoption phase if not designed properly.

Therefore, it is essential to carefully consider the organisational requirements and strategic goals when selecting and integrating new technologies into operational processes. This implies that a comprehensive understanding of the challenges is necessary before a well-planned framework can be developed; one that spans multiple dimensions of operations, strategy, and technology (Müller and Voigt, 2017 & Moica et al., 2018). Various frameworks that have emerged in response to these considerations are reviewed in the subsequent section.

3.4.3 Maturity/Readiness models as strategic frameworks

The articles discussed in the previous section have recognised the need to address the challenges faced by companies in implementing Industry 4.0 technologies. As a result, various maturity and readiness models were developed by various researchers as a foremost step to address the challenges faced by organisations concerning the lack of strategy to adopt Industry 4.0. Of the 124 articles selected in the study, 13 articles focused on the maturity or readiness model as steps for digital transformation as shown in **Table 3.3**. The sample includes several maturity and readiness models as presented in the **Table 3.3**.

The readiness of enterprises is imperative for the implementation of Industry 4.0 (Chonsawat and Sopadang, 2020; Alcácer et al., 2021; Hajoary et al., 2023). The definition of readiness is unclear in the literature and readiness and maturity models are used interchangeably (Simetinger and Zhang, 2020; Jesus and Lima, 2020; Khourshed, et al., 2023). The readiness model is defined as a tool to measure the characteristics, that manufacturing firms have for the transformation process and represents the 'as-is' analysis of digitisation within firms (Schumacher et al., 2016 & Blatz et al., 2018 cited in Chonsawat

and Sopadang, 2020). Readiness can be understood as the preliminary indication towards the transformation or implementation of Industry 4.0 which takes place before any engagement in the Industry 4.0 maturing process (Schumacher et al., 2016 cited in Chonsawat and Sopadang, 2020). An assessment of the readiness level within an organisation can avoid the risk and uncertainty triggered by Industry 4.0 (Agca et al., 2017 cited in Chonsawat & Sopadang, 2020). Literature suggests that all organisations are not on the same level (Crešnar, et al., 2020) and the success of implementing Industry 4.0 depends on the readiness level of an organisation (Chonsawat & Sopadang, 2020, Trstenjak, et al., 2022). Various readiness models have been found in the research as presented in **Table 3.3** for assessing the readiness level.

Table 3.3 : Summary of maturity and readiness models identified in extant literature:

Authors	Model	Key concepts	Methodology
Alcácer et al., (2021)	Readiness model	5-level scale of readiness level. Dimensions: Strategy and organisation, smart factory, smart operations, smart products, data-driven services, employees	Survey - Micro, small, medium and large enterprises (Portugal)
Ávila-Bohórquez and Gil-Herrera (2022)	Maturity model	5-levels scale of digital maturity (Service; Operations; Quality; Products; Documented information- Big Data; Leadership and strategy; Communication; and Culture and people)	Survey - SMEs (Latin America)
Bhatt and Kumar (2022)	Maturity and readiness model	Dimensions identified: Strategy, Organization, Supply Chain, Manufacturing, Operations, Customers, Product, Services, Business Model, IT, People, Culture	Literature review
Chonsawat and Sopadang (2020)	Readiness model	Rating score (0, 100%) Dimensions: Organisational resilience, Infrastructure system, manufacturing system, data transformation, digital technology	Single case validation in Small Enterprise (Plastic Industry) in Thailand
Hajoary et al., (2023)	Structured steps	Three-step process: measure, determine and depict (utilised weighted average technique using four-level scale across six dimensions: degree of strategy, leadership, measurement (KPIs), leadership, collaboration, employee capability, and skill acquisition	Single case validation in MNC
Jesus and Lima (2020)	Maturity model	Methodology for developing maturity models: Characterization of the application context; Literature review for conceptual characterization; Interaction with practitioners and experts; Development of surveys;	Literature review
Khourshed et al., (2023)	Readiness model	9 level ranks of factors (Barriers) that affect Industry 4.0 implementation	Survey - Manufacturing Industry (Egypt)
Rübel et al., (2018)	Structured steps	Implicit, Defined, validated, analysed, optimised	Literature review
Schroderus et al., (2022)	Maturity model	Dimensions identified: Organisational governance, strategy, risk management, competencies and culture, Product & Production Technology, Data Analytics, Product Lifecycle Processes	Literature review
Spaltini et al., (2022)	Maturity Model	5-levels scale of digital maturity (Product-Services, Processes, Platform, People, Partnership, Performance)	Survey - Manufacturing SMEs (Europe)
Simetinger and Zhang (2020)	Review study	Reviewed existing maturing model (dimensions identified: Strategy, Value Chain, organisation, Human Resources, Technology)	Literature review

Sütőová et al., (2020)	Structured steps and maturity model	The 5-level scale of maturity (weighted average). Dimensions: Business Model, Product and Service Portfolio; Market and Customer Access; Value Chains and Processes; IT Infrastructure; Compliance, Legal, Risk, Security; Organisation and Culture Steps: Measurement, calculation, visualisation, comparison of level among dimensions, benchmarking against best in segment, identification of needs, learning and development	Survey - Automotive Industry in Slovakia
Trstenjak et al., (2022)	Readiness model	Five levels scale (weighted average). Dimensions: smart process planning, infrastructure, organisation and human resources.	Single case validation in Croatia metal machinery company

Total number of studies = 13 studies

Further, according to Schroderus et al., (2022), the maturity of technology in an organisational context is one of the important factors for implementation, upgrading, and transforming various aspects of an organisation. The implementation of Industry 4.0 is highly guided by digital maturity of the firms. The concept of digital maturity is recently established in literature which explains the current state or degree of completion or perfection of the desired transformation within an organisation (Schroderus et al., 2022; Schumacher et al., 2016; Sütőová et al., 2020). The concept of maturity and readiness underscores the significance of these models within the digital transformation process highlighting their implications on the Industry 4.0 adoption. Rübel et al. (2018) & Sütőová et al. (2020) have explored the development of maturity models for managing business models in the context of Industry 4.0 which merged the business model canvas and Industry 4.0 concepts to identify the strategic and operational maturity of the firm. Further, Müller, et al., (2018) highlight the importance of addressing integration strategies to fully leverage the potential benefits of Industry 4.0, offering recommendations for investigating key activities, partners, new customer segments, new business models outlining value propositions, and new key resources related to Industry 4.0. Simetinger and Zhang (2020) compare prominent Industry 4.0 maturity models to identify the critical traits necessary for successful implementation, emphasising the need to integrate dimensions such as strategy, value chain, organisation, human resources, and technology in order to advance the maturity of organisations on the maturity scale, requiring a framework that supports the digital business model, strategies, and integration scenarios. Spaltini, et al., (2022) introduce a maturity model which includes "6Ps": People, Processes, Products, Platforms, Performance, and Partners, providing a comprehensive assessment of the digitalisation level of manufacturing SMEs, and help SMEs gauge their current maturity level in each of these areas and provide a roadmap to achieve Industry 4.0 capabilities but does not extensively explore the development of the roadmap itself. It primarily focuses on assessing the current state of SMEs and stepping up to reach the target level of digital maturity, rather than exploring the development of the roadmap.

Sütőová et al., (2020) developed an Industry 4.0 learning and development model that helps determine the competencies and skills required by the workforce for successful implementation of Industry 4.0 technologies, emphasising the importance of prioritising the horizontal integration of processes and data flows with customers and suppliers, along with the adoption of new and innovative business models. Jesus and Lima (2020) have identified essential factors that are necessary for developing maturity models for Industry 4.0, both generic and specific. They suggest critical factors that must be considered when developing a specific maturity model aimed at SMEs. On the other hand, Ávila-Bohórquez and Gil-Herrera (2022) have validated the maturity model proposed by Schumacher et al. (2016) for assessing Industry 4.0 readiness and maturity of manufacturing enterprises. However, the need for further research to advance the strategy and operations dimensions to facilitate the adoption of Industry 4.0 in SMEs has been identified.

In summary, the authors have each used dimensions most suited in the context of their respective research to identify the readiness level across firms. Literature on the process of digital transformation suggests that maturity/readiness models are a structured approach to guiding organisations towards an ideal state, taking into account accounts various dimensions (as listed in **Table 3.3**). However, while these models provide a comprehensive overview, none specifically cater to the needs of the Indian auto component manufacturing industry and the general nature has not fully addressed the complexities of the automotive supply chain. Although these dimensions could collectively benefit auto component firms, there is a notable absence of models in the literature specifically designed for them. The assessment of digital maturity not only facilitates the identification of gaps and determination of critical focus areas for digital transformation in the context of Industry 4.0 but also underscores the importance of understanding that manufacturing firms exhibit different ways of perceiving the various dimensions (Leyh et al., 2016 cited in Chonsawat and Sopadang, 2020).

3.5 Industry 4.0 technologies in modern manufacturing

The theoretical facets of digital transformation, along with the maturity models outlined in earlier discussions, offer insights into overcoming the challenges associated with digital transformation. This section shifts focus to the practical applications of Industry 4.0 technologies within the manufacturing processes highlighting the outcomes of the application of Industry 4.0 technologies. The profound impact of digital transformation on manufacturing practices is underscored by increased connectivity and integration across the manufacturing ecosystem (Zulu, et al., 2022), as well as customisation and personalised production (Ivanov, et al., 2022; Grabowska & Saniuk, 2022). The exploration is critical for understanding practices adopted by the firms before the practical application of Industry 4.0 technologies can be translated into operational efficiency as documented in the reviewed studies.

These studies within the literature were based on field studies including surveys and case studies to understand how Industry 4.0 technologies impact various areas of the manufacturing supply chain

resulting in improved performance, real-time tracking, collaboration, and operational efficiency (Grabowska and Saniuk, 2022; Dalmarco et al., 2019; Guo et al., 2020; Pérez et al., 2022). The target sample for all the studies majorly includes firms which have implemented Industry 4.0 technologies, or companies which are on the pathway to transforming their manufacturing processes to achieve the underlying benefits of Industry 4.0. The results indicated that at the operational level, Industry 4.0 technologies result in improving efficiency by including all the actors in the supply chain and for enhancing supply chain collaboration (Zulu, et al., 2022 & Bansal et al., 2023). Further, a few technologies like 3D printing and blockchain technology proved to significantly impact product customisation thus achieving a greater customer value proposition (Ivanov, et al., 2022 & Grabowska and Saniuk, 2022).

Botha, (2019) & Safar et al., (2018) highlighted that digital transformation has reshaped manufacturing business models by increasing the potential for partnerships across value networks, where the real-time availability of data with all the stakeholders in the supply chain enables data-driven decision-making. However, Zulu, et al., (2022) contend that networking extends beyond stakeholders in digital transformation, it also encompasses the interconnection of machines and processes, representing a strategic issue that impacts corporate, business and functional strategies. These studies have provided a deep insight into the areas within the manufacturing operations and supply chain where Industry 4.0 technologies hold the potential to transform the existing supply chain into a digital supply chain.

Bogner et al. (2016) extended the research into the application of Industry 4.0 technologies across production processes and vertical value chains to enhance digitalisation to boost competitiveness and efficiency. The authors focus on the integration of Industry 4.0 technologies into the functional aspects of the production process and vertical value chain in the German manufacturing industry. The study analyses the current state of digitalisation in medium and large-sized companies in the manufacturing industry in Germany and recognises the importance of automation and digitalisation in improving a company's success. Nonetheless, the research emphasises the need for more efforts to enhance digitalisation to boost competitiveness and efficiency. However, the article lacks a precise framework for achieving these objectives, and additional research is crucial to develop a comprehensive approach to digital transformation in the manufacturing sector. Moica et al., (2018) revealed how Industry 4.0 can boost business growth and competitiveness. The production company's adoption of Industry 4.0 technologies resulted in financial benefits, including increased revenue and profitability. However, the absence of a clear framework explicitly mentioning Industry 4.0 initiatives raised the importance of such a framework to guide companies in leveraging the full potential of Industry 4.0. While the company utilised an ERP system to digitise communication with customers and product development, this falls short of demonstrating transformation into other operational areas triggered by Industry 4.0.

Hopkins, (2021) conducted a study to investigate the impact of Industry 4.0 technologies specifically on the supply chain and assessed the level of preparedness of large and small firms where large firms are more ready and have adopted Industry 4.0 technologies. The results further showed that the adoption of Industry 4.0 technologies provides significant benefits to supply chain operations, including increased efficiency, cost reduction, and improved customer satisfaction. Chatterjee et al., (2021) investigated the adoption of artificial intelligence in manufacturing and production systems using technological, organisational, and environmental factors. The results highlighted the factors that influence the adoption of AI including leadership support, competency of organisation, and existing technological infrastructure. The results align with the findings of a study conducted by Arnold et al., (2018), where top management support has a significant positive effect on the adoption of Industry 4.0 technologies. Patrucco, et al., (2022) emphasised the significant impact of integrating big data analytics, cloud computing, and simulation and modelling software on supply chain performance. However, the study called for additional research to investigate how these technologies across various operational processes in the manufacturing industry improve overall supply chain performance beyond just the buyer-supplier relationship. Taghipour, et al., (2022) indicated the necessary adjustments across procurement areas including supplier selection, and digital procurement for digital transformation which impacts forecasting accuracy, reduces downtime, enhances product quality, and ensures effective inventory management. However, there is a lack of empirical evidence to establish the relationship between digital transformation requisites and operational performance.

In the same context, Ivanov et al. (2022) introduced the cloud supply chain as a generalised model, which offers a comprehensive approach to managing the supply chain infrastructure by leveraging third-party providers and Industry 4.0 technologies. This highlighted the role of technology experts towards the Industry 4.0 adoption process. This model covers various operational processes, including logistics, manufacturing, procurement, sales, returns, and warehousing, and enables businesses to outsource the management of their supply chain infrastructure effectively. Additionally, it encompasses all supply chain actors, such as suppliers, manufacturers, distributors, and customers. The model enables businesses to outsource the management of their supply chain infrastructure to third-party providers who offer physical or digital assets and cloud-based solutions to improve supply chain management. Although the research integrated various aspects of the supply chain, the effect on supply chain performance is briefly touched upon indicating efficiency and resilience as the key performance indicators. Maalmi et al., (2021) proposed a model that highlights the potential of Industry 4.0 technologies in enhancing sustainable supply chain processes in the Moroccan industrial field. The study has established the relationship between supply chain integration and environmental, social and economic outcomes with technology usage including ERP, big data analytics and collaborative technologies. The study highlighted the need for strategic and operational planning to ensure the successful implementation of the proposed model.

Realising the value of Industry 4.0 in enhancing supply chain performance, many commentators supported the idea of increased efficiency and customer satisfaction (Bogner, et al., 2016; Hopkins, 2021; Ivanov, et al., 2022), however, little evidence was found on the accepted definition of these two areas. These studies have demonstrated that Industry 4.0 technologies significantly improve manufacturing and supply chain performance by addressing issues in procurement, production, warehousing, and distribution briefly (Grabowska & Saniuk, 2022), a gap persists in the literature as to what entails Industry 4.0 initiatives. The operational performance outcomes are briefly considered by Arnold et al., (2018); Maalmi et al., (2021); Chatterjee et al., (2021); Hopkins, (2021); Patrucco et al. (2022). These studies also highlighted the relationship between Industry 4.0 preparedness and enhanced operational efficiency. Gadekar et al., (2022) conducted an empirical study that established the positive relationship between Industry 4.0 drivers and Industry 4.0 adoption. Organisational strategies, smart products and operations, government policies and stakeholders as employees and customers are identified as key enablers of Industry 4.0 adoption. The study further established the positive relationship between Industry 4.0 adoption and sustainable operational performance. While the study is significant in understanding the relationship between Industry 4.0 drivers and Industry 4.0 adoption, it does not directly address the relationship between Industry 4.0 drivers and operational performance.

To conclude, the above studies have highlighted the need to realign some key areas within the manufacturing arena including supply chain, procurement, inventory management, production system, machinery, communication system, strategy including leadership support (Bogner, et al., 2016; Moica, et al., 2018; Safar et al., 2018; Botha, 2019; Chatterjee et al., 2021; Patrucco, et al., 2022; Taghipour, et al., 2022). However, a comprehensive understanding of characteristics that reflect readiness across all these areas among the firms that have successfully leveraged Industry 4.0 technologies to impact operational performance has not been documented in the literature. Given these considerations, further investigations are required to clarify the relationship between Industry 4.0 readiness factors across manufacturing operations, supply chain and resulting operational performance. Additionally, the majority of these studies were conducted in developed economies (see **Table 1.9 – Appendix 1**), it is important to understand the requirements and bottlenecks within the growing economies for aligning the Industry 4.0 practices with the current practices in the developing economies. Based on the foregoing review in sections 3.5, an Industry 4.0 readiness framework in the context of the Indian auto component industry was not addressed in the literature, which leads to the following questions:

RQ1. What are the key readiness factors in the context of Industry 4.0 to enhance operational productivity and efficiency?

RQ 2: What are the prevailing practices in the Indian auto components industry in the context of Industry 4.0 within the horizontal and vertical value chain comprising suppliers and customers?

As no explicit Industry 4.0 readiness framework/ factors or prerequisite for the adoption of Industry 4.0 and performance measures could be identified in literature reviewed so far, section 3.6 investigates the literature on the adoption of blockchain technology in manufacturing operations and supply chains to understand readiness factors.

3.6 Blockchain adoption in manufacturing operations

One stream of research focuses on the adoption of Blockchain technology across manufacturing operations and supply chains to enhance efficiency (Lohmer and Lasch, 2020; Xu et al., 2020; Sun et al., 2022; Nuerk and Dařena, 2023). The comprehensive review of Industry 4.0 technologies adoption in manufacturing operations has guided the discussion emphasising the adoption and implications of blockchain technology across various aspects of an organisation (Lohmer and Lasch, 2020; Schlecht, et al., 2021; Li, et al., 2022; Pérez, et al., 2022). This technology is at the forefront of digital transformation, capturing the attention of researchers for its application across various domains including business models, operations, supply chain management and the Internet of Things (IoT) (Nowiński and Kozma, 2017; Weking et al., 2020; Guo, et al., 2020).

Through its intrinsic characteristics viz. decentralisation, transparency and visibility – blockchain emerges as a pivotal technology in transforming the landscape of industrial operations by fostering trustworthy collaboration across production networks through digitising the basic processes and information as noted by Xu, et al., (2020). Coupled with the Internet of Things (IoT) which revolutionises automation by machine-to-machine communication in the production fields blockchain integration amplifies the potential of digital transformation in manufacturing as highlighted by Lohmer and Lasch, (2020). Blockchain acts as a foundational technology for processing data collected from IoT systems, ensuring the security of information exchanged among interconnected machinery (Choo et al., 2020 cited in Schlecht et al., 2021). Tian et al., (2022) imply the need to integrate data capture devices or IoT systems for the adoption of Blockchain technology.

Blockchain's implications on business models have also garnered similar attention. Nowiński and Kozma (2017) investigated the effect of blockchain technology on the value and revenue elements of the business model proposing three different ways in which blockchain technology can affect the business model by authenticating traded goods, disintermediation, and lowering transaction costs. The suggested ways target the service and cost elements. Blockchain enables the addition of differentiating services of authenticating traded goods and services. The cost element is triggered because of the decline in operating cost by shortening the time for transactions. Marikyan et al., (2022) conducted a study to examine the impact of blockchain technology on value shops, value networks, and value chains. The study primarily focused on the technical characteristics of different blockchain types, including public, private, and consortium. The findings revealed that the introduction of blockchain technology brought significant changes to the existing business activities and processes, resulting in strategic

transformations in the business model. On the other hand, adopting blockchain necessitates reevaluating operational frameworks, shifting from isolated, centralised processes to a more collaborative, integrated network structure of machinery and processes, aligning with blockchain's decentralised characteristics (Xu, et al., 2020; Queiroz, et al., 2020 cited in Sun, et al., 2022; Balachander and Murugan, 2022). These studies highlight the prerequisites necessary for the adoption of blockchain technology.

The above discussion and findings from the SLR process reveal two main areas within the extant literature 1) Weking et al., (2020) developed a taxonomy of blockchain-based business models for the creation of new business models: where studies were focused on developing; Levis, et al., (2021) studied the impact of blockchain-based applications on firm's organisations, innovation and strategies by 2030, and Schlecht et al., (2021) provided an analysis of blockchain's expected future value creation potential for organisations; and 2) blockchain for operational efficiency: concerned with real-time tracking, decentralised networks improving collaboration across supply chain partners, and data sharing (Sun et al., 2022 & Balachander and Murugan, 2022). The review of the literature so far reveals that there are distinct approaches when dealing with the application of blockchain. The operational efficiency is muddled with the business model innovation and presented as an outcome rather than a standalone aspect for improving operational performance. The next section discusses these business models to understand how blockchain is adopted across business models.

3.7 Digital Business Model

A digital business model is defined as an extension of Amit and Zott's, (2012) definition of creating, delivering and capturing value by employing digital technologies. The key dimensions encompassing digitised processes, integration of customers, data analytics and collaboration with technology partners are considered preconditions required by companies to create new (digital) business models (Ahmad, et al., 2020). The study by Lee et al. (2021) highlights the importance of adopting a digital business model in manufacturing companies to create value and improve the production and customer experience.

In the reviewed literature, two forms of digital business models have emerged: digital servitisation and product service systems (Westphal, et al., 2016 & Torre and Sánchez, 2022). Digital servitisation primarily focuses on service aspects, using digital tools for value creation compared to traditional models that emphasise product delivery (Torre and Sánchez, 2022). The servitisation approach is increasingly used in smart manufacturing, characterised by customised and personalised products and data transparency along value chains, indicating the organisation's transition into a service business model (Culot et al., 2020). A new business model, the product service system (PSS), integrating products and services, has also been identified in the literature (Westphal, et al., 2016). PSS has gained recognition for facilitating the adoption of innovative services by embedding Industry 4.0 technologies (Gaiardelli et al., 2021; Boßlau, 2021). Although these models have utilised the components of digital

business models including data analytics and customisation (Safar et al., 2018 & Ahmad et al., 2020); configurations of these models within operations and processes in a manufacturing context are unclear. These models are more focused on the end result rather than the pathway for achieving those results, for enhancing the competitive advantage. Further, these models are contextualised from the perspective of the solution provider and not from the industrial operation perspective (Müller, 2019). The above studies indicate the creation of new business models that would integrate data analytics, and digitised processes within existing businesses with the advent of Industry 4.0 (Wecking, et al., & 2018; Müller, et al., 2021). Preconditions for a digital business model that would facilitate the adoption of Industry 4.0 were identified from the reviewed literature as presented in Table 3.4 (discussed in section 4.2.3).

Table 3.4 : The preconditions of the digital business model as identified in the extant literature

Digital Business model	Authors
Customer co-creation	Paschou, et al., (2018); Kohtamäki, et al., (2019); Ahmad et al., (2020); Boßlau, (2021); Linde, et al., (2021)
Collaboration and partnership – stakeholders' involvement	Kohtamäki, et al., (2019); Boßlau, (2021); Ahmad et al., (2020)
Data-driven decision	Ahmad et al., (2020); Paschou, et al., (2018); Linde, et al., (2021)

3.8 Readiness Level Assessment

An assessment of Industry 4.0 readiness level is crucial as evidenced by the numerous models found in the literature (See section 3.4.3). The readiness level measures the state of factors regarding the specific target as indicated by the readiness factor (Alcácer et al., 2021). The readiness indicators scores vary across different readiness models. Chonsawat and Sopadang's (2020) model for SME readiness measures Industry 4.0 readiness on a scale from 0 to 1 (0-100%) where 0 indicates no capability and 1 signifies full capability. The scale was divided into four levels where 0-15% indicates no Industry 4.0 activity is achieved, 15-50% suggests Industry 4.0 activity is partially achieved, 50-80% indicates achieved and 80-100% denotes full achievement. However, the distinction between “achieved” and “fully achieved” is not clearly defined, which limits the model's clarity. Leyh et al., (2016) cited in Chonsawat and Sopadang (2020) proposed the System Integration Maturity Model Industry 4.0 (SIMMI 4.0) model which measures the IT system readiness through five stages: Stage 1 for the basic digitisation level; Stage 2 for cross-departmental integration; Stage 3 for horizontal and vertical digitisation; Stage 4 for full digitisation, and Stage 5 for optimised full digitisation. In this model, Stage 1 indicates that the company has not addressed Industry 4.0 considerations while Stage 5 showcases full adoption of Industry 4.0, with comprehensive digitisation of internal and external operations.

Trstenjak et al., (2022) developed a model which features four levels, where each level is assessed using a 5-point scale. The results are calculated on a scale from 0 to 1, where 0-25% indicates the manual and traditional manufacturing approach. From 25% to 50%, the model indicates the intuitive manual approach with the use of simple mathematical models in process planning. The range of 50%-75%

indicates the use of process simulation, computer-aided calculation and a computer database. Finally, 75% to 100% indicates the use of advanced simulation and predictive analytics methods.

The IMPULS tool was designed to assess Industry 4.0 readiness, with results ranging from 0 to 5 where 0 represents an “outsider” and 5 is a “top performer”. This scale is further categorised into three groups: “newcomers”, with little or no Industry 4.0 technology; “learners”, who have taken some initiative to implement Industry 4.0 technologies and “leaders” representing companies that have made significant efforts to implement Industry 4.0 (Lichtblau, et al., 2015). Alcácer et al., (2021) adopted the same scale to assess the readiness level in an industrial cluster in Portugal, further categorising “newcomers”, “learners” and “leaders” into five levels including outsider, beginner, intermediate, experienced, expert and top performer. The Industry 4.0 readiness assessment tool developed by Warwick University (Agca, et al., 2017 cited in Chonsawat and Sopadang, 2020) delineates four levels of readiness, ranging from 1-4 where level 1 indicates beginner, level 2 an intermediate, level 3 indicates experienced and level 4 an expert.

Based on the preceding discussion, the technology readiness measurement levels are not uniform across the reviewed literature. Further varied readiness scales demonstrated different measurement definitions given the context of the study (Alcácer, et al., 2021; Chonsawat & Sopadang, 2020; Trstenjak et al., 2022). These models, which have been designed and tested in different countries, industries and different sizes of firms are vital for measuring Industry 4.0 readiness as this measurement enables and guides the company to effectively design its digital transformation process (Alcácer, et al., 2021). Additionally, these models have been identified as management tools for realigning organisations' practices and capabilities (Felch, et al., 2019). These models generally assess a company's readiness on a spectrum of least ready to most ready, however, not all readiness models are equally relevant or applicable, as pointed by Sony and Naik, (2019). Because of the variation in business sectors, scales, the definition of readiness, and the components of one model change based on the business sector, as asserted by Lucato et al., (2019). Nevertheless, any readiness model in the context of Indian auto component industry was not clearly laid out in the literature. Therefore, according to Alcácer et al., (2021) this gap raises the requirement of measuring the technology usage against the readiness metrics in the context of the Indian auto component industry and thus answering the following research question:

RQ3: How do the current practices in the Indian auto components industry be systematically measured to assess Industry 4.0 readiness level and evaluate its effect on operational performance?

3.9 Industry 4.0 in Developed and Developing Countries

This section discusses the empirical studies conducted to understand the adoption of Industry 4.0 within the literature. These studies were conducted across developed and developing countries. Empirical studies conducted in both developed and developing countries showcase different readiness factors

based on the country in context. There is a vast amount of literature conducted in developed countries, including Germany, Italy, Sweden, Australia, Canada, USA to understand the practices adopted by companies before adopting Industry 4.0 (see **Figure 1.3 and section 1.3.3 - Appendix 1**). Hopkins, (2021) conducted a study in Australia to understand the adoption of Industry 4.0 technologies for supply chain innovation. Lohmer and Lasch, (2020) conducted a study across Europe to understand the promising practices for the manufacturing industry for the adoption of Blockchain technology. The insights were gathered from experts who have already adopted Blockchain technology in operations management and manufacturing-related areas. Pozzi et al., (2023) conducted a study in Italian companies that have initiated the process of Industry 4.0 technology implementation. The study highlights the importance of top management leadership, and inter-functional teams as implementation-related factors for the adoption of Industry 4.0. Črešnar et al., (2022) conducted a study in the Slovenia region to understand the Industry 4.0 readiness factors, including companies that have experienced the greatest effect of Industry 4.0 in the manufacturing sector. These studies indicate that digital transformation practices should be strategically planned to adopt Industry 4.0. Arnold et al., (2018) studied Industry 4.0 driving factors among German manufacturing companies. The relative factors including increased production flexibility, increased resource efficiency, top management support, and external support of experts for implementation of Industry 4.0 are identified as key drivers of adopting Industry 4.0. This also indicates that companies recognised the perceived benefits of higher Industry 4.0 readiness (Arnold et al., 2018). Paiola et al., (2021) conducted a study including Italian companies involved in Industry 4.0-related activities to understand the factors for adoption of Industry 4.0 technologies. Results highlighted prior knowledge, automation of function, data analysis, and in-house technological capabilities as critical resources for the adoption of Industry 4.0. Schuh et al., (2019) study across German manufacturing companies also indicated similar results indicating the use of information and communication technologies, data analysis, machines and equipment, and collaboration within and outside organisations for successfully monetising Industry 4.0.

The studies conducted in developing countries focus on the adoption of Industry 4.0 in various contexts. For example, Perez-Lara et al., (2020) developed an instrument to evaluate the current system in terms of horizontal and vertical integration in the context of Industry 4.0 to be applied in Mexico's manufacturing industry. However, the scale is yet to be used in the productive sector. Further, Chatterjee et al., (2021) conducted a study in the Indian manufacturing sector to understand AI adoption. The data was collected from non-adopters, and thus presents a gap in terms of understanding the practices followed by companies that have adopted Industry 4.0. Maalmi et al., (2021) conducted a study on Moroccan enterprises to understand the factors leading to innovative supply chains, where supply chain integration has a significant impact on supply chain innovation. The study indicates future research to include strategies and operational areas for innovative supply chains. Gadekar et al., (2022) conducted a study in India including participants having first-hand experience in Industry 4.0 applications to

achieve sustainable operational performance by advancing Industry 4.0 adoption. Further, drivers identified for Industry 4.0 adoption to improve operational performance include the adoption of Industry 4.0 technologies encompassing IoT, Virtual Reality (VR) and BDA. However, the study lacks the factors for the adoption of Industry 4.0 technologies. These studies conducted in developing countries present contextual factors to understand the Industry 4.0 readiness factors for supply chain innovation, and operational performance which are integral to understanding manufacturing operations (Moica et al., 2018; Stornelli et al., 2021; Lee et al., 2021). However, these studies lack any specific Industry 4.0 readiness factors, showing the knowledge gap and opportunity for conducting studies for Industry 4.0 adoption in developing countries. Additionally, the adoption of Industry 4.0 technologies is more challenging in developing countries due to factors including insufficient technology infrastructure, lack of awareness, and lack of strategies to adopt Industry 4.0 technologies (Pérez-Lara et al., 2020; Trstenjak et al., 2022; Moica et al., 2018). Based upon the review in the context of Industry 4.0 readiness across developed and developing economies, the following research question is derived:

RQ4. *What is the readiness level of the Indian auto component industry?*

3.10 Industry 4.0 Across SMEs and Large-Scale Companies

Most of the studies conducted within SMEs focused on exploring the role of Industry 4.0 technologies (Leso et al., 2023 & Bansal et al., 2023), the challenges of adopting the technologies (Herceg et al., 2020; Ericson, et al., 2020), the strategy for redefining the business model (Safar et al., 2018; Müller, 2019; Paiola, et al., 2021), and assessing the maturity/readiness level of Industry 4.0 (Chonsawat & Sopadang, 2020; Alcácer et al., 2021; Spaltini, et al., 2022; Ávila-Bohórquez and Gil-Herrera 2022). These studies combined indicate that SMEs need more support to unlock their potential in the transition journey into Industry 4.0. Further, Hopkin's (2021) established that SMEs require more attention than large-sized companies when it comes to adopting Industry 4.0 technologies. This is because of the variation in Industry 4.0 readiness levels across large and small-scale companies. The study confirmed organisational size as a key factor for technology adoption. On the contrary, Bogner, et al., (2016) found that the size of the company does not have any impact on the level of digitalisation. Further, Herceg, et al., (2020) confirmed that SMEs face varied challenges in the adoption of Industry 4.0 including a lack of competencies and a lack of integrated communication protocol across departments. Consequently, several studies developed readiness models and integration strategies specifically focussing on SMEs including Chonsawat & Sopadang, (2020); Müller & Voigt, (2017); and Spaltini, et al., (2022). A significant number of authors emphasised the difficulty faced by SMEs in attaining the potential strategic and operational benefits which include insufficient resources, lack of innovation management, and limited knowledge (Mittal, et al., 2018; Horváth & Szabó, 2019; Masood & Sonntag, 2020; Khanzode, et al., 2021; Stentoft, et al., 2021; Müller, et al., 2021; Estensoro, et al., 2022).

Research focusing on large-scale companies mainly focuses on understanding the Industry 4.0 adoption process as followed by these companies. For example, Schaefer, et al., (2017) studied the principles of adopting data-driven business models within MNCs. Pozzi, et al., (2023) identified the critical success factors for the adoption of Industry 4.0 within large-scale companies. Sütőová et al., (2020) assessed the maturity and adoption level of intelligent technologies within large-scale companies that have already implemented Industry 4.0 technologies. Črešnar et al., (2022) also conducted a study to understand technological and non-technological factors for the adoption of Industry 4.0 within large-scale companies. The analysis of research focus across large and small-scale companies clearly demonstrate that SMEs face more difficulties while large-scale companies have already adopted Industry 4.0 technologies, and the literature focuses on gaining practical insights from large-scale companies to understand readiness factors. This also indicates the varied strategies for the adoption of Industry 4.0 based on the existing resources and capabilities of large-scale companies as compared to SMEs (Müller, et al., 2021; Hopkins, 2021).

Larger firms typically have more financial resources, enabling them to invest in Industry 4.0 technologies, while small to medium-sized enterprises (SMEs) often lag due to limited capital (Kumar et al., 2023). The uneven adoption of Industry 4.0 technologies among suppliers can hinder overall supply chain performance, emphasising the need for targeted support for these firms (Piepoli et al., 2024). Further, successful Industry 4.0 implementation requires proactive innovation, long-term partnerships with technology providers, and early worker involvement in technological changes (Arcidiacono et al., 2019). Organisational-level actions and investment strategies are crucial during the planning stage of Industry 4.0 initiatives, impacting business performance significantly (Piepoli et al., 2024). The RAMI 4.0 framework provides a structured approach for optimising value chains, but effective visualisation methods are necessary to translate this framework into actionable insights (Javaid et al., 2021). Conversely, while larger firms may lead in Industry 4.0 readiness, the potential for SMEs to innovate and adapt could foster a more balanced industry landscape if adequately supported. This highlights the importance of collaborative efforts in driving sector-wide advancements. Müller & Voigt, (2017) emphasised the need to conduct a quantitative comparative study including large and small enterprises to understand the existence of Industry 4.0 specific characteristics for an industry-wide transformation. Consequently, the following research question arises:

RQ5. Is there any significant difference between the readiness level of SMEs and large-scale companies?

3.11 Industry 4.0 readiness and auto component operational performance

Studies on Industry 4.0 adoption focusing on enablers, drivers, readiness dimensions, determinants, and drivers of digitalisation have indicated the impact of these factors on operational performance across the key themes as discussed in this chapter including manufacturing, supply chain, and business model

(Bogner, et al., 2016; Ibarra et al., 2018; Hopkins, 2021; Zhang, et al., 2023). Strategy across all these areas is identified as an integral part of Industry 4.0 adoption (Schaefer, et al., 2017; Guo et al., 2020; Herceg, et al., 2020; Ericson, et al., 2020; Grabowska and Saniuk, 2022; Pérez et al., 2022). However, framework(s) that would assess the overall readiness of an Indian auto component firm with readiness factors has not been identified. Studies on Industry 4.0 readiness showed indecisive results regarding readiness factors. Studies have shown that top management (Arnold et al., 2018; Chatterjee, et al., 2021; Pozzi et al., 2021) visibility (Xu, et al., 2018; Patrucco, et al., 2022; Ivanov et al., 2022), and automation (Moica, et al., 2018; Bogner, et al., 2016; Schuh, et al., 2019) are prerequisites for the adoption of Industry 4.0. Few studies indicated IT infrastructure (Fernández-Miranda, et al., 2017; Herceg et al., 2020; Alcácer et al., 2021; Stornelli, et al., 2021) and supply chain integration (Pérez-Lara, et al., 2018; Maalmi et al., 2021; Črešnar, et al., 2022). Additionally, the studies conducted so far to assess the readiness level are contextualised in various manufacturing industries distinct from the focus of this study.

Further, the existing literature reveals a significant gap in empirically establishing the statistical relationship between Industry 4.0 readiness and operational performance. However, there is an indication towards the positive impact of Industry 4.0 drivers on operational performance. For example, Bogner, et al., (2016) highlighted the importance of automation in improving a company's success. Patrucco, et al., (2022) indicated the impact of cloud computing on supply chain performance. Taghipour, et al., (2022) highlighted the impact of supplier evaluation on forecasting accuracy, effective inventory management and enhanced product quality. Across all these studies, there is a lack of statistical relationship between Industry 4.0 prerequisites as highlighted in these studies and operational performance. Gadekar, et al., (2022) found a positive relationship between Industry 4.0 enablers and Industry 4.0 adoption and Industry 4.0 adoption and firm performance. However, no relationship was identified between Industry 4.0 enablers and firm performance.

Based on this, the review was further expanded to include technology adoption literature covering key manufacturing areas that demand realignment for Industry 4.0 adoption as identified from reviewed literature including supply chain, procurement, inventory management, production system, machinery, communication system, strategy including leadership support (Bogner, et al., 2016; Pérez-Lara, et al., 2018; Moica, et al., 2018; Ivanov, et al., 2022; Črešnar, et al., 2022; Patrucco, et al., 2022; Taghipour, et al., 2022). These studies focused on the impact of technology adoption across operational areas on operational performance. Eighteen studies were identified that establish the relationship between technology adoption across manufacturing areas and operational performance as listed in **Table 3.5**. These studies have discussed the same concepts as those found in Industry 4.0 literature, but not within the same context.

Table 3.5 : A summary of extended literature on the impact of technology adoption across manufacturing areas and operational performance

Authors	Independent variable	Dependent variable	Study result
Khanchanapong, et al., (2014)	Automated manufacturing system	Operational performance	Significant positive relationship
Weeks, et al., 2022	Automation	Operational performance	Significant positive relationship
Ko, et al., 2020	Manufacturing technology	Manufacturing performance	Significant positive relationship
Zhu, et al., 2022	ICT; Internal Integration (II)	Operational performance (OP)	ICT > OP – Not significant II > OP significant
Ordanini and Rubera, 2008	Procurement capabilities	Operational performance	No significant relationship
Hallikas, et al., (2021)	Digital Procurement	Supply chain performance	Significant positive relationship
Koufteros, et al., 2012	Supplier selection	Operational performance	Significant positive relationship
Panigrahi, et al., 2021	Inventory management	Operational performance	Significant positive relationship
V.W. and Namusonge, 2015	Inventory management	Operational performance	Significant positive relationship
Ye and Wang, 2013	IT alignment; Information sharing	Operational Performance	Significant positive relationship
Chae, et al., 2014	IT-based planning resources	SCM operational performance	Significant positive relationship
Aydiner, et al., 2019	Information system	Firm performance	Not Significant
García-Alcaraz, et al., 2020	ICT integration	Supply chain flexibility and agility	Significant positive relationship
Kim, 2009	Supply chain integration	Firm performance	Significant positive relationship
Flynn, et al., 2010	Customer integration; supplier integration	Operational performance	Significant positive relationship
GunaSekaran, et al., 2017	Big data analytics	Supply chain performance	Significant positive relationship
Sriyakul, et al., (2019)	Leadership	Supply chain performance	Significant positive relationship
Purwanto and Juliana, (2022)	Leadership	Supply chain performance	Significant positive relationship

Majority of studies found a positive relationship between technology adoption in manufacturing areas (independent variable) and operational performance (dependent variable) presented in **Table 3.5**. However, Aydiner, et al., (2019) did not find any significant relationship between information systems and firm performance. Ordanini and Rubera, (2008) also found no significant relationship between procurement capabilities and operational performance. Similarly, Zhu, et al., (2022) found no relationship between ICT and operational performance. This reflects another gap in the field of technology adoption across operational areas, showing dissimilar impacts on operational performance. Additionally, operational performance measures also vary across all these studies as presented in **Table 3.6**.

Table 3.6 : Operational Performance Measures

Operational performance measures	Authors
Cost, quality, lead time, flexibility	Khanchanapong, et al., (2014)
Supply chain efficiency	Weeks, et al., (2022)
Cost reduction, performance of smart factory	Ko, et al., (2020)
Quick product launch; on-time delivery; short lead time; high-level customer service	Zhu, et al., (2022)
Level of productivity; growth in sales; cash flow	Ordanini and Rubera, (2008)
Increase flexibility; Increase resource efficiency; Decrease costs in the supply chain; Reduce delivery time; Increase delivery reliability; Increase visibility	Hallikas, et al., (2021)
Product innovation; quality; competitive pricing	Koufteros, et al., (2012)
Responsiveness; reduction in production cost; decision making; quality control; fewer damages; visibility	Panigrahi, et al., (2021)
Price, quality, delivery, dependability, time to market, product innovation	V.W. and Namusonge, (2015)
Cost efficiency; customer responsiveness	Ye and Wang, (2013)
Order fulfillment; Delivery as promised; Delivery flexibility; Flexibility to change output volume; Flexibility to change product mix	Chae, et al., (2014)
Return on sales; distribution cost; reduced inventory; customer loyalty	Aydiner, et al., (2019)
Ability to change (quantity; delivery time; delivery schedule; production volume; production mix; throughput time; cycle time) Speed (lead time; development cycle time; product customisation; responsiveness)	García-Alcaraz, et al., (2020)
Market performance; financial performance; customer satisfaction	Kim, (2009)
Product modification; new product introduction; quick response to market changes; outstanding on-time delivery; short lead time; high customer service	Flynn, et al., (2010)
Visibility; minimise product cost; on-time delivery; zero-defects; minimise waste; respond fast to competitors	GunaSekaran, et al., (2017)
Lead time; cost; quality	Sriyakul, et al., (2019)
Quality; delivery; cost reduction	Purwanto and Juliana, (2022)

Due to inconsistencies in operational performance measures, it is essential to understand the impact of Industry 4.0 readiness on operational performance by examining the performance measures of Indian auto component firms. The measures used in previous studies were tested based on their specific focus, which differs from the focus of this study. Additionally, no study was found in the context of Indian auto component firms. This study will therefore attempt to close this gap to identify the impact of Industry 4.0 readiness factors on operational performance within Indian auto component firms by answering the following research question:

RQ6. *What is the relationship between the readiness level and operational performance in the context of the Indian auto component industry?*

3.12 Research Questions

The foregoing literature review has provided insight into the existing studies with the goal of deriving the research questions. The research questions provide a focused approach to understand the readiness factors that can be studied within the Indian auto component industry to accelerate the preparedness towards Industry 4.0. The research questions are listed as follows:

RQ 1: What are the key readiness factors in the context of Industry 4.0 to enhance operational productivity and efficiency?

RQ 2: What are the prevailing practices in the Indian auto components industry in the context of Industry 4.0 within the horizontal and vertical value chain comprising suppliers and customers?

RQ 3: How do the current practices in the Indian auto components industry be systematically measured to evaluate the effect on operational performance?

RQ 4: What is the readiness level of the Indian auto component industry?

RQ 5: Is there any significant difference between the readiness level of SMEs and large-scale companies?

RQ 6: What is the relationship between the readiness level and operational performance in the context of the Indian auto component industry?

3.13 Conclusion

Based on the review of literature, it is established that there is a lack of a framework with limited maturity and readiness models that lack the specific resources of auto component firms and implementation patterns. Further, RBV is not used in the reviewed literature in terms of assessing the readiness level and its impact on operational performance. Also, the reviewed literature mainly focuses on readiness assessment for specific technologies and specific cases of companies. The framework for this study is designed in the context of the Resource-based view theory of the firm and contextualises the resources required for Industry 4.0 adoption and competitive advantage (Grant, 1996). Further, RBV is used as a theoretical lens to investigate the relationship between resources that characterise Industry 4.0 readiness and operational performance.

Chapter 4: Populating the framework

4.1 Introduction

This chapter provides an account of the practices adopted by the firms that have already implemented Industry 4.0 technologies. The literature has thus far discussed manufacturing operations broadly without delving into the specific intricacies of auto component manufacturing. Further exploration is required to discern the operational practices comprehensively, with a particular focus on the technological landscape across operations. Even though the literature reviewed so far indicated numerous benefits of Industry 4.0 including cost savings, and operational efficiency (Moica, et al., 2018; Momo, et al., 2019; Hopkins, 2021), it also faces a multitude of implementation challenges (discussed in **section 3.4.2**). It is not comprehensively defined in the literature, and provides only general guidance on what steps to undertake leaving a gap in comprehensive Industry 4.0 readiness factors that would facilitate the transition of Indian auto components firms to Industry 4.0 (discussed in **section 3.4.3**).

The literature on readiness models, maturity models, and enablers of Industry 4.0 adoption is reviewed within the extant literature. The term digitalisation is used in some studies in the context of Industry 4.0 (Simões et al., 2021). While Industry 4.0 readiness factors are also understood as digital transformation drivers (see **section 3.4.1**), Industry 4.0 enablers and preconditions for Industry 4.0 adoption (summarised in Table 3.1) and readiness dimensions (presented in **Table 3.1**) are discussed in the reviewed literature. These readiness factors are discussed in this chapter according to themes identified in Chapter 3 to determine gaps. These comprise literature on Industry 4.0, which was empirically and theoretically identified in the extant literature and understanding practices as incorporated by the firms before the implementation of Industry 4.0 technologies. This chapter concludes with a summary of the literature on the Industry 4.0 readiness factors and the conceptual framework.

4.2 Industry 4.0 Readiness Factors

Industry 4.0 readiness refers to the extent to which companies are digitally prepared for Industry 4.0 technologies. The existing technology used in the company contributes to Industry 4.0 readiness (Schumacher et al., 2016 cited in Chonsawat and Sopadang, 2020). Industry 4.0 readiness is discussed in several aspects for example the need for integration of network structure, and level of automation (Charro and Schaefer, 2018; Weking et al., 2018; Chonsawat and Sopadang, 2020; Herceg et al., 2020; Lohmer and Lasch, 2020; Stornelli et al., 2021), strategy (Schaefer et al., 2017; Martínez-Olvera & Mora-Vargas, 2019; Tonder et al., 2020; Favoretto et al., 2021; Stornelli et al., 2021; Hopkins, 2021; Koh et al., 2022; Grabowska and Saniuk, 2022) organisational structure, internal processes in terms of manufacturing operations including procurement practices, inventory management (Tonder et al., 2020; Ahmad et al., 2020; Levis et al., 2021; Grabowska and Saniuk, 2022); external processes including collaboration with technology partners and, stakeholders (Simões et al., 2021 & Moica et al., 2018)

communication between suppliers and customers (Ibarra et al., 2018 & Grabowska and Saniuk, 2022); and existing capabilities of the firm in terms of data collection and data-driven decision making (Schaefer et al., 2017; Morkunas et al., 2019; Tonder et al., 2020; Boßlau, 2021; Stornelli et al., 2021).

However, only a few (empirical) studies indicated the prerequisites towards the adoption of Industry 4.0 and most firms are still unclear in terms of how to proceed with the process (Ericson, et al., 2020; Chonsawat and Sopadang, 2020; Alcácer et al., 2021). Additionally, within the reviewed literature, the impact of Industry 4.0 readiness on operational performance has not been empirically studied. Moreover, the empirical research is mainly restricted to developed countries (as established in **section 3.9**).

A range of readiness factors were identified from the literature which are believed to improve the performance of the manufacturing operations. Based on the reviewed literature on Industry 4.0 adoption, the readiness factors are categorised into four key areas including manufacturing and operations, supply chain (see **sections 3.5 and 3.6**), business model (see **section 3.7**) and strategy (see **sections 3.5 and 3.6**). Furthermore, existing readiness models as developed by Alcácer et al., 2021 and Schumacher et al., 2016 indicated that readiness needs to be broadly incorporated across manufacturing, business models, strategy and supply chain for a comprehensive Industry 4.0 transition in the context of the manufacturing industry. Building upon the same, few scholars have used the same areas to assess the readiness level in a manufacturing context (see **Table 3.3**). Therefore, based on the previous readiness tools and reviewed literature, four areas were identified in the context of the current study to assess the Industry 4.0 readiness of the Indian auto component manufacturing industry, which are discussed below. Additionally, drawing on the themes identified in the reviewed literature and the readiness factors identified from the readiness and maturity models (presented in **Table 3.3**), the following section discusses the prior empirical studies that have utilised these factors to transition to Industry 4.0 within the manufacturing industry. These factors are further grounded in the theory discussed in **section 3.3**.

4.2.1 Manufacturing and Operations

Manufacturing and operational areas are the foundation for smart factories and digitally transforming the activities and operations involved in the production field. The motivation for the implementation of Industry 4.0 within a company is reliant on the existing automation in the production field with a significant emphasis on collecting digital information and analysing data for predictive maintenance (Simonis, et al., 2016). The use of automated machinery with the integration between machinery and computing devices seamlessly collects real-time data on maintenance and production output, reducing the need for human labour (Radziwon, et al., 2014). Müller, et al., (2018) identified companies where production machinery is not automated and heavily reliant on humans. These companies are found to be misaligned with the Industry 4.0 paradigm. Conversely, companies with higher levels of automation

demonstrate a high motivation for innovating processes through extensive data collection from automated production systems (Simões et al., 2021; Schlecht et al., 2021; Müller et al., 2018). The key difference between these two categories lies in the level of automation and data collection mechanism implemented for production process efficiency. The literature has significantly emphasised the importance of data collection (Culot, et al., 2020 & Patrucco, et al., 2022), which is closely linked with the automation and integration of machinery and computing devices (Zhong et al. 2017; Fatorachian and Kazemi, 2021; Unhelkar et al., 2022). Many factors found in studies as manufacturing and operations factors indicate firms' readiness towards Industry 4.0 adoption. For example, Radziwon, et al., (2014); Toro, et al., (2015); and Gerlitz, (2016) found machine and computer integration as the readiness indicator for Industry 4.0 adoption; Schuh, et al., (2014); Simonis, et al., (2016) and Črešnar et al., (2022) identified automation as the enabler of Industry 4.0. Table 4.1 summarises factors identified in the extant literature across manufacturing and operations.

Table 4.1 : Summary of manufacturing and operations readiness factors identified in extant literature:

N	Readiness Factors	No. of studies
1	Automation	9 studies (Miranda et al., 2017; Müller, 2019; Schlecht et al., 2021; Gaiardelli et al., 2021; Simões et al., 2021; Črešnar et al., 2022; Tian et al., 2022; Grabowska & Saniuk, 2022; Trstenjak et al., 2022)
2	Machine and computer integration	3 studies (Simões et al., 2021; Gerlitz, 2016; Zhu, et al., 2022)

This study grouped the factors in the manufacturing and operations areas in a systematic way to examine each of the areas viz. automation, and machine and operating system integration that indicates Industry 4.0 readiness.

4.2.1.1 Automation

Automation in production is identified as a cornerstone for enhancing interconnectivity and real-time monitoring within the interconnected machine economy. Tian et al., (2022) found that remote monitoring, and control of the production line demonstrate the efficient production platform for co-ordinating the resource utilisation with reduced labour. Automation in the production system accelerates the machine economy, facilitating real-time decision-making through the interconnectivity of machines and monitoring systems (Miranda et al., 2017; Schlecht et al., 2021; Simões et al., 2021). The shift in manufacturing concepts and technologies brought about by the integration of systems within the organisation, along with automated machinery and processes denotes an advanced level of alignment with Industry 4.0 (Črešnar et al., 2022). Furthermore, automation enables companies to respond to fluctuating customer demand & preferences, and improves product quality and enterprise performance with the use of real-time data analytics collected from the integrated components within the production ecosystem (Oesterreich and Teuteberg, 2016, cited in Savastano, et al., 2019). Gaiardelli et al., (2021) confirmed that the Industry 4.0 scenario is characterised by flexible machines having the ability to produce in lot size. Additionally, the automation of production lines assists in meeting personalised

customer needs (Grabowska and Saniuk, 2022). The automated machinery with predictive maintenance features along with optimisation of the production system through anticipated maintenance requirements enhances responsiveness, which is crucial for meeting customer needs and staying competitive (Müller, 2019; Trstenjak et al., 2022).

Khanchanapong, et al., (2014) asserted that manufacturing technologies characterised by automated manufacturing systems with real-time monitoring of production systems are valuable resources for achieving operational performance. The study confirmed the positive association between manufacturing technologies and operational performance. Various studies confirm automation as a valuable resource (Ngamsirijit, 2011; Weeks, et al., 2022; Moderno, et al., 2023) to improve operational performance. Weeks, et al., (2022) empirically established the positive relationship between automation and operational performance. Based on RBV and reviewed literature, the existence of automation in the production field is identified as an Industry 4.0 readiness factor that positively influences operational performance (Ngamsirijit, 2011; Müller, 2019; Grabowska & Saniuk, 2022; Weeks, et al., 2022) thus the following metrics will be used to measure the readiness of automation across Indian auto component firms:

An advanced level of automation where the production system can autonomously monitor and adjust its operations without continuous human intervention, optimising efficiency and minimising errors.

4.2.1.2 Machine and ICT integration

Radziwon, et al., (2014) state a system where machines possess computing capabilities to act independently is identified as the prerequisite for a smart factory. ICT infrastructure, advanced control and monitoring through connected machinery provide computing abilities to the production ecosystem. Further, data collected from the automated machinery enables the optimisation of the production process for higher productivity (Simões et al., 2021). The hardware and software should be integrated into a smart factory which requires transforming the standalone machinery into interconnected units. In a case study conducted by Gerlitz, (2016), the production process between two plants was found to be interrelated and synchronised through an integrated company-wide system which acts as an enabler of Industry 4.0. For companies to be ready for Industry 4.0, the production system and operations should also be integrated for systematic processes and collaboration across departments.

Manufacturing technologies that integrate machinery and computer programs, for example, CNC have been identified to improve the operational performance of the firm. However, manufacturing technologies alone do not create a competitive advantage as these resources can be acquired by any firm (Clemons & Row, 1991). Nonetheless, Fang, et al., (2006) argued that the combination of manufacturing technologies and ICT resources can improve work efficiency by developing technical interconnectivity for internal integration. In the context of Industry 4.0 smart factories, this integration plays a crucial role as a reconfigurable production system depends on the integration of ICT with shop

floor machinery to improve operational performance (Ko, et al., 2020). While some research attempted to explore the competitive advantage by deploying ICT and manufacturing technologies separately (Khanchanapong, et al., 2014; Zhu, et al., 2022) none have looked at whether machine and ICT integration in combination can improve operational performance. Therefore, this research will first assess the readiness of Indian auto component firms towards machine, and ICT integration with its subsequent impact on operational performance. The following metrics will be used to measure the readiness of machine and ICT integration across Indian auto component firms:

The production machines and computing devices are highly integrated facilitating seamless coordination and communication between machines and software components with real-time data exchange capability.

4.2.2 Supply chain

The current practices within the supply chain, particularly regarding vertical and horizontal integration influence supply chain transparency and decentralised decision making thus enhancing visibility across the supply chain (Marwah et al., 2014; Dubey et al., 2018; Pérez-Lara, et al., 2020). Additionally, existing technologies significantly impact a firm's ability to transition to Industry 4.0. Several areas have been consistently emphasised in the literature concerning the improvement of supply chain performance including communication between stakeholders (Črešnar, et al., 2022 & Ávila-Bohórquez and Gil-Herrera, 2022) and the availability of real-time information across production areas, such as procurement processes (Botha, 2019; Safar, et al., 2018; Hopkins, 2021). The roles and duties of each stakeholder in the value network contribute to the overall value created within an organisation. The value network comprising internal stakeholders and external stakeholders (suppliers, OEMs, logistics providers, and technology partners) compliments the value creation. Therefore, the role of these stakeholders significantly contributes towards supply chain performance (Tian et al., 2022). The vertical and horizontal integration of the supply chain is therefore identified as an important aspect of the digital transformation process (Bogner, et al., 2016 & Sütőová et al., 2020). Many factors found in studies as supply chain factors that indicate the firm's readiness for Industry 4.0 adoption. Tian et al., (2022) found e-procurement as the influencing factor of Industry 4.0 adoption. Patrucco, et al., 2022 indicated the need for supplier evaluation; while Saucedo, et al., (2018) identified that collaboration between suppliers, customers and production is the first step to achieving the Industry 4.0 vision. Črešnar et al., (2022) indicate automated inventory management as a prerequisite for Industry 4.0 to manage demand and supply. Table 4.2 presents the summary of readiness factors identified in the reviewed literature across the supply chain for assessing Industry 4.0 readiness.

Table 4.2: Summary of supply chain readiness factors identified in extant literature:

N	Readiness Factors	No. of studies
1	E-procurement	3 studies (Simões et al., 2021; Tian et al., 2022; Patrucco, et al., 2022)
2	Inventory management	2 studies (Crešnar et al., 2022 & Patrucco, et al., 2022)
3	Communication between suppliers and customers	7 studies (Moica et al., 2018; Müller et al., 2018; Guo et al., 2020; Crešnar et al., 2022; Trstenjak, et al., 2022; Črešnar, et al., 2022; Ávila-Bohórquez and Gil-Herrera 2022)
4	Integration between suppliers and customers (supply chain visibility)	14 studies (Pérez-Lara, et al., 2020; Müller, 2019; Culot et al., 2020; Chonsawat & Sopadang, 2020; Ahmad et al., 2020; Guo et al., 2020; Maalmi et al., 2021; Giudice, et al., 2021; Simões et al., 2021; Lee et al., 2021; Gaiardelli et al., 2021; Tian et al., 2022; Ivanov et al., 2022; Crešnar et al., 2022)
5	Real-time tracking	2 studies (Patrucco, et al., 2022 & Ivanov et al., 2022)

This study grouped the factors indicating Industry 4.0 readiness related to supply chain activities in a systematic way to examine each of the areas viz. e-procurement, supplier evaluation, inventory management, communication between buyers and suppliers, and integration between buyers and suppliers

4.2.2.1 E-Procurement

Electronic procurement (e-procurement) is identified as a firm's capability to leverage information technology tools for managing the procurement process (Ordanini and Rubera, 2008; Hallikas, et al., 2021) encompassing purchase requests, vendor selection, and purchase orders (Jr., 2003). The Internet-based infrastructure, electronic data interchange, and cloud-based solutions are pivotal for collecting and managing data at every stage of the procurement process (Calatayud, et al., 2018) and are identified as valuable resources for competitive advantage (Ordanini & Rubera, 2008). Further, the internet serves as the foundation for digital data gathering which enables the record of customers, as well as and market requirements as well as terms of vendor management (Simões et al., 2021). The procurement system that possesses real-time monitoring capabilities, facilitates the coordination of demand and supply and thus satisfies customer needs through analysis and forecasting of raw material requirements (Tian et al., 2022). Hallikas, et al., (2021) confirmed the positive relationship between e-procurement and operational performance. This technology-driven approach across the procurement process supports supply chain integration and enables the adoption of Industry 4.0 (Patrucco, et al., 2022). Based on RBV, and reviewed literature, e-procurement signifies Industry 4.0 readiness that positively influences operational performance. The following metrics will be used to assess e-procurement readiness across Indian auto component firms:

The procurement process is characterised by the use of digital tools and technologies to collect and manage data at every stage of the procurement lifecycle (procurement software, e-procurement, electronic data interchange, cloud-based solutions).

4.2.2.2 Inventory Management

An automated inventory management system utilising smart gadgets and sensors for capturing real-time inventory status throughout the supply chain demonstrates the readiness of the organisation for the adoption of Industry 4.0 (Crešnar et al., 2022). According to a study conducted by Patrucco, et al., (2022) covering companies in European, North and South American regions, it was found that the use of track and trace technologies improves supply chain performance through effective management of inventory. These technologies enhance buyer-supplier visibility by facilitating the sharing of information about inventory and demand forecasting. Although tracking and monitoring tools improve visibility along the supply chain, they also aid in optimising the inventory level by providing real-time data for flow management. Tools such as RFID, smart sensors, and real-time tracking and tracing software enable the monitoring and position of items in the supply chain through automated inventory management systems (Unhelkar et al., 2022). All these studies have indicated that Industry 4.0 is characterised by automated inventory management which represents Industry 4.0 readiness that directly leads to enhanced operational performance through the optimisation of inventory management (Dantas and Barbalho, 2021 & Panigrahi, et al., 2022). Various studies have established the relationship between inventory management and competitive advantage (V.W. & Namusonge, 2015; Saleem, 2020). Drawing upon this, Industry 4.0 readiness is characterised by automated inventory management that leads to enhanced operational performance (Unhelkar et al., 2022 & Panigrahi, et al., 2022). In terms of the readiness level used for identifying the technology usage level across Indian auto component firms, the following metrics will be utilised for assessing the readiness of automated inventory management:

An advanced, autonomous system continuously monitors and dynamically adjusts inventory levels in real-time, leveraging smart devices and real-time databases for seamless and precise inventory management.

Further, based on the above discussion, the role of real-time tracking for monitoring the movement of products to optimise inventory levels demonstrates the firm's readiness for Industry 4.0. According to Unhelkar et al., (2022) and Panigrahi, et al., (2022), real-time tracking of products across the supply chain enhances the visibility and transparency across firms thus improving production planning through optimised inventory levels (Patrucco, et al., 2022). Therefore, this study will utilise the following metrics for assessing the readiness of real-time tracking across supply chain partners including supplier, manufacturing unit and distribution unit

The product can be tracked throughout the supply chain comprising the supplier, manufacturing unit, and buyer distribution centre.

4.2.2.3 Communication between suppliers and customers

Communication between suppliers and customers highlights the interconnectedness of manufacturers with their suppliers and customers facilitating instantaneous responses to market shifts (Müller et al., 2018 & Crešnar et al., 2022). Industry 4.0 is recognised for adapting concepts that enhance connectivity with suppliers and customers for order placement and payment processing. The ease of communication and connectivity through digital communication between supply chain partners fosters real-time data enabling effective demand management (Müller et al., 2018).

Moica et al., (2018) have pointed out that transitioning from conventional production methods to Industry 4.0 necessitates evaluating existing resources, including communication channels. The capability for real-time communication is instrumental in achieving a rapid response rate and minimising lead times (Guo et al., 2020). Furthermore, Trstenjak, et al., (2022) emphasised the necessity of enhancing computer infrastructure to enhance companies' readiness level for Industry 4.0. This improvement aims to increase the volume of data captured from supply chain partners, thereby improving connectivity through the collection and storage of data. However, the realisation of these benefits is contingent upon the exchange of information between customers and suppliers facilitated by effective communication platforms (Crešnar et al., 2020). Therefore, communication between suppliers and customers is identified as the enabler of Industry 4.0 adoption (Črešnar, et al., 2022; Ávila-Bohórquez and Gil-Herrera 2022).

According to RBV, organisations must have sufficient ICT infrastructure to share information with external parties that form the basis of supply chain integration (Xu, et al., 2014 & Vafaei-Zadeh, et al., 2020). Various studies have shown the direct relationship between ICT resources and operational performance within the RBV framework (Ye and Wang, 2013; Chae, et al., 2014; Zhu, et al., 2022). Within Industry 4.0, the use of inter-organisational systems (IOS) characterised by network-enabled information systems for real-time sharing of information between suppliers and customers for coordinating supply chain activities influences operational performance (Chi, et al., 2017; Aydiner, et al., 2019; García-Alcaraz, et al., 2020). Therefore, integration of IOS and ICT infrastructure is critical for enhancing operational performance as a preparatory measure for Industry 4.0.

To conclude communication between suppliers and customers using advanced communication platforms is an indicator of a firm's readiness towards Industry 4.0. The application of RBV in the context of Industry 4.0 highlights the significance of communication platforms as key resources to improve operational performance. To assess the technology usage level across Indian auto component firms, the following metrics will be used to measure the readiness of communication between suppliers and customers:

Fully integrated system with every party having access to the real-time flow of information allowing stakeholders to have access to the most up-to-date data for example real-time visibility across all parties.

4.2.2.4 Integration between suppliers and customers

Integration between suppliers and customers involves interconnectivity among suppliers, manufacturers, distributors and customers across various stages of the production process through a decentralised supply chain (Pérez-Lara, et al., 2020). All stakeholders participate in product design, ensure material and equipment availability and manage warehouse and delivery services thereby integrating the production process (Tian et al., 2022; Guo et al., 2020; Maalmi et al., 2021; Simões et al., 2021). According to Culot et al. (2020), the visibility of data among all stakeholders facilitates a fully integrated supply chain which is identified as the key driver of Industry 4.0. Ivanov et al. (2022) further state, within an organisational ecosystem, the identification and relationship with customers significantly influence the value-creation process of an organisation. Ahmad et al., (2020) and Lee, et al. (2021) point out that value is captured by zooming into customer identification, customer engagement, and value delivery. Müller (2019) confirms this integration enhances the productivity of the firm, availability, performance, and quality of customer satisfaction, and improves customer value by delivering the value proposition.

According to a study conducted by Gaiardelli et al., (2021) which involved experts in the field of Industry 4.0, it was discerned that collaboration and integration between supply chain stakeholders act as an enabler of digital transformation. This transformation is facilitated by the utilisation of ICT infrastructure and control and monitoring tools including enterprise information systems. This indicates effective integration hinges on the presence of monitoring tools and effective communication mechanisms in place (see **sections 4.2.2.2 and 4.2.2.3**) (Crešnar et al., 2022; Chonsawat and Sopadang, 2020). These tools possess the capability to leverage constant data from various stages of operations and production systems thereby making the supply chain more proactive, collaborative and responsive to customer needs (Chonsawat and Sopadang, 2020; Giudice et al., 2021). All these studies in the context of Industry 4.0 indicate the integration between suppliers and customers as an initiative for Industry 4.0 (Pozzi et al., 2021).

RBV identifies supply chain integration as a strategic resource characterised by a strategic collaboration of the firm with its suppliers and customers that leads to improved operational performance (Barney, 2012). Strategically collaborating with suppliers and customers and leveraging monitoring tools to link and align activities and processes with suppliers and customers guarantees material and information flow from these parties that improves customer satisfaction, and this creates a competitive advantage for the firm (Kim, 2009). Many studies have recognised the relevance of RBV to supply chain integration. Leuschner, et al., (2013); Thoo et al., (2016); Huo et al., 2016; Chahal et al., (2020) have

recognised the relevance of RBV to supply chain integration. Rungtusanatham et al., (2003); Flynn et al., (2010); Chahal et al., (2020) have indicated a positive relationship between supply chain integration and operational performance.

In conclusion, the application of RBV in the context of Industry 4.0 underscores the importance of supply chain integration as a critical resource that defines the firm's readiness. By utilising this resource, organisations can enhance their operational performance. In terms of the readiness level that would be used for identifying the technology usage level across Indian auto component firms, the following metrics will be used for assessing the readiness of integration between suppliers and customers:

Real-time visibility of site locations, capacities, inventory, and operations where data is actively used for monitoring and optimisation of operations and processes throughout the supply chain.

4.2.3 Business model

Ibarra et al., (2018) and Zhang et al., (2023) explain a digital business model further allows the implementation of new functions and processes for the development of value propositions. Ahmad, et al. (2020) & Lee, et al. (2021) state an integrated and optimised value chain is imperative for the development of value propositions through the digital refinement of existing products. Safar et al. (2018) further confirm digital refinement brings into the picture new types of functionalities and services characterised by a differentiated value proposition and acts as a facilitator of Industry 4.0 adoption.

A digital business model further allows the implementation of new functions and processes for the development of value propositions (Ibarra et al., 2018 & Zhang, et al., 2023). An integrated and optimised value chain is imperative for the development of value propositions through the digital refinement of existing products (Ahmad, et al., 2020; Lee, et al. 2021). Digital refinement brings into the picture new types of functionalities and services characterised by a differentiated value proposition and acts as a facilitator of Industry 4.0 adoption (Safar et al., 2018).

After reviewing the literature on digital business models three main elements were identified. The identified elements are understood as the main pillars of digital business models which include data-driven decision-making (Ahmad, et al., 2020; Paschou, et al., 2018; Linde, et al., 2021), customer co-creation (Kohtamäki, et al., 2019; Boßlau, 2021; Ahmad, et al., 2020; Paschou, et al., 2018; Linde, et al., 2021), and collaboration with technology partners (Ahmad, et al., 2020) to accelerate the digital transformation process (Moica et al., 2018 & Simões et al., 2021). Information and communication technologies are the premise of such infrastructure which bridge the gap between the existing traditional business model, and digital business model by facilitating partnership between all actors. Business model definitions underline one common idea which is the creation of value for the customers and thus emphasise what customers want, how they want it, and how the firm delivers it to gain a competitive

advantage (Herceg, et al., 2020; Averina et al., 2021). According to Gerlitz, (2016); Müller, (2019); Linde, et al., (2021) using Industry 4.0 technologies, companies will need to revise their business model for technology adoption and integration. Mihardjo, et al. (2019) advise an initiative to the Industry 4.0 business model is thus indicated by strategically changing the role of partners and customers in a decentralised setting through co-creation strategies for the refinement of products. This section has systematically summarised the Business model's readiness for Industry 4.0 adoption (presented in Table 4.3) which is identified as an enabler of the digital business model in the context of Industry 4.0.

Table 4.3: Summary of business model readiness factors identified in extant literature:

N	Readiness Factors	No. of studies
1	Data-driven decision	5 studies (Müller, 2019; Dalmarco et al., 2019; Simões et al., 2021; Crešnar et al., 2022; Trstenjak, et al., 2022)
2	Customer co-creation	10 studies (Moica et al., 2018; Dalmarco et al., 2019; Guo et al., 2020; Crešnar et al., 2020; Chonsawat & Sopadang, 2020; Simões et al., 2021; Giudice, et al., 2021; Gaiardelli et al., 2021; Tian et al., 2022; Grabowska & Saniuk, 2022)
3	Collaboration with technology partners	6 studies (Moica et al., 2018; Chatterjee et al., 2021; Müller, et al., 2021; Simões et al., 2021; Simões et al., 2021; Paiola, et al., 2021)

4.2.3.1 Data-driven decision making

Müller, (2019) highlights data management, data analysis and data mining are recognised as the cornerstones of knowledge-based decision-making. This entails leveraging IT technologies for digital data collection and analysis where data is processed to inform decision-making, emphasising customer demands and the use of data received from customers and market research for product development (Crešnar et al., 2022 & Parente et al., 2022). In an organisational setting, decisions regarding the company's direction and partnerships are centralised where top-level executives leverage big data analytics internal and external data to make strategic decisions. GunaSekaran, et al., (2017) confirmed the positive impact of big data analytics on organisational performance. On the contrary, tactical operational decisions are decentralised giving the autonomy to managers to control operations. Simões et al., (2021) also emphasised decentralisation of the decision-making process, enabling workers to make decisions in the operational areas without involving top-level management. This bifurcation of decision-making into strategic and operational areas underscores the significance of data utilisation for decision-making. It can be inferred that while top-level management steers strategic directions, without getting involved in day-to-day operations, middle and lower-level managers control day-to-day operations provided they are granted the authority and access to data (Trstenjak, et al., 2022).

The use of big data analytics to analyse data from emails, web and tracking tools including RFID and sensors improves decision-making and knowledge management. Dalmarco et al., (2019) indicate that these tools serve as the foundation for the adoption of Industry 4.0 without necessitating significant alterations in the existing processes. Following RBV, data management tools are identified as firms' resources to collect data while analysing data to gain useful insights for data-driven decision-making

and managing supply chain activities is identified as a firm's capability (Su & Yang, 2010; Chae, et al., 2014). Following RBV and reviewed literature data-driven decisions is identified as Industry 4.0 readiness factor that positively influences operational performance. The following metrics will be used for assessing the readiness of data-driven decisions across Indian auto component firms:

Top management leverages big data analytics to gain valuable insights across multiple stakeholders and departments, enabling them to guide production efficiency and drive advancements within the organisation without direct involvement in daily operations.

4.2.3.2 Customer-co-creation

The customer has emerged as a key focus in the digital business model with a strong emphasis on catering to ever-increasing and varying customer demand through continuous customer engagement. Therefore, the creation of new products, services, business processes, and strategies should be all aligned with the customer's needs. Synchronising all these areas with customer needs provides considerable added value and a competitive advantage. However, it's important to note that value creation isn't solely dependent on meeting customer needs. Dalmarco et al., (2019) and Simões et al., (2021) have emphasised the shift towards a more customer-oriented approach, involving personalised or customised production which triggers the change in manufacturing processes.

Guo et al., (2020) & Tian et al., (2022) explain, for a customer-centric business model, the manufacturing process should accommodate on-demand (make-to-order) production, offering fast response times and zero lead time. The concept of co-creation as identified by Kagermann, et al., (2013), cited in Müller, (2019) underscores the importance of meeting customer needs with the smallest batch size, treating each customer as unique. Co-creating products with customer involvement through the exchange of knowledge and enhanced communication leads to the creation of customised products (Giudice, et al., 2021; Grabowska & Saniuk, 2022; Moica et al., 2018). This necessitates the deployment of flexible machines which can produce with lot sizes equal to aligning with make-to-order strategy (Gaiardelli et al., 2021). The capability of machinery to be flexible for a make-to-order strategy is identified as the driver of Industry 4.0 (Giudice, et al., 2021 & Grabowska & Saniuk, 2022). Such capabilities can be further enhanced by the availability of real-time information and reconfiguration of the production process.

The utilisation of data for product development and orientation of processes towards the customer requirement is one of the characteristics of Industry 4.0. Crešnar et al., (2020) suggest that non-technological factors including customer-orientated models serve as an enabler for leveraging benefits from technological advances. The process of co-creation further facilitates a deeper understanding of the customer. Chonsawat and Sopadang, (2020) explain the concept of smart manufacturing is embedded in the creation of customised products allowing for customisation in product design and volume to provide tailored solutions. Gaiardelli et al, (2021) point out that within Industry 4.0 co-

creation with customers is recognised as a critical resource for aligning a firm's offering to customer demand. From the RBV perspective, customer relationship is identified as an intangible asset that improves the competitive advantage (Barry, et al., 2005 & Bag & Pretorius, 2020). As Industry 4.0 emphasises quickly adapting to customer needs through customised products, customer co-creation implies Industry 4.0 readiness. Thus, firms can increase operational performance by focusing on customer-oriented model Crešnar et al., (2020). The following metric is used to measure the readiness of customer co-creation across Indian auto component firms:

Make-to-order manufacturing that combines personalised customisation with an efficient production process.

4.2.3.3 Collaboration with technology partners

Müller, et al, (2021) explain the utilisation of external knowledge is identified as a driver towards the adoption of the technology, particularly when environmental changes are more technology-specific. During the initiation phase, sharing knowledge regarding the intricacies and benefits of technology not only promotes the culture of innovation within organisations but also enhances employees' ability to adopt innovative technology (Chatterjee et al., 2021 & Müller, et al., 2021). When all the stakeholders collaborate to bring value to the organisation, such collaboration results in value added for the organisation.

Schuh, et al., (2019) note, apart from value creation, the infrastructure created with the mix of internal and external stakeholders enables knowledge sharing, integrated business units and cooperation. Moreover, collaboration simplifies the process of digital transformation for companies that lack resources both in terms of tools and know-how to advance their processes. These companies can leverage technological partners to accelerate the adoption of innovative technologies (Simões et al., 2021). In a case study by Moica et al., (2018), a Romanian production company's transition from a conventional to an "Industry 4.0" production system was explored. Among the primary initiatives adopted by the company, a notable activity involved engaging in collaboration activities by creating interfaces to compare its production processes with top-performing companies and thus identifying the gap. Additionally, the company partnered with a local university to drive the innovation process. This underscores the importance of forging connections with technology partners to foster innovation. Paiola et al. (2021) reiterated similar findings, emphasising that technology partners play a key role in the learning process. It was suggested that merely investing in Industry 4.0 technologies would not be sufficient to bridge the strategic gap for technology adoption. Instead, companies and knowledge partners should collaborate to facilitate innovation. Access to technological resources relies on the capability of firms to discover external resources and in that regard, collaboration with technology experts is identified as a tool to benefit from external resources (Hernández-Linares et al., 2021 cited in Giudice et al., 2021) to gain competitive advantage. In conclusion, collaboration with technology

partners underscored its importance for the implementation of Industry 4.0 and thus identified as an Industry 4.0 readiness factor (Moica et al., 2018 & Paiola, et al. 2021). The following metric is used to measure the readiness of collaboration with technology partners across Indian auto component firms:

Partnership and collaboration with external experts and consultants are involved in redesigning processes and technology implementation and also digitally transforming business through an overhaul of processes, technologies, and business models.

4.2.4 Strategy

In the context of Industry 4.0, it is crucial to define the business strategy clearly, outlining the expectations from the Industry 4.0 technologies based on the product and service design as expected to be delivered by an organisation. At the core of driving this strategy forward lies the collaborative efforts of the management team and the organisation's leadership capability (Chonsawat and Sopadang, 2020 & Pozzi et al., 2021). Pozzi, et al., (2021) further explain, the adoption of new technology relies on the commitment and awareness exhibited by top-level management. Hu, et al., (2024) observes, the Industry 4.0 strategy emphasises creating a link between the current organisational strategy and the Industry 4.0 concept within businesses. This connection should clearly define the areas of action regarding Industry 4.0 adoption. The Industry 4.0 concept is commonly linked with the term "smart", encompassing smart manufacturing, smart machines and factories, and smart products and services. The key strategy for implementing this concept involves the creation of internally aligned processes that engage employees, integrate effective leadership, and foster a learning culture (Downs, 2005, cited in Gerlitz, 2016; Narula, et al., 2020; Trstenjak et al., 2022; Tortorella, et al., 2024).

Further, integrating the technology into the business strategy facilitates control (Fraga-Lamas & Fernández-Caramés, 2019), monitoring, and stakeholder relationship (Patrucco, et al., 2022). Therefore, the adoption of Industry 4.0 technology significantly relies on the internal components including company leadership, the learning process, culture, technical expertise, and organisational structure. These components are broadly classified as drivers for digital transformation strategy which are discussed in this section. A number of factors found in studies as strategy factors impact the Industry 4.0 adoption. For example, Schumacher, et al., (2016); Narula, et al., (2020); and Mason, et al., (2022) found leadership as the influencing factor for driving the Industry 4.0 initiative strategy. Matt, et al, (2021); Hajoary, et al, (2023); Moica et al., (2018) and Crešnar, et al, (2020) identify that collaboration within an organisation is a key strategy for Industry 4.0 adoption. Table 4.4 presents the summary of factors identified in the extant literature across strategies for Industry 4.0 adoption.

Table 4.4: Summary of readiness factors for Industry 4.0 adoption strategy identified in extant literature:

N	Readiness Factors	No. of studies
1	Collaboration within organisation	7 studies (Moica et al., 2018; Schuh, et al., 2019; Kiraz et al., 2020; Crešnar et al., 2020; Ávila-Bohórquez and Gil-Herrera, 2022; Schroderus et al., 2022; Bhatt & Kumar, 2022;)
2	Leadership	14 studies (Miranda et al., 2017; Arnold et al., 2018; Kiraz et al., 2020; Crešnar et al., 2020; Herceg et al., 2020; Lohmer & Lasch, 2020; Pozzi et al., 2021; Chonsawat & Sopadang, 2020; Chatterjee et al., 2021; Spaltini, et al., 2022; Bhatt & Kumar, 2022; Kumar et al., 2022; Ávila-Bohórquez and Gil-Herrera 2022; Hajoary et al., 2023;)

4.2.4.1 Collaboration within Organisation

Moica et al., (2018) conveys, collaboration and communication across different departments within an organisation are identified as a pivotal driver for the adoption of technology. Schuh, et al, (2019); Crešnar et al, (2020); Ávila-Bohórquez and Gil-Herrera, (2022); Schroderus et al, (2022); Bhatt and Kumar, (2022) report, the culture of sharing ideas and knowledge and forming partnerships with external parties is highly emphasised in the literature as an enabler of Industry 4.0, and thus recognising it as a foundational pillar for Industry 4.0. The organisational culture of sharing ideas and knowledge facilitates vertical integration by streamlining operations through dynamic collaboration. Further, the dynamic collaboration in the value creation network including suppliers and customers enables a smoother transition towards Industry 4.0 (Schuh, et al., 2019). Kiraz et al., (2020) discovered, the organisation and corporate culture demonstrated by integrated management systems have a positive influence on Industry 4.0 tendency, where tendency denotes the criterion which gets influenced by nine factors across the organisation including leadership, strategy, culture and management as one of the factors. Crešnar et al., (2020) and Pozzi et al., (2021) evidence that the non-technological dimensions such as organisational strategy which emphasises a culture of cross-functional collaboration with open communication channels are in alignment with the principles of Industry 4.0. Moreover, Crešnar et al., (2020) emphasise the imperative of cultivating open cooperation between departments where the culture based on data gathering and analysis defines the formulation of learning within the organisation for knowledge transfer and decision-making. Further, Schroeder, et al., (2022) asserted that internal learning and knowledge sharing within manufacturing plants is identified as a valuable resource to improve manufacturing performance. In the context of inter-functional collaboration, Prahalad and Hamel, (2006) emphasised collective learning in organisations as a core competency for coordinating production skills and activities. The way organisations manage varied skills within different departments makes core competency unique and difficult to replicate (Raghunathan, 2007 & Wang & Wei, 2007). Furthermore, a variety of resources are found across functions, and by configuring these resources, collaboration within departments enhances process efficiency (Frohlich and Westbrook, 2001 & Barratt, 2004). Based on RBV and reviewed literature, collaboration within the organisation implies Industry 4.0 readiness for improving the operational performance and the following metrics will be used for assessing the readiness of these factors:

The company actively participates in cross-company collaboration, forming partnerships with external parties to drive continuous improvements.

4.2.4.2 Leadership

Spaltini, et al., (2022); Bhatt & Kumar, (2022); Ávila-Bohórquez and Gil-Herrera (2022) acknowledge, leadership support entails the willingness and engagement of top-level management in the implementation of new systems or technology. People are identified as valuable resources for implementing Industry 4.0. For instance, Caldeira and Ward, (2003) assert that top management is identified as a determinant factor for IT adoption. Antony, et al., (2021) and Sureshchandar, (2023) affirmed top management as the necessary resource for adopting Industry 4.0. In a study conducted by Yang, et al., (2015) cited in Chatterjee et al., (2021), it was found that leadership commitment significantly influences the adoption of new technology. According to Kiraz et al., (2020), there is a positive association between leadership commitment and the inclination towards industry 4.0 adoption. Additionally, the literature emphasises that the recognition of the value and benefits of Industry 4.0 investments by the leadership team is a crucial component of digital maturity (Chesbrough, 2007 & Hajoary et al., 2023). This is further confirmed by Arnold et al., (2018) that a positive commitment from the top management towards the new technology is critical for successful implementation. The ability to recognise the value that can be generated from the new technology is dependent on the leadership's cooperation in facilitating innovation (Crešnar et al., 2020). An organisation with a very strong supportive culture, where leaders promote the culture of innovation amongst employees accelerates the adoption of Industry 4.0 (Simões et al., 2021).

The underlying factor driving leadership encouragement is the awareness of the technology and its benefits. The literature identifies a lack of knowledge and awareness as the main barrier to Industry 4.0 adoption (Herceg et al., 2020; Kumar et al., 2022). On the contrary, leadership support in the network establishment with other companies, and technology partners is recognised as a key enabler of adoption (Lohmer and Lasch, 2020). Given that the leadership team plays a key role in defining the vision and strategy for the firm, their involvement and knowledge become fundamental in the digital transformation process (Chonsawat and Sopadang, 2020 & Pozzi et al., 2021). Moreover, Chatterjee et al., (2021) surveyed companies that have adopted or are planning to adopt AI, confirming that the adoption or acceleration of AI is only achievable with strong leadership support within the organisation. Further, Sriyakul, et al., (2019) and Purwanto & Juliana, (2022) affirmed that leadership has a positive effect on operations performance.

Based on RBV and reviewed literature, Industry 4.0 readiness is characterised by leadership support showcasing a strong commitment that positively influences operational performance. In terms of the readiness level that would be used for identifying the technology usage level across Indian auto component firms, the following metrics will be used for assessing the readiness of leadership:

The adoption of Industry 4.0 technologies is embraced positively by the leadership team and employees with a collaborative mindset, showcasing a strong commitment to leveraging them for the organisation's success and growth.

To conclude, this study identified twelve readiness factors from the reviewed literature that will be used to measure the readiness level, based on the metrics identified from the reviewed literature and RBV as presented in Table 4.5. The studies indicated the impact of readiness factors on operational performance; however, no study was found to establish the statistical relationship between the two. This study will therefore assess the readiness level and its associated impact on operational performance.

Table 4.5: Industry 4.0 readiness metrics identified from reviewed literature across 12 readiness factors

1	Automation	An advanced level of automation where the production system can autonomously monitor and adjust its operations without continuous human intervention, optimising efficiency and minimizing errors.
2	Machine and ICT integration	The production machines and computing devices are highly integrated facilitating seamless coordination and communication between machines and software components with real-time data exchange capability.
3	E-procurement	The procurement process is characterised by the use of digital tools and technologies to collect and manage data at every stage of the procurement lifecycle (procurement software, e-procurement, electronic data interchange, cloud-based solutions).
4	Inventory Management	An advanced, autonomous system continuously monitors and dynamically adjusts inventory levels in real-time, leveraging smart devices and real-time databases for seamless and precise inventory management.
5	Real-time tracking	The product can be tracked throughout the supply chain comprising the supplier, manufacturing unit, and buyer distribution centre.
6	Communication between suppliers and customers	Fully integrated system with every party having access to the real-time flow of information allowing stakeholders to have access to the most up-to-date data for example real-time visibility across all parties.
7	Integration between suppliers and customers	Real-time visibility of site locations, capacities, inventory, and operations where data is actively used for monitoring and optimisations of operations and processes throughout the supply chain.
8	Data-driven decision making	Top management leverages big data analytics to gain valuable insights across multiple stakeholders and departments, enabling them to guide production efficiency and drive advancements within the organisation without direct involvement in daily operations.
9	Customer co-creation	Make-to-order manufacturing that combines personalised customisation with an efficient production process.
10	Collaboration with technology partners	Partnership and collaboration with external experts and consultants are involved in redesigning processes and technology implementation and also digitally transforming business through an overhaul of processes, technologies, and business models.
11	Collaboration within organisation	The company actively participates in cross-company collaboration, forming partnerships with external parties to drive continuous improvements.
12	Leadership	The adoption of Industry 4.0 technologies is embraced positively by the leadership team and employees with a collaborative mindset, showcasing a strong commitment to leveraging them for the organisation's success and growth.

4.3 Gaps in Literature

There were few studies on Industry 4.0 in the Indian context (see **Table 1.9 – Appendix 1**). Hajoary et al., (2023) conducted a single case study to understand Industry 4.0 adoption in steel manufacturing. Gadekar et al., (2022) carried out an empirical study in manufacturing companies that established a positive relationship between Industry 4.0 drivers and Industry 4.0 adoption. Chatterjee et al., (2021) investigated the adoption of artificial intelligence in manufacturing and production organisation. Meanwhile, Bansal et al., (2023) studied drivers and challenges towards the adoption of digital technologies in the manufacturing sector. All these studies were conducted in the manufacturing sector leaving a gap for understanding the technology adoption patterns and challenges specifically for the auto components industry. Further, Hajoary et al., (2023); Gadekar et al., (2022); Chatterjee et al., (2021) attempted to understand the variables that influence the adoption of Industry 4.0, but none of them studied the variables that influence the adoption of Industry 4.0 in the auto component industry.

The literature review revealed a small portion of the literature has attempted to measure Industry 4.0 readiness level where studies have indicated the overhaul of operational processes (Lee, et al., 2021 & Stornelli, et al., 2021), strategy (Zulu, et al., 2022), and business model (Savastano, et al., 2019; Favoretto, et al., 2021; van Tonder, et al., 2021; Cruzara et al., 2021), but what possesses readiness of operational processes, strategy and business models in the context of the auto component manufacturing industry is not clear in Industry 4.0 literature. These studies indicate the preconditions for business models that would reflect a firm's readiness (see **Table 3.5**), while few pointed out aligning supply chain activities to make firms Industry 4.0 ready (discussed in **section 4.2.2**). No study was found in terms of an all-inclusive framework that would demonstrate the overall readiness of manufacturing operations.

A small number of studies focused on different levels of Industry 4.0 readiness (discussed in **section 3.8**). It was found that there is no consensus in terms of the number of levels, the definition of each level and the dimensions or factors these models intend to measure (presented in **Table 3.3**). The limitations of these models are highlighted by various authors resulting from defined dimensions and levels identified for one particular industry, which can vary across sectors based on the difference in factors and readiness for adoption of Industry 4.0 (Demeter, et al., 2018; Schumacher, et al., 2016; Alcácer et al., 2021). It is therefore important to understand the readiness level across manufacturing operations in the context of auto component firms that would align better with their activities and processes to improve operational performance (Stornelli, et al., 2021 & Trstenjak, et al., 2022). Various studies indicate the necessity to focus on defining the readiness levels according to the context of the study (Alcácer, et al., 2021; Chonsawat & Sopadang, 2020; Trstenjak et al., 2022).

Industry 4.0 literature is limited from the RBV perspective. Only two studies were found where business model design was identified as a key resource to improve product innovation (Zheng, et al. 2021 & Li

et al., 2022). Though the reviewed literature highlights the relationship between Industry 4.0 readiness factors and operational performance (discussed in **subsections of section 4.2**), this relationship was not empirically tested from an RBV perspective.

There is a lack of research conducted to investigate the impact of Industry 4.0 readiness on operational performance as explained in **section 3.11**. Most studies have highlighted the positive impact of readiness factors on operational performance (discussed in **Chapter 4**). But the impact of overall readiness level which includes all factors comprehensively was not found in the literature. This underscores the need to focus on the adoption of Industry 4.0 from this perspective. Operational performance would motivate the firms to advance to a higher level of readiness for Industry 4.0 adoption. Any study that would indicate the operational measures for the auto component Industry or operational performance measures in the context of Industry 4.0 readiness was not empirically tested.

Further, the reviewed literature demonstrated varied Industry 4.0 readiness variables for assessing readiness. For example, Alcácer, et al., (2021) used strategy and organisation, smart factory, smart operations, smart products, data-driven services and employee's dimensions to assess the readiness level. Chonsawat & Sopadang, (2020) encompass organisational resilience, infrastructure system, manufacturing system, data transformation, and digital technology to assess readiness. Trstenjak et al.'s, (2022) readiness model assessed readiness across smart process planning, infrastructure, organisation and human resources. This demonstrates that Industry 4.0 readiness indicators are not uniform and can vary based on the objective of the research. Literature in the context of measuring Industry 4.0 readiness within the auto component industry could not be identified in the literature. Only three studies were conducted focusing on the automotive industry and, only two studies were conducted in an empirical setting including the study by Sütöová et al., (2020) in Slovakia region and Moica et al.'s, (2018) study in Romania. Both these studies confirmed the adjustments in Industry 4.0 readiness factors according to the specifics of the respective industry. Sütöová et al., (2020) indicated that the significance of readiness dimensions should be studied from the perspective of organisations' current state. While Moica, et al., (2018) focused on studying the Industry 4.0 preconditions in the context of automotive SMEs. This caused a lack of knowledge in understanding preconditions for large-scale companies that may vary depending on the availability of resources (Hopkins, 2021).

The Industry 4.0 research in terms of large-scale and MSMEs emphasising readiness and digital transformation showed inconsistent results. Hopkins, (2021) pointed out that SMEs are behind large scale in terms of digital transformation due to variations in resources. The study confirmed organisational size as a key factor for technology adoption. While Bogner, et al., (2016) found that the size of the company does not have any impact on the level of digitalisation. Literature on the adoption of Industry 4.0 largely emphasises on devising strategies for the adoption of Industry 4.0 across SMEs due to challenges faced in transition strategies. Research including large-scale companies focuses on

learning from the Industry 4.0 transition strategies adopted by these companies. No research was found to establish the difference between the readiness of large-scale and SMEs for digital transformation.

4.4 Preliminary Research Framework

The studies have classified the factors identified as enablers, and drivers of Industry 4.0 adoption or dimensions of Industry 4.0 readiness into categories of manufacturing and operations (Bogner et al., 2016; Savastano, et al., 2019; Chatterjee, et al., 2021), Business model (Safar et al., 2018; Gerlitz, 2016; Arnold et al., 2018; Ibarra et al., 2018; Herceg, et al., 2020), supply chain (Hopkins, 2021; Núñez-Merino, et al., 2022; Taghipour, et al., 2022) and Strategy (Downs, 2005 & Zulu, et al., 2022) that would require to be ready for Industry 4.0 adoption. Therefore, readiness across these areas will be assessed using the metrics identified (see **section 4.2/ Table 4.5**) from the reviewed literature and RBV. Additionally, existing readiness models included the same dimensions for measuring the readiness level (Chonsawat & Sopadang, 2020; Sütőová et al., 2020; Alcácer et al., 2021; Schroderus et al., 2022; Hajoary et al., 2023). Therefore, current research classified the Industry 4.0 readiness factors into manufacturing, supply chain, business model and strategy (See **Figure 4.1**). Industry 4.0 readiness level is not assessed across all these categories comprehensively in the literature within Indian auto components firms. This new context of Industry 4.0 readiness serves as originality in this research, as no prior study has been found that would integrate all these categories into one framework. The designed preliminary framework is presented below in Figure 4.1.

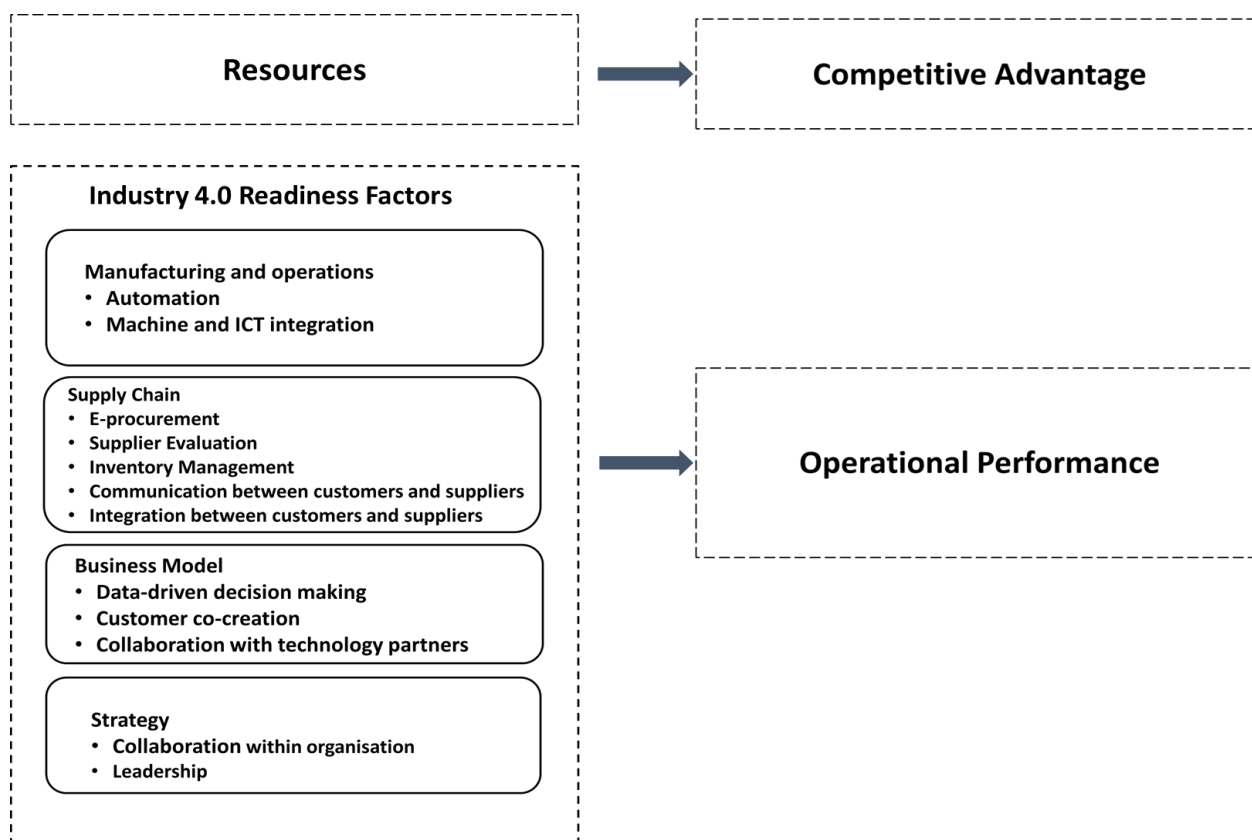


Figure 4.1: Preliminary Research Framework (Source: Author)

Regarding operational performance measures, since the impact of Industry 4.0 adoption in manufacturing is highly aimed at achieving operational efficiency, and the literature highly emphasised attaining operational performance, this research further examines the impact of Industry 4.0 readiness level on operational performance (discussed further in **sections 7.2, 7.4.1, and 7.4.2**). The reviewed literature in section 4.2 revealed the relationship between readiness factors and operational performance, however, no study was found to empirically test the relationship between Industry's readiness level and operational performance. This study will test this relationship based on the current readiness level of the Indian auto component industry which will be assessed using the exploratory study. For operational performance, the reviewed literature discusses operational measures across manufacturing (see **section 3.11**) and any study that would indicate the operational measures for the auto component industry were not empirically tested. Therefore, an exploratory study will investigate the operational performance resulting from the current practices of Indian auto component firms to explore the operational performance measures.

12 factors identified from the literature review and theory will be studied through an exploratory study in Indian auto component firms to design the measurement scale, where the current practices will be measured qualitatively against the readiness metrics identified across all the factors (as presented in **Table 4.5**). Additionally, operational performance measures as identified during the semi-structured interviews (discussed in **sections 6.5 and 7.3**) will be used for understanding the impact of Industry 4.0 readiness level on operational performance.

4.5 Chapter Summary

This chapter discussed the Industry 4.0 readiness factors as identified from the reviewed literature and resource-based view. Further, the chapter is structured based on the discussion in chapter three to identify the readiness factors around the manufacturing operations as no study was found focusing on the operations of auto component firms. Four key areas emerged focusing on transitioning the operations including manufacturing, supply chain, business model and strategy. Additionally, chapter four specifically focused on the empirical studies conducted to understand the prerequisites for the adoption of Industry 4.0 including companies that have successfully transitioned to Industry 4.0. Further, no theory was found that would cover the readiness framework, and understand the relationship between Industry 4.0 readiness factors and operational performance. This is the first study in terms of assessing the readiness level which is underpinned using RBV.

The chapter concludes by presenting the preliminary framework that will be studied further using exploratory study. This framework will assist in first developing the readiness scale based on the current practices in the context of Industry 4.0 within Indian auto component firms. Additionally, the operational performance measures will be identified as linked to current practices that will establish the link between the practices and operational performance.

Chapter 5: Research Methodology

5.1 Introduction

Chapter 4 has set the course for this research by identifying the Industry 4.0 readiness factors across manufacturing operations. Since the literature has discussed manufacturing operations broadly without delving into the specific intricacies of automotive manufacturing in terms of the technology adoption patterns, further exploration is required to discern the operational practices comprehensively, with a particular focus on the technological landscape across operations within the Indian auto components industry. Additionally, the impact of the current readiness level on operational efficiency has not been empirically studied in the context of this study (discussed in **section 3.11**). Moreover, the empirical research is mainly restricted to developed countries (as discussed in **section 3.9** and presented in **Table 1.9 – Appendix 1**), and the perceived value of technology differs in developing countries (Dalenogare, et al., 2018).

Hunziker and Blankenagel, (2021) emphasised the prominence of an adequate research design to produce intellectual contribution. A research design facilitates answering the research questions through a systematic and logical strategy for mitigating the challenges of the research process (Sidharth, 2023). Additionally, the merit of the research is rooted in the systematic and methodological approach to answering the research question and attaining the research objectives (Jongbo, 2014). The elements of coherent research design encompass research methodology, research methods, techniques of data analysis, setting of the research, population, sample and ethical issues (Hancké, 2009; Adebiyi & Abayomi, 2016; Basias & Pollalis, 2018; Chali, et al., 2022). Considering this, the researcher needs to choose an appropriate research design. Afterwards, the choice of suitable research methodology and appropriate technique for collecting data assist in addressing the research gaps and achieving the overarching research objectives (Bryman, 2016). The research methods are a function of the research problem, and relevant research variables associated with the research objectives (Taherdoost., 2021). Therefore, a full consideration of the research design including research methodology, and research methods is conducted in this chapter. The chapter begins with the philosophical beliefs underpinning the knowledge being investigated in this research. The literature synthesised in the previous chapter leads to the research method adopted in this study, focusing on Industry 4.0 and operations-oriented research strategies as frequently being adopted within this field. Subsequently, data collection instruments for conducting semi-structured interviews and surveys are discussed. The data analysis techniques used in interviews and surveys are discussed following time horizon and ethical considerations.

5.2 Research Philosophy

According to Saunders et al (2016), research philosophy is underpinned by an array of assertions, and each holds a unique claim to the production of knowledge, through conducting research. The

methodological choice, research strategy, data collection, and analysis technique are guided by the chosen philosophical approach to research Bennett, et al., (1994). As discussed by Saunders et al (2016), the philosophical approach that resonates with the researcher and is subsequently applied moulds the shape of the research approach throughout, particularly the chosen modes of data collection and analysis. Research philosophy can be broken down towards two fundamental questions. One on ontological reasoning and the other on epistemological reasoning. According to Onwuegbuzie et al., (2009) ‘ontology’ or an ‘ontological question’ seeks to understand the nature of reality. This can further be broken down into the ‘what’ factor. Meanwhile, ‘epistemology’, or an ‘epistemological questioning’ according to Bell et al., (2022) seeks to understand how knowledge about reality is manufactured and maintained. Epistemology can also be understood as the ‘how’ factor of research. The following section will reflect on the ontological and epistemological reasonings that have been applied throughout this research, thus establishing the chosen research philosophy.

5.2.1 Research Ontology

Two major branches of philosophical ontology; objectivism and subjectivism (Jacquette, 2002 & Neuman, 2014) are likely to be accepted by the research community in combination with the production of valid knowledge (Saunders, et al., 2023). Objectivism is the belief that the world is external and made of material things which are more real. These exist independent of human experience and the human mind (Fleetwood, 2005). Objectivists suggest that social phenomena exist whether we are aware or not. The objective reality is independent of the role of the observer or social actors (Leavy, 2022).

On the other hand, subjectivism is the belief that reality is constructed within the human mind where reality is ungoverned by natural laws and is relative to an individual’s experience and consciousness (Williams, 2016). Contrary to objectivists, subjectivists suggest that social actors continually accomplish the social phenomenon and socially construct their meanings, and therefore subjectivism is associated with constructionism (Saunders, et al., 2016). There is enough sufficiently extensive debate in the literature perceiving that constructivists and objectives are two opposites underpinned by two completely different philosophies (Scotland, 2012; Don-Solomon, et al., 2018; Otoo, 2020). Cronjé, (2006) argues that the choice of one branch does not exclude the other.

Through a critical encounter with the literature on Industry 4.0, it has been identified that strategies, processes, business structures, knowledge creation, and methods within the businesses do not act without human agency and subjectivity of top-level management and employees (Bratman, 2022; Valmohammadi & Ahmadi, 2015). The business processes and models cannot be understood in isolation from the human observers (Auernhammer and Hall, 2013). The processes and strategies adopted are the product of the knowledge, experience, and perceptions that are constantly reshaped and rebuilt by the understanding and interpretation of human actors (Paiola, et al., 2021; Müller, et al., 2021; Hu, et al., 2024). On the other hand, research also encompasses non-behavioural patterns which include

operational performance. The common objective of the firms to maximise profit from the operational activities irrespective of the perception and principles of social actors assumes objectivism. Additionally, supply chain management encompasses interconnected components exhibiting separate identities from their environment (Christopher, 2022). Further, the key assumption that organisations are perpetual entities and are independent of the founders, owners and employees is often associated with objectivism (Fleetwood, 2005).

5.2.2 Research Epistemology

Once an ontological approach has been consolidated, it is inevitable that an epistemological questioning will occur. Epistemology emphasises how knowledge is created and how it is known to the world in the truest possible way (Cunningham and Fitzgerald, 1996). The two key epistemological approaches are interpretivism and positivism (Alharahsheh and Pius, 2020). Typically, the adoption of a positivist epistemology is aligned towards an objectivist ontology. Meanwhile, an interpretivist epistemological position is aligned towards a subjectivist ontology (Burgess, et al., 2017). To be an interpretivist means to make sense of social reality through self-reflection. The self's own interpretation and sense-making of what is physically in front of them in addition to the symbolic and linguistic connotations attached (Matthews and Ross, 2014). However, a positivist will make sense of social reality by applying techniques historically and to date favoured in the natural sciences, particularly experimenting, hypothesising and validity testing (Rand, 1990). As manufacturing firms are assumed to be external to the researcher, the researcher takes the view that operational performance could be measured objectively. The multidisciplinary nature of business indicates the presence of different types of knowledge varying from numbers, reports, and interpretations to visual data. In view of its complexity, organisations are understood as the structure which results from the perceptions and actions of social actors. Therefore, it is necessary to study the situations within an organisation in detail to understand different opinions and narratives that account for performance variations. Therefore, a mixed epistemological approach combining interpretivism, and positivism will be applied. It is maintained that business organisation and management occur because of the human condition, however much of the progression and delivery outputs occur through processes that can be observed in the natural sciences and so too amongst positivists.

5.2.3 Linking philosophy to research: ontological and epistemological assumptions

The ontological and epistemological underpinnings of this research, towards a 'research paradigm' will enable new knowledge to be founded. In this study, factors including awareness of the advanced technology to improve operational performance and the sharing of knowledge across the organisation, influence the adoption pattern of advanced technologies across multiple organisations (Leso et al., 2023; Pozzi et al., 2021). This can be further understood through conducting an exploratory study to enhance the understanding of existing processes reflective of top management's subjective views to shape the

organisational business model and operational practices (Pozzi et al., 2021). Moreover, operational performance can be measured independently of human interpretation, while taking a subjectivist approach will enable the understanding of the processes and strategies to be positioned alongside the existing knowledge and experience of the organisation (Paiola et al., 2021; Serrat, 2017). The research aimed to assess the technological readiness level in the context of Industry 4.0 that impacts the operational performance of the firm through the collection of quantitative data to validate or refute the hypotheses. In such a situation, the researcher is independent of the data obtained from the firms with little or no alterations to the data leading to statistical analysis, and this reflects the philosophy of positivism (Saunders et al., 2016). Factors leading to the readiness level could not only be understood from the adoption or application of technology but could be interpreted from the motivation of top-level management in transforming the business models, and business practices adopted so far to bring strategic changes in processes (Chonsawat and Sopadang, 2020; Pozzi et al., 2021). The interpretive research is also embedded into the purpose of research, such as creating a new, in-depth understanding of social worlds and context, depending upon different circumstances, including awareness and technology usage patterns intertwined with the technological readiness index that varies across economies (Dutta and Lanvin, 2023). Due to the involvement of different circumstances and the complexities within the organisational and social world, interpretivism is explicitly subjectivist (Alharahsheh and Pius, 2020).

5.3 Research Approach

According to Saunders, et al., (2023), there are three key approaches for theory development: deductive, inductive and abductive. In deductive reasoning, a conclusion is derived logically by evaluating propositions or hypotheses related to existing theories (Antwi and Hamza, 2015). The deductive approach is closely associated with the realist ontological approach (Pearse, 2021). In the deductive approach, hypotheses are designed based on existing knowledge, data is collected, and the hypothesis is then tested to support or reject the theory underlying the hypothesis (Hyde, 2000). Forasmuch as it focuses on the association between events, the approach lacks a detailed explanation that underpins the associations between events. Deductive reasoning requires the facts to be measurable for theory testing. Generalisation of ideas or results necessitates the careful selection of a sample with sufficient size for generalising the theory. Deduction proceeds with a general premise and ends with a more specific conclusion (Hyde, 2000).

The inductive approach to theory development goes beyond the deductive approach by not establishing the cause-effect link, but rather understanding the relationship and variables in the way it is interpreted by humans in the social world (Hayes, 2007). The theory is built inductively based on the experiences and consciousness of social actors (Heit, 2000). The inductive reasoning utilises the collected data for the identification of patterns and thus drawing a meaningful conclusion. It begins with observations and concludes with providing or generating more generalised ideas (Hayes and Heit, 2017). It permits the

alternative explanation of an event which facilitates a flexible research design (Saunders, et al., 2016). Inductive reasoning emphasises the context in which an event takes place which means that a detailed understanding can be obtained of a phenomenon in each context with an alternative explanation (Arthur, 1994). Since explanation-seeking is a crucial aspect of making generalisations from specific observations in the inductive approach, studying a small sample is deemed more appropriate for producing detailed data (Patton, 2002). By focusing on a small sample, researchers can obtain in-depth information and gain a more comprehensive understanding of the phenomenon being studied. This approach allows for a more thorough exploration of the participants' experiences and perspectives, enabling the generation of rich and nuanced insights. Additionally, the inductive approach allows for the incorporation of new information and perspectives during the research process, which enhances the validity and reliability of the findings (D'Cruz and Noronha, 2000). Based on the above discussion, it can be inferred that while deduction is about theory testing, induction investigates the nature and nuances of a problem for the broad generalisation of specific observations.

According to Saunders et al., (2023), abduction follows the middle ground between inductive and deductive approach and moves back and forth for theory development. Much of this, according to Conaty (2021), is enacted through obtaining data and understanding the phenomenon with rich and detailed explanations. The findings from the data are then integrated into a conceptual framework. Building on the ideas of theory regeneration and novel theoretical explanations, the framework is used as a theory, which is then tested using evidence from new and existing data (Bamberger, 2019). The inferences thus drawn from the close examination can be used for making the necessary changes in the existing theory or suggesting a new theory entirely, as discussed by Haig (2005). The abductive approach, therefore, seeks to develop an explanatory hypothesis while deduction derives a conclusion from preexisting premises (Haig, 2005). On the other hand, an inductive approach generalises the patterns in the context of the specific instances.

According to Broekman et al. (2013), deduction has limitations in terms of failing to elaborate new theories. Adams & Levine (1975) argued that the conclusion from the use of deductive theory already exists in the premises and thus fails to increase the knowledge. On the contrary, inductive theory allows access to new information by identifying themes and patterns from an observation (D'Cruz and Noronha, 2000). However, Popper demonstrated that the conclusions drawn are rather probabilistic with susceptibility to bias and subjectivity in interpretations of observation (Morse and Mitcham, 2002). Pierce (1934) takes a critical stance on the use of inductive and deductive reasoning for knowledge creation and argues that knowledge can only be extended in its truest form by abductive reasoning. While inductive and deductive reasoning attempt to explain the known facts and characteristics to new cases, abductive reasoning infers the existence of something different through an iterative process of formulating hypotheses and creating a bridge between the logic of discovery (inductive) and the logic of justification (deductive) (Dong et al., 2015). Abductive reasoning facilitates the refinement of an

emerging argument through constrained empirical phenomena and adjusts the theoretical framework for its applicability to grouped empirical phenomena. The conclusion that can be drawn from the preceding arguments is that knowledge creation in social science cannot rely exclusively on inductive or deductive reasoning. This study therefore employed abductive reasoning following the exploratory sequential mixed methods design due to the iterative process this research followed by moving back and forth between data and prior knowledge. An inductive approach is used by analysing the data collected from the auto component firms and identifying patterns of technology usage and resulting operational performance (rationale further discussed in section 5.3.1). Abductive reasoning is used to develop new theoretical insights from the qualitative study and develop hypotheses (Haig, 2005). Following hypotheses development, a deductive approach is used to test the relationship within the refined research framework.

According to Bruke (1992), the research framework assumes greater significance in the abductive approach for combining empirical data and theory. Miles and Huberman (1994) suggested that abduction starts from empirical findings and does not involve a strict framework design. However, according to Bryman (2003), the prior theoretical knowledge provides the background for seeking meaning from empirical observations. These ideas are supported by Blumer (1954), who argued that before entering the empirical field, the concepts from literature should be used as a guideline. It can be inferred that abductive reasoning may or may not include the initial theoretical framework. In this research, the literature on Industry 4.0 was reviewed to understand the Industry 4.0 readiness factors and the preliminary research framework was designed based on the synthesis of existing literature. The framework indicated the relationship between Industry 4.0 readiness and operational performance, with the need for further refinement in the context of the Indian auto component industry due to a lack of studies in the chosen context (as discussed in section 3.11). Therefore, based on Blumer (1954), this study used the preliminary research framework as a guideline during the qualitative data collection process. Thereupon, following Bryman (2007), the theoretical concepts, including Industry 4.0 readiness and operational performance, were refined using abductive reasoning through an iterative analysis of data and literature. The iterative process of continuously reflecting on empirical material and literature (Haig, 2005) provided a refined conceptual framework with the development of hypotheses (as discussed in Chapter 7). Following the iteration process, deductive reasoning is used to test the hypotheses (as discussed in Chapter 9) and the efficacy of the refined framework. This study thus followed the cycle of inquiry as proposed by Morgan (2007), integrating inductive, abductive and deductive across the qualitative and quantitative stages as shown in Figure 5.1, which is further discussed in the following section.

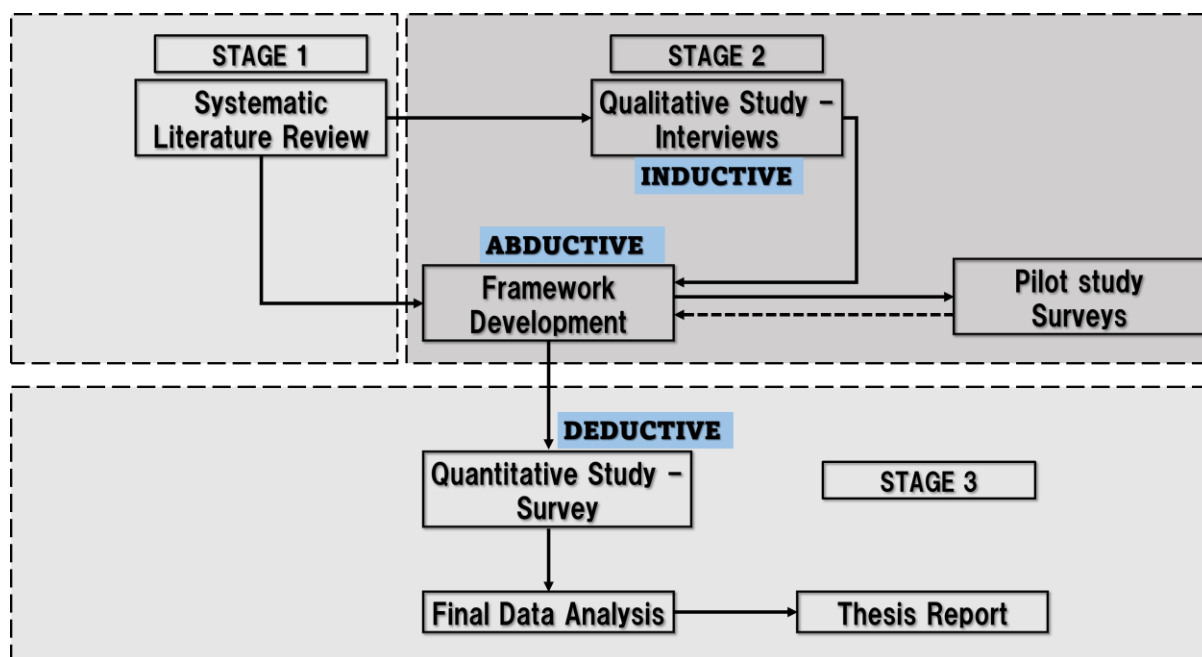


Figure 5.1: Research approach process

Source: Adopted from Shishank and Dekkers (2013)

5.3.1 Cycle of inquiry

It is maintained by Gardas et al., (2024) that the inductive phase ensures coherence with the available literature while assessing the current technology infrastructure that would result in enhanced operational performance within a sector-specific context. Existing literature demonstrated the effectiveness of the inductive approach for understanding Industry 4.0 readiness, emphasising the context-specific assessment (Dalmarco, et al., 2019; Khoureshed et al., 2023). Additionally, the inductive approach is significantly used in the digital transformation area to explore the themes (inductive) and test the relationships (deductive). Ghobakhloo, (2021) adopted the inductive approach for identifying the technology implementation determinants from the literature review, followed by interviews for refining identified factors. Consistent with Ghobakhloo (2021) and Gardas et al. (2024), this study adopted an inductive approach during the qualitative study. The existing literature has been extensively analysed to identify Industry 4.0 readiness factors within the manufacturing industry to ensure that themes central to the research were fully explored. The inductive approach allowed for the identification of emerging themes related to technology usage patterns and the operational performance within the Indian auto component industry. The inductive approach in the context of Industry 4.0 readiness would emphasise understanding the readiness unique to the context and manufacturing practices of the Indian auto component industry.

Nevertheless, previous literature suggested (Sony and Naik 2019; Kumar et al., 2021) that the technology readiness model does not fit with every industry, and therefore, the abductive approach is useful to tailor Industry 4.0 strategies according to the current situation of the Indian auto component industry which was not previously documented in the literature. Further, focusing on specific areas

within manufacturing which would influence operational performance, it is important to understand areas that are highly prioritised by auto component firms. The inductive reasoning is therefore further supplemented by the abductive approach to develop hypotheses using the operational performance measures as identified from the findings of the qualitative study. To summarise, the qualitative data from exploratory interviews were used to inductively generate themes, which were then interpreted using existing literature to develop hypotheses. This process reflects the abductive reasoning approach in line with Timmermans & Tavory (2012) and Dubois and Gadde (2002). Further, according to Sütőová et al., (2020) the development of readiness models needs to be based on the company's current situation and then analysing the gap by comparing the current situation with theoretical models of Industry 4.0. This will ensure that the existing developed model is grounded in the reality of organisations for effective implementation of Industry 4.0 strategies to increase the readiness level. By using this approach, the initial framework designed with the current literature was further refined using the interview findings. through a close examination of individual cases. Drawing from the concept of abductive analysis as described by Timmermans & Tavory (2012), abduction allowed the formulation of hypotheses which are foregrounded in qualitative data and theoretically supported by the existing literature. The developed hypotheses were subsequently tested by employing deductive reasoning to evaluate the relationship between Industry 4.0 readiness and operational performance.

5.4 Research methods overview of the current study

In the purview of the preliminary research framework and the researcher's ontological position of subjectivism and objectivism (as discussed in **section 5.2.3**), the current research employs mixed method involving the combination of qualitative and quantitative method. With respect to the varied levels of technology usage which characterise Industry 4.0 readiness, their operational performance and the researcher's ontological position, in combination, they have laid down the foundation of the research method adopted in this study. This approach is particularly suited to understand the readiness variability rooted in the heterogeneous patterns of technology infrastructure across industry (as discussed in **section 2.6.1**). Additionally, the lack of a framework to understand and measure the context-related operational priorities tailored to the auto component industry shaped the choice of methodological framework (discussed in **section 3.11**). This choice is driven by the objectives of this research, where the qualitative method is adopted to explore the patterns and refine the framework for the quantitative study by using findings from qualitative study. The refined framework is subsequently tested using the quantitative method (further discussed in **section 5.7**).

The methodological framework encapsulates two phases, including qualitative and quantitative. The qualitative phase acted as a foundational component to capture the nuanced realities of technological infrastructure and operational priorities through in-depth interviews with key operational leaders and key decision makers within the auto component firms. Qualitative data played a key role in providing detailed insights and propositions (discussed in **sections 6.4 and 6.5**) that can be further tested and

generalised through quantitative data. The qualitative exploration is preliminary as the models developed in the Western context may not account for the challenges and current technological landscape within the Indian auto component ecosystem as noted by Sony and Naik, (2019); Lucato et al., (2019) and Alcácer et al., (2021). Building upon the qualitative insights derived from the focused inquiry into the predetermined areas, the quantitative phase tests the relationships by using measures refined from the initial interviews using a survey instrument. The survey instrument's construction is grounded in the contextual variations related to Industry 4.0 readiness level across the Indian auto component industry, which further translates into operational performance improvements.

In summary, by employing mixed methods, the researcher aimed to achieve the following:

- i) A context-related readiness measurement tool to be developed using qualitative interviews.
- ii) The need for qualitative data via semi-structured interviews to obtain rich insights into the current technology usage patterns and the resulting impact on operational performance. Additionally, detailed insight into operations performance indicators prioritised by Indian auto component manufacturing that they aim to achieve based on the current manufacturing practices in alignment with OEMs.
- iii) Objective data to be collected from respondents for measuring the readiness level based on the contextual readiness levels and operational performance measures identified from the qualitative study and analysed by the researcher.
- iv) The expectations of the outcome to be generalisable to the Indian auto component population in the wider Indian economy.

It is maintained by Paiola et al., (2021) that less-researched fields like Industry 4.0, which are still less explored in developing economies (see **Figure 1.3** and **section 1.3.3 - Appendix 1**), can be better understood by conducting in-depth interviews (rationale further discussed in **section 5.8**). This study further extends the exploratory approach by statistically testing the relationship between Industry 4.0 readiness and operational performance. The measures refined from semi-structured interviews are utilised during the quantitative study using structured survey questionnaire to test the relationship between Industry 4.0 readiness and operational performance. Additionally, the research methods adopted for this study address the challenges of measuring varying readiness levels, including the requirement to account for distinct technological readiness, as pointed out by Hopkins (2021).

5.5 Research Methodology

Research methodology encompasses the combination of different elements of research that include philosophical assumptions that underpin the study, research strategy, research approaches and time horizon (Goundar, 2012) into a coherent plan, detailing how the research project will be carried out in the specific context to attain the desired objectives (Jonker & Pennink, 2010; Davidavičienė, 2018). Although the terms “research methodology” and “research methods” are often used interchangeably,

they represent different aspects of the research process (Blair, 2016; Bryman, 2016). While research methodology assumes logical order pursued by the researcher for achieving the results, research methods focus on the concrete steps undertaken to collect and analyse data leading to the interpretation of results (Jonker & Pennink, 2010). Traditionally, research methodologies are divided into two main types: qualitative and quantitative. Qualitative research conducts an in-depth investigation of experiences, beliefs, and perceptions through textual data, audio and visual data and observations, placing a strong emphasis on subjective interpretation of social realities (Marshall & Rossman, 2014). Qualitative research involves understanding the phenomenon through non-numerical data which can be in the form of text, video, or audio (Saunders, et al., 2023). The qualitative data offers a rich and detailed view of organisational realities and thus proposes a new understanding of the world which would not be possible with the choice of the quantitative research approach and is therefore identified with interpretivism (Gall, et al., 1999). Qualitative research aligns with the research objective to measure the current operational practices and technology usage of the Indian auto component industry in the context of Industry 4.0 within the horizontal and vertical value chain comprising suppliers and customers. The qualitative researcher draws upon non-standardised methods of data collection to follow a research process that is naturalistic and interactive (Creswell, 2018). The data is interpreted to make sense with the acknowledgement that practices and strategies are created by the social actors involved within the businesses. Therefore, the qualitative research approach with the constructive ontological approach and interpretivism epistemology as guided by the literature suggests that the business practices are relative and created by the stakeholders involved (Grabowska and Saniuk, 2022; Ibarra, et al., 2018; Favoretto, et al., 2021; van Tonder, et al., 2021). The qualitative research could answer the research question of ‘What’ are the prevailing practices in the Indian auto components industry in the context of Industry 4.0 within the horizontal and vertical value chain comprising suppliers and customers, and ‘How’ the current practices in the Indian auto components industry could be systematically measured to evaluate the influence on operational performance.

Quantitative research on the other hand, centres on numerical data, striving for objectivity (Creswell, 2018 & Basias and Pollalis, 2018). Quantitative research includes the investigation of phenomena through the processing of numerical data. The key characteristics of quantitative research include i) the use of a close-ended questionnaire (Balnaves and Caputi, 2001; Swift & Piff, 2014); ii) the quantification of findings (Newman and Benz, 1998; Black, 1999; Goertz and Mahoney, 2012); and iii) using advanced statistics tools for analysing the relationship between constructs (Black, 1999; Martin & Bridgmon, 2012). It is usually selected to verify the hypotheses or test the theory. Quantitative research is distinguished from qualitative research, whereby it assumes that behaviour is highly predictable (Merriam, 2009). Quantitative research operates under the assumption of objectivity and therefore fits into the positivist paradigm. Quantitative research employs questionnaires, surveys and experiments for gathering data, which allows the data to be analysed by measuring variables on a sample

to establish the relationship between variables (Bryman, 2016). In this research quantitative research is required to facilitate answering the research question ‘What’ is the readiness level of the Indian auto component industry; the difference in readiness level between large-scale companies and MSMEs and statistically testing the relationship between the readiness level and operational performance.

There is a divide in belief within the academic literature reflecting contention over the application of research methodologies (Hartas, 2015 & Mulisa, 2021). Various researchers argue that research can be either qualitative or quantitative and cannot go hand in hand (Denzin & Lincoln, 2011; Petty, et al., 2012; Patton, 2015; Smith & Sparkes, 2016). However pragmatic researchers contend that mono-methods control the advancement of social sciences and undermine the credibility of findings derived from singular methods (Greene, et al., 1989; Kelle, 2006; Greene, 2008; Lee and Smith, 2012). In the following section, qualitative, quantitative, and mixed research methodologies are analysed to justify the mixed methodology adopted for this research. Based on the preceding arguments, the evaluation of the right methodology is thus critical based on the research questions and research objectives (Saunders, et al., 2016).

This research employs a mixed methodology involving the combination of qualitative and quantitative research in the same research. The concept of mixed research methodology was introduced by Campbell and Fiske (1959) integrating multiple research methods for validation by blending quantitative and qualitative research approaches. The synergetic combination of aspects of qualitative and quantitative research are combined including different perspectives, philosophical assumptions, and data sources (Greene, 2008; Creswell, 2008; Tashakkori and Teddlie, 2010; Sharlene Nagy Hesse-Biber, 2015; Clark & Ivankova, 2015). Based on the reviewed literature, some previous studies investigating Industry 4.0 readiness factors employed qualitative research methodology (Chonsawat and Sopadang, 2020; Trstenjak et al., 2022; Hajoary et al., 2023), while some studies have used quantitative research methodology (Alcácer et al., 2021; Ávila-Bohórquez and Gil-Herrera 2022; Spaltini et al., 2022; Khoureshed, et al., 2023). However, no study was conducted using mixed methodology. Therefore, this research contributed to filling this gap in the literature. To address the research objective, this research deployed mixed methodology following an exploratory sequential mixed method design. As no framework could be found in the reviewed literature to measure Industry 4.0 readiness of the auto component industry (section 4.3), a qualitative study is first conducted to explore the technology usage across the factors identified from the literature (Chapter 4). Additionally, what constitutes operational performance measures could not be identified from the reviewed literature (section 3.11), exploratory qualitative study will help in identifying these measures rooted in the current technology usage across operations. Subsequently, the conceptual framework as developed from qualitative study and literature (See **section 7.4 and Figure 7.2**) is evaluated quantitatively to measure the overall readiness level of the auto components industry and its impact on operational performance.

5.6 Research design approach

After establishing the basis for the adoption of mixed methodology by synthesising qualitative and quantitative research methodology, it is imperative to identify the means for collecting data that aligns with the research design. Research design is typically linked with three basic forms of research objectives including exploratory, descriptive and explanatory research. The optimal use of these approaches is based on the purpose of the research (Creswell, 2018). Exploratory research seeks to gain new insights and assess phenomena in a new light by addressing research questions that begin with ‘what’ or ‘how’ (Ragab & Arisha, 2018). The aim of conducting exploratory research is to identify the main variables and generate hypotheses for further investigation (Swedberg, 2020). This type of research is adopted to attain more understanding as the concepts are not clear enough to develop an operational definition (Robson, 2002).

Descriptive research aims to provide an accurate profile of events, people and situations while addressing ‘who’, ‘what’, ‘where’, ‘when’ or ‘how’ for describing the research phenomenon (Sreejesh, et al., 2013). Descriptive research though lacks in providing the reasoning behind the occurrence of the phenomenon which is sufficiently considered in explanatory research (Wilson, 2014). Explanatory research establishes the causal relationship between variables by answering ‘why’ or ‘how’ and assists in getting fresh insight into the situation to build, elaborate, extend or test a theory as posited by (Cohen, et al., 2017).

In this research, the qualitative research method would answer the exploratory, broad-based question (Creswell, 2008) of ‘how’ the current practices across the auto components industry within developing countries influence its operational performance. Furthermore, the quantitative method would assist in answering the research questions “*What* is the technology readiness level of the Indian automotive industry?” and “*What* is the impact of readiness level on operational performance?” Exploratory research can be conducted in several ways, including literature review, interviewing experts and focus group interviews (Saunders, et al., 2023). In determining the choice of appropriate data collection method for qualitative methodology for this study, an in-depth exploration of the participants' thoughts can provide insights into how the technology is currently being used to achieve operational efficiency. Whereas, for measuring the readiness level and relationship between variables, statistical analysis would facilitate testing the relationship. The appropriate research strategy for the two purposes, including in-depth exploration and statistical analysis is discussed in the next section.

5.7 Research Strategy

The choice of research strategy in this study is rooted in the research philosophy, research approach and subsequent choice of method to collect data (Denzin & Lincoln, 2011). With respect to the current operation practices of the Indian auto components industry in the context of Industry 4.0 and the impact of Industry 4.0 readiness on operational performance, the researcher’s ontological position of

subjectivism and objectivism in this study guided the choice of research strategy. The research strategy that belongs to the inductive approach associated with qualitative research design includes ethnography, grounded theory, and narrative inquiry. Ethnography strategy is concerned with describing human behaviour, and social life and revolves around the study of different cultures in their natural setting (Ejimabo, 2015). Grounded theory is used as an attempt to explain behaviour grounded in the data produced from the experience of social actors (Goulding, 2002). The case study strategy provides an understanding of the problem, by investigating contemporary phenomenon in real real-life setting by using multiple sources of empirical evidence (Yin, 2009).

The research associated with quantitative research design includes surveys and experiments. The survey strategy is used to answer 'what', 'who', 'where', 'how much', and 'how many' research questions in exploratory and descriptive research (Saunders, et al., 2023). Survey strategy can further utilise quantitative research strategies, qualitative research strategies or both in mixed methodology utilising questionnaires and semi-structured interviews as part of the survey strategy (Rossi, et al., 1983; Mauceri, 2014).

Since the current research context is less explored as demonstrated in Chapter 3, a qualitative approach is adopted for research problems with little or no knowledge (Voss, et al., 2002). Previous studies within Industry 4.0 readiness factors/digital transformation have utilised qualitative survey strategy by conducting interviews (Chonsawat and Sopadang, 2020; Trstenjak et al., 2022) and quantitative strategy using surveys (Sütöová et al., 2020; Alcácer et al., 2021; Spaltini et al., 2022; Ávila-Bohórquez and Gil-Herrera, 2022). To understand the current practices in the context of Industry 4.0 encompassing challenges and opportunities, Dalmarco, et al., (2019) conducted interviews to comprehend the integration strategies and opportunities for the manufacturing processes. Cruzara, et al., (2021) conducted interviews with Brazilian small enterprises to understand the transformation process. Moica, et al., (2018) conducted an interview to assess the strategy required for changes in the production system that facilitated the transition into Industry 4.0. Therefore, to meet the second research objective (RO), and assess the current operational practices, this study used interviews consistent with the previous studies. Additionally, the qualitative study in this research is aimed at systematically developing the readiness scale for measuring the readiness level of the Indian auto components industry, and examining the impact of current practices on operational performance thus attaining RO3. The developed framework was subsequently used in measuring the readiness level using a quantitative study prior thus attaining RO4.

A quantitative survey strategy was further utilised to measure the readiness level of the Indian auto components industry by integrating the framework developed from the qualitative study to meet RO4. Bogner et al., (2016) adopted a quantitative survey strategy for assessing the readiness level of operational practices in the context of Industry 4.0 in the manufacturing industry in Germany. Further,

no empirical study was found to measure the statistical relationship between Industry 4.0 readiness level and operational performance (see **section 3.11**). Only one study that distantly studied Industry 4.0 readiness and sustainable operational performance was found (Gadekar et al., 2022), which empirically examined the impact of Industry 4.0 drivers as one of the independent variables, and sustainable operational performance as the dependent variable. The study adopted a survey strategy to test the relationship using PLS-SEM. To meet RO5, this study investigated the relationship between readiness level and operational performance by using structural equation modelling (See **section 9.3.1**) to test the hypothesis and establish the relationship. Hence, the survey strategy is identified as the appropriate strategy to investigate RO4 and RO5.

In conclusion, given the nature of the research problem and the fact that sufficient evidence from the literature is not found to evaluate the readiness level of the Indian auto component industry, it is deemed that the qualitative survey adopting an exploratory design approach would be most suitable for identifying the technology usage level using the industry 4.0 readiness factors identified from the literature. Additionally, operational performance measures could not be identified from the reviewed literature and an exploratory study using interviews assisted in understanding these measures. Further, to measure the readiness level of the Indian auto component industry, and statistically test the relationship between Industry 4.0 readiness and operational performance, a quantitative survey strategy is the most suitable choice. The steps adopted for attaining the research objective by adopting the discussed research strategy are depicted in Figure 5.2.

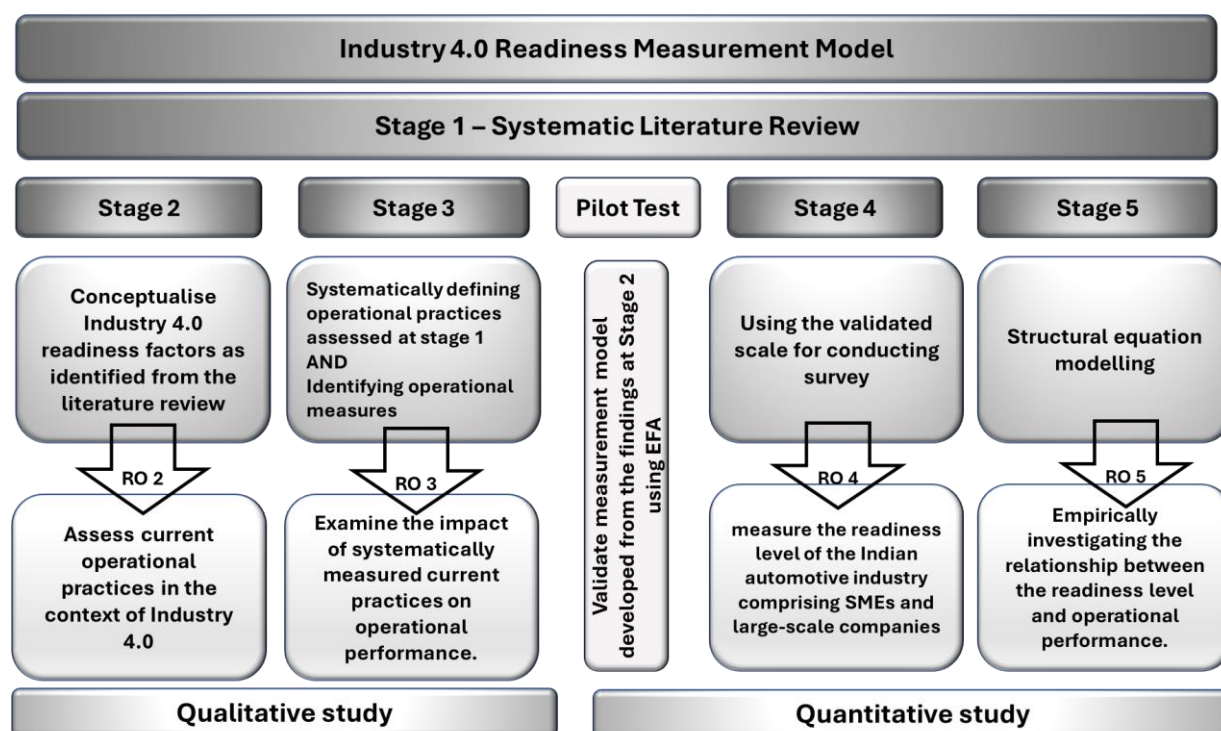


Figure 5.2: Research strategy and research steps

(Source: Author)

Considering the previous discussion on research philosophy, approach and methodology, and the research strategy, an exploratory sequential mixed method strategy is found appropriate. Johnson et al., (2007) also labelled this as qualitative dominant mixed method research where reliance is on the qualitative research with concurrent recognition of the quantitative research to benefit the research project. The qualitative data was collected through exploratory study to understand the technological adoption level across manufacturing operations, and explore the operational performance stemming from the current practices. The survey strategy was used to test the research measures identified from the qualitative data following the pilot test (discussed further in **Section 7.6.1**). Exploratory factor analysis (EFA) was performed to validate the constructs to ensure that all the measures sufficiently reflected the underlying constructs (See **section 7.7**). The proposed framework tested the relationships between the technology readiness level and operational performance using the validated survey questionnaire (discussed in **section 7.6.1**) by utilising structural equation modelling (as discussed in **section 9.3.1**). In the following section, the choice of data utilised in this study and the data collection techniques are justified.

5.8 Standpoints for conducting exploratory study

The exploratory study has been recognised as a widely used methodology for studying the application of novel technologies like Industry 4.0 as indicated by research from Müller, (2019); Dalmarco et al., (2019); Ericson et al., (2020); Spaltini et al., (2022). Since research on Industry 4.0 readiness that would demonstrate the technology usage level across the Indian auto component industry was not found in the literature (see section 4.4), an exploratory investigation will contribute to developing the research framework. Further, the impact of the current readiness level on operational performance is not studied within this specific setting (see section 3.11). Thus, exploratory study explores this area to investigate the current operations along with technology usage across operations and the associated impacts on operational performance. Majid et al., (2017) notes, this empirical approach complements the sparse literature. Müller, (2019) advises, assessing the readiness level across Industry 4.0 readiness factors as identified from the literature within the context of emerging countries. The field-based data collection provides a detailed insight into the conduct of manufacturing operations and the activities involved. It is necessary to identify all the possible levels of technology usage across the manufacturing operations and activities of auto component firms as the level of readiness can vary across companies (Hopkins, 2021). Based on the findings the readiness scale is developed that would reflect these varied levels of readiness. Further, the literature on measuring operational performance is not consistent and offers a range of variables within technology adoption literature (see Table 3.6). The qualitative study facilitated the understanding of operational performance resulting from the current practices as reflected through readiness levels which are further tested through quantitative survey. Given that India's auto component industry is going through industrial changes in terms of its global presence and technological advancements, as accelerated by the megatrends in the automotive industry (discussed in section 2.4.3),

it presents the foundation for exploring the technological landscape within the Indian auto component industry.

5.9 Research Data

Two main sources are identified for research data, including primary and secondary (Taherdoost, 2021; Saunders, et al., 2023). Primary data source refers to data collected for the problem at hand, and thus aids in answering the research question within the scope of the current study (Flynn, et al., 1990). Secondary data source entails data collected in the past for different purposes and scopes than the current study (Rabianski, 2003). Secondary data encompasses data collected from government reports, surveys conducted by other researchers or any kind of published data (Pandey & Pandey, 2021). The following section provides an overview of the data sources used in this research.

5.9.1 Secondary Data

In this study, secondary data was collected using online resources including published articles within the field of Industry 4.0. Additionally, data was collected using government sites, business directories, and reports published by trade associations. The collected data provided an overview of the auto component industry's growth and trends in the Indian economy. Further, the review of previously published articles facilitated gathering information on the Industry 4.0 readiness factors for the auto component industry. Therefore, secondary sources assisted in drawing informed conclusions based on the existing knowledge in the field of Industry 4.0 and industry reports. Besides that, secondary data is used to triangulate the findings from the primary study (Jack & Raturi, 2006). Despite the valuable opportunities provided by the secondary data in understanding the research field closely, this research encountered issues in relying only on secondary data as the reviewed literature failed to reflect the population parameter that this research aimed to study (Rabianski, 2003). Further, Industry 4.0 readiness factors are not measured within the context of the current study (Section 4.2 and 3.8). The secondary data thus fell short of spanning the scope of the current study (Flynn, et al., 1990). To overcome these limitations, this study utilised primary data in conjunction with secondary data.

5.9.2 Primary Data

Primary data is directly collected from the population and includes techniques like observations, surveys, and interviews (Saunders, et al., 2016). This indicates that when collecting primary data, consideration should be given to qualitative and quantitative research strategies. The qualitative strategy focuses on producing non-numerical data, and thus includes techniques such as interviews and observations (Taherdoost, 2021). While the quantitative strategy focuses on collecting numerical data and tests the relationship between variables (Ghauri, et al., 2020). According to Harrison, et al., (2020), mixed methods involve conducting exploratory studies utilising qualitative data followed by quantitative data. Morse, (2010) established that using two qualitative methods can mitigate the confusion of textual and numerical data. These kinds of studies mainly involve understanding human

behaviour, experiences and attitudes, and limit the investigation in establishing the relations and testing the hypothesis (Morse, 2010).

Along with the aforementioned arguments, this study considered the main theoretical motivation, including inductive or deductive as defined by the research question towards the choice of data collection. The main theoretical motivation of this study is qualitative, based on the lack of literature on Industry 4.0 readiness factors for the auto component industry (section 4.3). The second component is chosen to measure the readiness level, which cannot be assessed using the qualitative study due to the lack of measurement aspects in the first study. Furthermore, the additional investigation through quantitative data will allow the testing of the hypothesis developed based on the exploratory study. Therefore, this research emphasises the qualitative theoretical driven mixed method including qualitative and quantitative, indicating qualitative as the main data, and quantitative data implemented sequentially after the collection of qualitative data. Further, this exploratory mixed method design is adopted due to the lack of variables and instruments to measure the readiness, and establish the relationship between variables identified from the exploratory study.

This research therefore conducted semi-structured interviews during the exploratory stage to collect qualitative data. Quantitative data was collected for measuring Industry 4.0 readiness level, and statistically testing the relationship by employing a survey questionnaire. The justification for the choice of these instruments is further discussed in section 5.10.1. and 5.10.2. As the research employed primary data collection, it is preliminary to design the research sample as discussed in the following section.

5.10 Data Collection

This section discusses the choice of data collection instruments and processes for the adopted survey research strategy as previously discussed in section 5.7. This section discusses the choice of semi-structured for qualitative study and self-administered questionnaire for the survey.

5.10.1 Qualitative study - Semi-structured interviews

Saunders (2016) identified interviews as an important instrument to gather valid and reliable data relevant to the research question. There are two further perspectives viz. objective and subjective which can be applied to the interview approach. The objective approach emphasises factual data and treats reality that exists independently of social actors. On the other hand, adopting the subjective approach considers the views and interpretations of respondents (Mezmir, 2020), and recognises the role of the interviewer in constructing meaning using the responses of participants. Further, the typology, that is associated with the objective and subjective perspective is categorised as either structured, semi-structured, or unstructured interviews. The structured interview is used to collect quantifiable data while semi-structured or unstructured interviews are associated with qualitative research (Creswell, 2008). The semi-structured interviews are designed and rooted in the themes generated by the researcher (Chapter 3). These themes are further used to design the possible key questions for the interview. Semi-

structured interviews do not follow a strict order of questions, which means that the flow of conversation guides the order of questions (Ruslin, et al., 2022). This also provides the flexibility of asking additional questions to explore the research questions further depending on the nature of events within an organisation. The form of interview is chosen depending on the purpose of the research (exploratory as discussed in **section 5.6**).

The literature suggests that patterns of adopting advanced technology across manufacturing processes and operations involve managers and employees for firms' transformation (Moica, et al., 2018; Westphal, et al., 2016; Schuh, et al., 2020). These actors possess critical knowledge management capabilities, including their awareness and understanding of manufacturing operational processes, that are essential to drive value creation (Müller, et al., 2018; Weking, et al., 2018). Therefore, the effective management and utilisation of this knowledge is important for the assessment of technology readiness levels (Sütöová et al., 2020). As this research aimed to gain a comprehensive understanding of horizontal and vertical supply chains comprising customers and suppliers, and how advanced technology is utilised to integrate the supply chain and manufacturing activities, as well as the associated impacts on operational performance, the involvement of top-level management is crucial as they act as drivers of change in the adoption of technology (Stornelli, et al., 2021; Lee, et al., 2021). The data for interviews is collected from the CEO/owners, managers, and technology managers of the firms who were responsible for overseeing all the processes or were involved in key internal processes of manufacturing operations in the auto components industry, such as procurement, supplier evaluation, order processing, inventory management, production, quality control and distribution.

The subjective views of the respondents were analysed to understand their perspectives towards the adoption of novel technology, and this information was used to understand the leadership team's commitment towards the adoption of advanced technology for improving operational performance by zooming into the processes and strategies of the organization. Overall, semi-structured interviews were identified as an appropriate tool for data collection for this research as they allow for an in-depth exploration of the phenomenon in a real-life context, which is essential to understanding the current state of the company's operational practices. The semi-structured interviews provided the opportunity to understand the meaning and reasons behind various phenomenon which takes place in an organisation. The ideas conveyed by the interviewees provided a ground to explore areas (technology usage levels) which were not explored in the current research context.

5.10.1.1 Exploratory process of the research

The exploratory study has involved an integrated design comprising semi-structured pilot interviews and semi-structured interviews. Interviews were chosen as the suitable method for data collection as it is preconditioned to determine some areas based on the previous knowledge gathered from the literature (Turner, 2010). Before conducting the interviews, a pilot test was carried out to assess whether the

questions were clearly comprehended (Saunders and Lewis, 2011). The input data for the pilot interview guide was obtained from the combination of research questions, objectives, and, theoretical framework derived from the systematic literature review, serving as a directing instrument for developing the interview guide. A pilot test was conducted with three potential participants to make necessary changes to the interview guide, and to eliminate any weaknesses in terms of the framing of the questions (Kvale, 2007). Therefore, to make informed changes within the semi-structured interview guide, expert assessment and field testing were performed. The assessment was conducted involving industry specialists from the field of the supply chain by discussing the relevance of the questions to meet research objectives. Based on the field testing, two modifications were made to the interview guide. First rephrasing the question to include the industry vocabulary, and secondly some follow-up questions were removed as they resulted in repetitive information. The complete semi-structured interview guide after modifications was used for collecting data. The interview guide (see **Appendix 5**) was informed by literature but allowed flexibility to accommodate for penetrating questions to generate novel themes (readiness levels) to emerge (Mashuri, et al., 2022) corresponding to Industry 4.0 readiness factors and metrics identified from literature (discussed in **section 4.2/ Table 4.5**). Further, the impact of current practices as demonstrated through varied technology usage levels on operational performance is studied. The study of these areas facilitated the refinement of the framework by developing an understanding towards the constructs of the framework that need to be incorporated to address the performance measures across operations. Further, interviews provided rich in-depth data and knowledge about the processes, network structure, technology usage, and organisational structure. The interviews broadly explored the following two areas:

- i) The technology usage level across the Industry 4.0 readiness factors – for instance, the tools utilised for the communication between suppliers and customers.
- ii) The operational performance outcomes stemming from the practices identified in the first part were examined.

5.10.1.2 Research Samples for the Exploratory Interviews

Within this study research population refers to the auto component manufacturers located in India. Further, based on the research aims, the selection criteria are designed to include manufacturers located in India, and operating in the auto component manufacturing industry, further classified by the size of the company (large, medium or small) to meet the research objective. The manufacturing sector's small and medium-sized firms (SMEs) are classified following the definition supplied by the Ministry of Micro, Small, and Medium firms, as published in the Indian Gazette (SME Chamber of India, 2020). Such businesses are distinguished by their annual turnover. The classification of the sample firms was made based on the following criteria:

- Micro, small and medium enterprises: an annual turnover not exceeding Indian Rupee (INR) 250 crores (£23.14 Million) in the preceding financial year.
- Large enterprises: turnover exceeding INR 250 crores (£23.14 Million) in the preceding financial year

Qualitative research typically employs non-probability sampling procedures. Non-probability sampling is feasible to gather insights and reveal understandings for theoretical generalisations (Saunders, et al., 2016; Bryman, 2016). Non-probability sampling entails picking samples based on judgment about the characteristics of the target population. To answer research questions, qualitative research often employs purposive sampling, volunteer sampling, quota sampling, or haphazard sampling (Saunders, et al., 2023).

This research employed non-probability sampling in the qualitative phase with the need to be statistically representative, which was done through probability sampling (See section 5.10.2.2) during the quantitative phase (Patton, 2013). Purposive sampling is preferred for this research to gain an understanding of the current operational practices and processes within the industry. The only way to truly assess the current practices of the auto component industry is by collecting data from respondents who possess comprehensive knowledge about the topic under investigation (Shishank & Dekkers, 2013). Therefore, the sample comprises potential respondents who were responsible for overseeing all the processes or were involved in key internal processes of manufacturing operations within the auto component industry. For instance, procurement, supplier evaluation, order processing, inventory management, production, quality control and distribution. Purposive sampling necessitated the researcher's judgement (judgement sampling) in selecting participants which allowed the researcher to answer the research questions (Tongco, 2007).

The sample selection was purposeful, guided by the conceptual framework, research objectives and research question (Adeoye-Olatunde et al., 2021). Purposive sampling was chosen as participants were strategically selected based on their relevance to the research questions (Fraenkel et al., 2015). In this research, data was collected from respondents possessing comprehensive knowledge of all activities involved in manufacturing operations to effectively assess the current practices within Indian auto component firms. Therefore, the sample comprises individuals who were responsible for overseeing the processes, or were involved in key internal processes of manufacturing operations such as procurement, supplier evaluation, order processing, inventory management, production, quality control and distribution as identified from reviewed literature (Bogner et al., 2016; Pérez-Lara et al., 2018; Moica et al., 2018; Ivanov et al., 2022; Črešnar et al., 2022). Additionally, homogeneous convenience sampling was utilised to examine the current operational practices of the Indian auto component industry in depth (Mweshi, 2020). The population was composed of participants chosen specifically to maintain

homogeneity in terms of geographic location and familiarity with the operational practices across auto component companies in India.

Bryman, (2016) highlighted that sample size poses a challenge in qualitative research. Unlike quantitative research, qualitative research cannot include a large sample size because it aims to capture nuanced insights from a limited number of participants (Dawson, 2019). It is maintained by various commentators that there are no established guidelines for determining the sample size in the literature (Sebele-Mpofu, 2021; Tutar, et al., 2023). Although various scholars, including Creswell, (2008) and Mocănașu (2020), have examined numerical guidelines, the literature still lacks consistent and definitive guidelines for determining the sample size. For instance, according to Guest, et al., (2006), the acceptable sample size for interviews ranges between 6-12 when the samples are homogenous. This sample size depends on homogeneity aiming to understand common practices rather than assess variation between participants. Lincoln and Guba, (1985) advocate for a slightly broader range of 12 to 20 participants for interview studies. Parse, (1990) suggests 2-10 participants for achieving saturation. The diversity of recommendations underscores the complexity of selecting an appropriate sample size. However, the selection of an appropriate sample size is influenced by several factors which help to reduce the complexity. These factors include the research question, available resources and time, the nature of selected groups and the attainment of data saturation. Saturation is widely accepted as a methodological standard to determine the adequacy of data from a study for the development of a robust understanding of the study phenomenon (Hennink et al., 2017).

Drawing from the above arguments, interviews were conducted with fifteen individuals, and the sample size is consistent with the size of 6-12 participants as suggested by Guest et al, (2006); Patton, (2015) & Lincoln and Guba (1985) to ensure data richness. Out of 402 large and medium-scale enterprises, 161 are from the North Cluster (see **section 2.6.1**). This forms 40% of the total firm population. Out of these 161 firms, participants from 7 organisations have been interviewed to obtain qualitative data. In addition to this, 8 participants from small and micro enterprises have been interviewed from a total population of 5,000 small, medium and micro enterprises (see **section 2.6.1**). Corresponding data with respect to Small, medium and micro enterprises in the North cluster is not available. However, considering the concentration of large and medium-scale companies & OEMs in the north cluster suggests a substantial number of auto component companies concentrated in the north region.

Therefore, the sample for this study consisted of fifteen different auto component firms located across different states within Northern India. The interviews were identified as individual cases and evaluated individually. To obtain rich data, interviews were conducted with 15 individuals from 15 different companies. The data was collected keeping in mind the different sizes of the company (see **Table 6.4**) to consider all the possible practices followed by the company's scale size and to fulfil the research objective. Additionally, the inclusion of Tier 1, 2 and 3 (see **Table 6.4**) emphasises the structural

diversity within the chosen sample to understand the prevalent technology adoption practices in the industry. It is acknowledged that 15 interviews cannot fully represent the auto component industry's ecosystem in providing comprehensive coverage; the objective was to conduct a nuanced analysis of supply chain dynamics within the Northern Indian auto component cluster. While the sample of 15 firms appears to be modest, the size of the sample in a qualitative study is dictated by theoretical saturation and not the statistical power, as suggested by Guest et al., (2006). Therefore, in this research, the qualitative study focused on the transferability of findings by generating the context-related insights as discussed by Lincoln and Guba (1985) rather than the generalisability of findings to the wider population. This approach is in line with previous studies which emphasised analytical generalisation within Industry 4.0 research for transferability of context-specific insights (see Sony et al, 2021; Qureshi et al., 2023; Antony et al., 2023). Moreover, the inclusion of large-scale companies and MSMEs within Northern India ensures the coverage of the organised and unorganised sectors within the auto component industry for analytical generalisation. This chosen sample size was further supported by the data and code saturation, an established approach used in previous studies (Antony et al, 2021; Eslami et al., 2023). Recurrent themes emerged in terms of the technology usage patterns and operational performance indicators, even though quantitative representativeness was limited. The coding of data, both in NVivo and manually, was conducted in parallel with data collection for iterative refinement of codes (Lincoln and Guba, 1985). It became apparent after the eighth interview that no new categories emerged, and the codes from subsequent interviews consistently mirrored earlier responses. The findings from the interviews offered exploratory insights rather than definitive generalisations, which were addressed during the quantitative study phase.

The interviews were conducted in person, each lasting approximately an hour and resulting in 139 pages of transcribed text. In addition to the transcribed interviews, the researcher notes, various documents provided by the company, and documents obtained from their websites were examined to enhance the validity of the results. Visits to plants aided in understanding the manufacturing processes on the factory floor for the assessment of the technology usage across the manufacturing processes. Patriotta, (2003) advise that issues such as low levels of automation, or reliance on manual machinery in the production process across the factory floor can be effectively evaluated through analysis of the factory layout, including access to relevant information by plant managers and supervisors. It also helps in understanding the decision-making process and the flow of information to decision-makers (Hermann et al., 2016). The size of the company and its reporting hierarchy further contributed to understanding the level of transparency and visibility across operations (Crešnar et al., 2022; Zhang et al., 2023). Overall, these observations contribute to strengthening the validity of research findings.

5.10.1.3 Semi-structured questionnaire

A pilot structured interview protocol was designed before entering the field. The protocol included open-ended questions and was designed from the systematic literature review. The literature suggested

the identification of key activities and processes for assessing the digitalisation level across firms (Hopkins, 2021 & Pérez, et al., 2022). Therefore, one of the areas of focus in the protocol was manufacturing operations to assess what exactly comprises operations. In addition, the researcher delved into the ways of using technology across these processes. Accordingly, the questionnaire comprised two key sections: operational processes and activities and technology usage across each area to assess technology readiness level.

5.10.1.4 Pilot testing of semi-structured interview protocol

Pilot test during the interviews is identified as the crucial element to ensure the validity and appropriateness of the interview protocol. Hence, before proceeding with the interview process with the selected participants, the initial version of the questionnaire was reviewed by a senior consultant with expertise in TQM and Lean Six Sigma to validate and refine the interview protocol. The consultant was selected based on their extensive experience in the field, particularly their role in delivering manufacturing best practices training across the auto component firms. Their familiarity with the current industry practices contributed significantly to ensuring the interview protocol was well-suited for a field-based study. The review emphasised the use of terminology and language, length, and relevance of questions in relation to research objectives. Based on the feedback, certain sub-sections were removed from the questionnaire on account of repetition and a few probing questions were further added to enhance the depth and relevance of responses.

The revised interview protocol was then employed to conduct a pilot study in April 2023. The pilot study involved participants occupying managerial roles in auto component firms. Three pilot interviews were conducted using Microsoft Teams, adhering strictly to the procedures laid out for the main study. Hence, the information sheet and consent form were emailed to the participants, and interviews were conducted upon receiving the signed consent form to test the practical implementation of the ethical protocol. The pilot study aimed to assess the appropriateness of questions and the viability of the research. Additionally, the pilot study helped the researcher become familiar with managing and executing the interview process, particularly with duration and data storage procedures.

The feedback obtained during the pilot study was instrumental in revising the questionnaire for the main study. Questionnaire terminology was revised to improve participants' understanding and eliminate ambiguity. During the pilot interviews, it became evident that certain terms were understood differently in academic and industry contexts. Clarifying the meaning behind the terminology to participants during the interviews extended the duration of the interview and disrupted the flow of conversation. Therefore, the terminology was further refined to align more closely with industry usage. Consequently, question regarding the company's business model was replaced with more targeted questions focusing on specific business model value-adding areas, including their suppliers, customers, partners, and key activities, which are more familiar in the auto component industry. Consequently, the final

questionnaire for the main study included 15 questions, which were further segmented into parts for the easy understanding of the participants.

5.10.1.5 Conducting Interviews

The interviews were conducted in person by visiting the manufacturing units located in India including the states of Haryana, Uttar Pradesh, Punjab and Delhi (see **Table 6.4**). The plants were visited as part of the protocol that facilitated the understanding of the manufacturing-related vocabulary utilised by the participants in the context of the manufacturing operations (for example CNC and PLC). The dynamic interplay between interview data and operational layout assisted the researcher in translating and understanding the meaningful events in the organisational setting (Patriotta, 2003). The interview data and the tour of the plant provided insights into the manufacturing processes on the factory floor, particularly regarding the automation employed across the factory floor for the production process. Key issues such as low levels of automation and reliance on manual machinery were assessed through the factory layout and integration of operations. Additionally, the tour provided a clear understanding of the decision-making process, the reporting hierarchy, and the flow of information through communication channels. This provided further insight into the transparency and visibility across operations.

5.10.2 Quantitative study – Self-administered questionnaire

The choice of the quantitative survey following the qualitative survey in this study is motivated by the lack of research in Industry 4.0 domain encompassing readiness framework and impact on operational performance (Rossi, et al., 2013). A quantitative survey translates the theoretical domain into the empirical domain by measuring the framework constructs operationalised from existing literature or exploratory studies (Sekaran & Bougie, 2016; Chatha, et al., 2018). Therefore, data for the quantitative study originated from the interviews conducted during the qualitative phase. The objective of the study is to measure the Industry's overall readiness level; considering the size of the industry it is not feasible to survey the whole population, an optimum situation is therefore to select a sample that is representative of the population (Cooper & Schindler, 2008). Therefore, the sampling method is chosen to achieve accuracy and more detailed information from fewer cases. This section discusses the sampling target population, the sample type used in this study, and the sample size.

5.10.2.1 Sampling Frame

The sample frame as pointed out by Bryman, (2016) should be related to the population in the research question and objective from which results can be generalised. Sampling is more plausible when it is impractical to survey the entire population and the research is constrained by cost and time (Saunders, et al., 2023). Various organisation websites were looked upon, including the Indian Brand Equity Foundation (IBEF), ACMA, and Society of Indian Automobile Manufacturers (SIAM), but no specific database was found that could provide the whole list of registered auto component manufacturers in

India. Therefore, based on the database found in business directories, the total listing was obtained from Fundoodata, which is the most used business directory and preferred company information provider. The selection of auto ancillaries retained a list of 5,152 companies (Fundoodata, 2023).

5.10.2.2 Sample Type

For statistical explanations which necessities statistical inferences and estimates, probability sampling is more suitable (Bryman, 2016). Probability sampling is defined as a sample which is selected at random with the research population having the same chance of getting selected to guarantee that the sample chosen is representative of the research population (Barnett, 1991). This is linked with survey questionnaires and experiment studies by using random, stratified, systematic, or cluster sampling techniques. This study's purpose is to generalise the findings from the qualitative study, the simple random sampling was deployed to give the population the same chance of being chosen and minimising the sampling error (Khalid, et al., 2012 & Sarker and AL-Muaalemi, 2022). Furthermore, for statistical explanation, the random selection of a sample from the frame comprising the Indian auto components manufacturing firms ensures that the characteristics and practices of the subjects are representative of the total population (Bogdan and Biklen, 2007 & Saunders et al., 2023).

5.10.2.3 Sample Size

Given the sample frame of 5,152 auto component companies, it is imperative to determine an adequate sample size that mirrors the target population (Fink, 2002). Moreover, to avoid sampling errors and biases in random sampling, the identification of an adequate sample size is indispensable (Lenth, 2001; Anderson, et al., 2017; Lakens, 2022). An adequate sample size ensures the validity of conclusions and the generalisability of results for the population under study (Singh & Masuku, 2014). The choice of sample size in this study is governed by a few factors, including the size of the target population from which the sample is drawn (5,152 companies) and the tolerance for margin of error (Saunders, et al., 2023). Therefore, this study used the sample size as advocated by Bartlett et al., (2001), suggesting a sample size of 119 with a population size of less than 10,000, with an acceptable margin of error, which in this case is 3%. Therefore, this research requires a minimum sample of 119.

5.10.2.4 Unit of Analysis

The unit of analysis answers the question of 'who' or 'what' is being studied in the research, which can vary from studying individuals, organisations, countries, or social artefacts (Kumar, 2018). It is essential to select a reasonable and appropriate unit of analysis to ensure the validity of research conclusions (Yurdusev, 1993). The objective of this research is to understand the current operational practices of the Indian auto component industry in the context of Industry 4.0 and thus examine the impact of current practices on operational performance, the unit of analysis would be an organisation based on which the analysis is conducted. Further, reconfiguring existing business practices to accommodate advanced

technologies necessitates a thorough understanding of the operational processes across the organisation (Hopkins, 2021; Pérez, et al., 2022; Sun et al., 2022).

5.10.2.5 Surveying Technique

The research adopted the web-based survey due to certain advantages over traditional paper-based surveys. One of the main reasons that web-based surveys were employed is due to the wide geographical reach at a substantially lower cost, avoiding the postage expenses incurred while employing paper-based surveys (Schleyer and Forrest, 2000 & Fleming and Bowden, 2009). Additionally, a web-based survey facilitates faster data collection with the possibility of automatically inserting data into a spreadsheet with minimal error in data entry (Lefever, et al., 2007). Considering these advantages, a web-based survey was thus employed to collect data from companies located in India in a timely manner. Microsoft forms were used for creating the online survey with automatic marking, and a survey link was generated for dissemination to potential participants. Responses could be directly exported to an Excel spreadsheet, saving time. The researcher went through the websites of companies selected from the sampling frame. The participants' names were identified from the key personnel information. The identified individuals were contacted through LinkedIn, and the questionnaire link was sent along with the information sheet and consent form. The participants were informed of the objective of the research through the cover letter requesting the completion of the survey. The procedure started in August 2023 and ended in February 2024. The questionnaire was sent in batches as LinkedIn allows only 200 invitations at a time. The questionnaire was sent to 800 individuals in several phases. 258 surveys were returned out of which 41 questionnaires were returned incomplete. Therefore, 217 completed survey responses were obtained yielding a response rate of 27.13%.

5.11 Data Analysis

5.11.1 Semi-structured interview

Meanings in qualitative data are derived from words and not numbers, there is the possibility of having multiple meanings for such data (Bryman and Burgess, 1994). The non-standardised data in the form of observations, words, and visual recordings need to be explored, analysed and synthesised to align it with the research objectives and thus answer the research questions. This section thus expands on how data was analysed keeping in mind the research-specific concepts for example the data which fits with the research objective and then linking it with the conceptual framework.

The research followed a thematic analysis approach to analyse the data obtained through interviews, observations or any document gathered about the processes and strategies of organisations. Thematic analysis is a flexible approach to analysing qualitative data. The purpose is to identify themes or patterns across different sets of data collected during qualitative study including interviews, observations, documents, or notes (Riger & Sigurvinsdottir, 2016). As the research follows interpretive philosophical assumptions, the key themes or patterns were identified through further exploration of different

phenomena focusing on current practices around operations and processes, stakeholder involvement, and technological aspects within the company's business model. The theoretical framework which is designed from the findings of a systematic literature review, needs to be studied in a practical setting as well for exploring organisational processes and strategies in a real-world context. The framework was thus examined independently from the theoretical foundation to identify new themes and thus modify the existing framework. The newly identified themes were affixed to the existing theoretical framework for development of conceptual framework. However, the whole process of identifying themes begins with the deductive approach by taking into consideration the existing theory which is the conceptual framework in this research and then modifying or revising it with the new themes identified through the inductive approach (Clarke and Braun, 2017).

The researcher faced difficulty in recording the transcript in English as most of the participants gave answers in Hindi and few participants did not give consent to record the interviews. Consequently, the transcripts were first translated into English and all the notes were then organised using MS Word. On the contrary, few participants did consent to recording the interview which were then transcribed using MS Teams to ensure all data and information were fully utilised during the analysis. While recording the interview, written notes were also taken on the key areas to utilise the same for data triangulation.

The thematic analysis then began with coding the textual data, transcript summaries, memos, and reflective diary data. These codes were first created manually by reading the transcripts followed by coding in NVivo (Welsh, 2002). This process helped in managing and organising the data as per the research objectives as not all data was relevant. Codes also facilitate condensing the large quantity of qualitative data for easy accessibility to further analysing the data at a later stage (Clarke & Braun, 2017). Coding followed both inductive and deductive approaches. The combined coding approach assisted in guiding how much data would be coded and what possible codes could be generated (Bingham, 2023). The coding began with using the themes identified in the literature review and conceptual framework for defining the codes and thus using a deductive approach. Further to mitigate the risk of limiting the codes to a conceptual framework, an inductive approach was used to explore other meanings in the data which were not identified in the literature review (Azungah, 2018 & Fife and Gossner, 2024). The combination of deductive and inductive approaches was thus suitable which commenced with using the codes derived from theory and conceptual framework, and then modifying or adding themes as data was further explored (Williams and Moser, 2019). Following Gioia et al., (2013) procedure, the expert statements were categorised into first-order themes which were consolidated into second-order themes. The aggregate dimensions were formed from the second-order themes. The study indicates three dimensions which need to be considered when measuring the readiness of the operational aspects of manufacturing processes. An overview of the dimensions and categories derived from the interview data with quotes from the participants is presented in Appendix 3.

5.11.2 Coding and validation of survey data

The survey responses collected through Microsoft Forms were downloaded into an Excel workbook. The quality of data is ensured through data cleaning, where incorrect survey responses on account of participants entering their names in the survey were removed to ensure anonymity. After that, all the items were coded for clarity to conform to the SPSS requirement. The coded data file was then transferred to SPSS and SmartPLS for descriptive and statistical analysis. The reliability and validity of the measures were assessed, and the results are discussed in Chapters 8 and Chapter 9.

5.12 Time Horizon

The time horizon within the research is classified into two types including longitudinal study and cross-sectional study depending on the research question, availability of resources and objective of the study (Saunders, et al., 2016). In this research, due consideration is given to whether to conduct a cross-sectional study or a longitudinal study. While the cross-sectional study focuses on studying the phenomena at one point, the longitudinal study emphasises carrying out the research over a specific period with the same sample to identify the change in one or more variables over time (Ruspini, 1999). Due to the variables in this study being identified by the exploratory study which were not tested previously in the current setting, the use of a longitudinal study is thus dismissed. Additionally, the objective of the study is not to study change, but rather to assess the readiness level based on the current practices of the Indian auto component firms, hence the study is cross-sectional (Cohen, et al., 2017). The strength of the cross-sectional study to enable inferential statistics assisted in comparing sub-groups including large-scale companies and SMEs within the sample (Rose & Sullivan, 1993).

The cross-sectional studies can be conducted efficiently with limited resources in terms of time and cost involved. The quantitative and qualitative data collection and analysis require a careful evaluation of the available resources and time (Creswell, 2018). Familiarity with both forms of research is a time-consuming and a complex process, and a longitudinal study was not feasible given the resource constraint. Further, a longitudinal study is more suitable for research that necessitates examining development and change over some time (Cohen, et al., 2017). The external environment in the context of the organisation is ever evolving which shapes the technology adoption patterns and business practices. The current practices may not remain the same as reflected by the readiness scale used in this study (Schumacher, et al., 2016; Xu, et al., 2018; Mittal, et al., 2018). Considering all these factors, the cross-sectional study was more feasible in such a situation.

5.13 Challenges encountered whilst conducting fieldwork

As discussed in Chapter 5, the research has been conducted across Indian auto component manufacturing firms in the Northern region to understand the technological usage level and its impact on operational performance. The research so far in the field of assessing Industry 4.0 readiness is limited in India (see **section 4.3**). The adoption of Industry 4.0 is identified as trivial by the Auto Component

Manufacturing Association of India and SIAM, where these bodies are encouraging companies to advance their processes in line with advanced technologies, including Artificial intelligence, additive manufacturing, and blockchain technology. Further, the increasing economic and political significance of the Indian auto component industry (see **sections 2.3 and 2.5**) has positioned this country as the appropriate choice for conducting fieldwork. Additionally, it seemed feasible to conduct the research in the researcher's home country due to easy accessibility to the contacts within the industry.

Data for this study were collected through 15 interviews and 217 survey questionnaires from auto component companies of different sizes. However, this research encountered a few methodological challenges during the fieldwork in both phases, which are discussed in the following section.

5.13.1 Gaining access to organisations

It is maintained by various commentators (Chidambaram, 2011; Vr et al, 2021; Nyemba and Carter, 2024) that developing countries like India face a disconnect between Industry and academia as research is not pronounced. While India contributes significantly and holds third position in the world for scientific publications, it falls short in patent applications, resulting in low recognition of academic research for industrial output (Vr et al, 2021). During fieldwork, the researcher struggled with the participants' lack of recognition of the research and the potential of translating research into industrial outputs. This showcases the gap between the practical applications and the benefits from research that can be translated for industry practitioners in developing countries (Tonukari, 2022). In light of this, the researcher faced participant recruitment difficulty in initially gaining access to those participants who understood the value and objective of the research. This process took a considerable amount of time, as no participant could be secured due to a low understanding of the potential participants' towards the objective of the research. A lack of a culture of collaboration between industry and academia became evident to researcher after the initial conversation with participants. As a result, the researcher leveraged existing contacts to secure access to the potential participants. After gaining access to one company, the snowball technique helped in gaining trust and enhancing the credibility of the research. Additionally, industry stakeholders were involved, and the researcher was accompanied by the industry consultant to bridge the gap between industry expectations and academic depth.

5.13.2 Gathering reliable data

Ethical considerations play a significant role in protecting the participants and the researcher and conducting the fieldwork in a morally ethical way. However, research participants do not often trust the ethics documentation that no information in terms of personal and organisational identity will be revealed. Research participants overlooked the assurance of the ethics committee, and as a result, only positive things were shared by the participants in terms of the organisation's processes and technology adoption practices. While the research objective was not to interrogate but rather have a discussion in terms of the manufacturing practices, a few participants took it otherwise due to the fear of facing

repercussions from management for sharing in-depth insights. As a result, the discussion was surface-level, and the researcher struggled to obtain rich data. Additionally, while asking for the paperwork or any documentation to triangulate the responses, participants were reluctant to provide any paperwork. Consequently, the researcher modified the research approach and collected only interview data to maintain consistency in terms of data collection techniques employed throughout the fieldwork. Additionally, the masculinity dimension influenced the quality of data as well. Few participants exhibited a dismissive attitude towards the research in general while displaying overconfidence in their ability to identify an industry solution. In one instance, a participant openly questioned the value of doctoral research, discouraging the researcher from continuing the interview on several occasions. In like manner, a few participants' attitudes came across as challenging the researcher's credibility. The researcher's credibility may have been influenced by participants' perceptions related to the gender of the researcher. As a female doctoral researcher engaging with the company's decision maker and senior professional in a male-dominated industry, the power dynamics rooted in gender and professional position became evident. However, the researcher removed her personal involvement on such occasions to maintain objectivity to ensure neutrality and logical reasoning for data interpretation. Although only two such incidents were encountered, the overall experience of the other participants motivated the researcher to continue the research process. Additionally, the supervisor's support helped ease the process in terms of making the researcher accept the attitude of the participants.

On one occasion, participants' responses were aligned to showcase achievement and success, rather than providing detailed insights. Such responses result in overstated answers and skewed responses. In such a scenario, the researcher improvised the research questions by framing the questions directing towards experiences rather than challenges or shortcomings. Additionally, the researcher communicated the purpose of the research, focusing on the general trends within the industry, to curb individual-focused answers. Further, the validity of the data was also affected by the unrelated information provided by the participants. The deviation from the topic and irrelevant information resulted in exceeding the scheduled interview time. Additionally, it resulted in difficulty in extracting meaningful data relevant to the research objective and exerted pressure on the researcher in terms of transcribing and filtering the relevant content.

5.13.3 Language Barrier

The language barrier is identified as a significant challenge when the sample population speaks multiple languages, while the data collection instrument is in English. This impacts the quality and reliability of data due to different interpretations of meanings by the participants, resulting in skewed data as highlighted by Yeong et al., (2018). The researcher recognised this challenge during the study, as few participants struggled to understand the academic language used in the instrument. While the majority of the participants managed to understand the English language, the researcher faced difficulty in translating the meaning of a few business words, for example, "business model" in layman's language.

It is maintained by Yeong et al., (2018) that the interview refinement protocol is a widely used tool to overcome the language barrier for enhancing the reliability of research findings. This was addressed during the pilot test, and as a result, the term business model was removed from the questionnaire to enhance understandability (Malmqvist et al., 2019). Additionally, while participants understood the questions, the lack of fluency made the researcher adopt a flexible approach and encourage participants to give the answers in the language they were comfortable with, which was predominantly Hindi and Punjabi in some instances. While the researcher was fluent in Hindi and English, understanding Punjabi completely was challenging. On such occasions, the researcher had to make the participants repeat their answers in Hindi to get a clear meaning.

As a consequence in light of the above, the second issue emerged during the transcription phase of the interviews. Microsoft Teams were used to record and transcribe the interviews and generate the transcripts to be analysed during the analysis process. Though all the participants understood English, responses were given in Hindi and English, which could not be clearly captured by MS Teams. Moreover, for English speech, MS Teams could not clearly recognise the accent, and the actual words were lost in the translation. As a result, the responses were translated into English before starting the coding process. Further, to ensure the reliability of interview findings triangulation approach was adopted by involving the research supervisor for cross-validation of translated data. This enhanced the consistency in the interpretation of responses for attaining the transferability of findings across wider perspectives (Clark & Creswell, 2014).

5.13.4 Changes in research design

According to Fjellström & Guttormsen, (2016), fieldwork is often challenging and unpredictable due to the involvement of external factors such as confidentiality concerns and corporate policies within the industry. It is maintained by various commentators (Hibbert et al., 2010; Palaganas et al., 2017) that in such situations, the reflexivity of the researcher is paramount for adapting the research design to ensure the quality of the process, facilitating knowledge creation. The challenges in the field in terms of collecting data obliged the researcher to change the research design from a case study to a survey strategy due to privacy concerns raised by participants. Due to the time constraint, the initial research design was set to conduct six in-depth case studies by utilising more than one data collection instrument, including 10-12 semi-structured interviews, observations and reports/documentation for triangulating the responses. However, the researcher faced challenges in accessing the company documentation and internal reports due to confidentiality and organisational policies. Large-scale companies were more reluctant to share internal reports due to data protection concerns. On the other hand, small and medium firms were flexible in approach as interviews were conducted with the directors, giving them more autonomy in sharing internal reports. However, this leads to inconsistency in data sources across all cases. Consequently, the initial plan was revised to include only interviews and observations for gathering rich data from 15 auto component companies to capture diverse perspectives on technology

usage and manufacturing practices. To compensate for triangulating the responses using company reports, secondary data through the company's website helped in providing the contextual background for the company's operational performance. Additionally, responses were compared across companies to ensure validity.

5.13.5 Non-response bias

Non-response bias generally occurs due to the respondent's lack of understanding towards the potential use of data. Additionally, data gathered from self-selected respondents might result in response errors failing to represent the entire population (Miller & Smith, 1983). The non-response rate was found to be higher in a survey study conducted by Wells, et al., (2011), with a response rate accounting for 13.8% as compared to a paper-based survey with a 96.9% response rate. Given this, measures were taken during the design stage of the survey questionnaire to curb non-response bias. Respondents were effectively communicated through a cover letter about the research objective and scope (Dillman, 2000) while maintaining anonymity for the accumulation of unbiased and accurate data (Meade & Craig, 2012).

5.14 Ethical Considerations

This section outlines the list of principles establishing the ethical standards that are followed by the researcher. The anticipated issues and risks were identified along with the mitigation measures undertaken to avoid conflict and harm to participants and researchers. The research complied with Birmingham City University guidelines and procedures for good research practice. The ethical principles were adhered to at different stages, including gaining access, data collection, and data analysis and protection. The avoidance of harm was identified as the first ethical principle. Any psychological harm to the participants was avoided by not including any sensitive topics which might cause distress to the participants. From the de-briefing sheet, the researcher made participants aware of limiting the amount of time that participants would spend to avoid any inconvenience on account of time management. Any risk surrounding safeguarding was addressed in the following two ways. First, the researcher developed a good working relationship with the participants and authority figures within the building. This will also be met with becoming familiar with the building and company safeguarding and safety procedures. Second, the researcher will never enter the personal homes of any participants or conduct research with them within an external, private, and isolated space. The ethics application along with the participants' information sheet and consent form was submitted to the BLSS Ethics committee and the approval for same was granted on 14th February 2023 (see appendix 4).

Further, the researcher provided sufficient information and time to allow participants to understand the research objective and obtain fully informed consent. The researcher obtained consent through the dissemination of the consent forms. Further, the participant information sheet informed participants of the aims and objectives of the study and their rights as participants. The ethical principle of voluntarily

participating in the research and the rights including not answering any question or modifying their consent were well adhered to. The participants were informed of their right to withdraw from the research at any time without giving any further explanation or stating a reason for doing so. They were also informed that data collected from that participant up to that stage would be immediately destroyed, except in the situation where the participant willingly gives consent and permission to use the data later. In the case where participants lose the ability to give consent due to unforeseen events, their data will automatically be destroyed. However, participants were made aware in the participant information sheet that they can withdraw their data anytime up until February 2024, whereby all data would have been coded, anonymised, and woven into the findings chapter and thesis submission. Additionally, the information sheet clearly outlined the strict adherence to anonymity and confidentiality with comments that will be anonymised. In guidance with general Data protection regulation (GDPR) compliance, data was stored on BCUs One Drive where only the research team had access to the data collected.

5.15 Chapter Summary

This chapter discusses the methodology adopted in this research. The justification for the choice of the research methodology was predominantly underpinned by a thorough analysis of its pertinence to addressing the research question and objective. An exploratory sequential mixed method was thus adopted with a qualitative dominant approach where quantitative research was conducted based on the variables identified from the qualitative research. This is because of the lack of existing research in the given context, particularly measuring the readiness level as technology readiness varies based on industry and country. Furthermore, the performance measures could not be identified from the extant literature as associated with the manufacturing operational practices, an exploratory study was thus essential. With respect to the research technique, qualitative data was collected using semi-structured interviews while quantitative data was gathered by employing a survey.

Following this, the chapter discusses the sampling process including the sampling frame, type, and size of the sample. The research participants comprised C-level executives, and managers with expertise in the fields of supply chain management, production and operations management and manufacturing technology and innovation within the auto component industry in India. During the qualitative phase, 15 semi-structured interviews were conducted to assess the current operational practices, while 217 survey responses were gathered for statistical analysis. Qualitative data was thematically analysed to generate different technology readiness levels across the industry, comprising MSMEs and large-scale companies. Quantitative data was analysed using descriptive statistics with SPSS software. Additionally, Structural equation modelling (SEM) was performed using SmartPLS software for inferential analysis. The next chapters present a comprehensive discussion of the results and findings from qualitative and quantitative studies.

Chapter 6: Qualitative Study - Exploring the Indian Auto-Component Industry

6.1 Introduction

This chapter aims to explore the current Industry 4.0 practices in the Indian auto component manufacturing industry. The existing literature does not provide a strong theoretical base for understanding the readiness of manufacturing operations and its impact on operational performance in this specific setting (see **sections 3.11 and 4.3**). Existing literature presented the factors that indicate the readiness level of the manufacturing operations with respect to their existing business domain (Schumacher et al., 2016; Fernández-Miranda et al., 2017; Sony & Naik, 2019; Stentoft et al., 2021). Therefore, it is necessary to identify and examine the current operations and practices employed by Indian auto component manufacturers. Further, the Indian manufacturing operations within this industry may exhibit distinctive characteristics and complexities as compared to other manufacturing industries and geographical regions (Schumacher, et al., 2016; Demeter, et al., 2018; Moica et al., 2018) due to the involvement of multiple tiers and components (Bhattacharya et al., 2014; Mutschler, 2023). An exploratory study is thus required to study the operational realities of this industry (as discussed in **sections 5.7 and 5.10.1**).

6.2 Demography of Participants and Companies

For this study, the current practices of fifteen Indian auto component companies across the Northern region were studied. Therefore, the sample comprised fifteen individuals (Table 6.1) from fifteen different companies (Table 6.4) located across various states within northern India. This region is particularly suitable because of the representative character of other companies as industrial clusters are largely concentrated in the National Capital Region (NCR) (see **section 2.6.1**). The northern region is one of the four auto component clusters that drive the Indian auto component industry (Dhawan, et al., 2019) (as discussed in **sections 2.6.2 and 2.6.3**). Further, companies that belong to the same cluster showcase similar characteristics and performance patterns (Okada and Siddharthan, 2007). The data collection involved interviewing key personnel in the companies including the director, managing director, executive director, quality head, CFO, and general manager involved in the operations of the companies and have detailed knowledge and experience of manufacturing processes as presented in Table 6.4.

Table 6.1: Distribution of participants by management level

Position of Interviewee	Frequency	Percentage
Director	7	47%
C – Level executive (CFO)	2	13%
Manager	6	40%
Total	15	100%

Further, the size of the company was determined based on the turnover of the company as defined by the SME Chamber of India, (2020) as shown in Table 6.2. The distribution of participants as per size of companies is presented in Table 6.3.

Table 6.2: Size of company based on turnover according to SME Chamber of India, (2020)

Small	Medium	Large
Annual Turnover between INR 10-50 crores.	Annual Turnover between INR 50-250 crores	Exceeding a turnover of INR 250 crores

Table 6.3: Distribution of firms by turnover

Size of the company	Frequency	Percentage
Micro, small and medium (INR 50-250 crores)	8	53.33%
Large (more than INR 250 crores)	7	46.67%
Total	15	100%

For the purpose of the analysis of data collected through interviews, the companies associated with interviewees are coded as individual cases as presented in Table 6.4. An overview of auto components manufacturers involved in the exploratory study is also shown in Table 6.4.

The companies chosen for the exploratory study were all automotive component manufacturers specialising in the production of various components (Table 6.4). These companies are dedicated to supplying automotive components to OEMs. The number of OEMs these companies cater to ranges from 2 to 250, including the pharmaceutical, automotive, and machinery industries. This indicates that the supply chain extends to other industries within the manufacturing sector showcasing the interlinked supply networks. Additionally, the number of suppliers involved for the procurement of raw materials also ranges from 2 to 210 suppliers. These suppliers hail from the iron and steel industry and electrical equipment manufacturers. The involvement of multiple stakeholders across the manufacturing process from multiple manufacturing industries demonstrate the complex network of the supply chain of these companies. Since the companies in the exploratory study operate within the same industry, their operations and supply chain networks are expected to exhibit similarities across different operations and activities.

Table 6.4: Overview of the Sample of Auto component manufacturers selected for in-depth interviews

Cases	Product	Tiers	Size of firm	Interviewee	Location	Number of buyers	Number of suppliers
Case A	Brake pads	Tier 2	MSME	Chief Executive Officer	Greater Noida (Uttar Pradesh)	5	15
Case B	Alternator dynamo, starter dynamo	Tier 1	Large	Purchase officer	Faridabad (Haryana)	90 (which comprises of 2 OEMS and other SME buyers)	100-125
Case C	Door latch assembly – four wheelers; switches, fuel tank caps for two-wheelers	Tier 2 and Tier 3	MSMEs	Director	Faridabad (Haryana)	100	100-140
Case D	Bike accessories	Tier 2	MSME	Director	Gurugram (Haryana)	Business to consumers (B2C)	2
Case E	Machining of small components like spacers, shafts, nuts, adapters, etc	Tier 3	MSME	Director	Chandigarh (Haryana & Punjab)	5	10
Case F	Hydraulic bars, precision, engine parts	Tier 1	Large	Director	Mohali (Punjab)	40	20
Case G	Tractor parts; shafts, and transmission gears	Tier 2	MSME	Quality Head	Chandigarh (Haryana & Punjab)	1	3
Case H	Manufacturing of hydraulic components for tractor manufacturers	Tier 2	MSME	General Manager	Chandigarh (Haryana & Punjab)	89	209
Case I	Electric motor, batteries	Tier 1	Large	Operations Head	New Delhi	18	5
Case J	Sheet metal press parts and machine parts	Tier 2	MSME	Managing Director	New Delhi	2	8-10
Case K	Pistons, rings engine valves	Tier 1	Large	Executive Director – Supply Chain Management	Ghaziabad (Uttar Pradesh)	8-10	150
Case L	Suspension and brake pads	Tier 1	Large	Director	New Delhi	90-100	150
Case M	Engine components including bolts, nuts and shafts	Tier 1	Large	Director	Ballabhgarh (Haryana)	30	20
Case N	Brake system	Tier 2 and 3	MSME	General Manager	New Delhi	15-20	10
Case O	Engine parts	Tier 1	Large	Operations Manager	New Delhi	30	6

6.3 Findings from Exploratory Interviews

To gain a comprehensive view of the current practices it is important to identify the manufacturing operations and processes involved in manufacturing the automotive components. Müller et al. (2018) identified the prerequisites for an effective and competitive value system which demands an alignment of organisational activities and external parties involved in supporting the organisation's operations. The ultimate objective of this kind of alignment is to enhance operational efficiency and thus create value for customers. Therefore, manufacturing activities are analysed to identify the existence of a linkage between the operations and external partners of the selected companies. The level of integration was identified in terms of operations associated with raw materials, including the procurement process, production process, and inventory management process (Hopkins, 2021; Pérez, et al., 2022; Sun et al., 2022). Internal integration is the foundation that develops and supports external integration viz. customers and buyers (Simetinger and Zhang, 2020 & Spaltini et al., 2022). To assess the same, the current practices around the inter-organisational processes (communication and integration between suppliers and customers, cross-departmental collaboration) were analysed individually to identify the supply chain integration in terms of suppliers, buyers, and inter-organisational processes. Additionally, the integration was recognised on the organisational level as to how closely departments operate in terms of the manufacturing process (Trstenjak et al., 2022). Lastly, the buyer's relationship was closely assessed in terms of the level of transparency in terms of detecting the changes in demand and exchange of information which is intricately tied to efficient production planning and delivery performance. Additionally, the technology adoption was investigated across all the areas which were identified as the precondition for Industry 4.0 adoption (Schumacher et al., 2016; Alcácer et al., 2021; Trstenjak et al., 2022). The operational performance is finally defined and understood from three key themes that emerged from the interviews including production process, network integration and responsiveness towards OEM demand.

This section discusses the results of the exploratory interviews related to the current practices within the auto component Industry to understand the existing technology usage across manufacturing operations and related areas. Subsequently, the research results discuss the operational performance resulting from the current practices.

6.3.1 Automation

In the manufacturing processes, automation of machinery plays a pivotal role in achieving efficiency, precision and quality in the produced output (Oesterreich & Teuteberg, 2016 cited in Savastano, et al., 2019). Automation in manufacturing processes has gained significant results in terms of increased efficiency, better quality, reduced lead time, and reliable operations (Simões et al., 2021). By analysing the interviewees' responses, *most* companies have deployed automated machinery where minimum, or no labour is required. VMC (vertical machinery centre) and CNC (computer numerical control)

machines are utilised to achieve high-quality end products. Case G reported the use of manual machinery requiring constant supervision by workers to ensure that the product manufactured is as per the required specifications.

“We face problems mainly with the machinery, we have manual machinery, so workers have to supervise all the machines” (Case G).

Cases B, C, D, E, J and K have fully automated machines, which means all the machinery used within these companies is automated. This is highlighted in Case E, where the director said:

“Manufacturing is based on a proper system, and we have the latest machinery, all computer-based machines. to make a specific part we have to make the program on the machine then it works automatically. No manpower is required only inspection is required. An inspection is required to monitor the tool wear” (Case E).

The Managing Director in Case J also confirmed the use of automated machinery stating that:

“We mainly rely on pneumatic presses. These presses are all controlled by a Programmable machine control system. Then automation progressive tools are capable of doing high production with high consistency” (Case J).

While Cases A, M, N F, H, I and O have semi-automated machineries involving a combination of manual and automated operations. This is understood from the response of the CEO in case A, indicating the use of automated machinery with the requirement of constant supervision by workers, thus lacking the integration of machinery with a computer system to identify machine breakdowns:

“We have a machine maintenance schedule for the whole year, maintenance department checks it from time to time irrespective of any failure. Another thing is we have a daily check sheet, we check the machinery daily, operators check the machine daily and production starts only after it is approved by the operator” (Case A).

Cases J and K integrate advanced technology including robotics, transfer lenses, vision cameras and PLC (Programmable Logic Controller) devices to capture the machine data for controlling the quality. This is highlighted by the Executive Director of Case K:

“Machines and ICT are not integrated for all lines, but we are gradually getting there, that is known as SCADA (supervisory control and data acquisition system) where we are recording all the data online so what it means is it will become integrated to the manufacturing process altogether. We follow TPM (total productive maintenance), TPM is already there, and apart from that we use value stream mapping, we use distance simulation. These tools are for controlling the quality. In manufacturing quality is in-built. We do not calculate the time taken in the quality as so in process verifications are there” (Case K).

However, apart from automated machinery, there is no automation in the processes meaning the number of units produced, and breakdown or downtime cannot be captured in real-time indicating the lack of coordination between machines and computing devices. Significant manual intervention is needed to track and monitor processes associated with these machines. Case K has some level of integration between machines and operating systems, and they are planning to make their lines automated for production flexibility. This will allow for multiple products to be manufactured using the same assembly lines, and the data from machinery will be captured through a supervisory control and data acquisition system for an effective control system. This is confirmed by Kiraz et al., (2020) whose findings indicate that production flexibility can be attained through parallel monitoring of systems.

The level of automation is identified across production/ machine operations. An intelligent production system emerges after using automated machinery and managing data from the production system which a few companies (Case K) are trying to achieve to gain more visibility into the production process and enhance quality (Oesterreich and Teuteberg, 2016). This exhibits the characteristics of digitalisation that require the integration of machines and processes where data is systematically collected, processed, analysed, and evaluated for decision-making across the production floor (Lee, et al., 2021). Currently, only production functions are automated using CNC/ PLC machines, robotic arms, 3D printers, and scanners in Cases J and K. Automation in machinery is identified as the carrier of competitive advantage by these companies (J and K) resulting in improved production efficiency and precision in the finished goods.

There is little or no evidence of systematically collecting the information which is further processed and evaluated for decision making across other areas as mentioned above. A high level of manual intervention across all activities is predominantly practised, which classified the organisation as rather automated in some areas, and organisations' reliance on manual processes in terms of collecting data from machinery is still prevalent. The machinery and processes are operating in an isolated manner with limited or no interaction between the two. The automation is confined or limited to machinery and in some cases, even machinery is manual where supervision is required to oversee the specification of the product manufactured to prevent rejection. Non-integration of the machine and ICT hinders the utilisation of data-informed decision-making, resulting in misalignment with the production schedule. These issues are pointed out by the Director and Quality Head of Cases M and G respectively:

“When supplying parts, there may be gaps or missing elements in the initial attempts. To prevent the same mistakes from happening again, we introduce additional elements to those parts, ensuring that the operator avoids repeating the error. Additionally, we communicate with the machine operator, informing them that the particular part was manufactured using specific machinery and that their inspection was inadequate” (Case M).

“We face problems mainly with the machinery, we have manual machinery so workers have to supervise all the machines, because if the machinery does not exactly manufacture the same products as per specifications, the product gets rejected, so workers will have to constantly check that machinery is meeting the required specifications” (Case G).

These findings align with Bogner et al. (2016) stating that high dependency on manual processes hampers the data continuity along the production process. Further, Bansal et al., (2023) noted that a lack of automation would result in compromised product quality, and faults may go undetected due to the absence of data from the production system.

Cases M and G reported problems such as delayed delivery due to machine downtime and gaps in quality control due to the non-availability of complete data.

“It affects the production process, in terms of buyers, because we follow the weekly schedule, we’ll have to update them that we will not be able to supply the given quantity so that they can procure from some other supplier” (Case G).

“We have to stop the production process because we don’t move ahead without analysing the cause of the problem and receiving complete report on the cause of the defect” (Case M).

Simões et al., (2021), found that data collection and analysis create a positive impact on product optimisation, reduction in machine downtime and higher productivity. Further, Müller et al. (2018) identified that SMEs face challenges in establishing an automated production system. It can therefore be inferred that a low level of automation and non-integration between machines and operating systems affects the production scheduling, and results in quality gaps and vice versa (as stated in Case K above). Three different levels of technology usage emerged across interviewed cases. Table 6.5 presents an overview of the sample distributed across three levels of technology usage within the identified areas (automation; machine and computer integration).

Table 6.5: Sample distribution for automation; machine and computer integration.

	Category I	Category II	Category III
Automation	Manual machinery: G	Partially automated: A, M, N, F, H, I, O	Significant tasks are automated B, C, D, E, J and K, L
Machine and computer integration	No integration: A, B, C, D, F, G, H, M, N, O	Possess information exchange capabilities but not integrated with computing devices: E, I, J	Partially integrated with planning to integrate all assembly lines K, L

6.3.2 E-procurement

The e-procurement process using electronic data interchange, and cloud-based solutions is the key to effective procurement for the availability of the right information for decision-making that indicates the preparedness towards Industry 4.0 (Boer, et al., 2001). It answers questions such as ‘what is required to

be purchased' and 'from whom can it be obtained which involves the exchange of information between internal (buyers) and external (suppliers) parties. Therefore, the procurement process and supplier evaluation process are interdependent. This involves requesting information from the supplier about the availability of raw materials, and negotiating the contract terms and conditions including price, quantity, and delivery timeframes. It became clear from the interviews that all companies identify procurement as acquiring raw materials, components, or other resources and services from suppliers for manufacturing the final product. These functions are carried out manually by most companies where purchase requests and purchase orders are raised over phone, email, or WhatsApp. For example, in cases A, B, C, D, E, F, G, I, M, N and O, no purchase orders are issued at all, and the companies communicate requirements on an ad hoc basis to their suppliers using emails as confirmed through Cases N and E:

"We raise the requirement of raw materials through purchase orders over emails, even the orders we receive from buyers, it's over email only" (Case N).

"We communicate with suppliers via email for raw material orders instead of issuing purchase orders due to fluctuating rates. Our buyer uses a purchase order system because of their SAP setup, which we don't have" (Case E).

In cases, J, K and L, procurement requests are initiated via purchase order. However, these companies are still managing inventory manually thus leading to similar issues as in other cases. Case J reported a twenty percent deviation in stock levels while case K reported difficulties in identifying a suitable supplier capable of meeting raw material demand. Moreover, the failure to place the order on time or any delay in processing the same increases the risk of not receiving the raw material in a timely manner as reported by case K. Time is identified as the critical factor in the procurement process. The practice of manual procurement where purchase requests and purchase orders are generated through emails, phones, paperwork and in some cases using tools such as Systems, Applications & Products in Data Processing (SAP) (J, K and L) remains heavily contingent upon human participation, particularly in inventory record maintenance. The Managing Director at Case J said:

"We have upgraded to a cloud-based ERP system for purchasing orders. Now, I can approve orders anytime, anywhere, even when I'm abroad. Our purchasing head can approve orders within a set limit, and I handle approvals for orders exceeding that limit" (Case J).

Notably, one manufacturer (Case H) indicated the utilisation of SAP for purchase requisitions, seamlessly integrated with the consumption master software employed for inventory level monitoring, thus preventing the need for recurrent inventory audits.

"My other plant is working on this software, we get the data every three months which shows an increase or decrease in prices in the past three months, we get the mean of that data, and it becomes easy for us

to predict the future price. We have an internal software called consumption master where all these details get recorded after deducting dispatches to check the requirement of raw material units. Because of this, we don't have to do the inventory count again and again, we don't verify it multiple times now" (Case H).

Table 6.6 presents an overview of the sample distributed across three levels of technology usage concerning data collection across the procurement process.

Table 6.6: Sample distribution based on technology usage concerning procurement.

	Category I	Category II	Category III
Data collection	phone, email, or WhatsApp A, B, C, D, E, F, G, I, M, N, O	SAP-ERP cloud-based J, K, L	Data analytics H

It is identified that the procurement system is linked with inventory management as reported by Cases J, K and L above and Case H below. Companies using the automated system have more control over the inventory resulting in fewer discrepancies as reported by Case H.

"The ERP is configured, you enter any component and look at the material and find inventory, you have access to number of units, so we have the visibility into inventory records. We are determined to operate on a just-in-time inventory system. Increasing inventory levels is not an option for us. We implemented research software for demand sensing as the customer's data moves. Consequently, we are strategically selecting raw materials to minimize inventory costs while still meeting demand and ensuring timely production" (Case H).

The digital collection of data provides flexibility in raw material procurement and inventory by coordinating both the demand and supply side. This corroborates with Tian et al., (2022) confirming that e-procurement and cloud-based solutions result in improving manufacturing performance by integrating the operations with suppliers from raw material procurement to inventory management.

6.3.3 Inventory Management

Inventory management refers to the process of calculating the stock which is conducted at multiple stages across the production line, including inventory count for planning the production, for placing the order of required material after production planning, on the arrival/receipt of raw material, and the final dispatch of the final component to the buyer. Additionally, it encompasses overseeing the storage and consumption of raw materials, work in progress, and finished goods which are vital for meeting operational needs. The effectiveness of inventory management hinges on accuracy in maintaining inventory records, facilitating quick assessment of raw material requisites for the production process, and informing dispatch personnel about available stock for shipping. In cases, A, B, C, D, E, F, and G, MS Excel and Tally are used for keeping the inventory records. The inventory received or available in

the company premises is counted physically by the production operator to support the record of material and finished components. This implied that there is no automated system for identifying the potential shortage. It is all contingent upon the accuracy of production staff. This is pointed out by Director of E:

“As such there is no software for managing inventory, it is all manual, in some cases, we are maintaining Excel. There are problems with this system, sometimes there are shortages, in my record it says 10 pieces, practically it may be 2 pieces, that kind of shortage. it is all a painful area for us, we are trying. We have a large variety of components, so it is very difficult to maintain all these things. Naturally, you can say, that shortages are there, mismanagement is there” (Case E).

Companies have reported the occurrence of a shortage of raw materials due to a lack of monitoring and management systems. Thus, manual inventory management is tied to multiple operational inefficiencies as identified across companies:

- i) Shortage of raw material (Cases E and L)
- ii) Rescheduling the production process (Cases F, G and H)
- iii) Delayed order delivery (Cases, E, F, G, and H)
- iv) Mixing of batches of different types of raw material (Case E)

“Our inventory management process is manual, sometimes there is an error, due to the non-recording of the items, for example, we received the process material after forging four units and the person responsible for doing the inventory in purchasing is not aware, and then the calculations get mixed up” (Case L).

“The buyer procures the material from other suppliers if the company delays meeting any buyer’s demand” (Case F).

Further, it can be inferred from Case M that the product cannot be tracked as it moves from supplier to buyer.

“We have been doing it manually. We have a huge variety of stock that is available, and the stock movement is not so fast. But these stock details are available on the computer when it goes below a certain level. Our teams scan it on the first week of every month, so whatever products are really below the, you know, acceptable level. Our team will note it down. We’ll think about it and we’ll order raw materials for that” (Case M).

This is the implication of manual inventory management where a lack of real-time tracking hinders the visibility into accurate inventory levels (Unhelkar et al., 2022). The warehousing and inventory involved a huge amount of human involvement resulting in errors as discussed above. The cases studied have not employed any kind of inventory management system, which could automatically track the movement of components across the supply chain which indicates a lack of visibility. While ERP is used in cases J and K for automating the ordering process. The system notifies the purchasing

department of requirement stock as it moves down below the safety stock level thus preventing stockouts and replenishment in a timely manner for smooth productions as compared to cases following manual inventory management procedures.

“We are determined to operate on a just-in-time inventory system. Increasing inventory levels is not an option for us. Consequently, we are strategically selecting raw materials to minimise inventory costs while still meeting demand and ensuring timely production” (Case K).

Case I is having an automated inventory control system where requirements directly reach the production and planning control department, reflecting the capabilities of the system.

“It is cloud based and I can check inventory record anywhere which gets updates as per requirement of customer” (Case I)

Patrucco et al., (2022) based on their results, specified that the use of real-time tracking and timely availability of data for inventory management significantly improves operational performance through optimised flow of inventory. Table 6.7 presents the sample distribution across three levels of technology usage for inventory management.

Table 6.7: Sample distribution based on technology usage for managing inventory.

	Category I	Category II	Category III
Inventory Management	Physical inventory counts: A, B, C, D, E, F, and G, H, L, M, N, O	Just in time, computerised database using ERP: J, K	real-time database integrated with the production and planning department I

6.3.4 Communication with Suppliers and buyers

Communication with suppliers plays a highly influential role in enhancing a manufacturer's performance across operations. The operational information such as demand and order planning facilitate the synchronisation of suppliers' and manufacturers' production planning (Müller et al., 2018). The level of transparency among the supply chain partners through an effective information-sharing system enables effective demand management (Müller et al., 2018; Crešnar et al., 2022). All the cases as presented in Table 6.8 follow the same communications tools viz, email, phone, and WhatsApp, to receive or provide any order details about the raw material requirement. Additionally, Table 6.8 presents the sample distribution across three levels of technology usage for communication.

Table 6.8: Sample distribution based on technology usage for communication.

	Category I	Category II	Category III
Communication with suppliers	A, B, C, D, E, F, G, H, I, L, M, N, O	J	K

Further, Cases N and F reported the use of emails and WhatsApp for communicating with suppliers for material availability and placing orders:

“For placing the order, we communicate through purchase orders over email, even the orders we receive from buyers, are over email only. We received the order in the last 2-3 days before the month ends” (Case N).

“Main communication channel is phone, WhatsApp, and email. We communicate with suppliers via email for raw material orders instead of issuing purchase orders due to fluctuating rates” (Case F).

Cases H, M and N have encountered challenges in maintaining communication over the phone or emails which include not acknowledging the order in time, delayed responses, and inadequate documentation by suppliers resulting in operational inefficiency such as inefficient production planning and delayed delivery to OEMs. These findings align with Pérez et al., (2022) and Müller et al. (2018) establishing that an ineffective communication system affects the responsiveness to meet customer needs through customer engagement.

“We face lots of problems in managing communication through email and WhatsApp like many suppliers don’t use or check emails/WhatsApp” (Case H).

“There is always a communication gap or wrong understanding of the customers” (Case M).

“Change in production schedule due to urgency from the OEMs side which does not get communicated in time results in delays in order delivery arising from the delayed responses from the supplier” (Case N).

Hu et al., (2024) identified that companies face challenges rooted in a lack of robust IT infrastructure which negatively impacts their information technology capabilities. However, case J has simplified the communication through the use of software to share only the necessary details in terms of predefined fields such as order details, and product specifications. Moreover, the payments system is automated, which is triggered upon the system’s material received note and approval process.

“When the requirement comes to my purchase person then he sends that requirement in terms of the purchase order and telephonic confirmation also for every supply there will be a purchase order. Recently we have stopped making open purchase orders earlier we make open purchase orders, but due to some miscommunication and too much fluctuation in prices, we are now relieving the purchase order I told you it is very easy, very user-friendly software it takes hardly 2-3 minutes we have supplier fixed, we have material fixed, we know the quantity only three or four entries in the system in the software purchase order will be there all other terms conditions are already existing so he has to fill the details and everything is mentioned there, you just need to search something particular and it will show up. He

sends the requirements to all his suppliers through purchase orders over the mail and also over the telephone” (Case J).

Further case K exemplifies an effective flow of communication among various stakeholders in the supply chain to ensure efficient procurement and, delivery processes to fulfil customer demand. They provide customers (OEMs) with access to data related to the point of origin of raw material, fostering a relationship built on trust and collaboration. This transparency enables both parties to navigate any changes in the market. Effective communication is also demonstrated by collaborative problem-solving efforts among different parties, particularly during times of demand fluctuation. There is a constant exchange of data in terms of inventory levels, demand variations and price fluctuations. This ongoing dialogue between parties enhances coordination within the supply chain. The findings are consistent with a study conducted by Patrucco et al., (2022) where the authors found that transparency in terms of inventory flow, and quality problems improves the supply chain performance and establishes a strong link between manufacturer and supplier for sharing information constantly. Hu et al., (2024) asserted that information technology capabilities result in increased production efficiency. Since the research was secondary, there is an opportunity to conduct future investigations by testing the relationship statistically.

“So, I’m benefiting from the purchase price and monitoring it throughout the day. If I notice that it has gone down for three consecutive points, I’ll focus on that. However, there’s also a risk involved because it might be a signal of declining prices. In such cases, I may decide to adjust inventory levels and even consider cancelling some orders, as necessary. We have software, we implemented research software that senses demand as the customer’s data moves. One day, the demand might be for 10,000 units, but the next day, they may cancel the order. To cope with such fluctuations, tracking various macroeconomic factors and keeping a close eye on the origins of these changes is essential. Timing is crucial, as within an hour, the situation can shift, and these changes can significantly impact the market” (Case K).

6.3.5 Integration between suppliers and customers

Supply chain visibility is identified as the ability and level of a company to share and access information related to supply chain operations with suppliers, and buyers (Ghadge et al., 2020) for decision-making (Alcácer et al., 2021), mitigating risk, and improving operational efficiency which is predicated on effective communication (Marwah et al., 2014; Dubey et al., 2018). Manufacturers in India exhibited an absence in the use of information for achieving visibility across supply chain operations (discussed in sections 6.3.2, 6.3.3 and 6.3.4). OEMs are demanding more visibility into the shop floor operations of manufacturers as reported by Case F:

“They want access to our inventory, how much-finished stock you have, how much raw material you have, what is your manufacturing capacity, can you supply the number of items which we require and would you be able to deliver. So, they want all these things” (Case F).

Data and stakeholder involvement are very low for monitoring and optimisation of operations and processes including product status, location, inventory level, and shipment status (as discussed in **section 6.3.4**) and presented in Table 6.9.

Table 6.9: Sample distribution according to the level of supply chain visibility

	Category I	Category II	Category III
Supply Chain Visibility	No integration A, B, C, D, E, F, G, H, I, L, M, N, O	share only the necessary details in terms of predefined fields such as order details, and product specifications. J	No real-time visibility although a continuous exchange of data between suppliers and customers K

The information accessibility level is low at the company level, which omits the visibility across supply chain stakeholders, supply chain partners, and customers. Most companies (Cases A, B, C, D, E, F, G, H, I, L, M, N, O) admitted that they do not have any visibility of their supply chain at any level including visibility at the organisational level. The second factor is, visibility in the supply chain is realised with the effective use of digital technologies which includes the adoption of RFID, enterprise resource planning, and electronic data exchange (Crešnar et al., 2022 and Chonsawat and Sopadang, 2020). As the level of investment of companies in these tools is low, it indicates the lowest level of visibility. When asked about the tracing system including RFID, Global Positioning System (GPS) or Quick Response (QR) code to identify the product status, location or inventory level, it was found that none of the respondents used any tracing system to increase visibility. The lack of visibility is coming from low integration, sharing only order details and product specifications within the organisation as reported by Case D:

“No scanning or RFID system. Just a code. Which is moving when he is releasing material from store to production and then from production to dispatch”.

In some cases, the inventory level is visible to suppliers, for example, Case J quoted:

“We know the quantity only three or four entries in the system in the software purchase order will be there all other terms and conditions already exist so he has to fill in the details and everything is mentioned there, we don’t use RFID”

Case K quoted:

“One way to simplify this process is by sharing the origin, alternating between Ghaziabad and the other site on different days. Whatever the reason or site status, it’s acceptable to me” (Case K).

The low level of visibility across the two factors affected the production planning, where the manufacturers will have to keep changing the production schedule based on the information coming from OEMs, and not having any real-time access to data demonstrates a non-integrated supply chain

resulting in non-optimised production plans. Further, the lack of visibility resulted in a shortage or overstocking of raw materials. Based on these results, the relationship between integrated supply chain and operational performance will be statistically tested.

It can be gathered from Case E that supply chain planning, scheduling, and forecasting are highly dependent on the level of visibility across manufacturing operations, and information sharing across these operations. Further, supply chain visibility played a significant role in the company's performance by quickly responding to buyer's demand and inventory management.

"Basically, one other major problem we face is that they give us the schedule on the 30th of every month for the next month. So, we start production as per the schedule. What they do is, they change the schedule to the 10th suppose. We started manufacturing, but because it's not serving their requirement anymore, they declined the order. This is the problem. This happens because of the demand fluctuation for the particular model, there is no more demand, and they cancel the order. This happens almost every month" (Case E).

The visibility in auto component manufacturing companies was assessed through the level of information sharing and use of ICT across procurement (see **section 6.3.2**), inventory management (see **section 6.3.3**), the status of resources – inventory, information related to the quality of product, and information across manufacturing processes (see **section 6.3.4**). It can be inferred that a low level of ICT for communication with suppliers and customers procurement process, and manual inventory management results in low visibility, and thus hampered the integration between supply chain partners. Patrucco, et al., (2022) asserted that visibility enhances the integration within the supply chain and has a positive association with supply chain performance in terms of optimisation of inventory flow for planning and scheduling the production process as well and increasing the responsiveness to meet buyer's demand. This mirrors the findings where low visibility and low integration are positively associated with operational inefficiency reinforcing the positive association between performance and visibility.

6.3.6 Data-driven Decision

Data is identified as a key resource for improving performance through data-driven decision-making as reported by Case K:

"Extrapolating data from various sources to strike the right balance between customer needs and supplier performance"

There are two important building blocks in data conceptualisation which include capturing data about organisational internal and external processes through sensors and information, and communication technologies as stated by the Executive Director of case K. The data captured is then further structured into information for informed decision making which creates value for the firm (Nwasuka et al., 2022).

“We have established forums for day-to-day communication which follow a hierarchical structure with clear delegation of authorities and accountability by using ERP that contains almost all the data. There is a specialised forum called ATM (Active Task Management) where we focus on discussing critical points and urgent matters.”

Based on the previous discussion in sections 6.3.2, 6.3.3, 6.3.4 and 6.3.5, it was identified that the level of ICT investment for the transmission of information is minimal, in terms of the practices and approaches across processes and network structure including supplier evaluation, order fulfilment, and inventory management. Further, top management utilises the data coming from the operators on the factory floor to manage production, including machine breakdown issues and placing orders for the raw material to enhance smooth operations. Operators, plant managers and supervisors diligently follow the instructions and orders descending from the top management. The non-involvement of other departments resulted in siloed processes, acting as a barrier to exchange, and hindering coordination as identified in Case F.

“the lower staff informed me about the requirement, so I addressed that issue, for example, the machine is not working now because of some issue with the tool due to an accident, and that tool is not in stock, which I basically keep in stock. So, I immediately have to order. Like how the supply chain works in a flow, that system is not possible here”.

As cases A, B, C, D, E, F, G, H, I, L, M, N, and O are not using any ICT and sensors to capture and process real-time data, it prevents supervisors and operators from accessing any information for decision-making in their divisions. The production stopped due to a machine breakdown and the information was conveyed only to the top management. Consequently, top management informed other personnel across other operations to stop the assembly line. This further established low visibility into operations and processes stemming from a limited or centralised flow of information.

In cases J and K, where companies are using Information technologies such as SAP/ERP, the involvement of top management are minimal in making operational decisions. Supervisors and managers have the autonomy in making operational decisions by tracking and analysing the data for optimisation of the production process, and thus providing greater flexibility to address the production inefficiencies timely.

“I’m leading the supply chain and parts of the customer order management in fulfilment of the whole cycle. So, there are different verticals, there is production planning and control, one is market planning, then there are plant leaders, then we have sales coordination, and in between there is a purchasing department. The planning game is central because there are many parts for which we don’t have competent plants, the other plants have that, so coordination has to be taken care of in the production planning and control department. Then there are common interfaces from the customer side, the plant

side, and the purchase side and then we have the plant leadership the monitoring teams, production teams. So based on that, we issue certain targets and then a tracking mechanism” (Case J).

This also indicates the level of fragmentation of information which is comparatively higher in all cases except J and K where companies have not employed any ICT. The finding corroborates with Dalmarco et al., (2019) and Parente, et al., (2022) studies that deficiencies in ICT directly impact decision-making, while the availability of data facilitate the improvement in quality and process efficiency.

Further, the autonomy of decision-making is associated with the organisational structure as observed from the cases. Companies with higher turnover (Cases J and K) follows decentralised decision -making mechanism. On the other hand, MSMEs follow the flat organisational structure where the owner oversees all the operations, processes and network structure – only one person is responsible for the decision-making autonomy resulting in communication challenges, and delays in addressing the potential inefficiency within operations. Companies having higher turnover follow more structured and segregated departments with a clear line of duties and responsibilities (for example Case J as quoted above). The firms which use data for decision-making demonstrated high performance as the decisions are guided by data-based analytics and not based on instinctual perspective (Case J, and K). Decision making ability of the organisation improves competitiveness by supporting decision-making from the strategic perspective. Based on this observation, the findings suggest that effective decisions can only be made by a decision-maker through access to the right information. However, decision-makers do not always have the correct information due to the limited use of digital tools and effective ICT. On the contrary, in companies (Cases J and K) which are using data analytics, SAP/ERP and where top management is not involved in day-to-day operational processes, companies have experienced adaptive production scheduling due to effective communication and timely decision-making. As the majority of companies have not implemented the ERP system as presented in Table 6.10, it clearly shows that companies are not utilising their potential maximum capacity in terms of performance preventing them from achieving a competitive advantage.

Table 6.10: Sample distribution assessing the data-driven decision patterns.

	Category I	Category II	Category III
Data-driven decision	Top management involved in operations decision-making A, B, C, D, E, F, G, H, I, L, M, N, O	Plant managers analyse data J	Top management is not involved in day-to-day operations but leverages data for decision-making K

6.3.7 Real-time Tracking

It is established from the discussion on supply chain visibility that the majority of companies are not using any technology for tracking raw material requirements or processes across the value chain as presented in Table 6.11.

Table 6.11: Real-time tracking

	Category I	Category II	Category III
Tracking	Limited product tracking using engravings on components (only for identifying finished product) A, B, C, D, E, F, G, H, I, L, M, N, O	Tracking across the manufacturing processes with the involvement of third-party K	Tracking system without the involvement of third-party J

Cases A, B, C, D, E, F, G, H, I, L, M, N, and O do not use any monitoring system at all.

“We use the traceability code though which is ingrained in the components. It’s like the identification code of the company and packing slip as well, but we don’t have any internal system” (Case D).

While Case K uses the tracking system of third parties for tracking any raw material, for instance, case K’s tracking system is consistent throughout the supply chain and involves various stakeholders such as feeders, consumers, and distributors. The tracking system for the first mile is managed by the company itself. However, for the last mile, companies rely on other entities. Additionally, Case J is working on an integrated optimisation network by utilising GPS to enhance the efficiency of the tracking system.

“The tracking system is already in place and consistent throughout the entire supply chain, which involves various stakeholders such as feeders, consumers, and distributors. The initial part of the supply chain, known as the “first mile,” is managed from our location. However, for the “last mile” of the supply chain, which involves distribution, we rely on other entities. In the distribution network, I need to have clarity on how much stuff I’m keeping there. So, they do have different effects and as planning system takes care of itself. And apart from that how much is in the transit, how much is my demand? There are common interfaces from the customer side, the plant side, and the purchase side” (Case K).

“We are working on enhancing the integration and efficiency of our tracking system to improve load consolidation and streamline the entire supply chain process. LION logistics integrated and optimisation network, because the biggest thing you want is that all your supplies need to be added to that. By utilising real-time data from GPS and automation systems, along with the computing power of quantum systems” (Case J).

6.3.8 Collaboration within organisation

The interdepartmental interaction and collaboration in which manufacturing processes are synchronised to achieve mutually acceptable operational outcomes, is highly emphasised in literature as one of the factors for determining technology readiness level in the context of Industry 4.0 (Schumacher et al., 2016; Crešnar et al., 2020). The internal integration was examined within the interviewed cases across departments, including procurement, production planning, inventory management, and logistics. Few companies do not have any segregated departments (Cases A, B, C, D, E, F, G, H, I, L, M, N, O). The

top management is highly involved in overseeing all the areas viz. procurement, order fulfilment, order processing, production planning and logistics. The top management communicates with the supervisors and operators employed on the factory floor to make any decisions around the said internal functions as quoted by Case G:

“it is managed by the company owners. We get schedules from buyers, then we plan our production, and then we communicate to our production staff like the foreman for the changeover of the production. It’s a small company so it’s direct communication and nothing is in writing, it’s all verbal” (Case G).

Any decision-making authority around the manufacturing processes in terms of procurement of raw materials, production plan, quality control, and logistics is the responsibility of top management. The shop floor and factory floor personnel rely on guidance and plans from the owners of the company as reported by Case C:

“There is always a communication gap or wrong understanding of the customers. By customer I mean internal customers, next man, operators within the departments. Miscommunication and misunderstanding affect internal customers. See our company is single owner type so whatever activity is done it is passing through the owner only. Everything from raw materials to end products, everything is covered by the owner only. But the system is not foolproof”.

Cases B, and D demonstrated rare integration with departments operating in functional silos with minimal interaction across departments revealing the significant difference and mismatch in strategic practices including the collaboration among departments for optimising production schedules and managing inventory as demonstrated through the following cases:

“Before starting the production process, we call the meeting where all departments are involved, after discussing the plan there is no need for any communication, we only discuss if any issue arises like a shortage of raw material, or defective raw material where we have to stop the production and then purchasing department handles all these issues” (Case B).

“We have meetings on the 29th of every month called production planning meeting (PPM), where we discuss the requirement for next month, we provide the schedule to supervisors and check the availability/requirement of raw materials” (Case D).

Further, the communication system across departments and with external stakeholders including suppliers and customers exhibited a lack of automated tools for sharing data, decision-making, and effective data analysis for smooth company operations (see **section 6.3.4**). The lack of a centralised communication system has resulted in limited visibility (see **section 6.3.5**). The effects of improper communication channels are multi-fold including delays in identifying bottlenecks, data inconsistency, delayed response time, and longer lead times.

On the contrary, companies (Cases J and K) that emphasise comparatively high collaboration across departments utilise ERP systems for accessing a wide range of information. Case J reported occasional collaboration while Case K reported each department having a clear line of authority which improves decision-making and avoids misunderstanding or mismanagement within the production process.

“We have established a specialised forum called ATM (Active Task Management) where we focus on discussing critical points and urgent matters” (Case J).

“For collaboration, we have well-structured systems in place. One of them is the development process, which is cross-functional and allows for flexibility. We also have forums established for day-to-day communication. These forums follow a hierarchical structure with a clear delegation of authority and accountability. Apart from that we have, operational review meetings monthly and all the plants share their newly implemented best practices for improving the efficiency of operations” (Case K).

The findings align with Dalmarco et al., (2019) suggesting that an integrated system facilitates the interactive environment to improve the production process. Table 6.12 presents the level of collaboration across the interviewed companies.

Table 6.12: Interdepartmental collaboration level

	Category I	Category II	Category III
Collaboration	Departments operating in silos A, B, C, D, E, F, G, H, I, L, M, N, O	Occasional exchange of data J	Departments engaged in knowledge sharing and best practices K

6.3.9 Innovation and Technology Management

When asked about the company’s involvement or collaboration with technology experts, most participants (Cases A, B, C, D, E, F, G, H, I, L, M, N, O) responded with “No”. The majority of the participants do not have the involvement of any external experts in terms of managing the new developments in the industry also reflected by the lack of awareness these participants exhibited when asked about Industry 4.0 technologies (Cases A, B, C, D, E, F, G, H). Case I has reported using expert consultation and hiring more technology experts to initiate the technology adoption process.

“As I mentioned we are working on Greenfield projects, and we are implementing certain technologies and machinery which are related to electric vehicles for which we do not have internal expertise or capabilities. So, we reached out to some consultants to understand the ways we can do so. It is for new technology for which we don’t have people internally. Therefore, we are using some support from outside” (Case I).

Case K has collaborated with the Indian Institute of Technology (IIT) - Delhi to explore and enhance the product portfolio including engines, electronic vehicles, and motor controllers for other legacy parts.

“We have tied up with the IIT Delhi, we have incubators, taken space for working around for engines, electric vehicle, motors controllers for other legacy parts. We have companies, like Honda company and companies in Germany, these are all technical collaborators” (Case K).

Collaboration with technology experts is identified as the driver of digital transformation to achieve competitive advantage as confirmed by Simões et al., (2021). Table 6.13 presents the level of collaboration with technology partners across companies.

Table 6.13: Level of collaboration with technology experts

	Category I	Category II	Category III
Technology management	No involvement A, B, C, D, E, F, G, H, I, L, M, N, O	Involved with consultancies for software and technology installation I	Collaboration with academic Institutions and companies to improve existing processes K

6.3.10 Leadership

The companies (Cases E, G, N, I) are willing to advance their manufacturing operations where they have shown openness to environment and industry requirements. The main obstacle identified in the findings is the lack of awareness around Industry 4.0 technologies and their adoption for the improvement of operations, and achieving efficiency and productivity (Cases A, B, C, D, E, F, G, H, J, L, M, N, O). The below direct quotes from participants identify the issues:

“Technology has always been useful, to adopt the technology and how the adopt the technology is the only issue” (Case G).

“One more thing which is important is knowledge of the technology” (Case N).

“We are in the stage of implementing IoT, multiple players are in the market. So, the first challenge is to select the right partner, who would provide us with the right output that we need” (Case I).

This indicates the lack of direction in the identification and adoption of an appropriate technology. Additionally, the companies’ knowledge of technology was emphasised as the key element for successful adoption. The manufacturers are keen to adopt tested and well-established technological solutions that would enhance the quality as they have experienced the change and benefits from adopting technology in the past as quoted by the Director of Case E and J:

“Due to advancements in technology, manufacturers have been able to improve the quality of their products. There are now all-in-one machinery setups where you can simply apply a part, and the entire process can be completed in one setup. This eliminates the need to manually handle minor tasks once the part is on the machine. As a result, Indian vendors are gradually adopting such technologies to enhance quality and increase production” (Case E).

“We started with mechanical presses then we went to pneumatic presses then pneumatic presses to progressive tools. We experienced an increase in production and increased efficiency. Quality consistency is maintained using progressive tools” (Case J).

Further Case I is exploring the adoption of IoT to optimise the production process for effective planning and scheduling, showing the leadership's willingness to invest in advanced technology to suit their processes. Operation Head at Case I reported:

“Many times, it happens I'm not able to capture the real percentage first-time-through (FTD) percentage. For example, what is my scrap rate? All those things can be calculated through IoT itself as we are exploring the benefits. We can get the final data which will tell me this was my input; this was my output and the scrap. Further, it automatically calculates the cost, and the issues I should focus on and then I accordingly take actions” (Case I).

Case K has already implemented blockchain for automating the transaction system with suppliers. This indicates that the leadership team acknowledges the benefit that can be attained from Industry 4.0 technologies within operational processes, and in the process of expanding the adoption across other areas including procurement.

“In terms of adopting advanced technology like say using Blockchain technology for our payment processing, that is one area, where we have already adopted this technology. We are currently working to integrate this into other processes” (Case K).

Overall, the leadership's willingness or initiative to adopt Industry 4.0 has significantly influenced the operational performance as indicated from the interviewees' perspective (Case I and K). The enhanced performance as achieved by the support and awareness of leadership, and top management towards the adoption of technology (Cases E, I, J, K) is a testament to the positive association between leadership support and operational performance. The findings partially align with the literature emphasising the positive association between leadership willingness and Industry 4.0 adoption (Yang, et al., 2015; Kiraz et al., 2020; Chesbrough, 2007; Hajoary et al., 2023). Table 6.12 presents the leadership team's recognition of Industry 4.0 investments.

Table 6.12: Leadership team recognising the adoption of advanced technology

	Category I	Category II	Category III
Leadership	The leadership team lacks awareness of A, B, C, D, E, F, G, H, J, L, M, N, O	Exploring the potentials of Industry 4.0 I	Investment in blockchain technology for automated payment systems K

6.4 Auto Components Firm's Operational Performance

The findings in terms of operational performance are classified into three different measures including production process, network integration and responsiveness towards OEMs needs. Participants

indicated that they face challenges to meet the identified operational performance, which indicates that firms are trying to achieve improvements in the mentioned area. These operational performance measures as reported by the participants are discussed in following section.

6.4.1 Production Process

The production process faces disruption due to inaccurate inventory calculations with an increase in stocking cost, unexpected stockouts resulting in order cancellation and diversification of supply chain by OEMs, and increased cost due to rescheduling of production planning (discussed in **section 6.3.3; quotations from Case F, Case E, and case M**).

There are two ways of reducing this effect, first is efficient inventory management (Patrucco, et al., 2022) and second is increased visibility of information (Culot, et al., 2020; Unhelkar, et al., 2022). Reintroducing the Indian auto component manufacturers in this context, the lack of information visibility has already been discussed in section 6.3.5 where most companies admitted to not having visibility in operations across the supply chain. Further, the improper system of information sharing and information quality coming from distorted communication channels is leading to a high proportion of variability in inventory as quoted by Case F. The lack of information sharing of customer demand across all the participants in the supply chain is another reason for inefficient inventory control as pointed out by Director of Case F:

“Sometimes we encounter a challenging situation where we place the order for the raw material but then the design gets changed from the buyer’s end, so it leaves us in a very difficult spot and that’s the reason we only keep one month of raw material in stock. Mahindra launched a tractor ‘Load’, which failed in the market. They pressured us so much that, I even went ahead and purchased new machines to fulfill the requirement, they gave us the schedule and I started the production process, and I planned the supply as well. ASN works for supply nowadays, advance shipment notice. When I started preparing the ASN I couldn’t see the schedule, so I asked them to give me the schedule. They told us that we didn’t need to send the component in the current month but rather in the following month. Unfortunately, the same issue repeated itself in the subsequent month, as we didn’t receive any schedule once again. Each time we sought clarification, they simply stated that they were facing certain problems, but they never disclosed the actual reasons or provided a truthful explanation”.

Overall, Case F demonstrated a mix of numerous complications including communication gaps, lack of visibility from OEMs, inventory management difficulties, lack of updated schedules from OEMs, and variations in demand. The purchase of new machinery only to meet the specifications of new product design, and production planning and then the failure of the OEM product launch resulted in the instability of the supply chain with wastage of resources, and fluctuations in production planning and scheduling at the manufacturer’s end. The current practices across auto component firms led to multiple implications on the operational efficiencies which are summarised in Table 6.14.

Table 6.14: Current practices' implications on operational efficiency

Operational inefficiencies identified	Quotes from participants	Cases
Discrepancies and mismanagement related to inventory	<i>"Sometimes there are shortages, suppose in my record it says 10 pieces, practically it may be 2 pieces, that kind of shortage" (Case E).</i> <i>"Sometimes there is an error, due to the non-recording of the items" (Case G)</i>	Cases A, B, C, D, E, F, G
Rescheduling the production process	<i>"Change in production schedule due to urgency from buyer side" (Case F)</i> <i>"Changing the production plan due to early requirement of the component by the buyer; stop the production for other units" (Case H).</i>	Cases A, C, D, E, F, G
Buyer's alternative sourcing in case of production disruption or inventory shortage	<i>"If any problem arises, they procure it from two-three sources, but then we face a loss in that situation" (Case D).</i> <i>"Can't delay the supply, it leads to rejection if there is any delay in order delivery" (Case G).</i>	Cases A, B, E, F, G, H, K, M, N
Limited visibility into inventory levels to address fluctuating customer demand.	<i>"Basically, one other major problem we face is that they give us the schedule on the 30th of every month for the next month. So, we start production as per the schedule. What they do is, they change the schedule to the 10th suppose. We started manufacturing, but because it's not serving their requirement anymore, they declined the order. This is the problem. This happens because of the demand fluctuation for the particular model" (Case E).</i>	Cases A, B, C, D, E, F, G, H, I, L, M, N, O
No integration in terms of integrating other processes like procurement, production, order fulfillment, and responding to market changes.	<i>"They want access to our inventory, how much finished stock you have, how much raw material you have, what is your manufacturing capacity, can you supply the number of items which we require and would you be able to deliver. So, they want all these things, but we don't have any system for that" (Case F).</i>	Cases A, B, C, D, E, F, G, H, I, L, M, N, O
Quality control gaps	<i>"quality issues of mixing bad pieces with good pieces" (Case N).</i> <i>"Sometimes quality issues get traced by the buyers; then they hold the material and perform the segregation process, in the segregation process they inspect the material and if 4-5 pieces are defective, then they reject the whole lot" (Case C).</i>	Cases C, D, F, N, H, O

Overall, current practices across Indian auto component firms demonstrated a positive relationship between low technology level and production process efficiency across Indian auto component firms. As highlighted by multiple issues that all signify disruption in the production process subsequently

affects firms' responsiveness to OEMs. This research will examine the relationship between Readiness level and production process efficiency and responsiveness to OEMs through a quantitative study.

6.4.2 Supply Chain Structure – Network Integration

The supply chain is identified as a set of activities performed in an organisation including procurement, production, quality control, and delivery of final products to its buyers from the interviewed cases. However, these activities are not limited to the organisational boundaries itself. It further involves external stakeholders and entities including suppliers, buyers (see **Table 6.4**), ancillary service providers, and logistics as quoted by the following cases:

“The material goes for surface treatment to ancillary service providers” (Case E)

“Likewise other processes also heat treatment and surface treatment again we have approved ancillary, which means to see all the processes has been approved by OEMs” (Case G)

“Right now, there's a logistics partner, who has been with us for more than 30 years” (Case K)

Auto component companies are involved in the procurement of a variety of raw materials procured from different suppliers to produce multiple components for an average of 10-20 buyers (see **Table 6.4**). This further involves diverse operations encompassing order processing, order placing, incoming inspection, production, quality control, and delivery to the buyers. Each operation works as per the scheduled timeline dictated predominantly by buyers (OEMs) in all the interviewed cases. The variety of data sources involved in the supply chain is evident from the number of buyers, suppliers and operations involved in the network of manufacturing process which contributes to the possibility of producing massive data and information along the network.

The interviews conducted with the Indian auto component manufacturers have provided strong evidence of not using any information, nor communication technologies to collect and manage supply chain information from suppliers, buyers, ancillary service providers, and transport companies (discussed in **sections 6.3.4 and 6.3.5**). The complexity of the supply chain network entailing procurement, production, and logistics operations demands an operational level of an integrated system that would support a high level of information sharing, and visibility to enhance the efficiency of operations within an organisation, and thus improve the supply chain performance including external stakeholders (Bogner, et al., 2016; Moica, et al., 2018; Safar et al., 2018; Botha, 2019; Chatterjee et al., 2021; Patrucco, et al., 2022; Taghipour, et al., 2022).

At present, within the Indian landscape, the non-integration of the supply chain has been identified as the most notable challenge. The non-integrated supply chain has resulted in a lack of visibility to manufacturers in terms of material requirements, inventory management, and production schedules (discussed in **sections 6.3.3 and 6.3.5**). These issues have further aggravated the issue of misalignments

with OEM's schedule, rescheduling the production process, and supply chain diversification by OEMs as reported by following cases.

"Sometimes we encounter a challenging situation where we place the order for the raw material but then the design gets changed from the buyer's end, so it leaves us in a very difficult spot and that's the reason we only keep one month of raw material in stock" (Case F).

"Changing the production plan due to early requirement of the component by the buyer; stop the production for other units" (Case H).

If any problem arises, they procure it from two-three sources, but then we face a loss in that situation" (Case D).

The supply chain plan within Indian companies is not focused on improving the external processes, but rather confined to internal processes, which is the main hurdle in attaining supply chain efficiency. The companies are operating in isolation except in a few cases (cases J and K), and relying upon outdated methods of obtaining any information from suppliers or other stakeholders using phone, email, or paper-based documentation (discussed in **section 6.3.4**). The partners in the supply chain share only fundamental details that too on demand, which include details, shipment status, basic product specification, price, and payment updates. Real-time flow of information is almost negligible showcasing a lack of integrated supply chain activities. The supply chain is more reactive and unresponsive where each stakeholder has limited access to the data and information for decision-making. Further, coordination of activities across multiple processes including procurement, production, order processing, and ancillary services is one-to-one. The non-integrated supply chain is also reflected through the inability of companies to track the fluctuations in price and how much raw material is required during the multiple stages is not visible due to the lack of an integrated system between manufacturers and suppliers.

The non-integrated supply chain results from the current practices followed by these companies which are listed below:

- i) Distorted communication channels: Companies employ varied communication channels including phone, WhatsApp, and meetings for communicating between different departments and stakeholders for discussing production planning, raw material availability, and potential challenges like machine breakdown, shortage of raw material, and quality issues (Cases B, C, D, E, F, G, I, M, N, O) (discussed in **sections 6.3.2 and 6.3.4**). There are very few companies that are using technology tools like MS Teams and SharePoint (Cases J, J and L) for communication but there is heavy reliance on traditional methods of communication (discussed in **section 6.3.2**).

- ii) Further, most of the companies (A, B, C, D, E, F, G, L, M, N, O) follow the single owner type structure where any activity or decision passes through the owner only from procuring raw material to the final distribution of the product (discussed in **section 6.3.7**). Case K is working on optimising the network structure so that all suppliers of raw material can be added to the integrated network structure for capturing the data in real-time for identification of the problems promptly facilitating required interventions. This shows that integrated network structures can manage the disruption across the supply chain.

“We are working on enhancing the integration and efficiency of our tracking system to improve load consolidation and streamline the entire supply chain process. LION - logistics integrated and optimisation network, because the biggest thing you want is that all your supplies need to be added to that. By utilising real-time data from GPS and automation systems, along with the computing power of quantum systems” (Case J).

There are several problems reported by the companies due to the non-integrated supply network (see Appendix 3) which are listed below.

- Information loss (B, C, D, E, F, G, H, I, L, M, N, O)
- Lack of transparency (A, B, C, D, E, F, G, H, I, L, M, N, O)
- Miscommunication and misalignment (Cases, A, B, C, D, E, F, G, H, I, L, M, N, O)
- Inefficient production planning and scheduling (Cases A, C, D, E, F, G)
- Supplier-associated material and quality issues (Cases B, C, D, E, F, G, I, M, N, O)

However, there are few companies that have started automation in other areas. For instance, Case K has recently automated the payment system by integrating the SAP and bank server for the optimisation of cash flow across the supply network. The purchase invoices are directly raised through this automated system where the payments are automatically made based on the purchase order. This also means that the buyer's (manufacturer) and supplier's ERP system, SAP in Case K is integrated for the seamless data exchange. This system is mainly used to provide additional insights into tracking payment trends, monitoring cash flows, and optimising financial processes, but it also helps in improving supplier relations significantly by complying with the payment terms and conditions of purchase orders.

This study found a positive relationship between low technology levels and network integration. Further, the non-integrated network is having an impact on responding to customer's demands in a timely manner. This research will further examine the relationship between readiness level, and network integration, as well as its subsequent impact on responsiveness to OEMs through a quantitative study.

6.4.3 Responsiveness towards OEM needs

Within the Indian auto component industry, the OEMs are making sure that manufacturers procure from the suppliers approved by OEMs to maintain the quality of the components as quoted by Case E and

Case G. As these suppliers are rather chosen by OEMs as reported by Case E and Case G, the price and delivery timeframe are not evaluated by the manufacturers themselves.

“OEMs have approved sources, so we cannot go out of approved sources, because we are supplying to the OEMs, and within that source, we must buy the raw material” (Case E).

“We don’t change the suppliers because they are approved by the buyers (OEMs), even for further processing like forging, it is also XYZ-approved suppliers. Outsourcing is also approved by buyers” (Case G).

The Indian auto component manufacturers work with a small number of suppliers for the swiftness of information flow and material between manufacturers and suppliers. However, it still results in a few challenges in terms of timely delivery of products and managing the production schedule effectively. Further buyers (OEMs) emphasised the quality of raw materials procured by manufacturers from the suppliers. These suppliers are selected by the OEMs, ensuring that manufacturers source from approved suppliers for better quality. The practice of ruling the upstream supply chain by OEMs to curb any inefficiency in their operations, which is reflected through the vendor approval practice, has been followed across all the cases. This kind of arrangement has been identified as a strategic approach to building long-term buyer-supplier relationships (Karthik, 2006) However, this kind of strategic arrangement is more ad-hoc based on convenience (discussed in **section 6.3.2**) rather than a careful evaluation of suppliers based on business objectives, operational requirements, cost, material quality, and delivery timeframes.

Further, companies face pressure from OEMs to upgrade the technology that would bring more visibility into manufacturers’ inventory systems, manufacturing capacity, and supply capabilities as reported by Case F:

“They want access to our inventory, how much-finished stock you have, how much raw material you have, what is your manufacturing capacity, can you supply the number of items which we require and would you be able to deliver. So, they want all these things, but we don’t have any system for that” (Case F).

Manufacturers have changed and improved the machinery from manual to automated on customer demand. This means that manufacturers are highly responsive to meet the demands of OEMs. For instance, manufacturers adopted CNC machines to fulfil customers’ requirements. Sometimes manufacturers also face difficulty in meeting the customer’s quality expectations and understanding their requirements in terms of quality control. Quality control is identified as a significant aspect for OEMs as one of the manufacturers (Case F) also received training in the areas where quality can be improved. This included training for total quality management and IOS training. Further, the misalignment with OEM requirements in terms of advanced shipment notice requirement, where the

ASN is required from the OEM side, and despite fulfilling each requirement, the customer sends the products back to manufacturers for non-availability of storage space. The second condition for keeping up to 40% of manufactured materials all the time does not fit the manufacturers' capability of adhering to the same which further impacts the manufacturing process and supply schedule at the manufacturers' end. All these factors indicate a huge market pressure for manufacturers, and the dependence of manufacturers on OEMs influences the decision-making and manufacturing process. Adhering to the OEMs' needs, by meeting all their expectations indicates a high level of responsiveness from manufacturers.

Companies are willing to adopt the technologies, which will help them in tackling the problems they face due to OEM's advancement/ practices. They are suffering major financial losses in terms of order cancellation at the end moment by these OEMs, fluctuations in demand, and time-consuming lengthy documentation/ paperwork requirements for quality control. The inability of these companies to comply with the hefty documentation, which follows the foreign companies format results in losing buyers (OEMs) on account of non-compliance.

"They are trying to update us about the system that would automatically give us all the information like they want access to our inventory" (Case F).

In light of the above observations, the operational performance is further defined by responsiveness to OEMs through the following measures:

- Suppliers experience significant pressure from OEMs to consistently enhance their manufacturing processes, upgrade machinery, enhance capabilities, and adopt advanced technologies (All cases indicated the same).
- Suppliers encounter considerable cost pressure including quality control costs, variable material costs, and unpredictable fluctuations in OEM demand (All cases).
- Misalignment with OEM's production schedule on account of delayed decision-making (All cases except Case J and K due to non-integrated supply chain as discussed in **section 6.3.5**).

This study found a positive relationship between the use of technology that integrates the supply chain and responsiveness towards OEMs' needs. Additionally, production process inefficiency negatively impacts the company's response to meet OEMs' needs effectively and vice versa. These relationships will be empirically tested using a quantitative study.

6.5 Impact of current practices on operational performance

The results have identified three key categories within the interviewed companies as follows:

- Firstly, those following non-formalised manufacturing operations with limited use of technology (Cases A, B, C, D, E, F, G, H, M, N, O).

- Secondly, those manufacturers which have partly adopted the technologies in specific areas and where the focus is on optimising these areas (Cases J, K, L, I).
- Thirdly, more advanced in comparison to the first two, where innovation and formulated business processes provide evidence of a defined line of responsibilities. These companies (Cases K, J) are working towards creating a more integrated and transparent supply chain while also optimising the production process.

As the number of the first-category companies is higher (A, B, C, D, E, F, G, L, M, N, O), maximum inefficiencies were identified related to the production process, network integration and responsiveness towards the OEM's demand. On the other hand, companies in the third category (Cases K, J, H and I) have fewer challenges and inefficiencies in managing their operations. These results indicated that there is a positive relationship between low levels of technology usage and operational inefficiencies. It can also be understood that as the technology level rises the inefficiencies are reduced, establishing a positive relationship between technology readiness level and operational performance (based on the discussion in **sections 6.5.4 through to 6.5.10**). However, current practices demonstrated that the Indian auto component industry is concentrated across category I across all the factors. This further confirmed that Indian auto component manufacturers do not have the appropriate preliminary infrastructure to start the adoption of Industry 4.0 technologies and as a result, operational inefficiencies are very common. The data has taken a different trajectory, but resulted in the same conclusion as what was followed in the literature. The literature broadly discussed the association of technology readiness with operational performance (Gerlitz, 2016; Chonsawat & Sopadang, 2020; Perez-Lara et al., 2020; Hopkins, 2021; Črešnar et al., 2022; Trstenjak et al., 2022; Patrucco, et al., 2022). The relationship has not been statistically tested in any of the studies which calls for the need of further investigation. Therefore, this research will examine the relationship between the Industry 4.0 readiness level and operational performance using variables as identified from this study.

6.6 Chapter Summary

Based on the thorough literature review and qualitative interviews, this study utilised twelve Industry 4.0 readiness factors. Those factors are automation, data collection, inventory management, communication with suppliers, supply chain visibility, data-driven decision, collaboration, real-time tracking, innovation and technology management and leadership.

Further three levels of technology readiness were identified based on the current technology usage in Indian auto component firms. The qualitative study resulted in gathering the levels of readiness across twelve factors. These factors influence the adoption of Industry 4.0 technologies as identified from the systematic review of literature. Therefore, these factors were utilised to assess the readiness level within Indian auto component firms. However, the Indian auto component industry is congregated across category I in terms of technology usage across all the factors. This further confirmed that Indian auto

component manufacturers do not have the appropriate preliminary infrastructure to start the adoption of Industry 4.0 technologies and as a result, operational inefficiencies are very common. Category II and Category III elucidate a small section of large-scale companies showing advancement towards technology usage across the studied factors. The results supported the findings that suggested differences in Industry 4.0 adoption across small and large-scale companies. Nevertheless, few large-scale companies have demonstrated a low level of technology usage. The identified levels further needed to be studied covering a larger population to measure the readiness level. Since the research comprises all sizes of firms, it helped in gaining a comprehensive understanding of the current level of readiness for Industry 4.0. A clearer picture of comparative insights will help in increasing the reliability of the results and fulfilling the research objective.

The metrics defined for Industry 4.0 readiness in Chapter 4 of the literature review could not be traced within the companies interviewed. Three categories as identified from the qualitative study will be used in combination with the Industry 4.0 readiness metrics identified from the literature. These levels are defined as level 1, level 2, level 3 and level 4 (discussed in **section 7.4.2.1**). This chapter is vital as these variations in technology level are grounded within the current practices of Indian auto component firms. This also resulted in attaining the research objective of designing a progressive readiness tool to measure the Industry 4.0 readiness level of Indian auto component firms.

This exploratory study further analysed the impact of current technology usage on operational performance. The research found that a higher level of technology usage across all factors positively influences operational performance. This suggests that as firms increase the level of readiness to adopt Industry 4.0, they can expect improvements in production process efficiency, network integration and responsiveness towards OEMs. The qualitative study was instrumental in identifying these measures of operational performance. The statistical relationship between overall readiness level and operational performance will be further tested in the quantitative study.

This chapter created a profile of the Indian auto component manufacturers which is useful in assessing the stages of development and progress towards the advanced level of technology adoption in the context of Industry 4.0. The next chapter discusses the revised research framework based on the findings from the exploratory study.

Chapter 7: Hypotheses Development

7.1 Introduction

The exploratory interviews provided valuable insights into the existing practices within the auto component industry regarding manufacturing operations across various areas including technology adoption and operational performance. This foundational understanding also enabled the identification of key operational performance measures derived from the current practices. Consequently, the focus of the research is to explore the relationship between readiness levels for Industry 4.0 implementation and operational performance measures. Given the limited number of studies conducted in this research context, the research will undertake an empirical statistical investigation into the relationship between technology readiness level and operational performance. This is to understand how the industry's preparedness for Industry 4.0 influences operational performance. This chapter presents the research framework based on the findings from the exploratory study is underpinned by the systematic literature review conducted in this study. The chapter begins by discussing the need for a conceptual framework in the context of the Indian auto component industry. Subsequently, operational performance measures, research hypotheses and research variables are explained. This chapter concludes by presenting the results of the pilot test conducted using EFA.

7.2 Current readiness level and operational performance

As established from the exploratory study, organisations need to consider the adoption of technology across different areas including production, inventory, decision-making, communication and integrating the supply chain as a tool to improve operational performance. The organisations that have implemented the technologies are looking to achieve a competitive advantage and serve their customers by optimising the production processes and integrating supply chains. These organisations have experienced improved decision-making, and effective production scheduling due to the continuous exchange of data between supply chain parties, including buyers, suppliers and ancillary service providers. These increased benefits have been outlined in literature establishing the relationship between technology adoption and operational performance (Črešnar et al 2022; Gadekar et al., 2022). Although previous studies explored the factors that would contribute to the readiness of firms for Industry 4.0 adoption (see **chapter 4**), there is a lack of empirical studies examining the relationship between technology readiness level and operational performance (discussed in **section 3.11**). Industry 4.0 preparedness enables the optimisation of processes and achieving sustainable operational performance through monitoring systems, and real-time availability of data for decision-making within the vertical structures comprising organisation, equipment and processes (Su & Yang, 2010; Chae, et al., 2014; GunaSekaran, et al., 2017; Pérez-Lara, et al., 2018). The vertical integration of the entire organisation optimises the production system (Bogner, et al., 2016). It is therefore utilised to optimise operational processes, and the interrelation and interdependency thus arise from the integration of technology and its benefit on the firm for operation

improvement (Rungtusanatham, et al., 2003; Flynn, et al., 2010; Bogner, et al., 2016; Patrucco, et al., 2022; Chahal, et al., 2020).

Further, performance measures in operations are not something that can be measured on a yardstick but understanding the benefits gives managers a good measurement system for improving performance (Serrat, 2017). Performance measures are manifestations of a company's strategy which defines the control within an organisation in terms of areas of responsibility for managers across divisions, departments or an entire organisation (Fraga-Lamas and Fernández-Caramés, 2019). While processes are not distinctive and do not vary within an industry (Bogner, et al., 2016), the difference is brought by organisational strategies and digital competencies that are leading to performance within operations (Schumacher et al., 2019; Gadekar et al., 2022; Ratte et al., 2023).

It is imperative that organisations assess the current state of digital competencies and processes to plan the strategic adoption of Industry 4.0 for operational performance (Sütöová et al., 2020; Spaltini, et al., 2022; Ávila-Bohórquez and Gil-Herrera 2022). With an understanding of the prevailing pain points and operational inefficiency, organisations can plan to develop a roadmap that would clearly define the goals and feature the milestones for the application of Industry 4.0 technologies (Giudice, et al., 2021; Pozzi et al., 2021; Kiraz et al., 2020). A readiness model is prepared to address all the requirements in terms of identifying the scope for improvement and then making a choice about the level of advancement they are willing to achieve in terms of transition to Industry 4.0. The model will first evaluate the current level of technology adoption and then understand the relationship with operational performance measures identified from the exploratory study.

The discussion in the extant literature regarding operational performance significantly focuses on broader concepts such as enterprise performance, supply chain resilience, operational efficiency or improvements, and competitive advantage rather than the operational performance measures explicitly (Chonsawat and Sopadang, 2020; Pozzi et al., 2021; Črešnar et al., 2022; Chatterjee et al., 2021; Hopkins, 2021). The impact of supply chain resilience to enhance firm performance is studied by Li, et al., (2022). Several operational performance measures aimed at increasing the firm's competitiveness were studied including visibility, capability to adjust production plan, and inventory reduction. This partially addresses the influencing factors of supply chain robustness on firm performance with an emphasis on the adoption of evolving technologies, rather than the direct impact of these technologies on performance. Additionally, Núñez-Merino, et al., (2022) highlighted the importance of supply chain resilience and integration of the supply chain as the capability of firms to improve operational performance by rapidly adjusting purchasing and procurement activities to address fluctuation in demand. Taghipour, et al., (2022) provided a comprehensive analysis of digital transformation's effect on various operational areas including, supplier selection, and digital procurement which impacts forecasting accuracy, reduces downtime, enhances product quality, and ensures effective inventory management. However, there is a lack of empirical evidence to establish the relationship between digital

transformation and operational performance. Maalmi et al. (2021) conducted a study to identify the factors of sustainable supply chain innovation (SSCI), where supply chain integration and Industry 4.0 technological systems were found to significantly impact SSCI. The study was limited in terms of clearly demonstrating the importance of the examined factors on the supply chain or operational performance. Considering the aforementioned studies, it is argued in this research that the technology readiness level impacts the operational performance of the firms (see Chapter 6; Section 6.4). In order to confirm or dismiss this argument, the constructs of operational performance are determined for empirical testing through hypotheses development from the exploratory study and literature review.

7.3 Development of research model based on literature and exploratory study

The combination of an exploratory study and reviewed literature shaped the developed propositions aimed at identifying the relationship between readiness level and operational performance outcomes (discussed in **sections 6.4.1, 6.4.2 and 6.4.3**). This section, therefore, provides the conceptualisation of these two main constructs with a detailed analysis of hypotheses derived from the association of Industry 4.0 readiness factors and operational performance measures as outlined in the theoretical framework introduced in Chapter 4.

The conceptualisation of readiness factors was primarily based on the reviewed literature (see **sections 4.2.1 to 4.2.4**). At the same time, the review of the literature revealed that readiness measurement levels are not uniform across the existing studies (discussed in **section 3.8**). Further, varied readiness scales demonstrated different measurement definitions given the context of the study (Lucato, et al., 2019; Alcácer, et al., 2021; Chonsawat & Sopadang, 2020). Accordingly, the research framework adopted the levels identified from the exploratory study (see **sections 6.3.1 to 6.3.10**) to accurately capture the Indian auto component firms' current state of technology usage in the context of Industry 4.0 readiness.

Additionally, due to a lack of research focusing on operational performance measures in context of Industry 4.0 readiness within Indian auto component industry (see **section 3.11**), the conceptualisation of operational performance was based on the indicative measures identified in the literature (Bogner, et al., 2016; Núñez-Merino, et al., 2022; Taghipour, et al., 2022) and further refined through findings from the exploratory study (discussed in **sections 6.4.1, 6.4.2 and 6.4.3**). The decision was informed by a thorough review of the literature on Industry 4.0, along with a review of the broader literature related to the impact of technology adoption on operational performance (Timmermans & Tavory, 2012) (see **section 3.11**). Therefore, the developed hypotheses in the following section are foregrounded in qualitative data and theoretically supported by the existing literature.

7.3.1 Operational Performance Measures: Production Process

Based on the investigation with research participants regarding the production process, most participants indicated the significance of meticulous planning and scheduling in the production process, owing to the multifaceted nature of production activities in the auto component industry. As confirmed

from the interviews with industry experts, production planning in the auto component industry entails determining the optimal sequence of operations, whereas production scheduling involves assigning resources and determining the timing of each operation, necessitating integration. However, the primary challenge identified in the Indian auto component industry is to optimise production processes to meet demand while minimising costs and enhancing efficiency. These challenges are identified in the previous work by Loos & Allweyer, (1998) within a wider manufacturing context.

Nevertheless, it is important to note that the auto component manufacturing sector is characterised by a complex network of suppliers, manufacturers, and distributors. Due to this intricate network, effective supply chain management assumes a pivotal role (Serdarasan, 2013; Bhattacharya et al., 2014). It is thus imperative to effectively coordinate a supply chain that ensures the timely delivery of raw materials, parts, and components to the production line while minimising inventory levels and associated costs. As previous literature offered limited insights into how Industry 4.0 readiness can improve production process efficiency, the findings from the exploratory study provided the relevant context.

An interesting link is identified between the existing technological infrastructure and the production process efficiency. Some participants highlighted that an automated inventory system enhances the visibility of inventory levels for efficient production planning while managing communication and collaboration across the supply chain network. Automated inventory tracking systems enabled by smart devices such as RFID, barcodes, QR codes and real-time databases using ERP for precise inventory counts, while minimising human intervention, allowed organisations to make timely adjustments in the replenishment process and regulate lead times. Various commentators have also confirmed the benefits of transparent communication and the use of smart devices for attaining production process efficiency (Avilés-Sacoto, et al., 2019; Mashayekhy, et al., 2022). Additionally, auto component firms that have used RFID have witnessed an enhancement in the performance of the whole supply chain by increasing the traceability and visibility of products. This supports the earlier research by Fernández-Caramés, et al., (2019) who argue that Industry 4.0 readiness, characterised by the existence of digital technologies, can optimise inventory management processes by enabling accurate demand forecasting and eliminating the situation of overstock or stockouts. Additionally, Ashton (2019) underscored the role of RFID as the precondition for the implementation of the Internet of Things.

It was also found from the interviews that the utilisation of automated machinery allowed for the production of higher-quality goods and waste reduction. This is facilitated by the capability of machines to self-regulate different phases of quality management, thus reducing the chances of non-detection, which is possibly not the case in manual machinery. The findings from the interview corroborate with the observations of Ali and Johl, (2023), who suggest that Industry 4.0 readiness facilitates the transition from traditional quality methods such as total quality management, poke-yoke, manually inspecting the quality, continuous improvement and standardised work. Based on the insights from

interviews and literature, it can be inferred that Industry 4.0 readiness, as characterised by automated machinery within the auto component industry, improves the precision of design and quality of performance. Some participants pointed out that the quality control achieved by automated machinery resulted in low rejection of products from the OEMs and thus improved the competitive advantage of auto component firms by delivering high-quality goods. Therefore, operational performance is achieved by the reduction in non-conformance cost and supplier defect rates, improved product design compliance, and on-time deliveries. This also saves cost and time on account of zero rejections and returns from customers.

The findings from the field suggested that the existence of RFID, ERP systems, and customer co-creation demonstrates the readiness of auto component firms, which positively impacts the quality control system within an organisation. Similar conclusions are drawn by various commentators (Sony, et al., 2020; Antony et al., 2021; Maganga and Taifa, 2023) within the Industry 4.0 field, who found that effective quality management can be achieved by integrating data and analytics within an organisation to generate real-time quality reports for decision-making.

As the literature from previous studies that correlates industry 4.0 readiness and operational performance is limited (see **section 3.11**) and only suggests a positive association without any empirical tests. Therefore, based on findings from the interviews and previous literature, this research argues that Industry 4.0 tends to positively improve production process efficiency. By relying on the previous studies in the context of Industry 4.0 that demonstrate the readiness of firms (as discussed in sub-sections of section 4.2) and by taking into account the current practices of auto component firms to improve the production process, production process efficiency is one of the constructs of operational performance. Thus, the following hypothesis is developed:

H1: Industry 4.0 readiness level positively impacts the production process efficiency

7.3.2 Network Integration

Most participants pointed out the complexity of managing network and data as generated due to the involvement of multiple stakeholders, operations and a multitude of transactions. Therefore, integrating these stakeholders and ensuring seamless information and product flow from suppliers to end-users assumes a critical role. However, most participants raise the concern over the transparency issue. Due to the complex nature of the supply chain within the auto component industry, a lack of transparency poses a significant challenge to stakeholders, as they struggle to have a complete overview of all the processes involved. The lack of trust among stakeholders further exacerbates this challenge, creating disparities in the information available to different entities. One of the impacts of the lack of transparency and trust is the inefficiency in production planning. For instance, participants reported that the absence of access to the production schedules of different suppliers results in delays, conflicts, and poor decision-making across the network. Furthermore, the lack of visibility into demand, process, and

operations intensifies operational inefficiencies (Bertling et al. 2018). This intricate and interconnected landscape underscores the need for an integrated network structure aimed at elevating transparency, fostering collaboration across stakeholders and optimising efficiency within the automotive supply chain.

To tackle the above challenges, a few auto component firms put in place effective communication channels with the timely exchange of information with suppliers and OEMs that enabled the seamless flow of data across the supply chain network. Participants reported that access to timely information enables transparency by providing insights and up-to-date information about operations and OEMs demand. This seamless information exchange between the parties also optimises the production schedules in alignment with OEMs demand. Further technologies like RFID enabled the auto component firms to track and trace material across the supply chain, which would also show the point of origin of the defective product at the supplier's end and improve the accuracy of inventory management and stockouts. Additionally, an automated inspection system prevents defects and thus responds swiftly to product quality issues which enhances the trust within the network structure.

The findings from the interviews mirror the previous literature where Kagermann, et al., (2013) and Hermann et al., (2016) emphasised the critical role of interconnectivity, highlighted through horizontal and vertical integration concepts. According to Chan, et al., (2012) the vertical and horizontal integration is manifested through wireless communication across a network that includes people, machines and sensors as one of the prerequisites of Industry 4.0. Hermann et al., (2016) advocated that such interconnectedness enables the possibility of decentralised decision making which increases the transparency of information among all the stakeholders within the production facility. This interconnectedness, facilitated by interconnected objects and people fosters effective communication and exchange of information, both within the organisation and outside the organisation, thereby enhancing horizontal and vertical integration. Based on the analytical results from the exploratory study, many research participants agreed that effective communication channels with timely exchange of information with suppliers and buyers can enable the seamless flow of data across the supply chain network. Many research studies also suggest that the vertical and horizontal integration across the supply chain as demonstrated by effective and transparent communication, facilitates the uninterrupted flow of data across the supply network (Danese et al., 2013; Roh et al., 2014; Rüßmann et al., 2015; Müller et al., 2018; Crešnar et al., 2022).

The practices within the auto component firms are in alignment with Industry 4.0 literature (Unhelkar et al., 2022), where Industry 4.0 readiness, characterised by supply chain integration, automated machinery and communication between stakeholders, can be identified as a major enabler in attaining network integration. Further, in agreement with Fraga-Lamas and Fernández-Caramés, (2019), it is also identified from the interviews that the timely response to OEMs demand and fulfilling the product design specifications prevent the firms from losing their contracts and sustaining long-term

relationships with OEMs. The capacity of firms to produce flexibility allows them to produce in small batches along with cost containment (Fragapane, et al., 2022; Kauppila et al., 2020). These benefits from the auto component make up a key factor that is considered in the literature in evaluating production process efficiency rooted in effective network integration (Chan, et al., 2012; Hermann et al., 2016, Juhara, 2024). Therefore, the following hypotheses are proposed:

H2: *Industry 4.0 readiness level positively impacts the network integration*

H3: *Network integration positively impacts the production process efficiency*

7.3.3 Responsiveness towards OEMs

The exploratory study indicated that cross-company collaboration and effective and timely communication between the OEMs and suppliers ensure the availability of data regarding product design and demand from OEMs for components. This data enables the auto component manufacturers to access all the developments and changes in the design documents or the number of units required by OEMs, facilitating smooth production and the company's responsiveness towards OEMs' demand. These findings are in line with conclusion drawn by Chonsawat and Sopadang, (2020) and Giudice, et al., (2021) in the manufacturing context suggesting the use of data for enhancing Industry 4.0 readiness to respond to the market demand.

Further, auto component firms with an automated production system can quickly adapt to the unpredictable fluctuations of demand from OEMs in a cost-effective manner without incurring additional material and quality control costs. Much of this according to Loopez-Morales, et al., (2023) is enacted through advanced technology used in the upgraded machinery that enables the adjustment in the production process in terms of quantity and design as per the requirement of OEMs. The capability of machinery to produce customised products in lot sizes as identified from the interviews demonstrates Industry 4.0 readiness as confirmed by Gaiardelli et al., (2021).

Moreover, effective communication and transparency between suppliers and OEMs greatly assist auto component firms in aligning with OEMs' production schedules by analysing OEMs' data in real-time and adapting to their preferences, thus exhibiting an agile supply chain featuring process flexibility. Process flexibility in the supply chain is defined as the capability of the firm to respond to changes in the market and potential disruptions in the production flow (Giudice, et al., 2021). The findings from interviews support previous research (Christopher, 2000; Braunscheidel & Suresh, 2009; and Flynn et al. 2010; Roy et al., 2024), which argues that strategic planning and collaborative planning within the supply chain network is posited to have a significant positive impact on strengthening customer responsiveness. However, this relationship was not statistically tested; thus drawing from the above discussion, the following hypotheses are formulated:

H4: *Industry 4.0 readiness level positively impacts the responsiveness towards the external pressure from OEMs.*

H5: *Production process efficiency positively impacts the responsiveness towards external parties.*

H6: *Network integration positively impacts the responsiveness towards OEMs.*

7.3.4 Research Hypotheses Summary

The hypotheses have been developed based on the literature review and findings from exploratory interviews. The research hypotheses summary is presented in Table 7.1:

Table 7.1: Summary of research hypotheses

Hypothesis 1 (H1)	Industry 4.0 readiness level positively impacts the production process efficiency
Hypothesis 2 (H2)	Industry 4.0 readiness level positively impacts the network integration
Hypothesis 3 (H3)	Network integration positively impacts the production process efficiency
Hypothesis 4 (H4)	Industry 4.0 readiness level positively impacts the responsiveness towards the external pressure from OEMs.
Hypothesis 5 (H5)	Production process efficiency positively impacts the responsiveness towards external pressure from OEMs.
Hypothesis 6 (H6)	Network integration positively impacts the responsiveness towards external pressure from OEMs.

7.4 Conceptual Research Model

7.4.1 Model constructs

The theoretical arguments above were analysed to establish the hypothesised relationship between technology readiness level and operational performance. As a result, conceptual research model is developed based on the hypothesised relationship as shown in Figure 7.1.

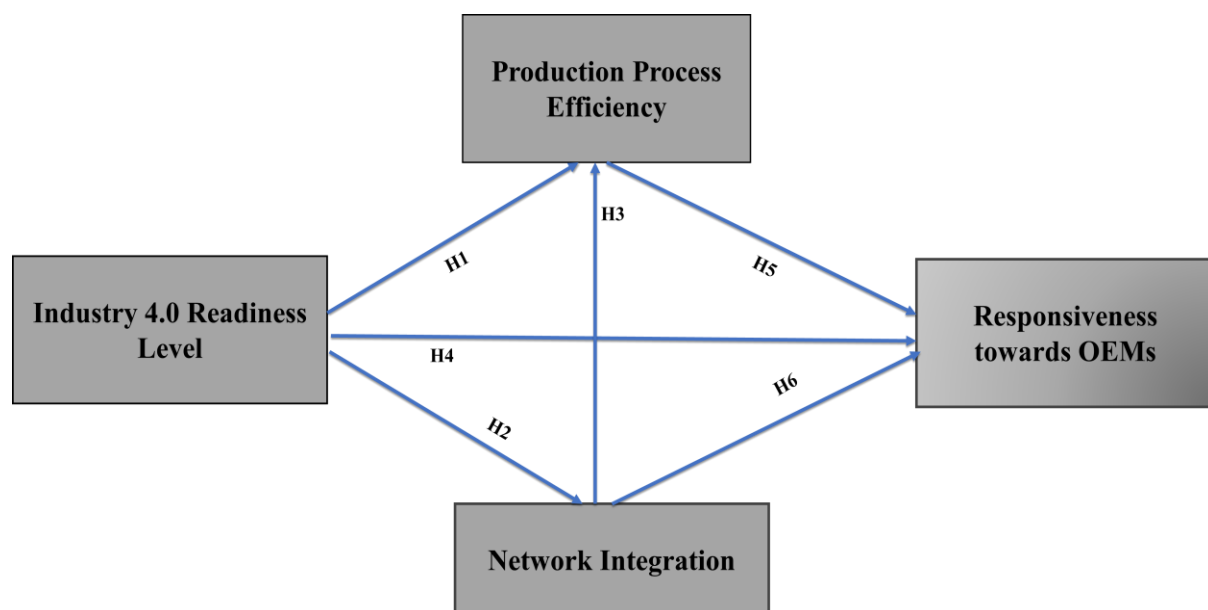


Figure 7.1: Conceptual Research Model (Source: Author)

7.4.2 Research variables

This section discusses the measurement employed in the study. The developed framework consists of two parts:

1. The first part evaluates the current readiness level of the Indian auto component industry in the context of Industry 4.0, this evaluation encompasses the assessment of readiness level across various factors including i) automation, ii) machine and operating system integration iii) e-procurement iv) inventory management; v) communication between parties; vi) visibility; vii) data-driven decision; viii) real-time tracking; ix) customer co-creation; x) collaboration; xi) interdepartmental collaboration, and xii) Industry 4.0 initiative by the leadership team.
2. The second part involves assessing the operational performance. Operational performance measures include production process efficiency, network integration and responsiveness towards the OEMs' demand. These measures are derived based on the findings from the exploratory study (discussed in **chapter 6 and section 6.4**). The model aims to understand the impact of Industry 4.0 readiness level on the operational performance of Indian auto component manufacturing firms. This research further consists of several measures to build the framework. The measures used to evaluate the readiness level comprise readiness factors that have been identified from the literature and the empirical insights derived from the exploratory studies. The exploratory study provides a robust understanding of Industry 4.0 preparedness for Industry 4.0 adoption.

7.4.2.1 Independent variable

Level of Industry 4.0 readiness

Taking into consideration the variations across readiness measurement levels (see section 4.3.1), the study proposes a readiness assessment model comprising four levels. The measurement level aligns with the models proposed by Agca, et al., (2017) and the model adopted by Alcácer et al., (2021) based on the IMPULS model. This study will employ a refined classification using beginner, intermediate, experienced and expert scales instead of five broad levels. This adjustment is based on the applicability and insights obtained during the exploratory study, aiding the alignment with the industry setting. Three categories of technology usage were identified across operational activities and systematically classified based on technological infrastructure. The fourth level as defined from systematically reviewing the literature (see **section 4.2/ Table 4.5**), could not be traced in the interviewed companies. Despite this, the fourth level is integrated to measure the comprehensive readiness and align the survey instrument to incorporate theoretical constructs for a robust measure (Mikalef and Pateli, 2016). Further, the percentage measurement limits the specifics of each stage, thus the scale provides clear delineations between each stage (as developed from exploratory study findings). The readiness level demands a detailed evaluation of each level reflecting unique attributes attached to the factor as gathered from the interviews is not previously identified in the literature, as the existing readiness models vary according

to the context of the study (Alcácer, et al., 2021; Chonsawat & Sopadang, 2020; Trstenjak et al., 2022). These models have been designed and tested in different countries, industries and different sizes of firms. The levels and scales were defined overall, rather than the detailing definitions of each level for each factor. Therefore, the readiness model in this study is developed by combining the readiness levels found in the literature, and the interview findings where various companies have demonstrated different levels across a range of areas which are used to develop the readiness model tool (Chapter 6, section 6.3).

The readiness model categorises companies into four distinct levels as follows:

- Level 1 – Beginner - indicates the company is a beginner in the Industry 4.0 field and has minimal experience and knowledge in the field.
- Level 2 – Intermediate - indicates that the company has explored Industry 4.0 technologies and progressed from the beginner stage, but still requires further development to understand the complexity and application of Industry 4.0 technologies.
- Level 3 – Experienced - indicates that the company has gained practical experience in the area and has been involved in multiple applications of Industry 4.0 technologies across different areas.
- Level 4 – Expert - signifies an advanced level of expertise in terms of the application of Industry 4.0 technologies and the transformation of the company's business model.

The readiness levels are informed both by extant literature and data gathered from interviews with Indian auto component firms, which revealed different levels of technology usage. The ideal standard, level 4 which is provided in the model could be used as a benchmark in comparison to the other three levels where it would help in identifying and defining the exact readiness of the company. The current situation of the company in the Indian industry is assessed using a more defined level.

Level of Industry 4.0 readiness was measured using the scale as developed from the exploratory study and literature review, including 4 level questionnaire items (Agca, et al., 2017; Alcácer et al., 2021). The scale was modified to include the current practices within the Indian automotive industry as no previous scale reflected the factors and practices within this specific context. To measure companies' readiness levels, the levels were compiled. When asked about Industry 4.0, it was not directly mentioned in the questionnaire, but rather measured in terms of the practices that would identify as Industry 4.0 practices. The decision was made to avoid confusion as the term Industry 4.0 is still not widely understood across the industry as established from exploratory interviews. Table 7.2 presents the measures used for Industry 4.0 readiness level.

Table 7.2: The conceptualisation of readiness level – 12 items employed in this research

Construct – Readiness level		
Indicators	Construct measure	References
TRL1	Our company's production field is automated, where the production system can autonomously monitor and adjust its operations without continuous human intervention, optimising efficiency and minimising errors.	Müller et al., (2018); Gadekar et al., (2022); Alcácer et al., (2021); Chonsawat et al., (2020); Črešnar et al., (2022)
TRL 2	Machines and operating systems are highly integrated, facilitating seamless coordination and communication between hardware and software components with real-time data exchange capability.	Müller et al., (2018); Gadekar et al., (2022); Alcácer et al., (2021); Chonsawat et al., (2020); Črešnar et al (2022); Khourshed, et al., (2023); Trstenjak et al., (2022)
TRL 3	Automated digital data collection across the entire process, with the use of digital tools and technologies to collect and manage data at every stage of the procurement lifecycle (procurement software, e-procurement, electronic data interchange, cloud-based solutions).	Alcácer et al., (2021); Chonsawat et al., (2020); Črešnar et al (2022); Trstenjak et al., (2022)
TRL 4	Our company uses self-regulating Inventory Control - An advanced, autonomous system that continuously monitors and dynamically adjusts inventory levels in real-time, leveraging smart devices and real-time databases for seamless and precise inventory management, minimizing human intervention.	Gadekar et al., (2022); Alcácer et al., (2021); Chonsawat et al., (2020); Črešnar et al (2022)
TRL 5	The supply chain is effectively integrated in terms of communication with both suppliers and customers, with every party having access to the real-time flow of information allowing stakeholders to have access to the most up-to-date data for example real-time visibility into levels across all parties.	Gadekar et al., (2022); Alcácer et al., (2021); Chonsawat et al., (2020); Črešnar et al (2022); Trstenjak et al., (2022)
TRL 6	Our company has real-time visibility of site locations, capacities, inventory, and operations where data is actively used for monitoring and optimisations of operations and processes throughout the supply chain.	Gadekar et al., (2022); Trstenjak et al., (2022)
TRL 7	Our company uses data for making decisions where executives and board members leverage internal (intra-organizational) and external (suppliers, buyers, stakeholders) data to make critical decisions about the company's direction, partnerships, and growth.	Müller et al., (2018); Gadekar et al., (2022); Alcácer et al., (2021); Črešnar et al (2022)
TRL 8	The product can be tracked throughout the supply chain comprising the supplier, manufacturing unit, and buyer distribution centre.	Gadekar et al., (2022); Chonsawat et al., (2020); Črešnar et al., (2022)
TRL 9	Our company co-creates products with customers	Gadekar et al., (2022); Chonsawat et al., (2020); Črešnar et al., (2020); Črešnar et al (2022); Khourshed, et al., (2023); Weking et al., (2020)
TRL 10	Our company is having partnerships and collaboration with external experts and consultants to drive innovation and advance processes within the organisation	Gadekar et al., (2022); Alcácer et al., (2021)

TRL 11	The company actively collaborates across departments and actively shares data and insights, works together, and collaborates on decision-making processes to achieve organisational goals	Alcácer et al., (2021); Chonsawat et al., (2020); Črešnar et al (2022); Khourshed, et al., (2023); Leso et al., (2023)
TRL 12	Leadership team recognise the value of Industry 4.0 investments encompassing technologies like Artificial intelligence, Internet of Things, Blockchain, Robotics, Additive manufacturing (3D printing), and cloud computing in the organisation's growth and operational improvements	Gadekar et al., (2022); Chonsawat et al., (2020)

7.4.2.2 Dependent variable

The conceptualisation of operational performance was based on the perceptual indicators mentioned in the extant literature rather than any objective measures. The decision was based on the impact of technology readiness level on operational performance (Gerlitz, 2016; Patrucco et al., 2022). Measures were refined from the findings of exploratory study (see **section 6.4**). For measuring production process efficiency (PP), respondents were asked to indicate the frequency of occurrence of six scenarios refined from the exploratory study including efficient inventory management, dynamic scheduling, adaptive capacity, inventory visibility, integration of production process and effective quality control measured using 5-point Likert questionnaire items with 1 = no occurrence and 5 = high occurrence. Network integration was operationalised as the firm's capability to use technology and data for assessing supply chain integration for horizontal and vertical integration. The network integration (NI) was therefore assessed using five items such as information integrity, transparency, strategic alignment within the organisation, collaborative planning and supplier quality management. A 5-point Likert scale where 1 indicates no occurrence and 5 indicates high occurrence was employed.

This research included items that tapped into firms' ability to respond to the OEM's demand. The responsiveness (REP) is measured using survey items that asked respondents to rate the ability of firms to modify their processes (Process flexibility) (Zhang, et al., 2023), accommodate unpredictable fluctuations (production flexibility) and alignment with OEM's production schedule. A 5-point Likert scale, with 1 indicating strongly disagree and 5 means strongly agree was employed.

7.4.2.3 Control variable

Regarding the effects of control variables on the operational performance, the level of management is used as a contextual variable to influence the performance outcomes as reported by Zhang and Dhaliwal (2009). The management's strategic decision coming from the top-level management plays a crucial role in driving operational excellence across manufacturing processes then the technology adoption itself, as noted by Fok-Yew and Hamid (2021). According to Muttaqin (2022), top-level management engagement with the strategic decision and innovation within the firm has a positive impact on the operational efficiency. Nevertheless, middle-level managers ensure to meet the directions within the

operations by facilitating cross-collaboration to achieve the performance objectives as noted by Dasgupta (2014). Additionally, it is maintained by Jaoua (2018) that middle-level managers' communication to lower-level managers in terms of achieving the desired results and practicalities of the objectives set by top-level management facilitates the dual role of middle-level management in executing and directing lower-level managers to achieve operational performance. However, it is contended by Wester and Hitka (2022) that the direct involvement of lower-level management on the shop floor results in the execution of objectives and has a direct impact on operational efficiency. This indicates that while the technology adoption has a direct bearing on the operational performance, the human element, precisely the hierarchical positions, cannot be ignored for achieving a more nuanced understanding of operational performance. Management level is therefore used as a control variable for analysing operational performance.

Furthermore, the firm's size is seen to influence the performance outcomes. Size of the firm is a widely used contextual variable within the operations management literature (Khanchanapong, et al., 2014; Chae, et al., 2014; Gunasekaran, et al., 2017). Firm size, measured by the turnover of the company, has been associated with the ease or difficulty of adopting advanced technology. Empirical research suggests that readiness levels vary across small and large firms, particularly in managing and integrating supply chains, which include ensuring effective communication with real-time data, where MSMEs are still behind in terms of supply chain integration as they consider production as the core process (Lassnig, et al., 2022). This is also established in previous studies that compared to large firms, SMEs operate with fewer resources (Zach, et al., 2014; Müller & Hopf, 2017). Furthermore, the operations and supply chain of large firms are more scattered which influences their decision to adopt advanced technologies for streamlining their operations (Lin, et al., 2023). On the contrary, the response strategies of MSMEs are often less flexible in adapting to external pressures and adjusting their operational processes towards new technologies, showcasing an immovable attitude as discussed by Müller, et al., (2018). In the same study, it is further contended that because OEMs are the driver of change and demand customers to comply with technological requirements through automation and connectivity, SMEs envision the adoption of advanced technologies for production process efficiency and effective data exchange between customers and suppliers. Horváth & Szabó, (2019) affirmed that due to the differences in adoption patterns among large and small-scale firms, their associated benefits tend to vary. Large-scale companies continually evolve as a result of new developments and opportunities offered by advanced digital technologies (Horváth and Szabó, 2019). Therefore, firm size is used as a control variable to attain a more nuanced understanding of the impact of technology readiness level on operational performance. Additionally, firm size is used as the control variable in a number of studies (Crešnar et al., 2022; Patrucco et al., 2022; Zhang, et al., 2023). The firm size in this study is defined by the turnover which is consistent with the definition of the SME Chamber of India (SME Chamber of India, 2020).

Firm size is therefore categorised into two groups: MSME (turnover of up to INR 250 crores/ £23.14 Million), and large scale (turnover of more than INR 250 crores/ £23.14 Million).

This study also covers years of experience as a control variable to assess its potential influence on the operational performance. Age is significantly utilised as a control variable in operations management research, as reported by Curado et al. (2023), which is directly correlated with years of experience. Hence, building on the work of Carlson and Wu (2012), this research used years of experience to understand the underlying performance based on the theoretical relationship between years of experience and operational performance. Previous research has accounted for employees' experience to positively influence the operational outcomes measured in terms of responsiveness, quality and efficiency (Alkhatib and Momani, 2023). Zhang and Dhaliwal (2009) used years of experience as a control variable in operations research. It is maintained by Sinnaiah et al., (2023) that seasoned employees are particularly well-versed in navigating operational challenges and making calculated strategic decisions for resource optimisation that ultimately contribute to improved performance. Using years of experience as a control variable could minimise the risk of confounding bias in understanding the relationship between Industry 4.0 readiness and operational performance.

Interrelation between SMEs and large-scale operations

The MSME's level of readiness could not be understood in isolation. MSMEs operate in a broader ecosystem. It is also necessary to understand how large counterparts contrast or are similar in their performance and practices when compared to MSMEs. In addition, large companies set the trend for MSMEs, the findings from the qualitative study helped in providing a benchmark as to what large companies are practising. By examining large-scale companies, the research provides insights into broader market dynamics affecting MSMEs in terms of market shift towards a more integrated supply chain, technology-driven processes and operations, customer co-creation and strategic collaborative partnership to drive innovation. The operations of MSMEs are influenced by these industry trends and the comparison was crucial for understanding this competitive landscape of the manufacturing sector. The comparative analysis (section 8.4) helped in identifying broader industry trends that will have implications for MSMEs.

Since the research comprises all sizes of firms, it will help in gaining a comprehensive understanding of the current level of readiness for Industry 4.0 by not only looking at the status of micro, small and medium-sized firms, it will also help in understanding how large firms are implementing the technological changes which will also help in understanding the best practices of technology implementation within the Indian context. A clearer picture of comparative insights will help in increasing the reliability of the results and allow for further generalisation.

7.5 Pilot Test

The survey instrument, developed from the literature and qualitative study, included twenty-six items distributed across two main constructs, namely technology readiness level and operational performance. This section expands on the pilot test stages and results of the exploratory factor analysis.

The questionnaire prepared from the literature review and the findings of the exploratory study were tested to examine the factor structure and internal consistency of survey items. Exploratory factor analysis (EFA) was carried out to identify whether the survey items are measuring the right construct. The pilot study was conducted in three stages. During the first stage, the survey was disseminated to five industry experts, including consultants possessing experience within the field of the auto component sector and who worked closely to implement lean and Six Sigma strategies across companies. Participants were informed of the objective of the pilot study and its relationship to the main study and were asked to provide critical feedback on the terminology and length of the questionnaire. A few statements were revised to accommodate the industry vocabulary.

During the second stage, the revised survey instrument was distributed to the determined sample. For the pilot study, a sample size of 40 participants is considered adequate to ensure the quality and adequacy of an instrument (Isaac and Michael, 1995; Johanson and Brooks, 2009). Accordingly, the pilot study sample comprised 70 participants from the auto component industry possessing experience in manufacturing operations, strategies, technologies, and industry challenges. During the third stage, EFA was conducted including twenty-six items for the further improvement of the scale which is discussed in the next section.

7.6 Exploratory factor analysis (EFA)

Exploratory factor analysis (EFA) was employed to ascertain the structure of observed data and identification of underlying relationships between measured variables. Confirmatory factor analysis (CFA) and Exploratory factor analysis (EFA) are two commonly used techniques to extract factors. EFA is a multivariate statistical method frequently used to validate instruments by mapping the relationship between constructs and indicator variables (Fabrigar & Wegener, 2011). EFA helps in examining the correlation between a large number of questionnaire responses and reducing the items to smaller groups which are homogenous, by loading them together under one factor as described by Cudeck, (2000). The dimensions produced through exploratory factor analysis can then be further utilised to establish the relationship between the latent variable or constructs (Haenlein and Kaplan, 2004). EFA is mostly used during the early stages of data analysis to discover the number or nature of factors that convey the covariation among variables (Stevens, 1996). In contrast, confirmatory factor analysis is used to test the hypothesis for the correlation of variables (Brown, 2015).

7.6.1 Standpoints for Employing Exploratory Factor Analysis (EFA)

The utilisation of EFA was deemed appropriate on account of the addition of new variables to measure operational performance to assess the dimensionality and subsequently test the hypothesis. According to Fabrigar et al., (1999: 277), EFA is considered a “*data-driven approach as the researcher has no clear idea about how many factors exist and EFA could provide the procedures for determining an appropriate number of factors and the pattern of factor loadings to be used in the subsequent hypotheses tests*”. To understand the interrelationship between the readiness level and operational performance, EFA reveals the cluster of items to justify their grouping together as a factor (Hooper, 2012). As noted by these authors, the relationship between construct and indicator variable is important to allow the mapping of theoretical constructs onto empirical evidence. Therefore, the EFA is performed keeping in mind two goals which align with this research: to explore how many underlying constructs there are within the given questionnaire items and further to locate the item within each construct. EFA as an initial factor analysis approach, explored how technology readiness level contributes to achieving operational performance. Although the statistical relationship between the main constructs is guided by the extant literature (Chonsawat and Sopadang, 2020; Taghipour et al., 2022; Črešnar et al., 2022), there is a lack of empirical basis in terms of a priori factors that could exist specifically for operational performance. This research followed three main steps while conducting EFA: assessment of correlation among items; factor extraction and factor rotation (Pallant, 2007) as elaborated upon in the following section.

7.6.1.1 Correlation among items

To determine the strength of the relationship within the model’s constructs, correlation analysis was performed (Hair, et al., 2009). Pearson’s correlation was used to identify the relationship between data. The coefficient ranges from -1 to +1 with 1 indicating a positive relation and -1 indicating a negative relationship (Baggaley, 1964 & Hair, et al., 2009). The person’s coefficient showed a positive correlation among variables as shown in Table 7.3.

Table 7.3: Pearson’s correlation matrix

		TRL	PPE	NI	REP
TRL	Pearson Correlation	1	.539**	.689**	.191
	Sig. (2-tailed)		<.001	<.001	.113
	N	70	70	70	70
PPE	Pearson Correlation	.539**	1	.749**	.440**
	Sig. (2-tailed)	<.001		<.001	<.001
	N	70	70	70	70
NI	Pearson Correlation	.689**	.749**	1	.290*
	Sig. (2-tailed)	<.001	<.001		.015
	N	70	70	70	70
REP	Pearson Correlation	.191	.440**	.290*	1
	Sig. (2-tailed)	.113	<.001	.015	
	N	70	70	70	70

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

7.6.1.2 Unrotated factor extraction

For identifying the number of factors to be extracted, a scree test and the percentage of variance explained were adopted (Churchill and Iacobucci, 1997 & Hair, et al., 2009). Eigenvalues greater than 1 are considered significant (Hair, et al., 2009). The total cumulative percentage of variance is the indicator of the success of the EFA solution where acceptable values lie between 50% to 90% (Hair, et al., 2009). The Scree test identifies the optimum number of factors before realising a common variance structure (Cattell, 1966). Four factors were extracted, explaining a cumulative variance of 67.361% and an eigenvalue greater than 1 as given in Table 7.4.

Table 7.4: Unrotated factor analysis

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.201	43.081	43.081	11.201	43.081	43.081
2	3.102	11.930	55.012	3.102	11.930	55.012
3	1.908	7.337	62.349	1.908	7.337	62.349
4	1.303	5.013	67.361	1.303	5.013	67.361

7.6.1.3 Rotated Factor

The next step after gaining the initial impression of the factors, the rotation procedure was performed. The two most commonly used factor analysis techniques include factor and component analysis (Velicer & Jackson, 1990). Factor analysis assumes that the set of observed variables is influenced by a smaller number of unobserved variables called factors. The principal component transforms the group of correlated variables into the group of uncorrelated variables called components (Hair, et al., 2009). The decision to choose the type depends on the objectives and a priori knowledge about the variance in variables (Hair, et al., 2009). Principal component analysis was chosen as the extraction method to identify the composite dimensions underlying the constructs. The goal of identifying these underlying variables is to reduce the dimensionality of data and, focus only on a small number of underlying factors. Varimax rotation was applied for a simpler and more interpretable structure. In theory, each item should be related to one factor only, therefore cross-loading items should be dropped from further analysis. During analysis, it was ensured that only those items having a certain absolute value (above 0.5) were finalised for further analysis (Conway & Huffcutt, 2003). Factor loading between 0.5 to 0.6 is acceptable, therefore the cut-off point of 0.5 was considered for retaining the items (MacCallum, et al., 1999). This means that the variables with a load of less than 0.5 were removed as they do not have much effect in measuring the primary factors. Results from EFA identified the presence of four factors with an eigenvalue above 1 as presented in table 7.5 below. The total cumulative percentage is another indicator of the success of the EFA solution where acceptable values lie between 50% to 90% (Dawson, 2019). Table 7.5 reflects 67.36 per cent of its total variance.

Table 7.5: Total variance explained

	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.201	43.081	43.081	11.201	43.081	43.081	5.273	20.281	20.281
2	3.102	11.930	55.012	3.102	11.930	55.012	5.017	19.298	39.578
3	1.908	7.337	62.349	1.908	7.337	62.349	3.988	15.340	54.918
4	1.303	5.013	67.361	1.303	5.013	67.361	3.235	12.443	67.361
5	1.116	4.291	71.653						

7.6.1.4 KMO and Bartlett's Test

The sample size is the influencing factor for identifying the accuracy of factors clustering together for the implementation of exploratory factor analysis. Kaiser-Meyer-Olkin (KMO) (Kaiser, 1974) and Bartlett's Test of Sphericity was executed to determine the suitability of the sample for running factor analysis. The data were appropriate for the factor evaluation as the Kaiser–Meyer–Olkin measure of sampling adequacy (MSA), which indicates the appropriateness of the data for factor analysis, was 0.841. Any value greater than .06 is considered a good indicator and justifies the adequacy of the sample size (Shrestha, 2021). The Bartlett's test of sphericity was statistically significant as shown in Table 7.6 with χ^2 (df = 231) = 1027.173 ($p < .001$) (Gorsuch, 1973 & Arsham and Lovric, 2011). Both the tests indicate that data is suitable for factor analysis with significant correlation among variables.

Table 7.6: KMO and Bartlett's Test Result

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.850
Bartlett's Test of Sphericity	Approx. Chi-Square	1481.484
	df	325
	Sig.	<.001

7.7 Examining the Factors – Clustering effect

The EFA has extracted four factors. This indicates that the items clustered into four factors which are considered for further analysis. The clustering effect ensures the homogeneity across each identified factor. Factor 1 represents the readiness level (independent construct) of the auto component industry, and factors 2, 3 and 4 represent the production process efficiency, network integration and responsiveness of companies towards OEM needs. These factors examine the pattern of the dependent construct, for example operational performance. In total twenty-five items were identified as presented in Table 7.7. Objects with loads below 0.5 (one item – TRL3) are adjusted further by making the questions and wordings more understandable. TRL 3 which represent e-procurement was identified as technology-driven approach across the procurement process that supports supply chain integration and enables the effective vendor management (Patrucco, et al., 2022). Therefore, this item was retained during the final survey and the final survey questionnaire was distributed in anticipation that when full data is collected, CFA will give the proper grouping, and all items (twenty-six items) will appear as if

they belong to the respective group. Final analysis using SmartPLS resulted in loading of 0.602 (discussed further in section 9.3.1.1).

Table 7.7: Rotated Component Matrix

	Component			
	1	2	3	4
TRL1	.535			
TRL2	.505			
TRL4	.696			
TRL5	.528			
TRL6	.667			
TRL7	.675			
TRL8	.679			
TRL9	.716			
TRL10	.540			
TRL11	.720			
TRL12	.512			
PP1		.856		
PP2		.811		
PP3		.711		
PP4		.692		
PP5		.766		
PP6		.750		
NI1			.738	
NI2			.807	
NI3			.679	
NI4			.609	
NI5			.537	
REP1				.914
REP2				.875
REP3				.946
Extraction Method: Principal Component Analysis.				
Rotation Method: Varimax with Kaiser Normalisation. ^a				

7.8 Reliability analysis for the measuring items

The internal consistency and reliability of the scale and subscale are measured by employing Cronbach's alpha. Alpha measures the extent to which items correlate with each other. The statistic ranges from 0.01 to 1.00. Cronbach's alpha test how closely related all items are within the given group (Amirrudin, et al., 2021). A coefficient of 0.70 is considered extremely dependable for measuring the same underlying construct (Christmann and Aelst, 2006; Vaske, et al., 2017). The Cronbach's alpha for each factor is computed. The results indicate the high-reliability standard ranging from 0.895 to 0.951 as

presented in Table 7.8 for all four factors. The reliability standards for each factor are higher than 0.7. Twenty-five components have Cronbach's alpha of 0.942. Overall, this suggests the sufficiency and reliability of responses. The result of the reliability of the construct is presented below:

Table 7.8: Construct Reliability Test

Construct	Cronbach's alpha	Number of items
Overall	.942	25
Technology Readiness Level	.895	11
Production Process Performance	.919	6
Network Integration	.925	5
Responsiveness towards external pressure	.951	3

7.9 Chapter Summary

This chapter articulated the research framework developed based on findings from Chapter 6 and Chapter 4. Additionally, the rationale for developing the research framework in the context of the current study was further discussed. The framework comprised two phases where the first phase measured the readiness level and the second measures the impact of readiness level on operational performance. Within the first stage, 12 factors as identified and studied in the exploratory setting were employed to assess the readiness level with four different technology adoption levels in the context of Industry 4.0. Within the second phase, the study identified three measures of operational performance based on the findings of the exploratory study. These two phases were used for further examination to test the statistical relationship between technology readiness level and operational performance through developed research hypotheses. A pilot test was conducted, where 70 completed survey responses were obtained to perform the exploratory factor analysis for exploring underlying constructs within the given questionnaire items and further locating the item within each construct (Hair, et al., 2009). The product of the analysis including twenty-six items across four components met the statistical criteria for acceptance, and was subsequently used for collecting data. The results are discussed in Chapter 8 and Chapter 9.

Chapter 8: Survey Findings: Descriptive data analysis

8.1 Introduction

This chapter discusses the descriptive analysis of the data set where responses were obtained through survey questionnaires. Two hundred and seventeen survey responses were obtained from auto component companies. The descriptive analysis is conducted to understand the data set, and thus present and summarise the key aspects of the data, including the participant's profile, company size and readiness assessment. The firm's demographic characteristics are analysed to align the findings with the research objective of measuring the readiness level of the Indian auto component industry comprising MSMEs and large-sized companies. The rationale behind choosing descriptive analysis is twofold. Firstly, it provides the tool for visualising and communicating the large data set involved in this study (Vanlalhriat & Singh, 2015). Secondly, it enables to understand the patterns and trends in the data (Cooksey, 2020). Such a pattern will help to form the general impression that would precisely represent the current industry's practices that are pertinent to the Indian auto component industry facilitating familiarity in the research context.

The following chapter will investigate the descriptive statistics analysing the participants' profile, distribution of participants as per company size and readiness profile of the firms in terms of the adoption of technology. The analysis criteria align with the questionnaire design, where the first part of the survey consisted of demographic information of the participants and companies. The second part acquired information related to the level of readiness of Industry 4.0 based on the current practices of firms across operational areas including manufacturing and supply chain. The responses were obtained through multiple choice questions to understand the overall readiness level of the Indian auto component industry for the adoption of Industry 4.0. The chapter ends with an analysis of the current level of readiness across the auto component industry. The need for understanding the readiness level aligns with the research objective of measuring the readiness level of the Indian auto components industry, comprising MSMEs and large-scale companies by designing a progressive readiness tool. The evaluation of readiness level is preliminary for the framework as it helps in understanding the current level to build on the industry 4.0 systems and processes that might need to be redefined and repositioned for achieving higher readiness. Following descriptive analysis, statistical analysis is discussed in Chapter 9 for understanding the relationship between technological readiness level and operational performance. The sequential process is described in Figure 8.1 giving an overview of the remaining chapters. Overall, the analysis will provide a comprehensive understanding of the current readiness level of the Indian auto component industry across operations as identified through readiness assessment.

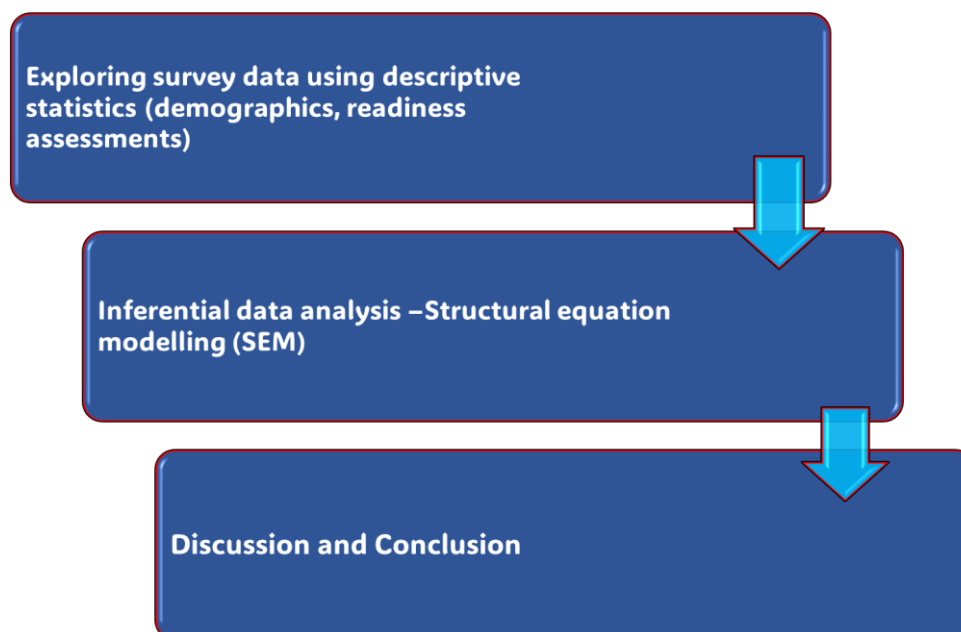


Figure 8.1: Chapters following quantitative analysis (Source: Author)

8.2 Descriptive data analysis

This section is structured into three parts. The first part provides information about the participant's profile including years of experience, level of management, and field of expertise. The second part describes the turnover of the participants' company. The third section assesses the overall readiness level of the auto component industry, including readiness across twelve factors that were identified from the extant literature review, which were further investigated through the exploratory study (semi-structured interviews). The descriptive analysis is performed using SPSS employing frequency analysis, bar charts, and cross-tabulations. In addition to frequency analysis, chi-square test and Cronbach's alpha measures are used. The chi-square test is used to assess the relationship between two variables, while Cronbach's alpha is used to assess the internal consistency and reliability of items on the readiness scale.

8.2.1 Participant profile

8.2.1.1 Years of experience of the research participants

The objective of the study requires an understanding of the current practices within the auto component industry. Therefore, to meet the research objective it is essential to gather insights from participants who have experience in the field, and possess knowledge of the manufacturing processes, strategies, technologies, and industry challenges. Table 8.1 and Figure 8.2 presents the distribution of respondents by year of experience within the industry. The highest percentage of respondents (30.4%) have the experience of more than 20 years. Followed by this 23% have experience of 11-15 years, and 18.9% have experience between 1-5 years. Additionally, 15.7% of respondents have experience ranging from 6-10 years, and lastly, 12% have experience ranging from 16-20 years. The prominence of respondents

having significant experience of more than twenty years reinforces the credibility and reliability of the responses. The significant representation of respondents with over ten years of experience accounting for 65.40% of the total respondents assures the validity of responses derived from the accurate and nuanced understanding of the field.

Table 8.1: Distribution of participants by year of experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1-5 years	41	18.9	18.9	18.9
	6-10 years	34	15.7	15.7	34.6
	11-15 years	50	23.0	23.0	57.6
	16-20 years	26	12.0	12.0	69.6
	More than 20 years	66	30.4	30.4	100.0
	Total	217	100.0	100.0	

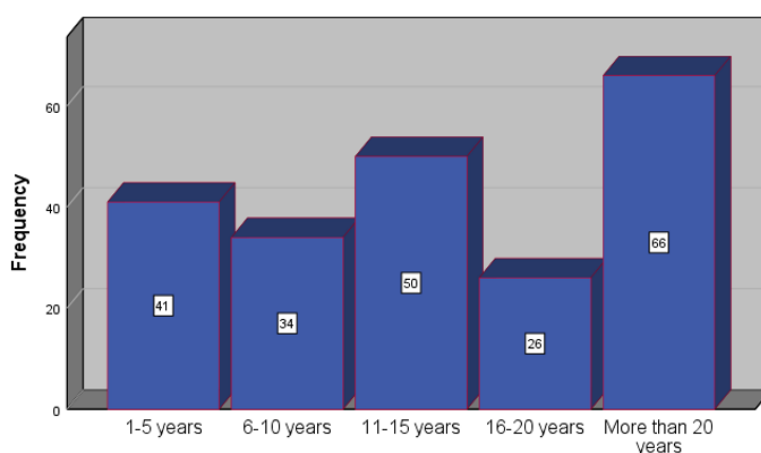


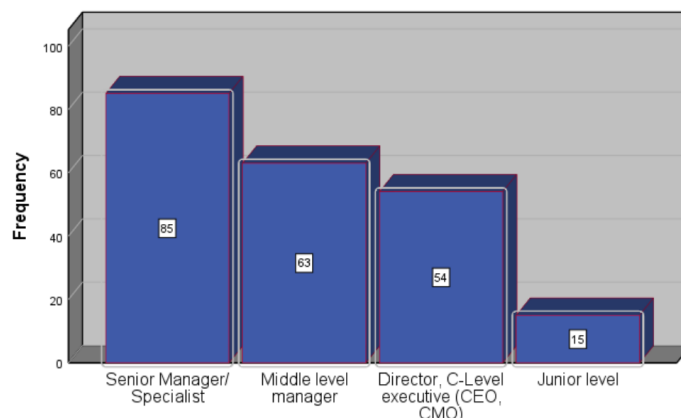
Figure 8.2 : Distribution of participants by year of experience

8.2.1.2 Position of the research participant in the firm

The distribution of the research sample according to the level of management of each respondent as presented in Table 8.2 and Figure 8.3 underscores the credibility of the research findings. Most of the participants held senior manager positions accounting for 39.2%, followed by middle-level managers at 29%, followed closely by Directors and C-level executives accounting for 24.9%. Only 6.9% accounted for junior-level managers. The dominance of the respondents from higher and middle-level management indicates a strong foundation of knowledge among participants. Consequently, survey results will provide a well-informed perspective on the readiness and operational performance of manufacturing firms. Senior managers, Directors and C-level executives play crucial roles in the strategic direction of the firm, and the strategic readiness can be assessed from their perspective (Khourshed et al., 2023). Meanwhile, the middle-level manager can provide reliable responses to manufacturing and operational activities given their involvement in day-to-day operations. The involvement of various management levels ensures a comprehensive understanding of the manufacturing landscape, further enhancing the reliability of the study's findings.

Table 8.2: Distribution of respondents by level of management

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Senior Manager/ Specialist	85	39.2	39.2	39.2
	Middle level manager	63	29.0	29.0	68.2
	Director, C-Level executive (CEO, CMO)	54	24.9	24.9	93.1
	Junior level	15	6.9	6.9	100.0
	Total	217	100.0	100.0	

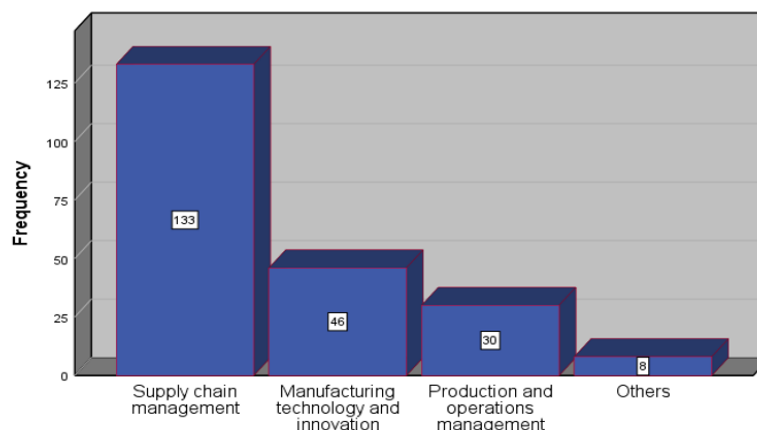
**Figure 8.3 : Distribution of respondents by level of management**

8.2.1.3 Field of Expertise

Table 8.3 and Figure 8.4 present the distribution of respondents as per the field of expertise. 61.3% of respondents are from the field of supply chain management, which show the significance of supply chain management in manufacturing operations. The management of the entire process within the manufacturing firms, starting from the procurement of raw material to the final delivery of product is identified as the key aspect of manufacturing operations. The understanding of supply chain dynamics provides more nuanced intricacies to the assessment of operational efficiency in manufacturing firms. Within the supply chain management, respondents have additional expertise in the area of process engineering, project management, and technology planning which underscore the need to optimise the manufacturing process with strategic planning and technological advancements. Additionally, 21.2% of respondents are from manufacturing technology, and innovation indicating the use of technology in manufacturing operations. This underscores the relevancy of technological advancement in manufacturing operations. Further, 13.8% of respondents held expertise in production and operations management, showing the relevance of managing day-to-day operational processes. The others accounted for 3.7%, including surveys filled by participants having experience in sales, Human Resource Management, risk analysis and digital marketing. Though fewer in numbers, it can be understood that they are involved in the manufacturing processes for optimising resources by providing insight into market trends through sales data, management of resources, and mitigating potential risks in operations. Overall, expertise is vital in understanding the effectiveness and efficiency of manufacturing operations. The comprehensive perspective provided by the experts across specialised fields in manufacturing operations enhances the reliability of the results.

Table 8.3: Distribution of respondents by field of expertise

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Supply chain management	133	61.3	61.3	61.3
	Manufacturing technology and innovation	46	21.2	21.2	82.5
	Production and operations management	30	13.8	13.8	96.3
	Others	8	3.7	3.7	100.0
	Total	217	100.0	100.0	

**Figure 8.4 : Distribution of respondents by field of expertise**

8.2.2 Firm Profile: Distribution of Manufacturing Firms by Turnover

The study determined the size of the company by the turnover. The sample comprised of small, medium, and large sized company. It is also established in the literature that size is one of the influencing factors in the adoption of Industry 4.0 technologies (Kumar et al., 2022; Müller et al., 2018). The findings from the exploratory study also confirmed that small and medium enterprises use fewer technologies as compared to large-sized companies which display the lack of strategy of SMEs towards the optimisation of processes (Herceg et al., 2020). This conclusion was drawn from assessing the level of technology awareness and integration across operations and departments within the participant firms. It is therefore important to validate if such a gap exists only for small and medium enterprises in comparison to large firms.

Table 8.4 and Figure 8.5 categorises the company into two distinct groups based on turnover. The first group comprises enterprises with a turnover of up to INR 250 crores (£23.14 Million) and are identified as micro, small and medium enterprises (SME Chamber of India, 2020). The second category encompasses large-sized companies with turnover exceeding INR 250 crores (£23.14 Million). Table 8.4 further highlighted the distribution of the sample into large-sized and small-sized companies, with 47.5% falling into the category of large-sized firms and 52.5% belonging to micro, small and medium-sized firms. There is a relative balance between large- and small-sized companies within the samples which indicates the proportionate representation of the different sizes within the Indian auto component industry. Further, it has been established through the findings of the exploratory research that because of the dominance of large-sized companies in shaping the dynamics in the industry, the competitiveness of the sector is influenced by the practices adopted by large-sized companies (Hopkins, 2021 & Müller,

2021) thus establishing the requirement for MSMEs to follow the same practices. Therefore, the study assessed the readiness level across different sizes of firms.

Table 8.4: Distribution of research firms by turnover

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Up to 250 crores	114	52.5	52.5	52.5
	More than 250 crores	103	47.5	47.5	100.0
	Total	217	100.0	100.0	

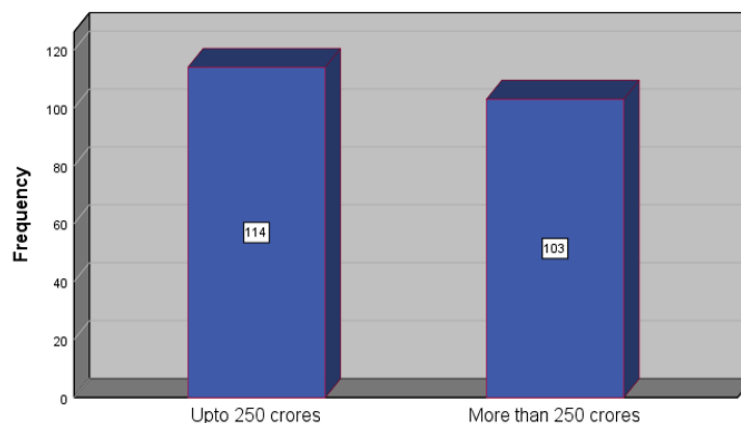


Figure 8.5 : Distribution of research firms by turnover

8.2.3 Readiness level profile

The study is measuring the readiness level of the auto component industry. This part demonstrates the readiness level by investigating the current practices within the Indian manufacturing industry, in terms of manufacturing operations. This framework to assess the readiness level was based on the findings derived from the exploratory study. Existing research discusses that the higher the level of readiness, the more the industry is involved in Industry 4.0 adoption (Chonsawat and Sopadang, 2020; Alcácer et al., 2021). Industry 4.0 features certain characteristics including networking, automated and customised production systems, availability, and processing of large volumes of data, the interconnectedness of machines and computing devices for real-time availability of data, and data-driven decision-making (See section 3.5; Hopkins, 2021; Bogner et al., 2016; Patrucco et al., 2022; Pérez et al., 2022). The fundamental Industry 4.0 concepts are automation, networking, and data analysis. Therefore, in this regard, the research measured the level of Industry 4.0 readiness across the factors including i) automation, ii) machine and operating system integration iii) data collection iii) operations data collection; iv) inventory management; v) communication between parties; vi) integration between suppliers and customers; vii) data-driven decision; viii) real-time tracking; ix) customer co-creation; x) collaboration; xi) interdepartmental collaboration and xii) Industry 4.0 initiative by leadership team. The answer provided reflects the level of readiness of that aspect within the organisation which results in a total score out of 4 for determining the organisation's readiness. Further, each item follows a scale of four levels where level 1 (L1) indicates the lack of fundamental concept necessary for Industry 4.0

(beginner) and level 4 (L4) represents the more advanced stage of accomplishment of Industry 4.0 attributes (expert). The results are discussed in the following section.

8.2.3.1 Level of automation in the production field

Table 8.5 and Figure 8.6 illustrate, the majority of the manufacturing firms (58.5%) are at an intermediate level. This means that some aspects of the production process are automated which mainly includes automated manufacturing machines. However, apart from that, manual intervention is still required, followed by (24.9%) of the manufacturing firms being at an experienced level indicating that a significant portion of the tasks related to production are automated and therefore there is a reduced need for manual involvement. 12.4% of the manufacturing firms are still at beginner level, signifying that the production process is predominantly carried out by human operators without significant automation. Finally, only 4.1% of manufacturing firms are experts denoting an advanced level of automation where the production system can autonomously monitor and adjust its operations without continuous human intervention, optimising efficiency, and minimising errors.

Table 8.5: Level of automation in the production field across research firms

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	27	12.4	12.4	12.4
	Intermediate	127	58.5	58.5	71.0
	Experience	54	24.9	24.9	95.9
	Expert	9	4.1	4.1	100.0
	Total	217	100.0	100.0	

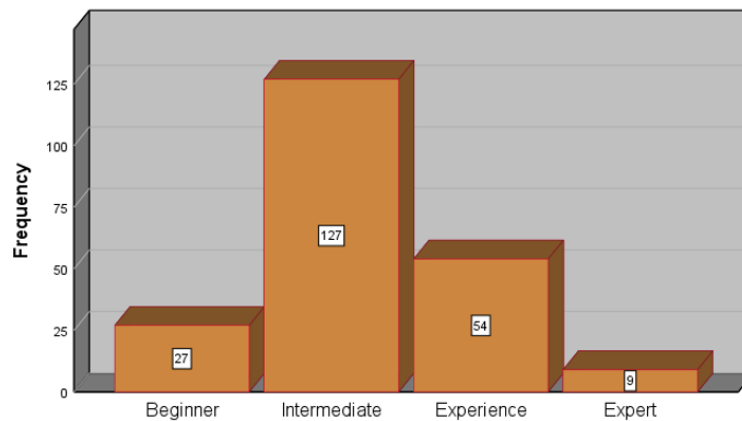


Figure 8.6 : Level of automation in the production field across research firms

8.2.3.2 Integration between production machines and computing devices

Table 8.6 and Figure 8.7 present the level of integration between the production machines, and computing devices in manufacturing firms where integration is referred to as the coordination between the production machinery and computing devices (Moica et al. 2018). 39.6% of the manufacturing firms are at the intermediate level, indicating that both the production machines and computing devices possess information exchange capabilities allowing for some coordination, and communication between the two. 28.1% of the manufacturing firms are experienced indicating the production machines and computing devices are partially integrated with communication, and coordination being limited with

the capability of further improvement to achieve better synchronisation between the two. 18.9% of manufacturing firms are at beginner level which means there is no integration. The production machines are not at all connected to the computing devices, with limited coordination between machines and computing devices, requiring significant manual intervention. Furthermore, 13.4% of manufacturing firms achieved the expert level where production machines and computing devices are highly integrated facilitating seamless coordination and, communication between machines and software components with real-time data exchange capability.

Table 8.6: Level of integration between production machines and computing devices

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	41	18.9	18.9	18.9
	Intermediate	86	39.6	39.6	58.5
	Experience	61	28.1	28.1	86.6
	Expert	29	13.4	13.4	100.0
	Total	217	100.0	100.0	

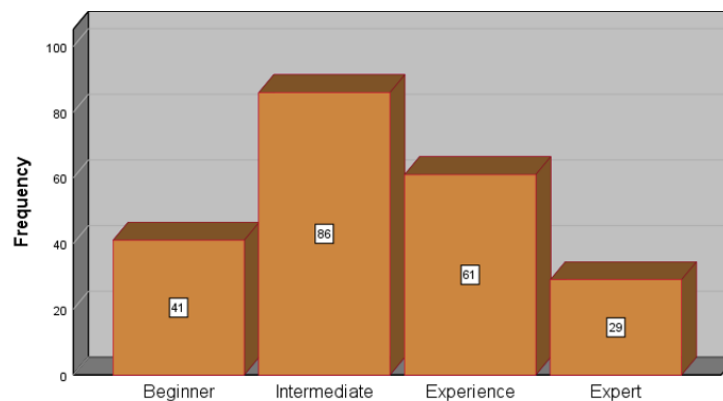


Figure 8.7 : Level of integration between production machines and computing devices

8.2.3.3 Data collection across the procurement process

Table 8.7 and Figure 8.8 present the level of the current method of data collection utilised across the procurement process in manufacturing firms, where the procurement process involves purchase requests, vendor selection, purchase orders, and record-keeping. 42.4% of manufacturing firms stand at the intermediate level. Data is collected through a combination of manual and automated methods. This means that some data is gathered through manual processes involving human input, while other data is collected using automated systems and digital tools (SAP-ERP). Following this 29.5%, of the manufacturing firms are experienced and collect data digitally in multiple areas. This scenario describes the data collection in various aspects of the procurement process is collected digitally. It specifies that multiple areas, including requesting, vendor selection, purchase orders, and record-keeping, rely on digital methods for data collection. While close to the same percentage 18.9% of the firms are at the beginner level, indicating the procurement process is carried out by human involvement, where purchase requests and purchase orders are generated and approved through paperwork or emails. At last, only 9.2% of manufacturing firms fall in the category of expert. This denotes automated digital data collection across the entire process with the use of digital tools and technologies to collect and

manage data at every stage of the procurement lifecycle (procurement software, e-procurement, electronic data interchange, cloud-based solutions).

Table 8.7: Level of data collection across procurement processes

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	41	18.9	18.9	18.9
	Intermediate	92	42.4	42.4	61.3
	Experience	64	29.5	29.5	90.8
	Expert	20	9.2	9.2	100.0
	Total	217	100.0	100.0	

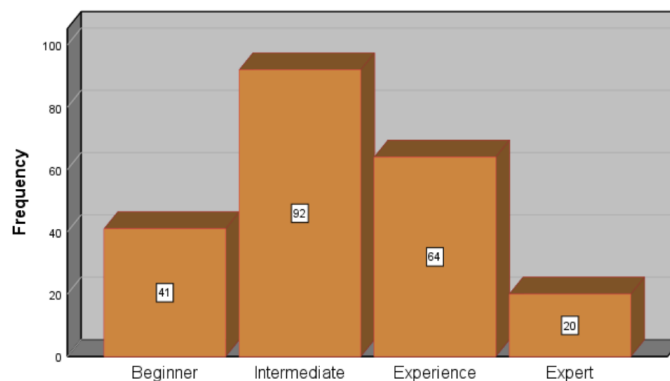


Figure 8.8 : Level of data collection across procurement processes

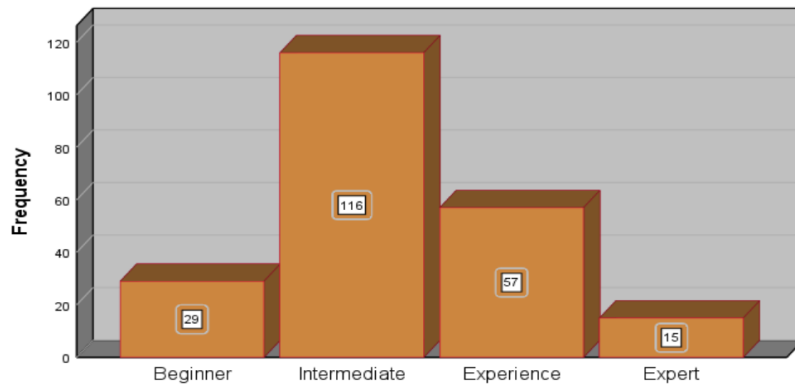
8.2.3.4 Managing Inventory Levels

In terms of inventory management, responses were obtained to check the practices followed by auto component firms for manual or automated inventory management. Inventory management is identified as one of the key operational functions within the manufacturing sector which is linked with operational efficiency. Effective inventory management significantly influences performance by fulfilling customer demand, and facilitating a smooth production flow (Panigrahi, et al., 2021). According to Ghadge et al., (2020), production planning and order fulfilment are intertwined with the level of visibility and traceability into inventory level and information sharing across supply chain members.

Table 8.8 and Figure 8.9 present inventory management practices adopted by manufacturing firms. 53.5% of the manufacturing firms are at intermediate level following a partially automated inventory control system where a computer database is utilised to track inventory levels. 26.3% of manufacturing firms employed highly automated inventory control. The inventory levels are constantly monitored, and promptly updated through a real-time database integrated with smart devices, ensuring efficient and accurate inventory management. 14.4% of the manufacturing firms are at beginner level and follow manual inventory control. The inventory levels are updated through human intervention and physical counting methods. Lastly, only 6.9% of firms are experts with automated inventory control systems. These firms have employed an advanced, autonomous system that continuously monitors and dynamically adjusts inventory levels in real-time, leveraging smart devices and real-time databases for seamless and precise inventory management, minimising human intervention. The findings indicate that inventory is managed utilising a computer database.

Table 8.8: Level of inventory management

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	29	13.4	13.4	13.4
	Intermediate	116	53.5	53.5	66.8
	Experience	57	26.3	26.3	93.1
	Expert	15	6.9	6.9	100.0
	Total	217	100.0	100.0	

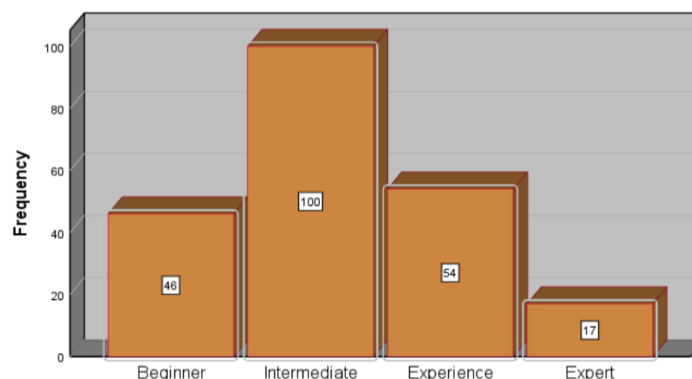
**Figure 8.9 : Level of inventory management**

8.2.3.5 Level of Communication

The level of supply chain integration depends on the communication between stakeholders. The higher the level of communication and flow of information, the more highly the supply chain is integrated (Črešnar et al., 2022; Ávila-Bohórquez and Gil-Herrera, 2022). Table 8.9 and figure 8.10 display that the supply chain across 46.1% of manufacturing firms relies on straightforward means of communication to fulfil immediate requirements with external partners by sharing only fundamental details such as order details, shipment status, basic product specifications, and payment updates. This means that they are at an intermediate level, but still require further development to integrate the supply chain through effective real-time communication. Further, 24.9% of manufacturing firms are experienced as these firms are highly exchanging data between key strategic suppliers and customers including the exchange of essential information, such as inventory levels, demand forecasting, price and cost details, and quality data. Following this 21.2% of manufacturing firms are at the beginner level where communication with suppliers and customers is primarily manual, relying on traditional methods such as emails, phone calls, and paper-based documentation for informal responsive communication. Only 7.8% of the manufacturing firms follow the fully integrated system with every party having access to the real-time flow of information allowing stakeholders to have access to the most up-to-date data for example real-time visibility into levels across all parties. The industry is at an intermediate level and demonstrates the information technology capabilities of firms using dashboards to provide managers with access to data, facilitating independent communication with suppliers without involving top-level managers. This enhances the production efficiency in the upstream supply chain. This is noted as one of the enablers of Industry 4.0 implementation by Herceg et al., (2020).

Table 8.9: Level of supply chain integration

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	46	21.2	21.2	21.2
	Intermediate	100	46.1	46.1	67.3
	Experience	54	24.9	24.9	92.2
	Expert	17	7.8	7.8	100.0
	Total	217	100.0	100.0	

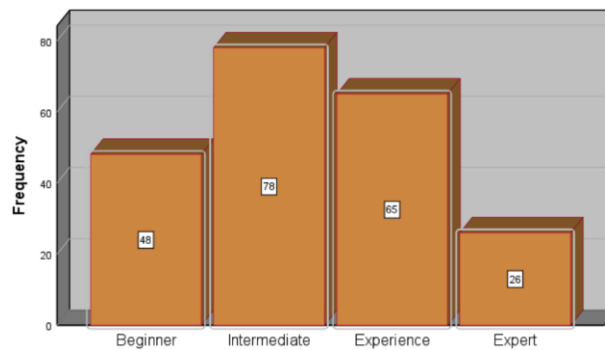
**Figure 8.10 : Level of communication between customers and suppliers**

8.2.3.6 Level of Supply Chain Visibility

The level of supply chain visibility is further defined by the level of data sharing across partners in the supply chain which provides more visibility into product status, location, and condition at various points for effectively tracking shipments, monitoring inventory levels, and analysing production processes to verify the availability of raw material with suppliers and the status of final products for OEMs (Alzoubi & Yanamandra, 2020; Kamble, et al., 2021). Table 8.10 and Figure 8.11 show that 35.9% of the manufacturing firms are at an intermediate level, with firms having access to the data in terms of site locations, capacities, inventory, and operations, but data is not actively utilised for the optimisation of operational processes. Further, 30% of manufacturing firms are experienced as they have visibility of site locations, capacities, inventory levels, and operations maintained between the suppliers and customers but excluding other supply chain partners which include third-party vendors and logistics partners. 22.1% of manufacturing firms are at the beginner level. This means there is no integration with suppliers or customers in terms of data sharing from both sides, and the organisation operates independently without any interconnected system in place. Lastly, 12% of manufacturing firms have real-time visibility of site locations, capacities, inventory, and operations where data is actively used for monitoring and optimizations of operations and processes throughout the supply chain positioning them as experts. The findings suggest that there is a varying level of data utilisation across the supply chain with only 12% having complete visibility for monitoring and optimising processes. This is consistent with the results of Alcácer et al., (2021) that data availability and quality is one of the significant challenges where incomplete, and inconsistent data across the supply chain affects the integration between suppliers and customers.

Table 8.10: Level of integration between suppliers and customers for supply chain visibility

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	48	22.1	22.1	22.1
	Intermediate	78	35.9	35.9	58.1
	Experience	65	30.0	30.0	88.0
	Expert	26	12.0	12.0	100.0
	Total	217	100.0	100.0	

**Figure 8.11 : Level of integration between suppliers and customers for supply chain visibility**

8.2.3.7 Level of data-driven decision making

Table 8.11 and Figure 8.12 show that 40.1% of manufacturing firms are at an intermediate level, where plant managers and supervisors analyse historical and real-time data to optimise production processes and improve overall quality. This indicates that decision-making at the tactical level, involving managers and supervisors may result in adaptive production scheduling due to timely decision-making based on data analytics. The research uncovered broader implications of tactical decision making, where on the positive side it is effective for improving efficiency and process at the shop floor level, it hinders coordination across other departments, preventing the firms from harnessing the potential of data for holistic decision making (Bento et al., 2020). 33.2% of manufacturing firms are experienced indicating top management leverages big data analytics to gain valuable insights across multiple stakeholders and departments, enabling them to guide production efficiency and drive advancements within the organisation without direct involvement in daily operations. The findings align with research by Ahmad et al., (2020); Paschou et al., (2018) and Linde et al., (2021), which emphasise the use of data for improving and regulating manufacturing processes. 17.1% of firms are at beginner level where top management utilises the data coming from operators on the factory floor to manage production, ensuring smooth operations and a rapid response to machine issues, while operators diligently follow the given instructions and orders. This further indicates the involvement of owners overseeing all the operations, processes and network structure. The decision-making autonomy lies in the hands of one person resulting in communication challenges and delays in addressing the potential inefficiency within operations. This also indicates that top management relies on the data coming from the operators demonstrating a lack of data collection strategy. Further, only 9.7% are experts where executives and board members leverage internal (intra-organisational) and external (suppliers, buyers, stakeholders) data to make critical decisions about the company's direction, partnerships, and growth which indicates

the existence of business model-focusing on collaboration between parties for decision making as identified in the literature (Frank et al., 2019 & Culot et al., 2020).

Table 8.11: Level of data-driven decision-making

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	37	17.1	17.1	17.1
	Intermediate	87	40.1	40.1	57.1
	Experience	72	33.2	33.2	90.3
	Expert	21	9.7	9.7	100.0
	Total	217	100.0	100.0	

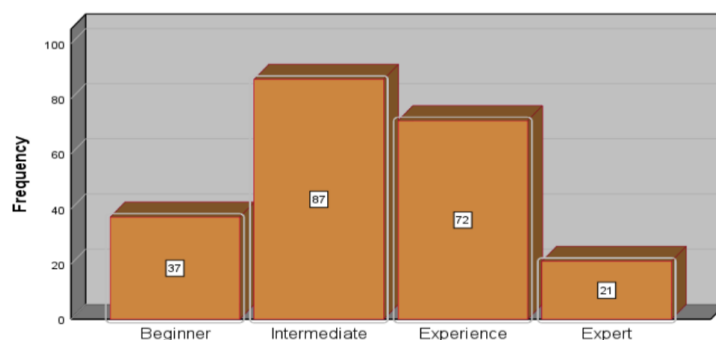


Figure 8.12 : Level of data-driven decision-making

8.2.3.8 Level of tracking across the supply chain

The level of tracking is defined as the extent to which the product can be tracked across the supply chain as it moves from the supplier to the final buyer (OEM). Table 8.12 and Figure 8.13 show that 29% of the firms are at an experienced level, indicating the product can be tracked as it reaches the company manufacturing site and final buyer without the involvement of any third party. Further, intermediate and expert share the same proportion at 29%. At intermediate level, the product can be tracked only within the organisation. At expert level accounting for 26.3%, products can be tracked throughout the supply chain comprising the supplier, manufacturing unit, and buyer's distribution centre. Meanwhile, 15.7% of manufacturing firms have limited product tracking systems. With the prevalence of intermediate and experienced levels, it can be understood that firms have developed the practice of tracking products.

Table 8.12: Level of tracking across the supply chain

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	34	15.7	15.7	15.7
	Intermediate	63	29.0	29.0	44.7
	Experience	63	29.0	29.0	73.7
	Expert	57	26.3	26.3	100.0
	Total	217	100.0	100.0	

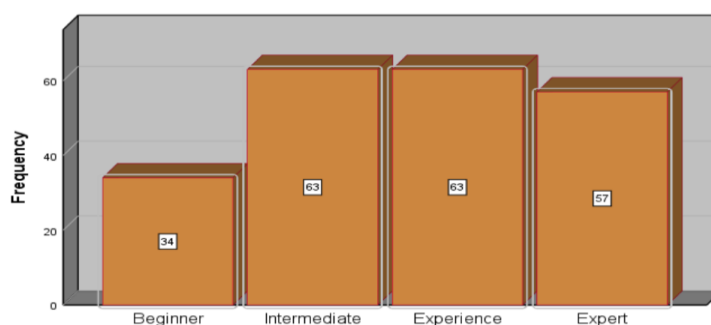


Figure 8.13 : Level of tracking across the supply chain

8.2.3.9 Level of co-creating products with customers

Co-creation describes the strategy employed by the company in co-creating products with customers and suppliers for managing product customisation (Guo et al., 2020; Tian et al., 2022; Kagermann, et al., 2013 cited by Müller, 2019). Table 8.13 and Figure 8.14 illustrate, 35.9% of manufacturing firms manufacture products in close collaboration with their customers and suppliers, and conduct market research for product improvements (customised products) with a standardised base which positions them as experienced. 24% of the firms are beginner level due to no individualisation as the company is manufacturing the same product as manufactured by other suppliers in the industry. Following this 21.2% of the companies are at an intermediate level where firms manufactures products in large quantities or batches with limited late differentiations, which include modifying the product at a later stage in the production process (for example shifting production from internal combustion engines to electric motors or battery management). 18.9% of firms are at the expert level following a make-to-order manufacturing strategy that combines personalised customisation with an efficient production process.

Table 8.13: Level of co-creating products with customers

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	52	24.0	24.0	24.0
	Intermediate	46	21.2	21.2	45.2
	Experience	78	35.9	35.9	81.1
	Expert	41	18.9	18.9	100.0
	Total	217	100.0	100.0	

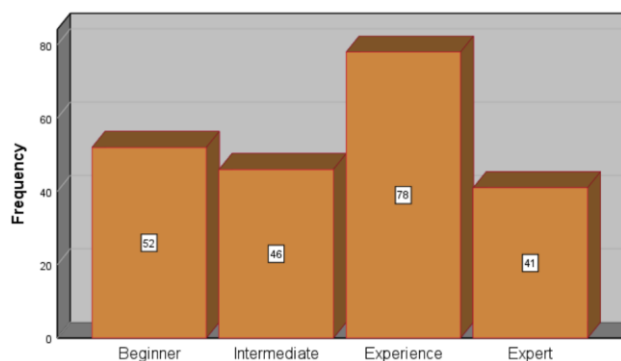


Figure 8.14 : Level of co-creating products with customers

8.2.3.10 Level of partnership and collaboration with external experts

The partnership and collaboration with external experts and consultants to drive innovation and advancing processes within the organisation, act as the major enabler for Industry 4.0 adoption (Schuh, et al., 2019). Table 8.14 and Figure 8.15 present that 38.7% of manufacturing firms are at an intermediate level where partnership and collaboration with external experts and consultants provide a foundational level of support in terms of introducing novel ideas and best practices. 28.1% are experienced meaning partnership and collaboration with external experts and consultants form a vital part of the organisation, and play a significant role in shaping innovation by redesigning the manufacturing process and integrating technologies in existing processes (for instance strategies

required for the smooth execution of a technological plan, strategies for reducing stockouts, minimizing excess inventory, redesigning procurement, and distribution process). Following this 21.2% are at the beginner level where external engagements are minimal in the organisation without the involvement of any external experts. Lastly, 12% of the manufacturing firms are experts denoting that partnership and collaboration with external experts and consultants form an integral part of the company's strategy which is not only involved in redesigning processes and technology implementation but also digitally transforming business through overhaul of processes, technologies, and business models.

Table 8.14: Level of partnership and collaboration with external experts

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	46	21.2	21.2	21.2
	Intermediate	84	38.7	38.7	59.9
	Experience	61	28.1	28.1	88.0
	Expert	26	12.0	12.0	100.0
	Total	217	100.0	100.0	

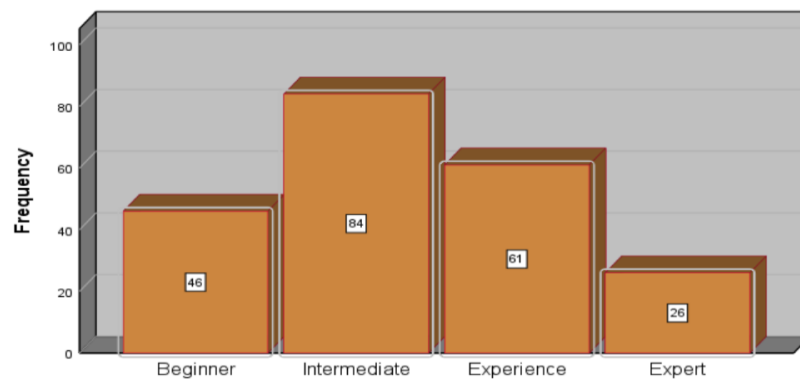


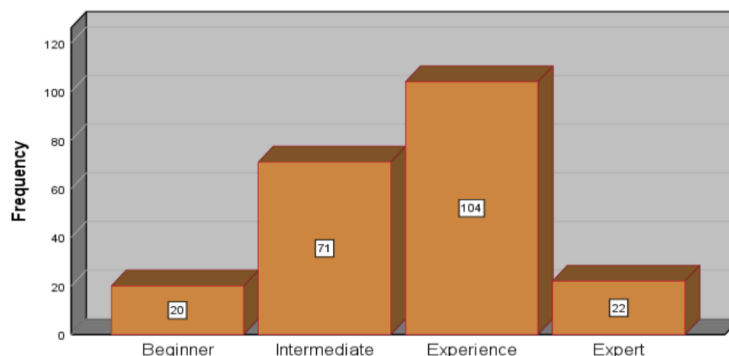
Figure 8.15 : Level of partnership and collaboration with external experts

8.2.3.11 Level of collaboration across various departments

The level of collaboration across various departments within the organisations is identified as the level of sharing information for decision-making. Collaboration refers to the extent to which departments actively share data and insights, work together, and collaborate on decision-making processes to achieve organisational goals (Perez-Lara et al., 2020). Table 8.15 and Figure 8.16 show 47.9% of the firms have a high level of interaction between departments and are engaged in sharing knowledge, insights, and best practices, contributing to a more comprehensive understanding of organisational processes which positions them as experienced in this dimension. 32.7% of the firms are at the intermediate level, which means there is limited interaction between departments, there might be occasional exchanges of data and insights, but it is not a systematic and consistent practice. 10.1 % of the firms are at expert level. They actively participate in cross-company collaboration, forming partnerships with external parties to drive continuous improvements. Lastly, 9.2 % of the manufacturing firms are at beginner level. These firms operate in silos, with limited communication and sharing of information. Each department primarily focuses on its own goals and objectives, resulting in isolated decision-making processes.

Table 8.15: Level of collaboration across departments

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	20	9.2	9.2	9.2
	Intermediate	71	32.7	32.7	41.9
	Experience	104	47.9	47.9	89.9
	Expert	22	10.1	10.1	100.0
	Total	217	100.0	100.0	

**Figure 8.16 : Level of collaboration within the organisation**

8.2.3.12 Level of Industry 4.0 recognition by leadership team

The level of Industry 4.0 recognition by leadership is defined as to what extent the leadership team recognise the value of Industry 4.0 investments encompassing technologies like Artificial intelligence, Internet of Things, Blockchain, Robotics, Additive manufacturing (3D printing), and cloud computing in the organisation's growth and operational improvements (Kiraz et al.,2020). Table 8.16 and Figure 8.17 show that 30% of firms are experienced, as the leadership team acknowledges the benefits that can be attained through Industry 4.0 within operational processes, and is in the process of formulating investment plans. 28.6% of firms are at an intermediate level where the leadership team is currently exploring the potential benefits of Industry 4.0. Following this 21.2% are at the beginner level. This means the leadership team lacks recognition of the value associated with Industry 4.0 investments in operational processes. 20.3% of firms acknowledge the benefits of Industry 4.0 technologies and the idea of adopting these technologies is embraced positively by the leadership team and employees with a collaborative mindset, showcasing a strong commitment to leveraging them for the organisation's success and growth.

Table 8.16: Level of Industry 4.0 recognition by the leadership team

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	46	21.2	21.2	21.2
	Intermediate	62	28.6	28.6	49.8
	Experience	65	30.0	30.0	79.7
	Expert	44	20.3	20.3	100.0
	Total	217	100.0	100.0	

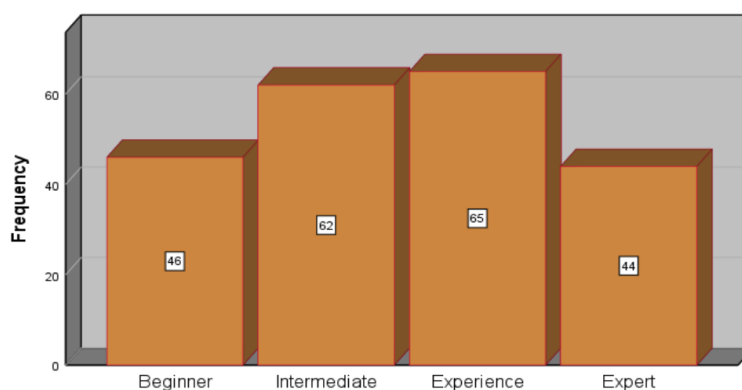


Figure 8.17 : Level of Industry 4.0 recognition by the leadership team

8.3 Overall Readiness of the Indian auto component industry

The overall readiness level exhibited an average score of 2.33 out of a total score of 4 as shown in Table 8.17. This indicates that the industry is midway to achieving complete readiness. Additionally, the distribution of participants shows that 53% of firms are at an intermediate level (Table 8.18; Figure 8.18), further emphasising the industry's current state of readiness. The scenario resembles Industry 3.5, a term identified by Chien, et al., (2017) and also proposed as a hybrid strategy representing companies which stand between Industry 3.0 and Industry 4.0. This underscores the potential of the industry to further transform the strategies to achieve digital transformation by integrating digital technologies for transforming traditional processes (Vial 2019; Cruzara et al., 2021; Imbar et al., 2022). While looking at the overall picture, the auto component industry including large and small-sized enterprises is at an intermediate level.

Table 8.17: Average score across all items

Readiness items	Score
Automation in the production field	2.21
Integration between machines and computing devices	2.36
Data collection	2.29
Inventory management	2.27
Communication between suppliers and customers	2.19
Integration between suppliers and customers for supply chain visibility	2.32
Data-driven decision making	2.35
Tracking across the supply chain	2.66
Co-creating products	2.50
Collaboration with external experts	2.31
Collaboration within the organisation	2.59
Industry 4.0 recognition by leadership team	2.49
Overall score	2.33

Table 8.18: Level of Industry 4.0 readiness across all factors

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Beginner	17	7.8	7.8	7.8
	Intermediate	115	53.0	53.0	60.8
	Experience	81	37.3	37.3	98.2
	Expert	4	1.8	1.8	100.0
	Total	217	100.0	100.0	

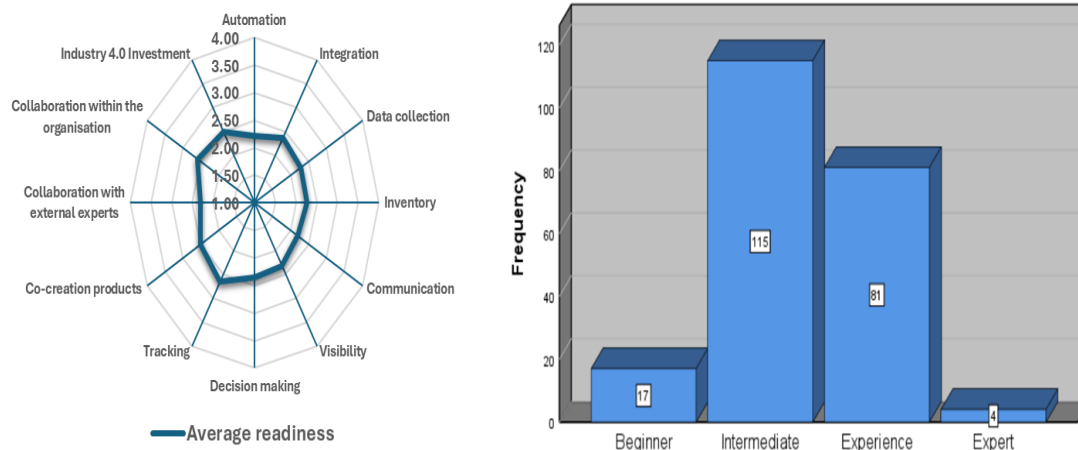


Figure 8.18 : Overall readiness score and readiness level

Although the industry does not belong to the lowest level of readiness (as shown in table 8.18), it still showcases the gap in terms of fully embracing Industry 4.0. Upon investigating all the factors one by one, the results indicated that all factors except customer co-creation (section 8.2.3.9), collaboration within an organisation (section 8.2.3.11) and Industry 4.0 initiatives are at the intermediate level (section 8.2.3.12). Automation in the production field, machine and computing system integration, inventory management, communication between suppliers and customers, supply chain integration for better visibility, data-driven decisions, and innovation and technology management are at the intermediate level. This reveals that the industry is still following the production process which heavily involves human intervention, and as a result, the integration between the production machinery and computing devices to capture any data is minimal. This demonstrates the non-formalised process followed by the industry in the production planning in line with the findings of Mittal et al., (2018) and Kumar et al., (2022). Further, firms are following the practice of collecting data through the combination of manual and SAP-ERP. This suggests that production processes and resources cannot be optimised in real time. SAP-ERP is a centralised platform which restricts the decision-making process based on real-time data acquisition (Moeuf, et al., 2017). Further, the findings align with Buer et al., (2021) and Björkdahl, (2020) which highlight the lag in supply chain digitalisation due to communication issues, low level of visibility into inventory levels and non-integrated customer and supplier networks showcasing low visibility into product status.

Meanwhile, customer co-creation, collaboration within an organisation and Industry 4.0 initiatives are at the experienced level. It is gathered from the exploratory study that companies work in close collaboration with OEMs to fulfil their demand in terms of design specification, order size, and ensuring the quality of the product. This reflects the value creation potential of the auto component industry business model as enhanced by creating products as per customer needs and adding customisation in manufacturing processes (Horvat, et al., 2018). Leaders' willingness to adopt Industry 4.0 technologies

and acknowledge the benefits of advanced technology also confirms the experienced level where the leadership team recognises the value of Industry 4.0.

8.4 Readiness level of MSMEs and large-sized firms

Pair plots were used across twelve factors to identify the level across MSMEs and large-sized firms. In pair plots (Figure 8.19) the diagonal plots are histogram plots of the feature corresponding to that row. The findings indicate higher technology readiness levels across large-sized firms as compared to MSMEs. For investigating the relationship between the firm size and technology readiness level, cross-tabulations as shown in Table 8.19 and Figure 8.20 for both variables were conducted across four levels, comparing large-sized companies (turnover of more than INR 250 crores) with MSMEs (turnover up to INR 250 crores).

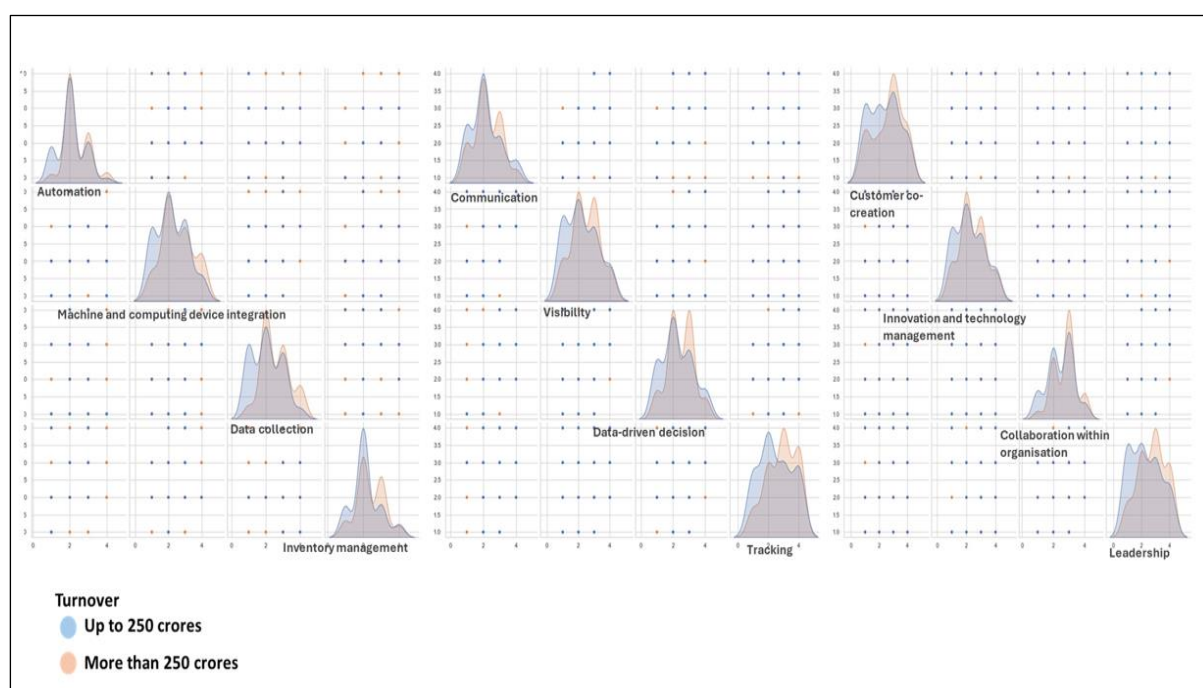
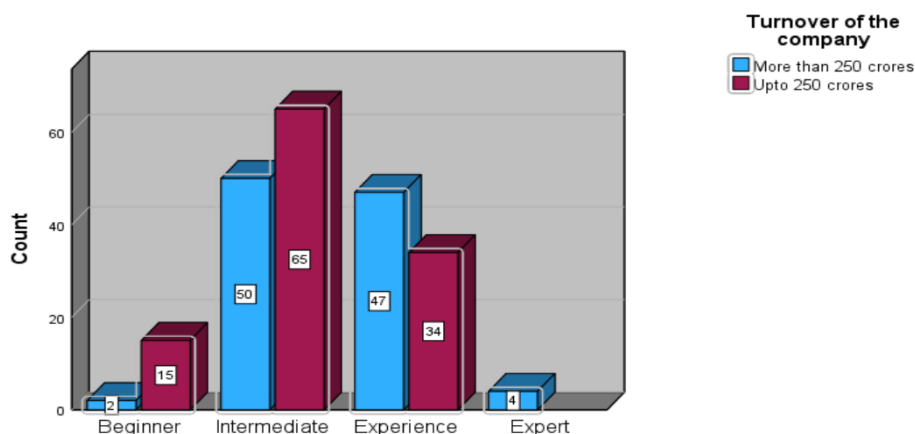


Figure 8.19 : Pair plots comparing readiness levels between MSMEs and large-sized firms

At the beginner level out of 7.8%, MSMEs represent 6.9% showing the dominance of MSMEs in comparison to large sized firms with 0.9%. Further, both size companies are prevalent at an intermediate level where MSMEs account for 30% and large-sized accounts for 23% out of 53% of the total sample size. Following this, the experienced and expert level is prevalent in large-sized firms. None of the MSMEs reached the expert level. Additionally, as can be seen from Figure 8.20, the intermediate level is prevalent across MSMEs while large-sized companies have advanced towards the experienced and expert level.

Table 8.19: Readiness level * Turnover of the company Crosstabulation

			Turnover of the company		Total
			More than 250 crores	<u>Upto</u> 250 crores	
TRL	Beginner	Count	2	15	17
		% of Total	0.9%	6.9%	7.8%
	Intermediate	Count	50	65	115
		% of Total	23.0%	30.0%	53.0%
	Experience	Count	47	34	81
		% of Total	21.7%	15.7%	37.3%
	Expert	Count	4	0	4
		% of Total	1.8%	0.0%	1.8%
Total		Count	103	114	217
		% of Total	47.5%	52.5%	100.0%

**Figure 8.20 : Cross tabulations of overall readiness level and turnover**

Key findings:

- Beginner level is predominant in MSMEs indicating that small firms are in the initial stage in terms of adoption of technology for optimisation of processes.
- Intermediate-level prevalence across large-sized companies (23%) and MSMEs (30%) accounted for 53% of the sample.
- The experienced level prevalence across large sized companies (21.7%) when compared to small sized companies (15.7%).
- The distribution of firms across intermediate and experienced levels demonstrates the engagement of firms towards the development of readiness levels.
- Large-sized companies have reached the expert level, though only four firms have achieved that level, showcasing the slow pace of the industry in reaching the highest readiness level.

Further, to approve this association between the level of readiness and the size of the company, a Chi-square test was conducted. The results of the Chi-square are presented in Table 8.20. The Chi-square value was 17.471a with $p < .001$. The result shows that there is a significant relationship between the level of readiness and the size of the company. This validates the findings from (Müller and Voigt, 2017; Hopkins, 2021; Müller, et al., 2021) that organisational size plays a significant role in advancing firms towards the adoption of technologies. Further Kergroach, (2020) and Buer et al., (2021) also suggested that large enterprises differ from SMEs in the level of digitalisation.

Table 8.20: Chi-square test result for the association between Industry 4.0 readiness level and turnover

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	17.471 ^a	3	<.001
Likelihood Ratio	20.297	3	<.001
N of Valid Cases	217		

Based on the findings from assessing the readiness level of large-sized firms and MSMEs, it was found that high turnover correlates with a higher level of readiness. Companies with turnover exceeding INR 250 crores are more likely at the experienced or expert level. On the contrary, MSMEs fall more in the category of intermediate and beginner level. The intermediate level showcased a balanced distribution of companies across large and small sizes. This means that a significant number of companies are still in the process of developing an understanding of the application of technologies for improving operations and processes. This also implies that overall, the auto component industry irrespective of size is yet to follow a pathway of progression for achieving the higher level.

8.5 Chapter Summary

In this chapter readiness level was identified for the auto component industry across different factors encompassing manufacturing operations and processes. The investigation aims to understand the industry's current state of readiness in terms of the adoption of Industry 4.0 technologies. The chapter began with the general descriptive analysis of the participants and firms to provide a comprehensive understanding of the industry, size and other characteristics of the participants including experience, and area of expertise for contextualising the findings of the study. The descriptive analysis also enhance the generalisation of the findings. The analysis was conducted using statistical tools including graphs, cross-tabulation, and statistical tests using chi-square. The descriptive analysis was categorised into three parts which included manufacturing industry profile, participants profile, and readiness level profile of firms in terms of the adoption of Industry 4.0. A comparative analysis of readiness levels across small MSMEs and large-sized firms was also provided. Chapter 9 will discuss the results of inferential analysis for testing the research hypotheses.

Chapter 9: Inferential Analysis - Structural Equation Modelling

9.1 Introduction

The modified questionnaire after incorporating changes resulting from the pilot test was distributed to the target sample and 217 responses were obtained. Chapter 8 discussed descriptive statistics; this chapter discusses the results for the reliability and validity of the constructs. Consequently, missing data and normality tests are conducted before statistical analysis. Additionally, EFA results are discussed incorporating twenty-six items identified during the pilot test. Further, to test the relationship between technology readiness level and operational performance, the choice of Structural equation modelling as a statistical method is justified following the results.

9.2 Examination of data before analysis

Hair, et al., (2009) recommend examining data prior to inferential analysis for an accurate assessment of dimensionality. The results from these tests guide the researcher further to adopt the most appropriate inferential tests thus enhancing the validity and reliability of results. For data analysis and hypothesis testing, the research employed IBM SPSS statistics and SmartPLS. SPSS was used for cleaning the data, data entry, descriptive statistics and missing value imputation. Consequently, SmartPLS was used to test the structural equation model. The research employed Partial Least Squares structural equation modelling (SMART PLS) software to assess the measurement and structural models. PLS-SEM is the widely adopted software for identifying the path relationships encompassing latent variables. This is also recommended by researchers for a complex framework where mediating and moderating variables are included in the framework. This study investigates the influence of technology readiness level on operational performance. Also, the framework examines the mediating effect between the dependent and independent variables. These tests are discussed in the next section.

9.2.1 Normality check

The normality test investigates the distribution of data. It determines if the data is obtained from a normal distribution sample. Skewness and kurtosis are frequently used tests for normality when using PLS-SEM (Hair, et al., 2014). While skewness assesses the symmetry in the distribution; kurtosis measures the peakness of the distribution. IBM SPSS was utilised to calculate the skewness and kurtosis of the data set. A skewness value between -1 and +1 is considered acceptable. Values beyond -2 and +2 indicate substantial nonnormality (Hair, et al., 2022). For kurtosis, a value close to +2 indicates the distribution is too peaked and -2 indicates the distribution is too flat. The normal distribution is indicated by skewness and kurtosis close to zero (George & Mallery, 2019; Hair, et al., 2022).

As shown in table 9.1, the skewness of variable TRL and NI are nearly symmetric with values close to zero. PP is slightly negatively skewed while REP is positively skewed. All values are within the acceptable limit of -1 to 1 ranging from -0.178 to 0.761. Kurtosis values are relatively close to zero

ranging from -0.485 to 0.105 indicating that distributions are not highly abnormal, and the difference might not have a substantial impact on statistical analysis as these values are within the threshold limit of ± 2 (Podsakoff, et al., 2003).

Table 9.1: Tests of Normality

Construct		Statistic	Std. Error
TRL	Mean	2.39	.606
	Skewness	-0.002	.165
	Kurtosis	-.417	.329
PP	Mean	3.28	.865
	Skewness	-.178	.165
	Kurtosis	-.407	.329
NI	Mean	3.2	.916
	Skewness	-.055	.165
	Kurtosis	-.485	.329
REP	Mean	2.37	1.056
	Skewness	.761	.165
	Kurtosis	.105	.329

9.2.2 Non-Response Bias

For the generalisation issue and removing the non-response bias, the extrapolation method was used for comparing early respondents to late respondents which is suggested as the most appropriate method by Lindner, et al., (2001) for the generalisation of results to the target population. It is contended by Miller & Smith, (1983) that late respondents are similar to nonrespondents. An independent sample t-test was conducted with the first 25% of respondents to the last 25%. This is a widely used criterion for addressing non-response error advocated by Collier & Bienstock, (2007). Paired sample t-test was conducted to compare the mean between the first 25% of responses and the last 25%. There was no significant difference between the mean of the two groups with $p > 0.05$. The 95% confidence interval for the mean difference between the two groups ranged between -0.175 to -0.091 indicating negligible difference (Table 9.2). This exhibits that results can be generalised to the target population as the survey is not affected by nonresponse bias. The results are given in the table below.

Table 9.2: Paired sample T-Test

	Mean	Std. Deviation	t-statistics	Sig (2-tailed)
Technology readiness level	-.114	.766	-1.101	.276
Production process efficiency	-.146	1.106	-.977	.333
Network Integration	-.175	1.054	-1.228	.225
Responsiveness	-.091	1.493	-.452	.653

9.2.3 Common method bias

Common method bias occurs when dependent and independent variables are measured using the same instrument with the same response technique (Podsakoff, et al., 2003). The distorting relationship between dependent and independent variables results in measurement error (Bagozzi, et al., 1991). Additionally, common method bias can impact the reliability and validity of the latent construct. Pace, (2010) and Baumgartner & Weijters, (2012) suggested that procedural controls should be actively engaged in the pilot testing (ex-ante) to avoid common method bias. Therefore, to control the common method bias, Harman's single-factor test was used by employing exploratory factor analysis (Harman, 1976). The test suggests that if the unrotated solution produces one factor that accounts for more than 50% variance, it indicates common method bias (Fuller, et al., 2016). An EFA was performed by including all the items used in the study. The results are given below in Table 9.3 showing 29.731% of variance which is within the threshold value of 50% indicating no common method bias issue in the study. Also, different scale types were used where production process efficiency and network integration were examined using a 5-point Likert scale with 1 no occurrence and 5 high occurrences. Moreover, the Likert scale for responsiveness towards OEM demand is a 5-point Likert scale with 1 = strongly disagree and 5 indicates strongly agree.

Table 9.3: Harman's single-factor test

Factor	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.313	31.972	31.972	7.730	29.731	29.731

Extraction Method: Principal Axis Factoring.

9.2.4 Correlation analysis

The correlation analysis revealed a significant relationship of technology readiness level (TRL) with network integration (NI) and production process efficiency (PP) as shown in Table 9.4. This indicates that firms with a higher technological level have a positive impact on the operational performance, characterised by a well-integrated network and improved production process efficiency. However, the relationship between technology readiness level and responsiveness towards OEMs while significant shows a weaker relation. It can be interpreted that while technology is an important factor and may contribute to meeting the demands of OEMs, it is not a key driver. Additionally, network integration (NI) demonstrated a strong positive correlation with production process efficiency (see Table 9.4), indicating the pivotal role of collaborative planning and transparency across the network in managing the inventory according to the demand in the market. An integrated network facilitates the adjustment in the production schedule as per changes in the stakeholders' needs, which includes the suppliers and buyers side (Fraga-Lamas and Fernández-Caramés, 2019). Moreover, NI and PP are positively correlated with REP. The positive relationship demonstrates the role of network integration along with an efficient production system in responding effectively to OEMs needs. These relationships are further discussed in detail in section 10.3.

Additionally, various demographic variables comprising management level, years of experience and firm size are also taken into account as shown in Table 9.4. These variables have not shown any significant relationship with the dependent variables. Nevertheless, firm size showed a significant relationship with the independent variable (TRL). It can be inferred that larger firms are better positioned to adopt advanced technologies, resulting in a higher readiness level than smaller firms. Much of this is enacted through the greater resource pool, strong R&D investment and an emphasis of the leadership team towards innovation, as asserted by various commentators (Müller & Hopf, 2017; Horváth & Szabó, 2019; Sony & Naik 2020; Weber et al., 2022).

Table 9.4: Spearman's correlation matrix

Variables	TRL	NI	PP	REP	Management Level	Experience	Firm Size
TRL	1						
NI	.431**	1					
PP	.456**	.740**	1				
REP	.164*	.214**	.268**	1			
Management Level	.142*	0.071	0.056	0.001	1		
Experience	-0.041	-0.064	0.023	0.046	-0.124	1	
Firm Size	.195**	0.042	0.105	0.052	.215**	.250**	1

Note: **Correlation is significant at the 0.01 level (2-tailed).

*Correlation is significant at the 0.05 level (2-tailed).

9.3 Measurement model analysis

9.3.1 SEM Methodology

Structural equation modelling is a multivariate data analysis method which is widely employed by researchers to test theoretically supported linear and causal models (Chin, et al., 2003). It assesses the model's "predictive capabilities and relationship between the constructs" (Hair, et al., 2017). There are distinct approaches to SEM which include covariance-based SEM (CB-SEM), and variance-based partial least squares (PLS-SEM). CB-SEM (covariance-based structural equation modelling) (Jöreskog, 1970) estimates causal relationships and tests hypotheses when data is normally distributed and the sample size is large and the model is correctly specified (Hwang, et al., 2010; Hair, et al., 2016). This method involves translating theory into a structural equation model where appropriate variables are linked together (Lowry & Gaskin, 2014). However, in practicality, it is difficult to meet these requirements with the collected data set. Additionally, in exploratory research, it is not always possible to identify the existing relationship between the variables. PLS-SEM (partial least squares SEM) is a soft model approach and is an alternative to CB-SEM which does not dictate the size of the sample and data normality (Hwang et al., 2010; Wong, 2011). The application is more suitable when the emphasis is more on exploring the relationships rather than confirming the theory (Hair, et al., 2011).

Further, Table 9.5 presents a summary of the methods employed in previous studies for understanding the empirical relationship between Industry 4.0 drivers and the impact of digital transformation on organisational performance. Structural equation modeling is predominantly used across research, particularly CFA-SEM and PLS-SEM (Arnold et al., 2018; Kiraz et al., 2020; Patrucco et al., 2022). CFA-SEM is primarily used for theory testing with preexisting hypotheses for confirmatory analysis. In contrast, PLS-SEM is broadly used in explanatory research for testing the predefined model, its application has increasingly expanded for exploratory studies where qualitative insights inform the subsequent quantitative testing (Leso et al., 2023; Kurtaliqui et al., 2024) for testing the new constructs in emerging fields. Therefore, consistent with the previous studies (Leso et al., 2023; Kurtaliqui et al., 2024) the current study follows the same methodological approach in alignment with the study's focus on refining operational constructs from a qualitative study to be subsequently tested using PLS-SEM. PLS-SEM is used as a part of a mixed-methods approach where an exploratory sequential mixed method allows for the development of a quantitative phase (Brown et al., 2021) based on the concepts derived from the qualitative study (Qureshi et al., 2023).

Table 9.5: Summary of data analysis techniques in existing Industry 4.0 studies

Methods	Authors	Research approach/design	Advantages	Limitations
Regression analysis	Zheng et al., (2021)	Deductive/ Explanatory (Surveys)	Used for direct effects	Fails to handle complex relationships and latent variables
Confirmatory factor analysis - SEM - AMOS	Arnold et al., 2018 ; Kiraz et al., 2020 ; Patrucco et al., 2022	Deductive/ Explanatory (Surveys)	Testing the theoretical model where relationships are well established. Confirms the structure of the factor while ensuring construct validity	Not used for prediction-focused studies
EFA, confirmatory factor analysis with SPSS – SEM- AMOS	Crešnar et al., (2020)	Inductive/ Exploratory	Identifies the factor structure, followed by confirmation	Not used for prediction-focused studies
PLS-SEM	Chatterjee et al., 2021; Gadekar et al., 2022; Li, et al., 2022; Zhang, et al., 2021	Deductive/ explanatory	Handles small samples and non-normal data. Appropriate for predictive analysis	Ignores model fit
PLS-SEM	Leso et al., (2023); Qureshi et al., 2023; Harikannan et al., 2025	Inductive/ Exploratory (Interviews/surveys)	Used for hypothesis development due to the lack of an existing model	Ignores model fit

PLS-SEM is advantageous over traditional regression analysis and CFA-SEM due to the ability of the technique to handle complex relationships and latent variables with multiple constructs and relationships. While CFA-SEM and regression analysis necessitate the testing of predefined models, these models limit their use in emerging fields like Industry 4.0 (Richter and Tudoran, 2024). On the other hand, regression analysis fails to account for measurement error and tests only direct relationships. However, SEM incorporates measurement models and testing direct and indirect relationships within a single framework (Gefen et al., 2000; Al-Emran et al., 2018). PLS-SEM has been effectively used in previous research to analyse factors influencing digital transformation in the context of Industry 4.0 (Qureshi et al., 2023; Harikannan et al., 2025). Moreover, PLS-SEM is increasingly used in exploratory studies to understand the relationship between Industry 4.0 drivers and organisational performance. Additionally, SEM is used in the prior studies due to its ability to estimate direct and indirect relationships within a single framework, unlike regression analysis, which fails to handle latent variables (Stoffels et al., 2023).

Drawing from the preceding discussion, and in alignment with the current study's objective, PLS-SEM is deemed a suitable method to explore the relationship between technology readiness level and operational performance. The approach aligns with the study's exploratory character in contrast to CFA-SEM, which is suitable for theory testing and confirmation. PLS-SEM is more appropriately suited to uncover relationships rather than confirming the pre-defined model, as is the case in CFA-SEM (Zia et al., 2023). Additionally, PLS-SEM is less prone to model misspecification, making it a reliable choice for this research as theoretical models are not fully developed in terms of the relationship between Industry 4.0 readiness and operational performance (Elafri et al., 2022).

Moreover, PLS-SEM is a more appropriate model for this study because of its flexibility and non-restrictive assumptions related to data. Notable, it is capable of handling complex models consisting of multiple latent and manifest variables which aligns with the multifaceted nature of Industry 4.0 readiness, where multiple factors interact to determine a company's readiness (Sasi et al., 2022). Further, PLS-SEM is chosen for its strength to provide an accurate estimate of the relationships with a small sample size (Hair et al., 2020). These advantages assist in overcoming multiple issues such as sample limitations and non-convergence issues that plague CFA-SEM. Although, PLS-SEM fails to provide model fit indices, it holds relevance in evaluating predictive quality using R^2 , Q^2 , and $PLSpredict$, making it more suitable for exploratory research to uncover predictive relationships (Lin and Huynh, 2024). To perform PLS-SEM in this research, SmartPLS software was employed.

9.3.1.1 Indicator reliability

Indicator reliability is understood as the condition for validity, which ensures that the associated indicators are loading on the same latent construct (Bagozzi, 1981). The standardised loading for each indicator should be higher than 0.7. Stevens, (1996) suggested that the value of factor loading should

be greater than 0.4 for interpretation purposes. While Hair et al., (2009) argued that factor loading value should be between 0.5 and 0.7. Further, as per Hair et al., (2011), the absolute standard loading of each indicator should be 0.7, and any indicator below 0.7 should be omitted only if such omission results in construct validity. Of the 26 indicators, 17 indicators have a standardised loading of >0.7 . Seven indicators have loadings greater than 0.6 but less than 0.7. The indicators include (TRL 2 = 0.630); (TRL 3 = 0.602); (TRL 5 = 0.663); (TRL 6 = 0.665); (TRL 8 = 0.676); (TRL 9 = 0.655); and (TRL 12 = 0.615). All these values were considered acceptable as these values are close to 0.7. Further two indicators with loading greater than 0.5 and less than 0.7 include (TRL 1 = 0.582; and TRL 11 = 0.563). These indicators were retained to enhance content validity. All 26 indicators were therefore used in the study. The outer loadings of all the constructs are shown in Table 9.7 and Figure 9.1.

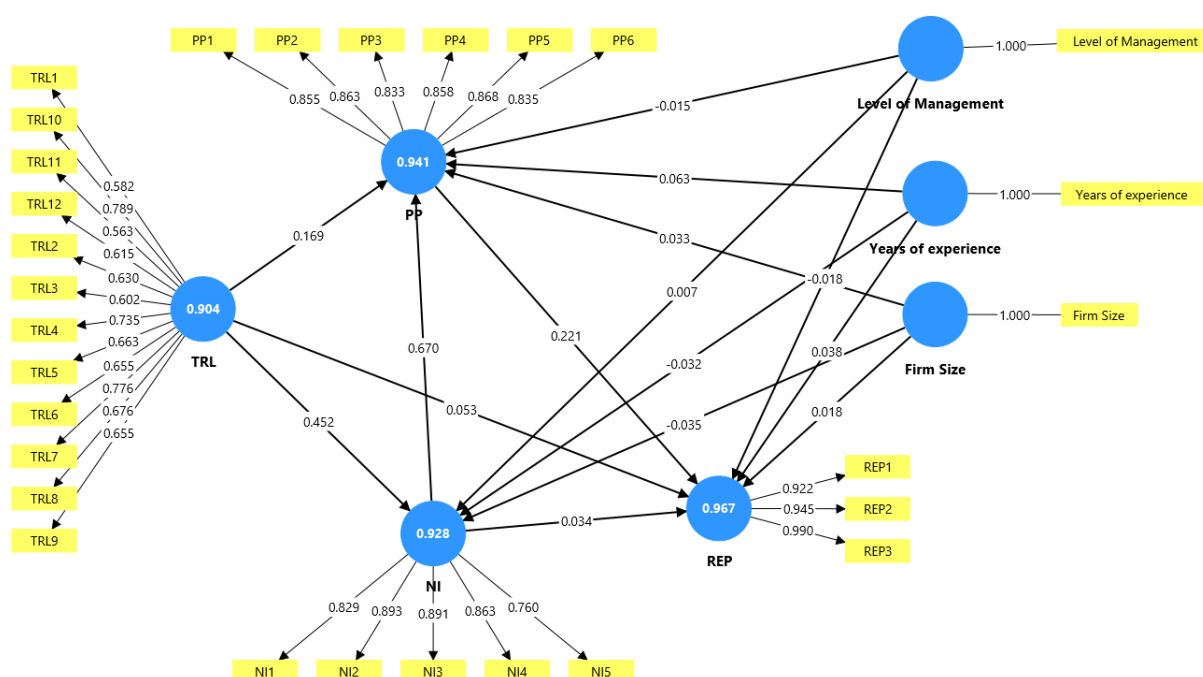


Figure 9.1 : Factor loadings

9.3.1.2 Collinearity Statistics (VIF)

Multicollinearity is a statistical phenomenon where two or more predictor variables in the regression model are highly correlated, indicating that a change in one predictor variable is associated with a change in another. Multicollinearity is one of the assumptions about the model while performing regression analysis. A multicollinearity test is conducted to test the reliability of the model. Upon violation, the model fails to be acceptable in estimating the population parameters (Lavery, et al., 2017). Therefore multicollinearity is used for successful regression model assumption. Further, multicollinearity is indicated by the variance inflation factor (VIF). The inner VIF for all the involved variables were less than 5.0 ranging from (1.000 to 2.290) for all the constructs as shown in Table 9.6. Therefore, multicollinearity was not an issue in this study (Hair, et al., 2017).

Table 9.6: Multicollinearity test for the exogenous constructs

Relationships	VIF
NI -> PP	1.251
NI -> REP	2.290
PP -> REP	2.350
TRL -> NI	1.000
TRL -> PP	1.251
TRL-> REP	1.320

9.3.1.3 Internal Consistency Reliability

The internal consistency test determines the consistency of the value of each item within the same construct. For measuring internal consistency reliability, Cronbach's alpha measure was used traditionally but it was believed to provide conservative measurement in PLS-SEM as it is sensitive to the number of items in the scale (Werts, et al., 1974). Therefore, composite reliability (CR) is suggested by Bagozzi (1981) to look at the internal consistency of the model. According to Hair et al., (2009), a composite reliability value of 0.7 or higher demonstrates good reliability. CR values ranged between 0.904 and 0.967 (as shown in Table 9.7). The composite reliability value is greater than the threshold value.

9.3.1.4 Construct validity

Construct validity refers to the extent to which different measures within the same construct are correlated. It involves establishing the validity of measures (observed variables) by exhibiting the relatedness in measures within the same underlying construct (unobservable or latent variable). A strong correspondence of measures advocates meaningful deduction from observed data which is theoretically related (Bagozzi et al., 1991). The construct validity is tested through convergent and discriminant validity (Campbell & Fiske, 1959). They argued that a single measure does not permit taking into account measurement error comprising of random error and method variance. Therefore, the measurement error can be mitigated by using multiple measures for assessing construct validity. Varied measures would disentangle the distorting influences of these errors on theory testing and thus enhancing the accuracy of evaluation.

9.3.1.5 Convergent validity

According to Campbell & Fiske, (1959), convergent validity underscores the correlation between the different measures of the same underlying concept. It refers to the level of agreement achieved by various methods employed to demonstrate the internal consistency of indicators that measure the same constructs (Bagozzi, et al., 1991). This study assessed the average variance extracted (AVE) to ascertain the convergent validity. AVE measures the extent to which variation in indicator variables can be attributed to the theoretically related latent construct (Fornell & Larcker, 1981). AVE values of three latent constructs ranged between 0.720 and 0.908, greater than the minimum threshold value of 0.50

(Bagozzi & Yi, 1988; Hair et al., 2009). This means that latent constructs account for no less than half of the variance in their associated indicators. Further, Cronbach's alpha of all the items was above 0.70 indicating the internal consistency of items (Carmines & Zeller, 1979). Table 9.7 below shows that all study constructs are reliable for further analysis. AVE and CR values are also shown in the Table 9.7.

Table 9.7: Outer loadings and reliability analysis

Construct	Item	Loading	Alpha	CR	AVE
Readiness level	TRL1	0.582	0.884	0.904	0.443
	TRL 2	0.630			
	TRL 3	0.602			
	TRL 4	0.735			
	TRL 5	0.663			
	TRL 6	0.655			
	TRL 7	0.776			
	TRL 8	0.676			
	TRL 9	0.655			
	TRL 10	0.789			
	TRL 11	0.563			
	TRL 12	0.615			
Production process	PP1	0.855	0.924	0.941	0.726
	PP2	0.863			
	PP3	0.833			
	PP4	0.858			
	PP5	0.868			
	PP6	0.835			
Network Integration	NI1	0.829	0.902	0.928	0.720
	NI2	0.893			
	NI3	0.891			
	NI4	0.863			
	NI5	0.760			
Responsiveness towards OEM demand	REP1	0.922	0.950	0.967	0.908
	REP2	0.945			
	REP3	0.990			

9.3.1.6 Discriminant validity

Discriminant validity is the degree to which measures of different constructs are distinct indicating no correlation between the valid measures (Bagozzi, et al., 1991). It is argued that employing fewer than three methods does not adequately assure discriminant validity (Henseler, et al., 2015). Therefore, this

study employed three tests to assess discriminant validity including cross-loadings, Fornell and Larcker (1981) criterion, and Heterotrait-Monotrait (HTMT) (Henseler, et al., 2015).

Cross Loadings

Foremost, cross-loadings were evaluated to measure the discriminant validity. To achieve this criterion, each factor should be connected to its corresponding latent variable than its cross loading on other latent variables. This implies that the loading of each indicator should be greater than all its cross-loadings (Chin, 1998). Table 9.8 presents the outer loading of each factor which is higher on its corresponding latent variable.

Table 9.8: Indicator cross-loadings

	TRL	PP	NI	REP
TRL1	0.581	0.286	0.329	0.111
TRL 2	0.626	0.256	0.212	0.158
TRL 3	0.598	0.22	0.215	0.172
TRL 4	0.737	0.389	0.362	0.082
TRL 5	0.662	0.276	0.232	0.108
TRL 6	0.656	0.299	0.306	0.09
TRL 7	0.774	0.391	0.352	0.209
TRL 8	0.679	0.332	0.336	0.081
TRL 9	0.657	0.307	0.25	0.07
TRL 10	0.789	0.433	0.417	0.15
TRL 11	0.566	0.236	0.206	0.02
TRL 12	0.615	0.202	0.238	0.076
PP1	0.376	0.854	0.605	0.177
PP2	0.391	0.863	0.648	0.274
PP3	0.401	0.832	0.597	0.206
PP4	0.375	0.858	0.603	0.272
PP5	0.429	0.868	0.675	0.237
PP6	0.429	0.835	0.657	0.223
NI1	0.384	0.548	0.828	0.191
NI2	0.368	0.599	0.892	0.192
NI3	0.374	0.684	0.891	0.178
NI4	0.421	0.679	0.863	0.183
NI5	0.351	0.622	0.762	0.184
REP1	0.135	0.206	0.16	0.922
REP2	0.186	0.296	0.236	0.945
REP3	0.152	0.261	0.214	0.99

Fornell-Larcker criterion (1981)

Following cross-loading, Fornell and Larcker's (1981) criterion was examined. This criterion examines the AVE of latent variables, where the square root of the construct's AVE is larger than its correlations with the latent variables (Fornell & Larcker, 1981; Henseler et al., 2015). Based on this criterion, all constructs sufficiently met the discriminant validity as presented in Table 9.9.

Table 9.9: Discriminant validity: Fornell and Larcker criterion (1981)

	NI	PP	REP	TRL
NI	0.849			
PP	0.742	0.852		
REP	0.218	0.272	0.953	
TRL	0.448	0.470	0.170	0.665

Heterotrait-Monotrait (HTMT)

Additionally, Heterotrait-Monotrait (HTMT) was used to establish the discriminant validity. HTMT compares the correlation between constructs and the correlation within constructs to check if the former is higher than the latter. The suggested threshold for HTMT is 0.85 (Henseler, et al., 2015). Table 9.10 shows all values below the threshold value of 0.85 confirming the discriminant validity.

Table 9.10: HTMT ratio

	NI	PP	REP	TRL
NI				
PP	0.808			
REP	0.231	0.283		
TRL	0.485	0.503	0.179	

9.4 Structural Model (Inner Model)

After confirming the reliability and validity of the construct, the hypothesised relationships of the conceptual model were examined using structural model assessment. The structural model supports the hypotheses through the assessment of the model's predictive capabilities and relationships between the constructs. Bootstrapping technique with a subsample of 5000 was applied for the assessment of the inner structural model and statistical significance of the path coefficient (Henseler, et al., 2015). Further, techniques like a confidence interval, path coefficient and effect size are recommended as good practice in contrast to accepting or rejecting the hypothesis based only on the p-value (Hahn & Ang, 2017). According to Hair et al., (2016), the p-value is significant at 0.001 to 0.005, and the acceptable t-value is greater than 1.645. This research employed five steps to assess the structural model. The steps include the assessment of path coefficients, coefficient of determination (R^2 value), effect size (f^2 value), predictive relevance (Q^2 value), and the predictive relevance of the model (PLSpredict). The structural

model is evaluated to test the correlation among Technology Readiness Level (TRL), production process performance (PP), network integration (NI) and responsiveness towards external pressure (REP). The PLS algorithm was used to determine the path coefficient, coefficient of determination and effect size, while the statistical significance was determined by applying the PLS bootstrapping procedure.

In the following section, path coefficients (beta values, β) and coefficient of determination (R^2 value) were examined to assess the causal relationship between the data. The bootstrapping approach was used to generate p-values and t-values for each path coefficient.

9.4.1.1 Coefficient of determination (R^2)

R^2 explains the variance in the endogenous variable (dependent) explained by the exogenous variable (independent). R^2 shows that the model explains 58%, 20.3% and 7.9% of the variance in the production process efficiency, network integration and responsiveness towards OEM demand. This shows that a 58% variance in production process efficiency can be attributed to TRL and NI. Further, a 20.3% variance in network integration can be attributed to TRL and lastly 7.9% variance in REP can be attributed to REL, PP and NI. As per Falk & Miller, (1992) R^2 value equal to or greater than 0.10 for the variance explained is deemed adequate. Cohen, (1988) suggested an R^2 value of 0.26 (substantial), 0.13 (moderate) and 0.02 (weak). Based on the recommended cutoff of .10, the model obtained acceptable R^2 statistics. The variance in the dependent variable is further explained below:

9.4.1.2 Production process efficiency (PPE)

$R^2 = 0.580$ (R^2 adjusted = 0.570) (Figure 9.2/ Table 9.12) for the endogenous latent construct production process efficiency, implying that technology readiness level substantially explains 58% of the variance in production process efficiency and is statistically significant. Considering that R^2 of 0.26 indicates a substantial predictive power of the model, also for the construct TRL ($\beta = 0.169$, $t = 2.754$) and NI ($\beta = 0.670$, $t = 11.332$) (as shown in figure 9.2) with direct path relationship to (influence on) production process efficiency, NI has the largest direct effect and positive effect on PP ($NI \rightarrow PP$: $\beta = 0.670$).

Network Integration (NI)

$R^2 = 0.203$ (R^2 adjusted = 0.188) (Figure 9.2/ Table 9.12) for network integration - dependent latent construct. This implies that the latent construct TRL ($\beta = 0.452$; $t = 6.258$) explains 20.3% of the variance in network integration. Considering that R^2 of 0.26 indicates a moderate predictive power of the model, the results $R^2 = 0.203$ are statistically significant and show that the model exhibits a substantial predictive power for NI.

Responsiveness towards OEM demand (REP)

$R^2 = 0.079$ (R^2 adjusted = 0.053) (Figure 9.2/ Table 9.12) for the endogenous latent construct responsiveness towards OEM demand, indicates that the latent construct NI, PP and TRL explains 7.9%

of the variance in responsiveness. Considering that R^2 of 0.13 indicates a moderate predictive power of a model, the result $R^2 = 0.079$ shows that the model exhibits a slightly moderate predictive power for responsiveness. Further for the constructs TRL ($\beta = 0.053$, $t = 0.619$); PP ($\beta = 0.221$, $t = 1.901$); NI ($\beta = 0.034$, $t = 0.298$) with direct path relationships to REP, only PP is statistically significant with the largest effect on REP (PP $\rightarrow$ REP: $\beta = 0.221$).

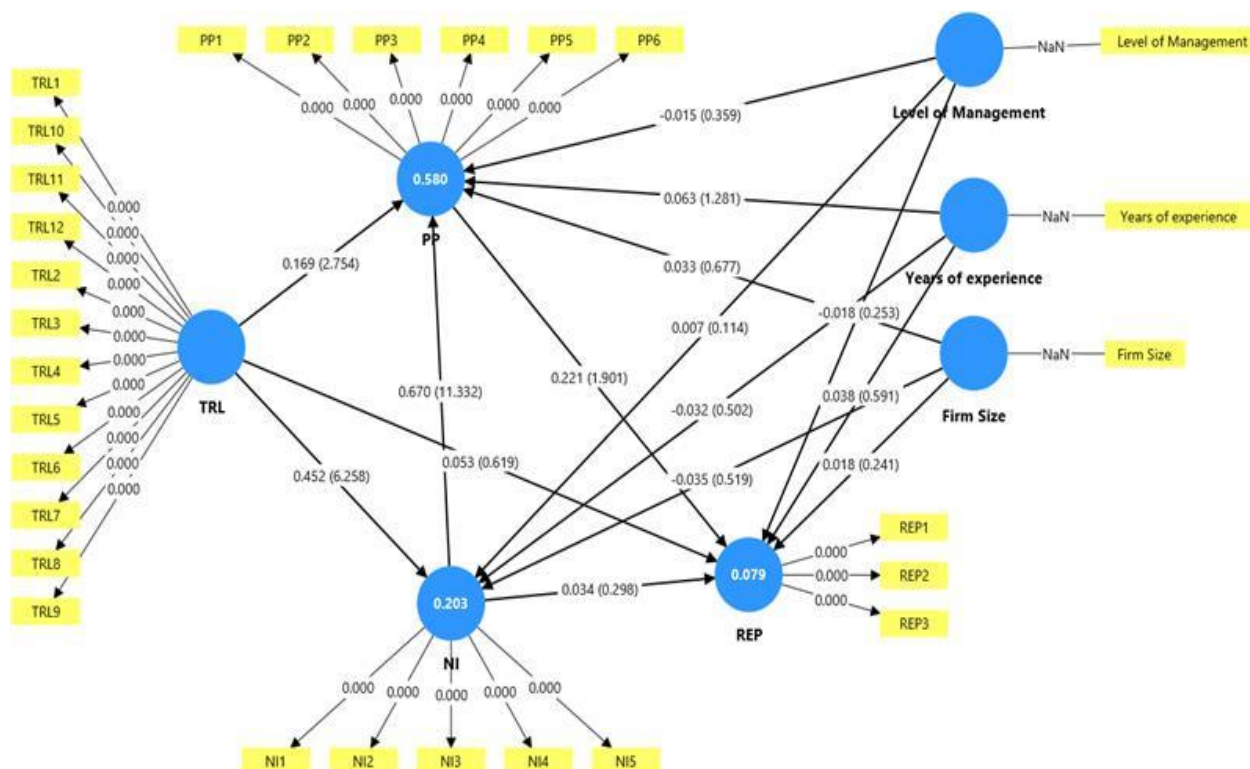


Figure 9.2 : Bootstrapping: Statistical significance of path coefficient and t value

In the present study, the influence on PP, NI and REP is assessed through several predictor variables. Hair et al., (2011) recommended that the f^2 effect size shall be reported as it specifies if the removal of an independent variable can create a substantial impact on the dependent variable. The analysis results of f^2 effect size are discussed in the next section.

9.4.1.3 Evaluation of the effect size f^2 of the structural model (f^2)

The hypothesised path relationship for TRL $\rightarrow$ PP has $f^2 = 0.052$ ($t = 2.754$), and TRL $\rightarrow$ NI has $f^2 = 0.242$ ($t = 6.258$). TRL $\rightarrow$ REP has $f^2 = 0.002$ ($t = 0.619$). These values show that the latent construct TRL does not affect R^2 in responsiveness towards OEM demand. In contrast, the latent construct has a small effect on the explained variance R^2 in network integration and production process efficiency. The f^2 value is in line with the parameter estimates to direct path coefficients from TRL $\rightarrow$ PP ($\beta = 0.169$); TRL $\rightarrow$ NI ($\beta = 0.452$) and TRL $\rightarrow$ REP ($\beta = 0.053$). This shows the steepest slope ($\beta = 0.452$) in the path relationship of TRL and NI. This implies that TRL contributes more to network integration than to either PP or REP. This is important as it highlights the difference in the endogenous constructs' (TRL)

contribution. However, the path relationship of TRL→PP is statistically significant as contrary to TRL→REP.

The hypothesised path relationship for NI→PP has $f^2 = 0.851$ ($t = 11.332$) and NI→REP has $f^2 = 0.001$ ($t = 0.298$). These values indicate that while there is no effect of NI on the R^2 of REP, it has a large effect on the R^2 of production process efficiency. The extent of contribution by NI validates the result of the estimate for path relationship NI→PP ($\beta = 0.670$) and NI→REP ($\beta = 0.034$). This shows the steepest slope for the relationship between NI and PP. The result also emphasises the importance of network integration performance on production process efficiency.

The hypothesised path relationship for PP→REP has $f^2 = 0.022$ ($t = 1.901$), and the latent construct PP has a small effect on the R^2 in the latent construct REP. Further. The medium contribution of TRL to R^2 of the REP and PP illustrates that contributions are also made to the operational performance (PP and REP) by TRL that have been deployed as a result of TRL as follows: PP, and NI also contribute to the R^2 of REP. The f^2 statistics are shown in Table 9.11.

Table 9.11: T statistics for f^2 value

	Original Mean (O)	Simple Mean (M)	f^2	t statistics	P values
TRL→PP	0.169	0.173	0.052	2.754	0.006
TRL→NI	0.452	0.462	0.242	6.258	0.000
NI→PP	0.670	0.666	0.851	11.332	0.000
TRL→REP	0.053	0.056	0.002	0.619	0.536
PP→REP	0.221	0.220	0.022	1.901	0.057
NI→REP	0.034	0.032	0.001	0.298	0.766

9.4.1.4 Predictive relevance of the model (Q2)

The PLSpredict/ Cross-validated predictive ability test (CVPAT) procedure of SmartPLS was employed to calculate the predictive relevance of the model. According to Geisser, (1974), the model is considered to have predictive relevance if Q^2 is greater than 0. The model had predictive relevance since the q-square value was greater than 0 as given in Table 9.12.

Table 9.12: Predictive relevance statistics

	R-square	R-square adjusted	Q^2 predict
Network Integration	0.203	0.188	0.157
Production process	0.580	0.570	0.180
Responsiveness	0.079	0.053	0.005

9.4.1.5 Significance of path relationship – Testing hypotheses

The structural model is evaluated using the hypothesised links between the variables. The significance of the structural path is determined using path coefficients and t value, where path coefficients correspond to Beta values ranging between -1 and +1. Further, the bootstrapping process was subjected

to a one-tailed test with t values less than 5% as significant values. The results indicate that technology readiness level has a significant effect on the production process and network integration. Further, network integration has a significant impact on the production process and the production process has a significant impact on responsiveness towards external pressure. In contrast, technology readiness level and network integration have no significant effect on responsiveness towards external pressure.

The association between TRL and PP was significant ($\beta = 0.169$, t value = 2.754, $p < 0.05$). Therefore, H1 is accepted. The result of H2 showed that TRL has a positive and significant association with NI ($\beta = 0.452$, t value = 6.258, $p < 0.05$). Hence, H2 was supported. The result of H3 showed that NI has a positive impact on PP ($\beta = 0.670$, $t = 11.332$ and $p < 0.05$). Hence, H3 was supported. The result of H4 showed that TRL has a positive and non-significant association with REP ($\beta = 0.053$, $t = 0.619$, and $p > 0.05$). Hence, H4 was not supported. Furthermore, the result showed an association between PP and REP was significant and positive ($\beta = 0.221$, $t = 1.901$, $p < 0.05$). Therefore, H5 was supported.

Additionally, the result showed that the association between NI and REP is non-significant ($\beta = 0.034$, $t = 0.298$ and $p > 0.05$). Hence, H6 was not supported. Thus, the structural model suggests that the strongest effect is that of the network integration (NI) on production process efficiency (PPE), while the weakest effect is that of the network integration on responsiveness. The path coefficients are presented in Table 9.13.

Table 9.13: Hypothesised relationship with path coefficients, t statistics and p -value

Hypothesis	Direct relationship	Beta	T value	P value	Findings
H1	TRL $\rightarrow$ PP	0.169	2.754	0.006 **	Supported
H2	TRL $\rightarrow$ NI	0.452	6.258	0.000 ***	Supported
H3	NI $\rightarrow$ PP	0.670	11.332	0.000 ***	Supported
H4	TRL $\rightarrow$ REP	0.053	0.619	0.536	Not Supported
H5	PP $\rightarrow$ REP	0.221	1.901	0.057 ***	Supported
H6	NI $\rightarrow$ REP	0.034	0.298	0.766	Not Supported

***Significant at 0.01 level*

****Significant at 0.001 level*

9.4.1.6 Effects of the control variable

To evaluate the confounding effect of control variables on the model's hypothesis test result, firm size, level of management and years of experience were included as control variables to control the effects they may have on the operational performance. Tables 9.14 (with controls) and Table 9.15 (without controls) demonstrate the comparative results. From Table 9.14, it is evident that the inclusion of control variables demonstrated no significant effect of control variables on network integration (NI), production process efficiency (PP) and responsiveness towards OEMs (REP). Therefore, it can be affirmed that years of experience, firm size and level of management are not confounding factor to explain operational performance since the value of statistical significance is greater than 0.05 as shown in Table 9.14.

Additionally, the inclusion of control variables does not affect the core hypothesised relationships of the model, showing similar results, particularly statistical significance as shown in Table 9.14. This shows that technology readiness level can impact the operational performance regardless of management level, firm size and years of experience of employees. This implies that firms with a sophisticated resource base characterised by automated machinery, data-driven decision making and communication technologies would be better positioned to improve operational performance. The absence of a significant relationship between the control variable and operational performance may also suggest that other variables, such as the level of investment and industry type, may be strongly associated with technology readiness level and performance outcomes. This is supported by the findings from the McKinsey report (Brinded et al., 2022), which indicated that capital expenditure is more strongly associated with performance outcomes.

Table 9.14: Path coefficients and statistical significance (with control variables)

With Controls					
	Original sample (O)	Sample mean (M)	T statistics (O/STDEV)	P values	Significance
Firm Size -> NI	-0.035	-0.038	0.519	0.604	Non-significant
Firm Size -> PP	0.033	0.032	0.677	0.499	Non-significant
Firm Size -> REP	0.018	0.018	0.241	0.810	Non-significant
Level of Management -> NI	0.007	0.006	0.114	0.909	Non-significant
Level of Management -> PP	-0.015	-0.017	0.359	0.720	Non-significant
Level of Management -> REP	-0.018	-0.017	0.253	0.800	Non-significant
NI -> PP	0.670	0.666	11.332	0.000	Significant
NI -> REP	0.034	0.032	0.298	0.766	Non-significant
PP -> REP	0.221	0.220	1.901	0.057	Significant
TRL -> NI	0.452	0.462	6.258	0.000	Significant
TRL -> PP	0.169	0.173	2.754	0.006	Significant
TRL -> REP	0.053	0.056	0.619	0.536	Non-significant
Years of experience -> NI	-0.032	-0.031	0.502	0.615	Non-significant
Years of experience -> PP	0.063	0.063	1.281	0.200	Non-significant
Years of experience -> REP	0.038	0.0400	0.5910	0.555	Non-significant

Table 9.15: Path coefficients and statistical significance (without control variables)

	Original sample (O)	Sample mean (M)	T statistics (O/STDEV)	P values	Significance
NI -> PP	0.665	0.662	11.087	0.000	Significant
NI -> REP	0.024	0.023	0.222	0.825	Non-significant
PP -> REP	0.230	0.230	2.030	0.042	Significant
TRL -> NI	0.448	0.458	6.563	0.000	Significant
TRL -> PP	0.172	0.176	2.737	0.006	Significant
TRL -> REP	0.051	0.055	0.632	0.528	Non-significant

Table 9.16: Model statistics without and with the control variable

	R-square with control variable	R-square without control variable
Network Integration	0.203	0.200
Production process	0.580	0.574
Responsiveness	0.079	0.077

9.5 Robustness checks - Unobserved heterogeneity

This research employed FIMIX-PLS segmentation of robust path analysis for unobserved heterogeneity, which is asserted as the best approach to PLS-SEM by Sarstedt (2008). The problem FIMIX is trying to solve is that there might be latent or hidden groups or subsamples within the samples that are not a priori theorised about or planned for, that may create hidden heterogeneity in the measurement model (Matthews et al., 2016). According to Rigdon et al., (2010), the hidden heterogeneity affects the parameters and estimates of the structural model and thereby invalidates the findings. FIMIX attempts to find those hidden segments within the model so that they can be accounted for, asserting that there are no hidden segments. This is similar to cluster analysis, as it tries to find hidden profiles.

In order to treat unobserved heterogeneity in PLS-SEM, the FIMIX-PLS segmentation procedure was applied. This procedure is consistent with Sarstedt et al., (2017) systematic procedure. Other studies have also used FIMIX-PLS to uncover unobserved heterogeneity (see Marques & Resis, 2015; Ambilichu et al, 2022). The minimum sample size was calculated first to ascertain the maximum number of segments to extract. Hair et al., (2016) suggested the minimum sample size requirement using the number of arrowheads pointing at any construct in the model (REP) for an assumed significance level at 5%. A minimum of 54 observations is required to reliably estimate the model. Dividing the total sample size (i.e., 217) by the minimum sample size (i.e., 54) yields four segments.

For running the FIMIX-PLS procedure, a one-segment solution using the default settings for stop criterion [$10^{-10} = 1.0E-5$], number of iterations [5000], and number of repetitions [10] was used. Following this, the same procedure was repeated for the second, third and fourth segments. According

to Hair et al., (2016), the best indices to use are AIC3, CAIC and EN (see table 9.17). For entropy (EN) the criterion should be higher than 0.5 Sarstedt et al., (2011), where segments two to four met the criteria (see Table 9.17). For AIC3 and CAIC, both should be minimised on the single segment, which is not the case here. The smallest number of AIC3 lies in segment 3 as shown in Table 9.17, and CAIC lie in first segment. Therefore, upon checking that all the segments have 5% of data, the next step was to create a new statistic named summed fit as suggested by Hair et al., (2016), and the lowest of the four segments was identified. As a result, the minimised value lay in segment 1 as shown in Table 9.18. This suggests no significant level of heterogeneity in the data, indicating the interpretation of results can be performed at the aggregate level.

Table 9.17: Fit indices for one to four segment solutions

Criteria	Segment 1	Segment 2	Segment 3	Segment 4
AIC (Akaike's information criterion)	1627.943	1579.968	1541.874	1530.635
AIC3 (modified AIC with Factor 3)	1645.943	1616.968	1597.874	1605.635
AIC4 (modified AIC with Factor 4)	1663.943	1653.968	1653.874	1680.635
BIC (Bayesian information criterion)	1688.781	1705.024	1731.148	1784.127
CAIC (consistent AIC)	1706.781	1742.024	1787.148	1859.127
HQ (Hannan-Quinn criterion)	1652.519	1630.486	1618.333	1633.035
MDL5 (minimum description length with factor 5)	2076.134	2501.249	2936.245	3398.097
LnL (LogLikelihood)	-795.972	-752.984	-714.937	-690.318
EN (normed entropy statistic)	0	0.544	0.694	0.749
NFI (non-fuzzy index)	0	0.597	0.689	0.7
NEC (normalized entropy criterion)	0	99.03	66.328	54.522

Table 9.18: Best fit indices according to Hair et al., (2016)

Criteria	Segment 1	Segment 2	Segment 3	Segment 4
AIC3 (modified AIC with Factor 3)	1645.943	1616.968	1597.874	1605.635
CAIC (consistent AIC)	1706.781	1742.024	1787.148	1859.127
EN (normed entropy statistic)	0	0.544	0.694	0.749
Summed fit	3352.724	3358.992	3385.022	3464.762

9.6 Chapter Summary

This chapter presented the results of the measurement model and structural model. The SmartPLS was employed to perform the analysis. The hypothesised relationships were tested where out of nine hypothesis, five hypotheses were supported. Results show network integration as the key operational performance measure considering it makes the largest contribution to production process efficiency, while technology readiness level contributes more to network integration than production process efficiency and responsiveness towards OEM demand. Further, technology readiness level influences the production process efficiency and consequently responsiveness only through network integration. The results are discussed in detail in the next chapter (Chapter 10)

Chapter 10: Discussion and Conclusion

10.1 Introduction

The aim of this research was to assess Industry 4.0 readiness level and its impact on the operational performance of Indian auto component manufacturers. Several factors were identified from the literature that contributed to the adoption of Industry 4.0 technologies, consequently facilitating the progression of an organisation towards the actual implementation of such technologies (Moica et al., 2018; Dalmarco et al., 2019; Chonsawat and Sopadang, 2020; Crešnar et al., 2020; Simões et al., 2021; Alcácer et al., 2021). Further literature has received significant attention to measure Industry 4.0 readiness in different contexts, including the size of the firm and country. The literature revealed that most of the studies were conducted in developed economies (Sütőová et al., 2020; Alcácer et al., 2021; Trstenjak et al., 2022) or in different manufacturing industries (Arnold et al., 2018; Spaltini et al., 2022; Khourshed et al., 2023) thus exhibiting the lack of research in the context of Indian auto component industry. These studies touched upon the association of readiness level with operational performance, but the concept was found rather abstract, and no framework could be located to identify the relationship between readiness level and operational performance. This research was motivated by the need to conduct research in the Indian industry by assessing the readiness level as captured through the investigation of current practices, and thus exploring the relationship between the current readiness level and its impact on operational performance. This research thus attempted to answer the following research questions:

1. What are the key readiness factors in the context of Industry 4.0 to enhance operational productivity and efficiency?
2. What are the prevailing practices in the Indian manufacturing sector in the context of Industry 4.0 within the horizontal and vertical value chain comprising suppliers and customers?
3. How do current practices in the Indian auto components industry be systematically measured to evaluate the effect on operational performance?
4. What is the readiness level of the Indian automotive industry?
5. Is there any significant difference between the readiness level of SMEs and large-scale companies?
6. What is the relationship between the readiness level and operational performance in the context of the Indian auto component industry?

The study identifies the different levels of Industry 4.0 readiness related to manufacturing practices in the Indian auto component industry. Therefore, new levels reflecting the current practices have been embedded in the conceptual framework of Industry 4.0 readiness metrics, as identified from systematically reviewing the literature focusing on empirical research. These practices primarily depicted the patterns as revealed by the companies, which have already implemented Industry 4.0.

Consequently, the framework reflects the preliminary steps undertaken by the companies before the full adoption of Industry 4.0 technologies, and thus answer the first research question.

An exploratory study was conducted to investigate the current operational processes and activities within the auto component industry. The technology usage pattern was studied across all the operations. The interviewed companies' responses were categorised into three levels based on the level of technology adoption thus capturing the wider patterns across sample firms. The resulting operational performance as intertwined with the current practices was also studied. The research thus answered the second and third research questions. To answer the fourth and fifth research questions, a readiness scale was developed by integrating the findings of the literature review and exploratory study resulting in a four-level Industry 4.0 readiness framework. This framework was employed in the survey study to measure Industry 4.0 readiness level and data was further analysed using frequency analysis, bar charts, and cross-tabulation. In addition to frequency analysis, chi-square test and Cronbach's alpha measures are used. To answer the fifth and sixth research questions, a statistical model was developed. The data for statistically testing the relationship between readiness level and operational performance was collected from 217 companies. The statistical relationship was tested using structural equation modelling which was performed by SmartPLS software. The hypothesised relationships were tested, and the results are discussed in the section that followed.

The research aimed to empirically examine the impact of Industry 4.0 readiness on the operational performance of the Indian auto component industry. The operational performance was explained with three variables including production process efficiency, measured by six items within the survey questionnaire; network integration performance measured by five items and lastly responsiveness towards OEM demand was measured by three items within the survey questionnaire.

10.2 Industry 4.0 readiness factors for operational performance

The researcher's argument is that Industry 4.0 readiness level can be understood by the several technology readiness level indicators characterised by self-regulating production systems (automation), machines and operating system integration, automated digital data collection for supplier evaluation and procurement practices including procurement software, EDI, cloud-based technologies, self-regulating inventory control with dynamic adjustment in real-time, fully integrated supply chain, real-time visibility of site locations and operations across supply chain partners, data-driven decision making, real-time product tracking, personalised customisation, collaboration with technology partners, inter and intra-company collaboration, and leadership team recognition towards Industry 4.0 technologies. As the research used the readiness variables identified from the literature in a single model having a significant impact on the production process efficiency, network integration and responsiveness towards OEM's demand, it could be inferred that the study contributed to the field of Industry 4.0. These aforementioned measures were not tested statistically in the previous studies,

consequently, the factors identified during the research (through employment of EFA) satisfied the statistical criteria for acceptance of these measures in measuring readiness and operational performance.

This research extended the study of Müller, et al., (2018) in quantitatively assessing the steps that can be used by manufacturing SMEs for the implementation of steps. The readiness assessment framework can be used by the auto component firms as a guidance framework for progressing towards the Industry 4.0 implementation.

10.3 The statistical relationship between Industry 4.0 readiness level and operational performance

The research found that Industry 4.0 readiness levels have a significant positive relationship with production process efficiency and network integration. There is no significant relationship between Industry 4.0 readiness level and responsiveness towards OEM demand. Network integration is the key operational performance measure, considering it makes the largest contribution to production process efficiency, while technology readiness level contributes more to network integration than production process efficiency and responsiveness towards OEM demand. The findings are summarised in Figure 10.1. Additionally, the control effect of the firm size on the direct relationship between operational performance constructs was analysed using the multi-group analysis function in SmartPLS. The significance was found stronger in SMEs as compared to large groups for technology readiness level effect on responsiveness, and network integration effect on production process efficiency.

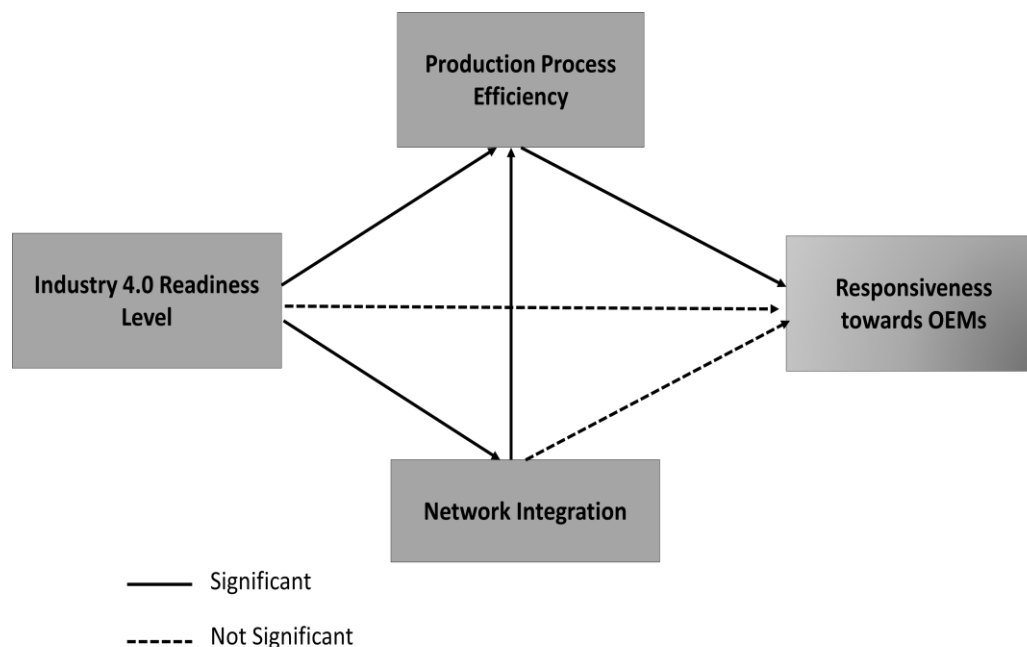


Figure 10.1 : Industry 4.0 readiness model for operational performance

H1: Industry 4.0 readiness level positively impacts the production process efficiency (supported)

The results of the hypothesis regarding the impact of Industry 4.0 readiness level on the production process efficiency has an empirical $\beta = 0.169$, t statistic = 2.754 (see Table 9.13). This implies statistical significance at $p=0.006$ ($p < 0.05$). The results indicate that firms that are better prepared for Industry 4.0 can achieve a competitive advantage through enhanced operational performance. The operational performance emphasising production process efficiency is witnessed through effective inventory management, efficient production coordination, dynamic production adaptation, and enhanced visibility. Further, it also improves the quality of the production, thus satisfying customer needs. This study was able to confirm the potential benefits of the existing technological infrastructure comprising real-time data integration capabilities, RFID and sensors in line with previous work (Zhong et al., 2013; Marcucci et al., 2022). The benefits can be assumed through reduction in downtime, predictive maintenance and efficient inventory management.

Further, vertical and horizontal integration among the supply chain network facilitates the autonomous dynamic response and forecasts possible failures using automated machinery, thus preventing the disruption in the production line. This mirrors the observations of Sony & Naik, (2019), suggesting that automated machinery allows for achieving higher quality products. According to Fernández-Caramés, et al., (2019), the existence of digital technologies enhances the optimisation of inventory management. This is also established through this study's result as the automated inventory system enhances the visibility for efficient production planning through effective communication and collaboration across the horizontal and vertical supply chain and the organisation. As discussed in sections 3.3.1 and 3.3.2, the RBV (Khanchanapong, et al., 2014; Weeks, et al., 2022; Zhu, et al., 2022) provides a strong theoretical argument to support the positive impact of Industry 4.0 readiness on operational performance. This research confirms the validity of Industry 4.0 readiness–performance links for production process efficiency.

H2: Industry 4.0 readiness level positively impacts the network integration (supported)

The results of the hypothesis in regard to the impact of Industry 4.0 readiness level on the network integration performance have an empirical $\beta = 0.452$, t statistic = 6.258 (see Table 9.13). This implies statistical significance at $p=0.000$ ($p < 0.05$). Based on the results, increased Industry 4.0 readiness contributes to the operational performance attributed to network integration, including information integrity, transparency, strategic alignment, collaborative planning and supplier quality management. These findings are in alignment with the arguments made by Marwah et al., (2014); Dubey et al., (2018); Pérez-Lara, et al., (2020) where consensus was found across all these studies on the positive impact of horizontal and vertical integration in supply chain on network alignment for collaborative planning.

Communication and integration between auto component manufacturers, their suppliers and OEMs can play a crucial role in improving the transparency within the network structure. Much of this is facilitated

through the constant information sharing between the stakeholders with the use of real-time tracking tools that prevent loss of information. These findings extend the study of Hermann et al., (2016), who emphasised the role of interconnectivity through vertical and horizontal integration among supply chain partners for increasing transparency in information. This study statistically tested the relationship and delved more deeply by examining how the vertical and horizontal integration can affect the impact of Industry 4.0 readiness on network integration. For instance, as the suppliers (Tier 1, Tier 2 and Tier 3) are closely integrated with one another and Tier 1 significantly linked to OEMs (discussed in **sections 2.5 and 2.5.1**), the network can rapidly transfer information to one another for tracing the defective product at the manufacturer's or suppliers' end. The non-tracking of the default sometimes imposes accountability on manufacturers (Tier 1 and Tier 2) even when the defect is in raw material, is at the point of origin, i.e. Tier 3 (as discussed in **section 6.4.2**). In this case, the risk of supply chain diversification is higher, as OEMs tend to switch to another manufacturer on account of quality issues. Vertical and horizontal integration can influence supply chain transparency by tracing the point of origin with real-time tracking and RFID. The supplier quality issues can be traced, thus preventing supply chain diversification and enhancing trust between auto component suppliers and OEMs.

H3: Network integration positively impacts the production process efficiency (supported)

The impact of network integration on production process efficiency has an empirical $\beta = 0.670$, t statistic = 11.332 (see Table 9.13). This implies statistical significance at $p=0.000$ ($p < 0.05$). These findings highlight the significance of network integration and production process efficiency as key operational performance measures. The interrelation between these two measures underscores the importance of information integrity, transparency, and collaborative planning across supply chain networks in optimising the production process. This optimisation is characterised by dynamic scheduling, adaptive capacity and improved inventory visibility, thus enhancing production efficiency. This affirmed that the integrated approach of network partners in strategically aligning supply chain activities enables manufacturers to optimise production schedules and inventory levels. This study was able to confirm the significance of this potential benefit in line with previous works (e.g. Chan, et al., 2012; Hermann et al., 2016; Juhara, 2024).

The findings extend the study of Rüßmann, et al., (2015) stating that data integration and flow of data across the supply chain enhances transparency and thus provides up-to-date information about operations and demand for improving the production process. This study statistically tested the relationship between network integration and production process efficiency. Similarly, the results extended Unhelkar, et al., (2022) study that supplier quality management ensures effective quality control within the production process as it significantly reduces the chances of product rejection.

The results point to the importance of transparency across supply chain stakeholders in terms of demand and supply for an enhanced and precise production planning. While studying the role of transparency,

Kauppila et al., (2020) and Jia et al., (2024) have found that transparency within the supply chain improves the production planning and has its foundation in the just-in-time inventory system. Just-in-time reiterates the relationship between network integration and production planning, where suppliers and manufacturers collaboratively plan the raw material orders to align with production schedules. This study delved deeply into examining how information transparency and integrity are linked with effective production planning. For instance, Indian auto component manufacturers face challenges with dynamic demand patterns of OEMs and last-minute order cancellations, resulting in frequent changes in production plans. Now, transparency in the supply chain, with suppliers having access to accurate information concerning OEMs' demand patterns, enables precise production planning. This can reduce the likelihood of delayed delivery on account of dynamic demand patterns from OEMs.

H4: Industry 4.0 readiness level positively impacts the responsiveness towards the external pressure from OEMs (not supported).

The results of the hypothesis regarding the impact of Industry 4.0 readiness level on responsiveness towards the external pressure from OEMs has an empirical $\beta = 0.053$, t statistic = 0.619 (Table 9.13). This implies no statistical significance at $p=0.068$. This finding seems to contradict the prior studies, such as Müller, (2019), who argued that predictive maintenance facilitates enhanced responsiveness by manufacturing firms. The findings also contradict the argument by Gaiardelli et al., (2021) that effective communication between suppliers and OEMs greatly assists manufacturers in aligning with OEMs' production schedules. Additionally, the findings challenge the argument made by Schuh et al., (2020) that analysing data in real-time improves process flexibility, thereby improving responsiveness to meet customers' demands. While during the qualitative findings, it was found that most of the firms use automated machinery to be responsive to OEMs' requirements for meeting product specifications, the quantitative study does not align with this assertion.

One possible explanation that can be drawn is the meaning of responsiveness, which has been used differently in the previous study, focusing more on the end users. This study primarily attempted to understand the responsiveness from an OEM-supplier relationship perspective. While participants indicated the use of automated machinery for meeting OEMs' requirements, it might be compliance-driven to fulfil OEMs' requirements for technology upgradation rather than being responsive to the auto components' demand.

H5: Production process efficiency positively impacts the responsiveness towards external pressure from OEMs (supported).

The results of the hypothesis regarding the impact of production process efficiency on the responsiveness towards external pressure from OEMs have an empirical $\beta = 0.221$, t statistic = 1.901. This implies statistical significance at $p=0.057$. The results indicate there is a significant positive impact of production process efficiency on the responsiveness towards external pressure from OEMs. These

findings indicate that Industry 4.0 readiness enabled capabilities, including adaptive capacity and inventory visibility, facilitate the agility in the production system to align more efficiently with OEMs' needs.

Digitally enabled process capabilities, such as real-time decision making and system integration, emerge from findings as critical drivers of agility within the production system. These capabilities enable auto component firms to quickly align with OEMs' requirements to adjust to changes in product specification and OEMs' schedules. In the context of Indian auto component firms, both of these requirements are identified as the critical factors in establishing a long-term buyer-supplier relationship. This is especially relevant in OEM-driven ecosystems where timely delivery and schedule adherence are observed as key performance benchmarks.

The results substantiated the theoretical assumptions as laid out by Flynn et al., (2010), establishing the linkage between lean integrated processes and enhanced responsiveness. This study extends their study by positioning Industry 4.0 readiness as the enabler of efficiency-responsiveness linkage in a digitally advanced supply chain. These findings are able to confirm the significance of this linkage in line with previous work of Roy et al., (2024), where inter and intra-firm integration are identified as the key capability to improve the firm's performance with production process agility.

H6: Network integration positively impacts the responsiveness towards external pressure from OEMs (not supported).

The results of the hypothesis regarding the impact of network integration on the responsiveness towards external pressure from OEMs have an empirical $\beta = 0.034$, t statistic = 0.298. This implies no statistical significance at $p=0.766$. The strength of network integration that comes with transparency of information and collaborative planning may ensure better integration across parties; it does not guarantee a firm's ability to respond rapidly to changes in demand. These findings contradict the previous work (Danese et al., 2013; Roh et al., 2014; and Dubey & Gunasekaran, 2015) where internal and external integration have a positive impact on responsiveness. The results show that despite the importance of network integration in achieving responsiveness in wider literature, network integration is neglected in Indian auto component firms to meet OEMs' requirements. This can be justified by the silos that exist in Indian auto component supply chain where OEMs do not fully integrate all the Tiers in product design, knowledge sharing and market changes. While information integrity can result in better decision-making, it does not necessarily support quick responses to market changes as directed by OEMs within the manufacturing environment. It can be understood that external factors such as market volatility can create challenges for the firms despite a robust network integration.

These results indicate that network integration across Indian auto component firms supports planning and accurate information exchange for decision-making across the supply chain, but it does not enhance production and process flexibility for achieving responsiveness. This contradicts previous findings

stating that transparency, strategic alignment and collaborative planning resulting from network integration enhance responsiveness to market needs (Christopher, 2000; Morgan et al., 2023). It further indicates that a firm's internal capability in the form of dynamic scheduling and adaptive capacity holds more weight to enhance responsiveness. While network integration would enhance collaboration across firms, it is not a driver towards enhanced responsiveness.

10.4 Research Contribution

The study focuses on investigating how the technology readiness level impacts the operational performance of an organisation with the aim of assisting companies in strategising their internal factors to be compatible with Industry 4.0. In doing so, the findings from the qualitative and quantitative research add to the number of contributions to the literature and knowledge as discussed in the following sections.

10.4.1 Contribution from Qualitative Study

10.4.1.1 Technology Readiness Level Measurement Tool

The research is one of the first studies to define each level of readiness indicators in the context of the Indian auto component Industry which aligns with their current practices. No previous scale has defined the levels in this specific context. These readiness levels are informed both by extant literature, and data gathered from interviews with various auto component companies which revealed different levels of practice. Although previous studies have validated the scale in other countries, where five-level scales were used based on the process planning or assessing the readiness level of the whole organisation including human resources, product and service portfolio, and compliance (Sütőová, et al., 2020; Trstenjak et al., 2022), this model is oriented to manufacturing operations. Further, various studies have indicated the necessity of defining the readiness levels according to the context of the study that would align better with their activities and processes (Alcácer, et al., 2021; Chonsawat & Sopadang, 2020; Trstenjak et al., 2022). This study's readiness level ranking demonstrated this outcome in defining the precise levels reflecting the current activities and processes.

Sütőová et al., (2020) addresses the significance of studying readiness dimensions from the perspective of organisation's current state. This study explored the readiness factors for the adoption of Industry 4.0 through extant literature and empirical data analysis. Based on the review of the literature, the study found various readiness factors including i) automation; ii) machines and operating system integration; iii) operations data collection; iv) inventory management; v) communication between parties; vi) integration between suppliers and customers; vii) data-driven decision; viii) real-time tracking; ix) customer co-creation; x) collaboration; xi) interdepartmental collaboration and xii) leadership. These factors were not studied in the prior studies conducted in the Indian context. Thus, this study contributed to measuring the current technology readiness level within the auto component industry to gauge their current position on the readiness scale.

Furthermore, previous studies have considerably focused on the challenges faced by SMEs specifically the lack of strategy to understand the roadmap they can adopt to initiate the transformation process to prepare themselves for Industry 4.0 (Horváth & Szabó, 2019; Masood & Sonntag, 2020; Khanzode, 2021; Stentoft, et al., 2021; Mittal, 2018; Müller, et al., 2021). Additionally, no study was found for the auto component industry in the Indian context which is one of the main GDP contributor industries in India. Therefore, this research extended the study to fill the roadmap gap through a readiness assessment tool for auto component manufacturers.

10.4.1.2 Current practices within the Indian Auto Component Industry.

Various researchers have emphasised the need for tailored solutions that would fit the requirements of firms based on current technological usage (Paiola et al., 2021; Spaltini et al., 2022). Therefore, this study contributed to the requirement of a tailor-made approach by assessing the current technology usage practices of the Indian auto component industry which were integrated into the readiness tool. To gain an in-depth understanding of the technology usage across processes and activities involved in the auto component manufacturing industry, fifteen semi-structured interviews were conducted with companies across the auto component industry of varied sizes, where different technology adoption patterns were found and were categorised into three levels comprising low, medium, and high. The results found that while a few companies are more inclined towards adopting advanced technologies and exploring Industry 4.0 technologies, most of the companies are still following the concepts from the third industrial revolution, with a focus on automation of either machinery or processes rather than the overhaul of the entire organisation. However, these companies have demonstrated flexibility in terms of the adoption of automated types of machinery for achieving the efficiency in production process while ensuring quality standards. This was in line with the OEMs' demand and strict policies for conforming to quality parameters. The findings have also revealed the inefficiencies stemming from the current practices resulting in miscommunication and misalignments between the stakeholders, inefficient production planning, discrepancies and mismanagement related to inventory, limited visibility into inventory levels, and quality control gaps. These findings are the first findings to reveal the association between the current technology level and operational performance.

10.4.2 Contribution from Quantitative Study

10.4.2.1 The relationship between technology readiness level and operational performance

Auto components manufacturing companies are constantly looking to streamline operations while dealing with the constant pressure from OEMs to survive and remain competitive in the market. Vast research on Industry 4.0 seemed to acknowledge the benefits of using advanced technology in terms of achieving competitive advantage, and fulfilling customer requirements, but little weightage has been given to determine the direct impact of advancing the readiness towards the adoption of Industry 4.0 on operational performance. These two areas were only partially discussed in previous studies (Perez-Lara

et al., 2020; Crešnar et al., 2020; Patrucco et al., 2022). This study examined the influence of technology readiness level in the context of Industry 4.0 on operational performance. Moreover, the study conducted a review of extant literature on technology readiness's impact on operational performance. The operational performance measures (Chonsawat & Sopadang, 2020; Črešnar et al 2022; Patrucco et al., 2022) were not investigated in this context, rather they were broadly tested in terms of linking the operational performance with specific technologies rather than assessing the technology level across the processes and practices including collaboration level across the organisation, and leadership agility. Therefore, this study provides empirical extension into understanding the current practices or technology readiness level impact on production process efficiency, network integration and responsiveness towards OEM demand. The study found that readiness level significantly impacts operational performance.

10.5 Theoretical contribution

This research attempts to filling the theoretical gap by including RBV within the readiness model of Industry 4.0 in several ways. First, the study showed how specific resources are combined across different levels of readiness towards Industry 4.0 to achieve operational performance. The results of the study extend the frontier of RBV as Industry 4.0 readiness has scarcely been analysed from the perspective of RBV. This study responds to the preconditions highlighted by previous studies (Moica, et al., 2018; Črešnar et al., 2022) for the implementation of Industry 4.0 and presents a more fine-grained view of the resources required to push companies forward to Industry 4.0. RBV is used in this research to understand auto component firms' existing internal resources and give emphasis to critical resources for advancing the Industry 4.0 readiness level to achieve operational performance. Previous studies emphasised the importance of top management support as a critical success factor for implementing Industry 4.0 (Arnold et al., 2018; Pozzi et al., 2021). In the context of Industry 4.0, leadership initiatives to Industry 4.0 underline the importance of strategic resources in the RBV model (Barney, 1991).

This research is among the few studies that attempted to understand the relationship between Industry 4.0 readiness and operational performance, thus connecting RBV to Industry 4.0. This highlights the pool of resources that can be combined to provide the core Industry 4.0 infrastructure for achieving a competitive advantage, in this case, production process efficiency and network integration. Further, this study extends Vial's (2019) previous work in understanding digital transformation by leveraging a firm's existing resource base to enhance operational efficiency. The study suggests that communication, connectivity and information contribute to an integrated network structure and provide the potential for an improvement in a firm's performance. However, the study was limited in terms of investigating specific relationships that emerged from the inductive framework as proposed by Vial (2019). This research framework therefore confirms the assumption that inter-departmental collaboration, availability of data and leadership lead to a positive impact on organisation's operational performance.

Further, in the context of RBV, this research confirmed that data collection from suppliers and customers requires a fully integrated system with access to the real-time flow of information, allowing supply chain stakeholders to have access to the most up-to-date data. Real-time visibility of site locations and inventory optimises the production process. Firms with a higher degree of readiness exhibit better control of the production process through effective quality control and effective inventory management to reduce wastage by aligning the production output with OEMs' requirements. These factors are identified as differentiation factors in this study to maintain a competitive advantage.

This model responded to the recommendation by Ghobakhloo and Morteza, (2018) and Sütöová et al., (2020) for identifying the right roadmap in the context of the industry studied, and existing capabilities that result in varying Industry 4.0 dimensions. Thereupon, this research guides the firms to acquire specific resources towards the developmental stages of Industry 4.0 readiness that are anchored in the current practices of Indian auto component firms. This fine-grained view was only partially discussed in existing literature in terms of the resources and not the varied stages to fully adopt Industry 4.0 (Pérez-Lara, et al., 2018; Črešnar et al., 2022). Further, the twelve key ingredients which are utilised in this research are interrelated with each other, which provides the strategy for horizontal and vertical integration across the supply chain, providing a comprehensive pool of resources to facilitate the adoption of Industry 4.0 (Kagermann, 2014; Schroeder, et al., 2022).

Furthermore, network integration and production process efficiency are contextualised as a competitive advantage in this research through the strategic deployment of technological and non-technological resources for Industry 4.0 implementation as suggested by Črešnar et al., (2022) and Pozzi et al., (2023). This extends the traditional view of RBV, where firms not only compete on the basis of existing resources but the competitive positioning is strengthened through a highly interconnected network that fosters collaborative planning across supply chain partners and reduces inefficiencies with a faster response rate and more streamlined production. Additionally, the framework indicated an evolution of the static view of RBV to incorporate automation, machine and ICT integration, and data-driven decision-making capabilities to sustain competitive advantage within the framework of Industry 4.0 and dynamic supply chain environments.

10.6 Managerial Implications

The findings of this study are important for managers, including operations managers, technology managers, and purchasing managers. The results can be beneficial to understand the relevant factors for Industry 4.0 readiness that would improve operational performance. The information will also assist them in allocating the required resources for the potential adoption of Industry 4.0 technologies.

The purpose of the research was to design a guiding framework for Indian auto component managers to assist them in measuring the readiness level within their vertical operations (procurement, inventory management, production planning) and horizontal partners (suppliers and OEMs) in the context of the

technological changes that Industry 4.0 introduces to the industry. The readiness tool can contribute to assessing the manufacturing operations vertically by measuring the factors, including real-time availability of data from operations (operations data collection), data-driven decisions, and collaboration within an organisation. Further, the tool will also facilitate assessing the readiness level across the horizontal value chain, including communication and integration between suppliers and customers through assessment of communication channels, and real-time tracking level for integrated planning with supply chain partners. The study highlights the importance of each readiness factor towards operational performance. Based on the practical needs of companies, in terms of understanding what factors can streamline operations, the study helps to understand the process of identifying the current readiness by deploying the readiness tool and helps organisations to identify their position in terms of readiness with their competitors and industry. This will be useful to support managers who are keen on digitally transforming their businesses to gain more benefits from technological readiness in the form of operational performance.

The findings of the research clearly demonstrate the effectiveness of Industry 4.0 readiness and enabling technologies as valuable resources to enhance various dimensions of operational performance, including production process efficiency and network integration. In particular, the result of PLS SEM discussed in section 10.3 showed a positive relationship between technology readiness level and production process efficiency. The application of RBV determined that Industry 4.0 readiness factors are strategic resources and also allowed that management of these resources in combination contributes to operational performance improvement (Dyer & Singh, 1998; Lubis, 2022). Therefore, from the RBV perspective, managers should view Industry 4.0 enabling technologies such as ERP, RFID, and automation machinery with predictive capabilities as strategic resource to achieve enhanced operational performance. The implications for firms and managers include a strong investment in technological infrastructure, including automated machinery, RFID, tracking tools and an ERP system to facilitate Industry 4.0 adoption and thus streamline the production process. However, based on the findings of this study (as discussed in **section 8.4**), the investment in technologies could be one of the major challenges to the auto component industry as the auto component firms, specifically small and medium firms, have a relatively lower level of technologies. This situation is mainly due to the fact that the acquisition and implementation of technologies requires significant investment, which many small and medium-sized enterprises cannot afford. Given this challenge, the firms must rethink the organisation's strategy to make provision for funding the process of digital transformation. The strategy may entail exploring the government subsidies for investment in advanced technologies or venture capital, and practising phased adoption of technologies for deployment of resources to spread the financial burden over time. This approach aligns with the current resource-constrained reality of Indian auto component firms, primarily Tier 2 and Tier 3 (as discussed in **sections 2.5, 2.5.1 and 2.7.2**).

The findings indicate by embedding the resources for Industry 4.0 readiness into auto component manufacturing operations, the firm can enhance production process efficiency through effective inventory management and data-driven decision making. Supply chain managers need to realise that vertical and horizontal integration of the supply chain has the capability to adapt the production processes to the changing market requirements in real-time. Therefore, managers should realise that investment in digital tools can achieve responsiveness to OEMs' needs when they are transferred to production process capability. The investment in digital tools will also necessitate collaboration with technology partners. This suggests that managers will need to shift their focus from traditional buyer-supplier relationships towards the establishment of strategic partnerships with technology experts for knowledge sharing. From the RBV perspective, this strategic partnership can extend the external resource pool of the firm, where technology partners are identified as external resources by Latunreng and Nasirin (2019) to achieve competitive advantage.

With respect to operational performance, the results demonstrated the impact of readiness on production process efficiency and network integration. This is a significant contribution to management decision-making where the priority is always effective production planning and scheduling, and quality control while integrating the supply chain network to fulfil OEM demands as discussed by Müller, et al., (2018); Guo et al., (2020); Simões et al., (2021); Patel, et al., (2021). Though prior studies have discussed the measuring tools, the implication of utilising those tools to improve operational performance has been insufficiently explored. The readiness assessment tool provides actionable recommendations based on the factors generated from the extant literature and the findings of the exploratory study in the context of Indian auto component firms. These findings can provide the potential for practical applications of increasing the readiness level to eliminate operational inefficiencies. For instance, managers should aim to increase the level of automation and integrate machines and computing devices for predictive maintenance to reduce downtime, which affects production schedules and delivery. Additionally, active utilisation of data needs to be considered by managers to enhance the visibility across the vertical and horizontal value chains that would facilitate access to real-time product status, enable effective monitoring of inventory levels, and allow for production rescheduling for the optimisation of operational processes. These are also identified as the resources for increasing competitive advantage.

Through the review of the extant literature, the relationship between the existing technology level and operational performance in the context of Indian auto component firms was underexplored. This study attempted to fill this gap by developing a scale which will be useful as a diagnostic tool for managers in the assessment of the organisation's potential towards digital transformation. This research can support managers in understanding different levels of technology readiness which suit their current pool of resources across manufacturing operations. Firms with expert levels of tangible and intangible resources are more likely to improve the strategic adoption of Industry 4.0 technologies. Additionally, management teams need to collaborate across organisations and should invest to optimise

communication and coordination across departments to break down functional silos as identified from the findings of qualitative study (see **section 6.3.8**). This research suggests that collaboration across different departments, such as procurement, production, and quality control, can reduce inventory stockouts and overstock and streamline workflows across teams.

Finally, the findings for Industry 4.0 infrastructure, which emphasises communication, information and connectivity, can be used by managers to control supply chain processes. The utilisation of data can empower managers to monitor and optimise operations and processes throughout the supply chain. Further, managers are required to expand the collaboration across different disciplines within the organisation, including IT. High utilisation of data from within the organisation and outside the organisation can empower managers to make informed, evidence-based decisions for facilitating forecasting and scenario planning to enhance production process efficiency for an inclusive global supply chain.

10.7 Policy Implications

Currently, the Indian government, in line with global advanced manufacturing practices leveraging Industry 4.0 technologies, is demonstrating considerable interest in enhancing digital transformation. The government's initiative through several policies, including 'Make in India 2.0' and 'Digital India', was set forth to enhance digital infrastructure (discussed in **sections 2.4.3.3 and 2.5**). Incentivising the manufacturing sector to enhance digital infrastructure is a strategic approach adopted by the government to increase Industry 4.0 readiness, which is required to make India a manufacturing hub. Additionally, Confederation of Indian Industry (CII) reaffirmed the requirement of an Industry 4.0 readiness roadmap for the adoption of Industry 4.0 within the auto component industry to extend the factories beyond traditional automation and insisted on the implementation of an ERP system as a foundational tool for digital transformation (Chouhan et al. 2017). Additionally, ACMA envisions positioning the Indian auto component manufacturing industry at the forefront of digital transformation to align Industry progress with the 'Make in India' initiative (Dhawan et al., 2018) (refer to **section 2.4.3**). The findings of this research provide guidance for policymakers to expand the digital strategies by formulating policies that effectively support industry readiness for Industry 4.0.

Large-scale firms showed higher readiness (see **section 8.4**), suggesting that policymakers should mandate the disclosure of digital maturity indexes by large-scale firms to MSMEs to ensure uniformity of readiness across the industry for reducing resource heterogeneity across suppliers (as discussed in **section 2.7.1**). The readiness infrastructure framework can be utilised by policymakers to standardise the readiness indices to close the disparities within the sector across large-scale and MSMEs in terms of resources.

The findings from the qualitative study revealed that auto component firms have limited awareness and prior knowledge of Industry 4.0 technologies and the consequent benefits of adopting such technologies

(discussed in **section 6.3.10** and presented in **Table 6.12**). This was further established from the results of quantitative findings, explained through slow progress towards Industry 4.0 as Indian auto component stands at an intermediate level (see **section 8.3**), suggesting the scope for firms to achieve an advanced level before the complete transition to Industry 4.0. From the RBV perspective, this indicates the underutilization of knowledge-based resources (Chuang et al., 2013) that might hinder the competitive advantage in Industry 4.0. Policymakers should therefore establish a training and awareness program to foster digital literacy and enhance the knowledge around basic Industry 4.0 concepts such as data handling and collaboration. The collaboration with technology providers and increasing the availability of technology support through on-factory trials that demonstrate the benefits of increased readiness on optimising operational performance can provide a positive experience for firms. Besides, the collaboration between technology providers and firms should be incentivised as firms are often reluctant to adopt advanced and novel technologies due to the high cost involved and the uncertain benefits, also noted by previous studies (Chen et al., 2023; Li et al., 2024).

The relationship between Industry 4.0 readiness and production process efficiency implies that firms having more advanced capabilities in the form of data-driven decision making and a highly integrated supply chain can enhance production process efficiency. From the RBV perspective, these resources that characterise Industry 4.0 readiness are identified as the strategic resources to achieve competitive advantage in this study. From the findings of this research, Industry 4.0 readiness, as manifested through the combination of data-driven decision making and integrated supply chain, is a strategic source that enhances production process efficiency. This suggests policymakers should place greater emphasis on the establishment of dedicated performance-linked incentives for auto component firms. Additionally, RBV supports that firms lacking in internal capabilities can extend the partnership with technology partners experts and buyers to develop internal capabilities (Latunreng and Nasirin, 2019). Consequently, technology transfer partnerships can be facilitated between OEMs with established R&D and auto component firms to share digital systems. While OEMs involve Tier 1 in the vendor development programme, Tier 2 and Tier 3 are often excluded from digital adoption mentorships within the Indian auto component industry. Policymakers can emphasise a collaborative ecosystem so that Tier 2 and Tier 3 can benefit from the collective knowledge of large-scale companies comprising OEMs and Tier 1.

10.8 Use and Limitations of qualitative and quantitative methods

The current study contributes to the research by following the integrative approach through the adoption of qualitative and quantitative studies. This integrative approach was adopted to identify the current technology usage across Indian auto component firms and draw a proposition for the relationship between readiness level and operational performance (see **section 6.5**). The research employed an exploratory sequential design to answer the research questions. The primary data was gathered through semi-structured interviews with fifteen participants across the Northern auto component cluster in India

consisting of Haryana, Delhi, and Uttar Pradesh, as leading states. The qualitative exploratory study was conducted to gain an in-depth insight into the technology usage across the firms and the resulting impact on operational performance (discussed in **Chapter 6**). The qualitative data revealed that firms with higher levels of technological readiness tend to improve the operational performance defined by increased production process efficiency, network integration and responsiveness towards OEMs (discussed in **sections 6.4 and 6.5**). While these findings provided a valuable foundation for the subsequent quantitative analysis, the qualitative study posed certain limitations in terms of sample size and generalising the findings. The sample size for the qualitative study was relatively small, including 15 participants (discussed in **section 5.10.1.2**), collected across the northern states, which may limit the applicability of findings to the broader industry. Additionally, the limitation of time posed a significant challenge for including samples representing varied auto components, including engine components, suspension and braking, chassis, drive transmission, and electronics. Stratified sampling could have provided detailed insights, differentiating the readiness level and technology usage patterns across different components by including a proportionate sample from each sub-sector. However, due to time constraints, this study focused on the subset of the automotive sector i.e. auto component industry, rather than classifying the sample according to the specialised auto component segments. It is also important to point out the difference in patterns of adoption of technology across MSMEs and large-scale companies, as the findings are grouped together during the qualitative study. However, this might not have impacted the findings, considering the sample size in the qualitative study with MSMEs ($N = 8$) and large-scale companies ($n = 7$) proportionately represents the patterns of technology usage across these two different groups. Additionally, self-reported data from participants suggested the potential presence of response bias. This was evidenced through the tendency of participants to overreport positive operational outcomes, which may have affected the accuracy of the information provided.

To address these limitations, the study further employed a quantitative method. EFA was utilised (discussed in **section 7.6**) to refine the constructs derived from the exploratory study (as discussed in **section 6.5**). Following this, the study employed structural equation modelling (see **Chapter 9**) to test the relationship between readiness level and operational performance using an online survey questionnaire from 217 respondents. The use of PLS-SEM, while lacking in model fit indices, was suitable for this study's aim to explore rather than confirm theory. The limitation of generalisability and response bias embedded in the qualitative method was addressed during the quantitative phase. To mitigate the generalisability issue, survey responses were gathered from the wider industry encompassing firms across all auto component clusters. The larger sample size of 217 responses is representative of the auto component firms population (discussed in **section 5.10.2.3**), addressing the generalisability issues of the qualitative study. Response bias due to overly reporting of positive operational outcomes was mitigated by incorporating operational performance metrics (see **section**

7.4.2.2) and measuring the readiness level (see **Chapter 8**) to validate the findings from semi-structured interviews.

The research was based on a cross-sectional study design (discussed in **section 5.12**) where data were collected at a single point in time. The results could discern different inferences provided data is collected at different points in time. However, cross-sectional studies are best suited when studying the prevalence of specific conditions, which is the assessment of Industry 4.0 readiness across the auto component industry and identifying the relationship between Industry 4.0 readiness and operational performance without drawing causal inferences.

10.9 Limitations of the Study

Even though the research employed a robust methodology by combining an exploratory and explanatory study, the research is not without its limitations, which should not be overlooked. Addressing these limitations will also create new avenues for future research. The research limitations and future research are summarised as follows:

1. RBV has received attention for its role in understanding the competitive advantage rooted in the firm's existing resources. This theory, however, has received some criticism as it postulates that firms already have the resources in the form of IT and ICT infrastructure, ERP, and other technologies. Antoni et al. (2020) and Shehzad et al. (2022) identified that firms with better IT infrastructure utilise the resources and technologies to influence competencies and develop capabilities. Another limitation is that RBV does not take into account the adoption decisions of firms based on the external factors, including market forces, and is criticised for its inward emphasis by Yang et al. (2015).

The resources within the context of the Indian auto component industry have been located across numerous commentators (Dubbey et al., 2018; Tambade et al., 2019). Across these studies, RBV was described as falling short in generalising the findings across different contexts. Considering this, in future research, the framework can be harnessed across various industries for adaptation based on existing internal resources. Moreover, as this thesis applied RBV to understand the current pool of resources, it would be arguably beneficial to explore how firms perpetually reconfigure these resources in alignment with external factors, including technological changes, thus holding capacity to expand the framework to include a dynamic capability outlook. Although throughout this research, the internal and external resources for assessing the Industry 4.0 readiness levels from an RBV perspective have been emphasised, there are a myriad of external pressures that ought to be considered. These particularly may include globalisation and state policy that can additionally contribute to the firm's practices of adopting advanced technologies and achieving competitive advantage. Industry 4.0 developments are still in the infancy within the MSMEs, and that is the reason that readiness

level assessment was necessary to assess which confined the scope of the current study with a focus on a few technologies including ICT, data collection, communication-related tools, data gathering, automated machinery, RFID, and sensors.

2. The exploratory study is useful to auto component manufacturers, it presents a limitation in understanding the OEM's perspective and how the activities and practices of OEMs influence the overall industry.
3. As the researcher travelled to India to gather data from the companies because the participants were reluctant to do interviews online, the time and location pose a limitation for exploratory study. The data was gathered within a small time-frame of two months by visiting the plants. Further, only a few companies located within the Northern region of India were studied which limits the generalisation.
4. The study has shortcomings in generalisations as the study is confined to Indian industry. The industry setting and business environment of each country provide different opportunities and challenges towards the technology adoption level and readiness level may vary based on the competitive setting, awareness towards advanced technology and resource availability. Therefore, the findings would not be applicable to any other market setting. Further, the qualitative study included MSME large-sized companies, and as Industry 4.0 is an emerging area, SMEs are less prepared owing to a lack of awareness which would only provide limited technology usage as a measure to be prepared for Industry 4.0. Including only large firms may generate better results. As a result, the current conceptual framework might not be suitable for high technology-oriented firms.
5. The qualitative study's sample size overlooks the representation of the industry in terms of the specialised areas characterised by different auto components. While the sample was categorised according to the auto components sectors and different tiers, it might not give clear picture focussing on the operational variations across different subsectors such as electrical systems, and engine components. For instance, the engine components focussing on ICE and EV have varied production process and market dynamics. While EVs manufacturing is gaining momentum, the research only focuses on ICE manufacturing which follows less technology intensive production system as compared to EVs. Therefore, the research findings may be more applicable to traditional auto component manufacturers.
6. The study mainly focuses on manufacturing operations, while the research can be replicated in other manufacturing sectors due to similarities in operations. However, the findings cannot be generalised to any other sectors such as services or banking. This is because the service sector

follows different processes and sets of activities with different performance objectives; therefore, using the same measurement tool would be incongruous.

7. The data for the quantitative study was gathered from auto component firms encompassing all three tiers, including Tier 1, Tier 2 and Tier 3 (not segmented according to Tier 1, Tier 2 and Tier 3). Although all these firms are broadly classified as auto component manufacturers, they produce a diverse range of components, which dictates the tier structure within the industry. Products from different auto component firms and the manufacturing processes may vary significantly based on the nature of the end product. Therefore, It remains unclear whether the impact of Industry 4.0 readiness on operational performance would differ across all these tiers.

10.10 Future Research

1. In the future, macro-level factors, including government policies, could be harnessed to understand how government policies may contribute to the readiness of firms for Industry 4.0 adoption. This research focused on the manufacturing and operations-related readiness. Future studies could look into other dimensions, including market forces, social aspects, for achieving successful transformation to Industry 4.0. Therefore, Industry 4.0 adoption in the Indian auto component industry could be understood from the combination of several theoretical lenses, including DCT, institutional theory and social-technical perspectives.
2. This research only investigated the impact of readiness level on the operational performance. In future research it may be conducted to investigate the association between Industry 4.0 readiness and other areas within the organisation, including financial performance, human resources, and marketing. Additionally, factors attributed to technology readiness level only examined the operational processes and activities, future research might accommodate employee awareness, financial capability, product-services portfolio and organisational structure styles.
3. Future studies might look into the Industry 4.0 adoption landscape including advanced technologies like IoT, Artificial Intelligence, cyber-physical systems, and big data analytics. Additionally, research might involve developing a maturity assessment tool to evaluate the maturity of the Industry across companies that have already implemented at least one Industry 4.0 technology. This would facilitate an understanding of their patterns of readiness that has been achieved before the actual adoption of Industry 4.0. The current readiness tool could be further refined by incorporating empirical insights derived from the Industry 4.0 preparedness pattern observed in technology-oriented firms. Besides that, Industry 4.0 is a rapidly evolving area, and conducting longitudinal studies would provide insights into the evolutionary pattern of Industry 4.0 adoption.

4. The exploratory study was constrained by the number of interviews conducted due to time limitations which also resulted in the geographic concentration of the sample. The sample size for the exploratory study was small. In the future large sample size may help researchers to get a more generalised picture of the situation regarding Industry 4.0 adoption and readiness. In future, it would be useful to do a cross-section exploratory study for the identification of the interconnectedness of small-scale and large-scale companies for shaping technological adoption and advancement. This study only focuses on the auto component manufacturers, and future research could include OEMs to understand the advancements of processes they are planning to implement, which will impact these manufacturers. The research could be extended into other industries for example IT, banking, infrastructure sector. The research could be replicated to have a comparison study between developed and developing countries.
5. The data for this research was collected in 2023, therefore, it is possible that some of the findings might not be generalised to the current setting, as technology is a dynamic capability. A longitudinal study based on the case study from the interviewed companies would provide the external validity of this research's findings.
8. Finally, while the data was comprehensively collected from all tiers, including Tier 1, Tier 2 and Tier 3, it is unclear whether the impact of Industry 4.0 readiness on operational performance would differ across all these tiers. Consequently, potential future research could involve examining the differences and similarities in the relationship between industry 4.0 readiness and operational performance across different tiers in more depth, for example, comparing Tier 1 vs Tier 2 vs Tier 3 based on the specific auto components they manufacture.

10.11 Final Remarks

Industry 4.0 provides new avenues to the manufacturing industry in the form of business models, data-driven decision making, and co-creating products with customers. However, all these advancements can only be manifested by realising the preparedness level that is imperative for the adoption of Industry 4.0. This research provides various inputs that could be used to make the company Industry 4.0 ready through the formulation of a readiness tool. The present research investigates the current operational practices in the manufacturing arena to explore Industry 4.0 readiness through exploratory study. Further, the survey results established the gap in operational readiness, indicating that the current readiness level of the manufacturing industry stands at 2.4 on a scale from 1 to 4. The automotive industry needs to gear up in the areas including automation in the production field, machine and computing device integration, inventory management, communication and integration between suppliers and customers, data-driven decision making and partnering with technology partners to facilitate the digital transformation.

The study demonstrates the necessity of the readiness factors, which interact with each other to respond to the changing needs of the industry in terms of achieving production process efficiency, integrated network, and responsiveness towards OEM demand. The direct and indirect relationship between the technology readiness level and operational performance constructs enable the firm to achieve an automated manufacturing ecosystem characterised by efficient and optimal operational performance, by digitally repositioning their current practices in line with the readiness factors.

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Appendix 1: Systematic Literature Review Methodology

1.1 Overview

The aim of this section is to gather an understanding of the literature published in the field of Industry 4.0 readiness and operational performance. To extend the reliability of the result, a critical examination of the extant literature is conducted to understand the applicability of existing frameworks or readiness factors within the Indian auto component manufacturing operations. Further, it assisted in identifying and evaluating the existing work to establish the inconsistencies and gaps thus justifying the proposed study's contribution to accumulated knowledge (Pare, et al., 2015).

A bibliometric analysis in conjunction with SLR is carried out to identify the trend in terms of the countries that contributed to Industry 4.0 research and recurring themes in the selected literature (quantitative evaluation) (Donthu & Satish Kumar, 2021) followed by gaining a deeper qualitative understanding through manual analysis (qualitative evaluation). Bibliometric analysis is a quantitative method of evaluating and interpreting a large dataset used to summarise the large quantity for presenting the current state and trends of a research topic (M.Merigó and Yang, 2017). The quantitative and qualitative literature evaluation is adopted for conducting a well-rounded literature review. Bibliometric analysis illustrates the key areas of focus within the selected articles and maps out the knowledge structure in terms of the keywords and text data (Ardito, et al., 2019). Apart from identifying the trends, bibliometric analysis ensures objectivity and consistency in evaluating the literature and thus establishing the relationship in the literature which is not feasible in manual analysis (Zupic and Čater, 2014 & Cuc, 2019). Bibliometric analysis served as a powerful tool for the article classification into clusters (discussed in section 1.3.7.2) (Chen, et al., 2009 & Rossetto, et al., 2018). The identified clusters were further investigated manually in the existing literature (Palmatier, et al., 2018) for existing models and conceptual frameworks which provided conclusive evidence of the research gap in this area. For these reasons, the combination of these two review methods viz. bibliometric analysis and systematic literature review is adopted in this research. The following section presents the process and results of the reviewed literature.

1.2 Literature review process

1.2.1 Locating Studies

In this research, four databases are chosen which align with the research questions in the field of Industry 4.0: IEEE Xplore, ScienceDirect, SCOPUS, and Web of Science (WoS). Web of Science and SCOPUS are multidisciplinary citation databases that encompass a wealth of literature in subject areas including manufacturing, management, business, supply chain and logistics (Zhu and Liu, 2020 & Pranikuté, 2021). IEEE Explore specialises in technological trends and engineering research (Wilde, 2016) which gives access to literature exploring practical applications and advancements in the field of Industry 4.0. Complimenting this, Science Direct provides access to peer-reviewed articles which cover

research on the scientific and technical domains. This source was chosen to identify research bridging the gap between technological innovation and business applications of Industry 4.0. Further, the choice to include these databases was based on pilot research focusing solely on Industry 4.0 keywords. The volume and relevance of articles that surfaced during the keyword were key factors in their inclusion in the study. These databases aim to create a comprehensive analysis of the Industry 4.0 field, which will enable not only identifying the trends but will also delve into the theoretical and practical aspects of Industry 4.0. Additionally, the use of multiple databases avoids the likelihood of publication bias and assures adequate coverage (Bramer, et al., 2017).

Moreover, these four databases appeared to be the most frequently used repositories for conducting literature reviews on Industry 4.0. Authors have extensively utilised these databases to understand the key concepts related to Industry 4.0 including definitions, implementation of Industry 4.0 technologies in companies, and associated challenges (da Silva, 2020; Yıldız, 2019; Maresova, et al., 2018; Rupp, 2021; Raut, et al., 2020; Kosacka-Olejnik and Pitakaso, 2019; Elibal and Özceylan, 2021). These studies have affirmed the credibility of these databases and the pertinent adoption of these databases in the field of Industry 4.0 serves as a clear indication that these databases encompassing information closely aligned with the research topic.

1.2.1 Study selection and evaluation

Databases were searched using the keywords Industry 4.0, Blockchain, and Business model with the use of the following search strings “Industry 4.0 OR Fourth Industrial revolution OR Industrial revolution 4.0 OR smart manufacturing industry 4.0” AND “Blockchain OR blockchain technology OR smart contracts OR distributed ledger technology OR Blockchain 4.0 technology AND “Business model OR Business model innovation OR business model framework OR Business transformation model OR 4.0 Business model”. The keyword “business model” was searched with the integration of both other keywords – Industry 4.0 and blockchain individually to trace any possible business models across these areas.

The term Industry 4.0 and Business model is cross-disciplinary which includes the field of management and technology. The three search strings given in Table 1.2 were utilised for extracting the relevant articles and creating a database.

Table 1.2: Keywords used in SLR

Keywords	
Industry 4.0	“Industry 4.0, Fourth Industrial Revolution, Industrial Revolution 4.0, smart manufacturing Industry 4.0”, and
Blockchain	“Blockchain, blockchain technology, smart contracts, distributed ledger technology, Blockchain 4.0 technology”
Business model	“Business model, Business model innovation, business model framework, Business transformation model, 4.0 Business model”

1.2.2 Search Results

The search was conducted in two sections, which were further narrowed down to four phases. The first section includes keywords related to Industry 4.0 and business model. While the second section covered only business models based on blockchain technology. Considering the high literature that surfaced during preliminary research stages, to eliminate any possibility of missing an article which would specifically focus only on this area and not Industry 4.0 as a whole, the research on blockchain technology was conducted separately. The keywords were determined using synonyms or alternate names for Industry 4.0, Blockchain, and business model. The following keywords were used across all databases to maintain the uniformity of the results.

Initially, only the keywords Industry 4.0, Blockchain, and Business model were chosen to keep the results as broad as possible to remove the possibility of missing any business model or framework in these areas across any industry. The results that emerged from the first research by using the keywords Industry 4.0, Blockchain, and business model with the search query “Industry 4.0, Fourth Industrial revolution, Industrial revolution 4.0, smart manufacturing industry 4.0”, “Blockchain, blockchain technology, smart contracts, distributed ledger technology, Blockchain 4.0 technology” and “Business model, Business model innovation, business model framework, Business transformation model, 4.0 Business model” respectively are shown in Table 1.2:

Table 1.2: First phase: Individual keywords search

Keywords	WoS	SCOPUS	IEEE	ScienceDirect	Total
Industry 4.0	26,081	36,051	8,865	5,084	76,081
Blockchain	15,249	30,068	10,342	2,828	58,487
Business model	18,669	48,050	4,132	6,789	77,640

The next phase combined the Business model query with Industry 4.0 and Blockchain query separately by using the Boolean operator ‘AND’ which narrowed down the articles by extracting only those articles that cover both these terms in combination and eliminating all other possibilities. The query during phase 2 is given in Table 1.3 followed by the number of articles that emerged from using the search query in Table 1.4:

Table 1.3: Search query

Web of Science	(ALL= (("Industry 4.0" OR "Fourth Industrial Revolution" OR "Industrial Revolution 4.0" OR "smart manufacturing industry 4.0")) AND ALL= ("Business model" OR "Business model innovation" OR "Business model framework" OR "Business transformation model")) (ALL= (("Blockchain Technology" OR "Smart Contracts" OR "Distributed ledger technology" OR "Blockchain 4.0 technology")) AND ALL= ("Business model" OR "Business model innovation" OR "Business model framework" OR "Business transformation model"))
SCOPUS	(TITLE-ABS-KEY (("Industry 4.0" OR "Fourth Industrial Revolution" OR "Industrial revolution 4.0" OR "Smart manufacturing industry 4.0")) AND TITLE-ABS-KEY (("Business model" OR "Business model innovation" OR "Business model framework" OR "Business transformation model"))) (TITLE-ABS-KEY (("Blockchain Technology" OR "Smart Contracts" OR "Distributed ledger technology" OR "Blockchain 4.0 technology")) AND TITLE-ABS-KEY (("Business model" OR "Business model innovation" OR "Business model framework" OR "Business transformation model")))
IEEE	ALL ("Industry 4.0" OR "Fourth Industrial Revolution" OR "Industrial revolution 4.0" OR "Smart manufacturing industry 4.0") AND ("Business model" OR "Business model innovation" OR "Business model framework" OR "Business transformation model") ALL ("Blockchain Technology" OR "Smart Contracts" OR "Distributed ledger technology" OR "Blockchain 4.0 technology") AND ("Business model" OR "Business model innovation" OR "Business model framework" OR "Business transformation model")
ScienceDirect	Title, abstract, keywords: ("Industry 4.0" OR "Fourth Industrial Revolution" OR "Industrial revolution 4.0" OR "smart manufacturing industry 4.0") AND ("Business model" OR "Business model innovation" OR "Business model framework" OR "Business transformation model") Title, abstract, keywords: ("Blockchain Technology" OR "Smart Contracts" OR "Distributed ledger technology" OR "Blockchain 4.0 technology") AND ("Business model" OR "Business model innovation" OR "Business model framework" OR "Business transformation model")

Table 1.4: Second phase: Combining business model query with Industry 4.0 and Blockchain

	WoS	SCOPUS	IEEE	ScienceDirect	Total
Industry 4.0 And Business Model	473	1,222	66	180	1,941
Blockchain And Business model	177	710	55	102	1,044

The third phase extracted articles as given in Table 1.5 to match the following inclusion criteria:

1. Journal articles
2. Proceeding papers
3. Review articles/conference review
4. Papers in English

At this stage, editorial material, early access articles, book chapters, magazines, books, and surveys were excluded from the research, to ensure the research was more rigorous by only including article types which were peer-reviewed. Further articles not related to the manufacturing sector were excluded.

Table 1.5: Third phase: inclusion/exclusion criteria

Inclusion	WoS	SCOPUS	IEEE	ScienceDirect	Total
Industry 4.0	457	907	55	128	1,547
Blockchain	173	505	52	73	803

2,350 papers selected after applying the inclusion and exclusion criteria were analysed by reading the abstracts. Only those articles which fit the research question were chosen. Articles closely related to Industry 4.0 and blockchain-based business models or frameworks were identified by manually screening the titles and abstracts. While reading the abstracts, the articles which emphasised Industry 4.0 and blockchain-based business models, or frameworks in the manufacturing industry, supply chain, and automotive industry were selected to fit the research question. This resulted in 451 articles as presented in Table 1.6. Further, 116 duplicated articles were eliminated across all databases. Following a thorough review of full-text reading, 124 articles were included in the analysis.

Table 1.6: Fourth phase: Abstract reading

	WoS	SCOPUS	IEEE	ScienceDirect	Total
Industry 4.0	119	155	28	52	354
Blockchain	24	52	5	16	97

1.3 Descriptive Analysis

1.3.1 Trend Analysis

The articles included in the dataset were published between 2016 and 2024 which demonstrates that research in this area is cutting-edge. Table 1.7 and Figure 1.1 shows the distribution of publications in the field of Industry 4.0 over the period 2016-2024.

Table 1.7: Distribution of relevant Industry 4.0 articles

Year	No. of Articles	Percentage
2016	4	3%
2017	4	3%
2018	9	7%
2019	11	9%
2020	25	20%
2021	27	22%
2022	35	28%
2023	8	6%
2024	1	1%
Total	124	100%

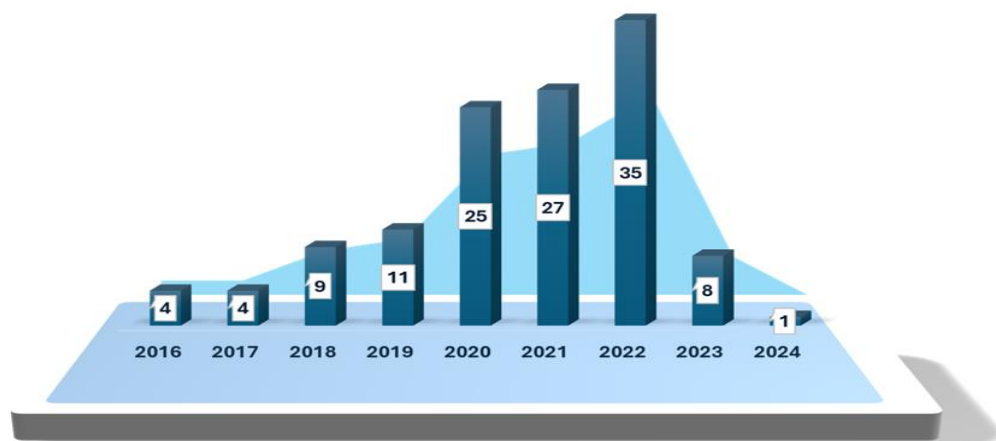


Figure 1.1: The trend of publications within the research field

Source: Author

Though many articles were published in the field of Industry 4.0, Blockchain technology, and Business model by considering these concepts individually, research on implementing these technologies from the perspective of business model transformation only gained momentum in 2016. The first article which utilised a combination of these keywords was traced in the year 2016, which verifies that the area is relatively new. The research started to gain popularity only in the year 2016 and since then, there was an upward trend in the number of publications. There was a significant increase in research in this area in the year 2020 to 2022; the number of articles almost doubled in the year 2020 compared to the previous three years (Table 1.7 and Figure 1.1). The significant increase was due to organisations becoming interested in the adoption of Industry 4.0 technologies, and exploring the opportunities developed by these technologies in a manufacturing context (Zheng, et al., 2021; Ghobakhloo, et al., 2021; Jamwal, et al., 2021) by adjusting or developing the new business model, which also suggests that innovation is not possible in isolation from the business model (Chesbrough, 2007). The research in the year 2022 was the highest. In 2023, there was a notable decline, not because of a limited number of publications, but due to the limited intersection between Industry 4.0 and manufacturing operations as the trend slightly shifted towards the sustainability theme (Lopes, et al., 2023 & Kopeinig, et al., 2024). It is also important to note that data for 2024 is still incomplete. The literature was last updated in May 2024, and only one study was found relevant upon utilising inclusion/exclusion criteria.

1.3.2 Industry 4.0 literature as per nature of the study

The research in the field of Industry 4.0 employed both empirical and non-empirical research. In the given study, as illustrated in Table 1.8 and Figure 1.2, 55% of the research is non-empirical based on theories, literature review, and conceptual analysis. In comparison, 45% of researchers used empirical methods and conducted interviews, surveys, and observations to collect data. The low percentage of empirical studies shows that many of the readiness frameworks were not tested with real-world data (Jesus and Lima 2020; Simetinger and Zhang, 2020; Bhatt & Kumar 2022; Schroderus, et al., 2022)

Additionally, as the Industry 4.0 area is relatively new (See Figure 1.1), most of the studies focus on understanding the concepts through secondary research.

Table 1.8: Literature distribution by nature of study

Nature of Study	Number of Studies	Percentage
Empirical	56	45%
Non-Empirical	68	55%
Total	124	100%

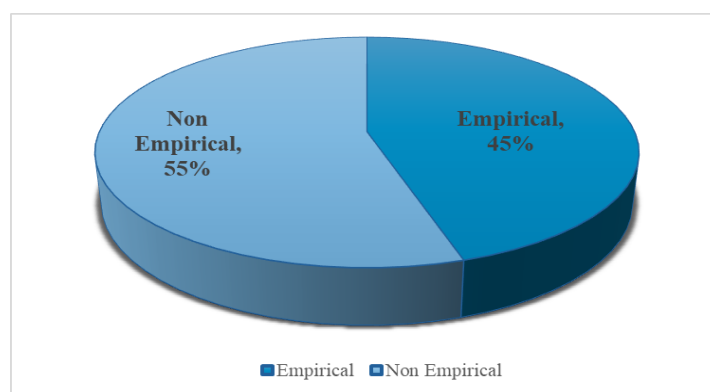


Figure 1.2: Literature distribution by nature of study

Source: Author

1.3.3 Industry 4.0 Research in Developed and Developing Countries

68% of the empirical research (38 studies) is conducted in developed countries as shown in Figure 1.3, which includes countries such as Germany, the USA, Italy, and Portugal as presented in Table 1.9. Studies in developing countries account for only 32% (18 studies) showing the need to conduct studies focusing on developing countries. Further, studies conducted in India only account for 7% as shown in Table 1.9 which positions the need to conduct this study in the Indian context. It is evident that the research area is more prevalent in developed economies, and developing economies need more attention to addressing the Industry 4.0 adoption strategy. It is also evident based on this distribution that Industry 4.0 adoption is not well understood or documented in developing countries.

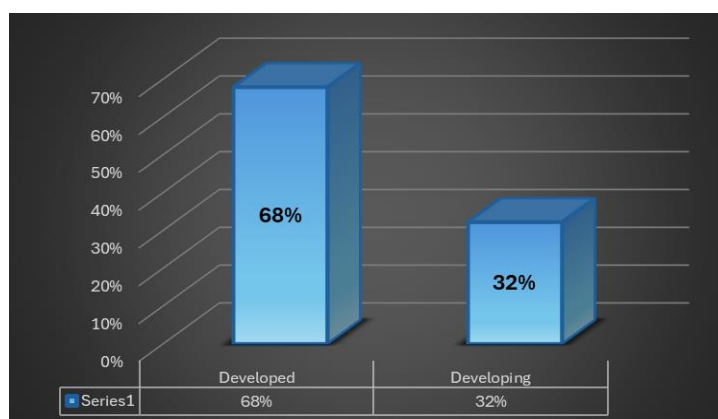


Figure 1.3: Literature distribution by country (Developed and developing)

Source: Author

Table 1.9: Distribution of empirical studies according to geographic location

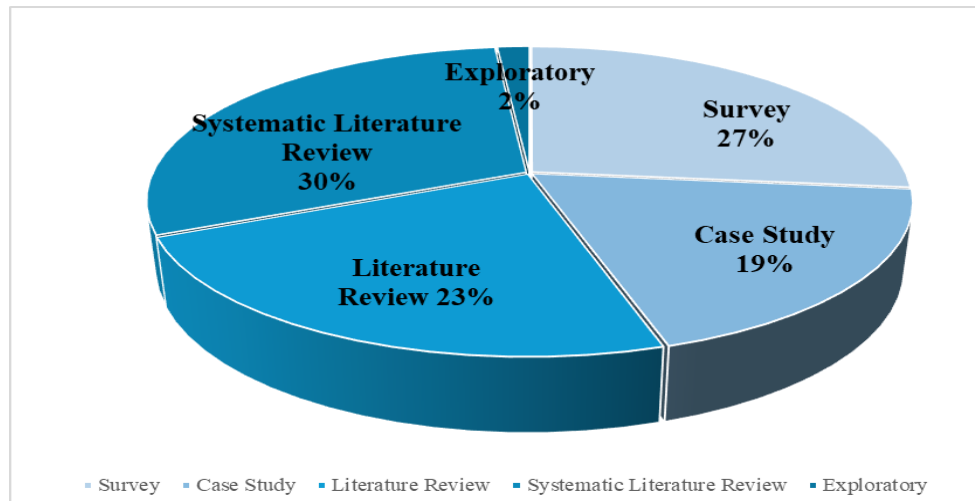
Studies conducted in Developed Countries		
Australia	1	2%
Canada	1	2%
Croatia	1	2%
Europe	5	9%
Europe and North America	1	2%
Europe, North and South America	1	2%
Germany	11	20%
Germany, Italy and USA	1	2%
Italy	4	7%
Portugal	3	5%
Serbia	1	2%
Slovakia	2	4%
Slovenia	2	4%
Sweden	2	4%
UK, Europe, America	1	2%
UK, USA, Singapore, China	1	2%
	38	68%
Studies conducted in Developing Countries		
Brazil	2	4%
China	4	7%
Egypt	1	2%
India	4	7%
Latin America	1	2%
Mexico	1	2%
Morocco	1	2%
Poland	1	2%
Romania	1	2%
Thailand	1	2%
Turkey	1	2%
	18	32%
Total Studies	56	100%

1.3.4 Methodologies and methods used in existing research

Concerning the research strategy adopted by the researcher in the given field, it is evident that a significant number of studies relied on a non-empirical research methodology with the literature review accounting as the most common approach as presented in Table 1.10 and Figure 1.4. 30% of the studies used systematic literature review, while 23% employed narrative literature review. In terms of the empirical studies, 27% of researchers applied a survey strategy, 19% applied a case study and 2 % applied an exploratory strategy.

Table 1.10: Research strategy adopted in the existing literature

Research Strategy	No. of Studies	Percentage
Survey	33	27%
Case Study	23	19%
Literature Review	29	23%
Systematic Literature Review	37	30%
Exploratory	2	2%
Total	124	100%

**Figure 1.4: Research strategy adopted in the field of Industry 4.0**

Source: Author

With respect to the research methods adopted within the selected articles, the majority of the studies were secondary and therefore researchers conducted a literature review accounting for 54% as shown in Table 1.11 and Figure 1.5. Further 23% of studies adopted questionnaires, followed by 22% of studies applied interviews.

Table 1.11: Research methods adopted in the existing literature

Research Methods	Number of Studies	Percentage
Systematic Literature Review	37	30%
Literature Review	30	24%
Questionnaire	28	23%
Interviews	27	22%
Others	2	2%
Total	124	100%

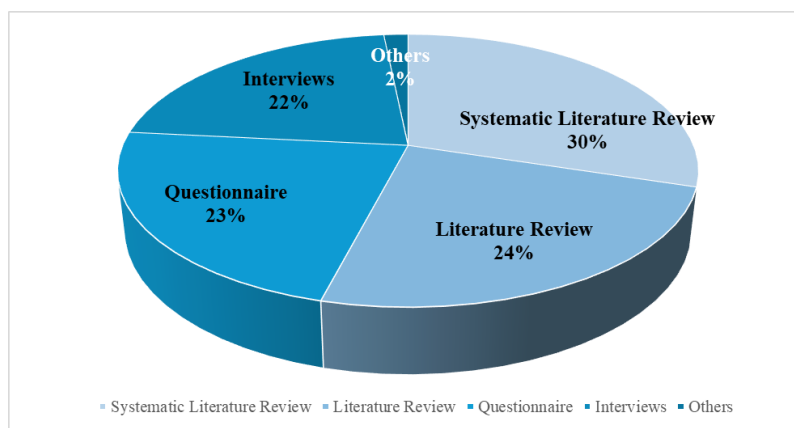


Figure 1.5: Research method adopted in the existing literature

Source: Author

1.3.5 Distribution of articles related to Industry 4.0 according to company size

Of the total empirical studies, a significant number of studies focused on small and medium enterprises (31%) as shown in Table 1.12 and Figure 1.6 because of the challenges associated with adopting digital technologies within SMEs as confirmed by Herceg, et al., (2020).

Table 1.12: Distribution of literature categorised as per company size

Size	No. of Studies	Percentage
Large Scale Enterprises	7	13%
Medium Sized Enterprises	3	5%
Small Enterprise	2	4%
Multi-National Corporation (MNC)	1	2%
Large and Medium Enterprises	4	7%
Small, Medium, and Large Enterprises	11	20%
SMEs	17	31%
Small and Large Enterprises	2	4%
Micro, Small, Medium and Large Enterprises	4	7%
Others (University, marketplace, startups)	5	9%
Total	56	100%

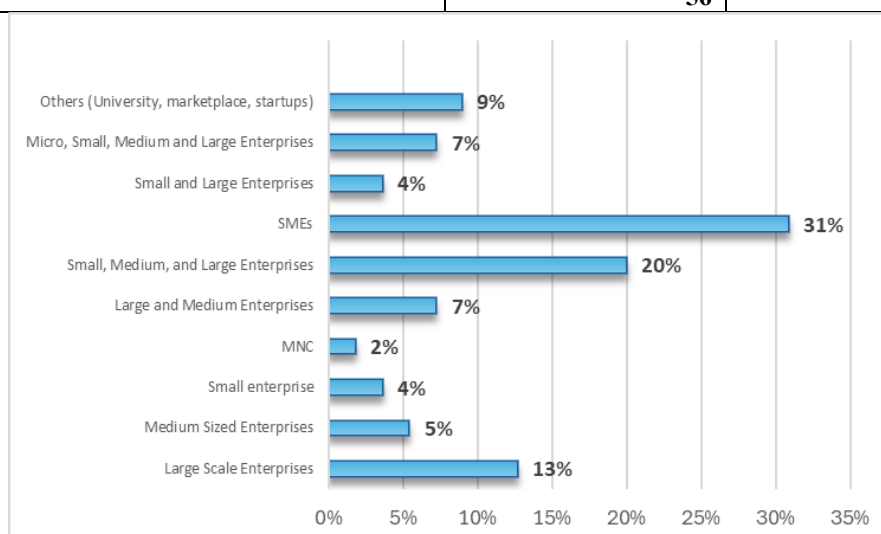


Figure 1.6: Number of studies related to Industry 4.0 categorised as per company size

Source: Author

1.3.6 Important publications and most cited articles in the field of Industry 4.0

Table 1.13 features the most highly cited article on Industry 4.0 and blockchain-based business models, which was selected for further investigation to examine the current state of research in this area. The literature reviewed thus far has primarily explored the impact of these technologies on business models, and has proposed taxonomies and archetypes for generating and capturing value (Nowiński & Kozma, 2017; Ibarra et al., 2018; Kohtamäki, et al., 2019; Weking et al., 2020). Despite some articles suggesting that technology-based business models may be advantageous for firms (Müller, et al., 2018; Weking, et al., 2020), there is still no established framework with empirical evidence demonstrating successful transformation or redesign of manufacturing firms' business models in the context of Industry 4.0.

Table 1.13: Most cited articles on Industry 4.0 or Blockchain-based business models

Title	Year	Citation count
Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0	2018	491
How blockchain technologies impact your business model	2019	242
Digital servitization business models in ecosystems: A theory of the firm	2019	237
How can blockchain technology disrupt the existing business models?	2017	215
Business Model Innovation through Industry 4.0: A review	2018	179
Leveraging Industry 4.0-A business model pattern framework	2020	120
The impact of blockchain technology on business models – a taxonomy and archetypal patterns	2020	116

From Table 1.14, it is evident that the majority of authors conducted a systematic literature review to gain a deeper understanding of the area; integrating Industry 4.0 and the business model. This clearly showed the relevancy of this research topic. These studies indicate the implication of Industry 4.0 on business model further emphasising the need for change in the business model that would align with Industry 4.0 technologies albeit are secondary and not focused on understanding the industry-specific needs of the Industry 4.0 business model in an empirical setting; thereby establishing the relevancy of undertaking this research. Further, the future direction calls for the incorporation of these concepts in the manufacturing or industrial setting (Ibarra et al., 2018; Weking, et al., 2020). The need to look at these concepts in conjunction with the industrial setting will be fulfilled in this research.

Table 1.14: Review of most cited articles

Author(s)/ Title	Focus	Research Strategy	Key findings	Future directions
Müller, et al., (2018)	Impact of Industry 4.0 business models on manufacturing SMEs	Survey (Interviews)	Industry 4.0 affects the three business model elements of manufacturing SMEs – value creation, value capture, and value offer.	Future investigation of how Industry 4.0 longitudinally transforms the business models of organisations that implement CPS.
Morkunas, et al., (2019)	Exploring how different types of blockchain impact business models.	Literature review/ conceptual	Linking nine blocks with the technology.	To explore which parts of the business model canvas are most affected by the implementation of a blockchain.
Kohtamäki, et al., (2019)	Understanding digital business models by using four theories: industrial organization, the resource-based view, organizational identity, and the transaction cost approach.	Systematic literature review	Preconditions of digital business models including customer co-creation and stakeholders' involvement.	To analyse internal capabilities for evaluating the fit of the business model.
Nowiński & Kozma, (2017)	To show that blockchain technology may disrupt the existing business models and to explore how this may occur.	Literature review	Blockchain technology affects business models by authenticating traded goods; facilitating disinter-mediation; improving operational efficiency.	Need for empirical research.
Ibarra et al., (2018)	the impacts of Industry 4.0 on Business Models as well as the possible innovations that can be applied to transform Business Models through Industry 4.0	Systematic Literature review	Emphasised the need for business model change by suggesting four ways viz. Internal and External Process Optimization, Customer Interface Improvement, New Ecosystems, and Value Networks, New Business Models: Smart products and services.	To provide a deeper understanding of the process of Business Model Innovation derived from the introduction of Industry 4.0 in the manufacturing world; a need for a wider survey of the research area.
Weking, et al., (2020)	Industry 4.0 Business Model Innovation	Case analysis (secondary data collected from literature and practitioner reports)	Identified 13 patterns of I4.0 Business models.	The taxonomy and patterns can be extended toward an I4.0 maturity model and further investigation of the digitization of manufacturing firms.
Weking, et al., (2020)	Blockchain business model	Conceptual	Identified five archetypal patterns of business models leveraging blockchain technology.	Further research into extending the taxonomy and patterns toward a maturity model.

1.3.7 Bibliometric analysis

Bibliometric analysis is a quantitative method of evaluating and interpreting a large dataset that is used to summarise the large quantity for presenting the current state and trends of a research topic (M.Merigó and Yang, 2017). Bibliometric analysis is conducted for numerous reasons which include investigating the authors, countries and institutions, and intellectual structure of extant literature within specific

research domains depending on the requirement of the author (Broadus, 1987; Donthu et al., 2020). Bibliometric analysis is performed in this research to obtain a clear picture of the knowledge gap in the areas of Industry 4.0 readiness factors by exploring secondary data. This analytic approach has been employed widely in the literature within Industry 4.0 fields, as evidenced by studies on the integration of blockchain within the Industry 4.0 platform (Bhatt, et al., 2021), Industry 4.0 and advanced manufacturing (Borregan-Alvarado, et al., 2020), business models in Industry 4.0 environment (Grabowska & Saniuk, 2022), and Industry 4.0 in the perspective of operations management (Sordan, et al., 2022). Given that Industry 4.0 is an emerging field with rapidly expanding literature where a large number of researchers are contributing to the field, by exploring the potential avenues in terms of its application across various fields, this study employs bibliometric analysis for the acquaintance with the previous informational foundation about Industry 4.0 to understand key terms and frameworks developed within the existing literature. The goal is to garner new insights into how these frameworks can be adapted within the auto component manufacturing processes to accelerate the preparedness towards Industry 4.0. Further, bibliometric analysis is conducted to identify the trends in the research field, and thus explore the depth of literature and the evolutionary traces of research within the captured data by creating a map based on text data (Emich, et al., 2020). In this research, VOSviewer is used as a visualisation tool for conducting bibliometric analysis to construct a network of co-occurrence links between terms based on text data (Eck & Waltman, 2009). VOSviewer has been widely used as an excellent scientific mapping tool in the technology literature due to the complexity of the research area in terms of multiple applications across varied domains (Oorschot et al., 2018; Sikandar, et al., 2021; Xu et al., 2021). 124 articles are visualised by presenting clear relationships between keywords using network visualisation and density visualisation which are discussed in the next section.

1.3.7.1 Co-occurrence analysis

VOS viewer is used to construct a network of keywords using co-word analysis which is a technique to examine the content of publication. The technique is chosen to understand the thematic relationship of words with each other (Liu, et al., 2019). Each keyword reflects the links, total link strength, occurrence of each term with other keywords, and cluster to which the keyword belongs. The occurrence indicates the number of documents in which the keyword has occurred (Eck and Waltman, 2014). The occurrence was based on full counting of title and abstract which indicates the total number of occurrences of a term in all documents. The terms were extracted from the full counting of the title and abstract field and as a result, 2,876 terms were identified. The threshold of this analysis was limited to the inclusion of keywords that occur a minimum of five times, and based on this criterion 299 out of 2,876 terms meet the threshold. Further, for each of the 299 terms, the most relevant terms based on the relevance score were selected. The final number of terms that were selected after applying the default choice of including only 60% of the most relevant terms narrowed down the selection to 179 terms split into eight clusters which are further visualised through the network, and density visualisation. The keyword with

the most frequent occurrence is presented in Table 1.15. Among the keywords selected, model and blockchain emerged as the significant keywords which can be explained by the number of occurrences of an item in the article, and the relationship represented through the linking lines.

Table 1.15: Highest occurred keywords

Keyword	Occurrence	Links	Total link strength
Model	322	172	5068
Blockchain	113	122	2368
Blockchain technology	97	110	1765
Implementation	62	130	1345
Adoption	53	99	1398
SMEs	49	116	1314
Data	46	99	1398
Relationship	44	130	1097
Capability	40	115	1029
Factor	36	96	851
Barrier	29	80	592
Dimension	28	89	826
Potential	28	100	533
Fourth Industrial Revolution	25	106	646
Information	25	107	788
Maturity model	24	87	527
SCR	24	28	1184
Efficiency	22	91	652
BMD	21	28	1057

1.3.7.2 Co-occurrence Network Visualisation

The clustering technique was used to identify the clusters. Further, items are categorised into clusters, and each cluster is determined by a different colour. The visualisation of the co-occurrence based on text data is displayed in Figure 1.7 and presented in Table 1.16. The size of the circle determines the weight of an item. The bigger the size of a circle, the higher the weight of the corresponding item, which also indicates the extensive body of literature in that area. While the thickness of linking lines displays the links and strength between the keywords (Eck and Waltman, 2014). Each colour (Table 1.16) constitutes a group of terms that are merged into the same cluster, and the distance between two items indicates the relatedness of the items. The closer the two items are located to each other, the stronger their relatedness. While the thickness of lines displays the links and strength of the topic area or keywords. Further, Figure 1.8 shows the index keyword density which reveals the general structure of the map which corresponds with the text co-occurrence map. Central themes include model, blockchain, potential, SMEs, implementation, fourth industrial revolution and SCR (supply chain resilience) based on density which indicates that these areas are commanding significant attention in the research area. The right side is heavily weighted towards the interconnected topics of blockchain technology including “trust”, “transparency”, “visibility”, “data”, “supply chain resilience” and “adoption”, indicating that these attributes are linked to the performance of the supply chain. These terms highlight the scholarly consensus on these attributes of blockchain technology which is the driving force in consideration of

this technology for improving the performance across the supply chain. Blockchain is recognised as a transformational technology for optimising the supply chain (Xu, et al., 2020; Li, et al., 2022; Chen, et al., 2022). Conversely, the left side of the map is more concentrated on Industry 4.0 technologies with terminologies like “additive manufacturing”, “big data”, “industrial IoT” and “3DP (3D printing)”. Industry 4.0 focuses more on optimising the production process and manufacturing industry with the highlighted terms including “manufacturing industry”, “production process”, and “production system” indicating the application of Industry 4.0 across the manufacturing sector (Savastano, et al., 2019; Guo, et al., 2020; Chatterjee, et al., 2021; Konstantinidis, et al., 2022; Pozzi, et al., 2023). The focused set of 124 articles was analysed based on keyword similarity and further categorised into eight clusters as shown in Table 1.17.

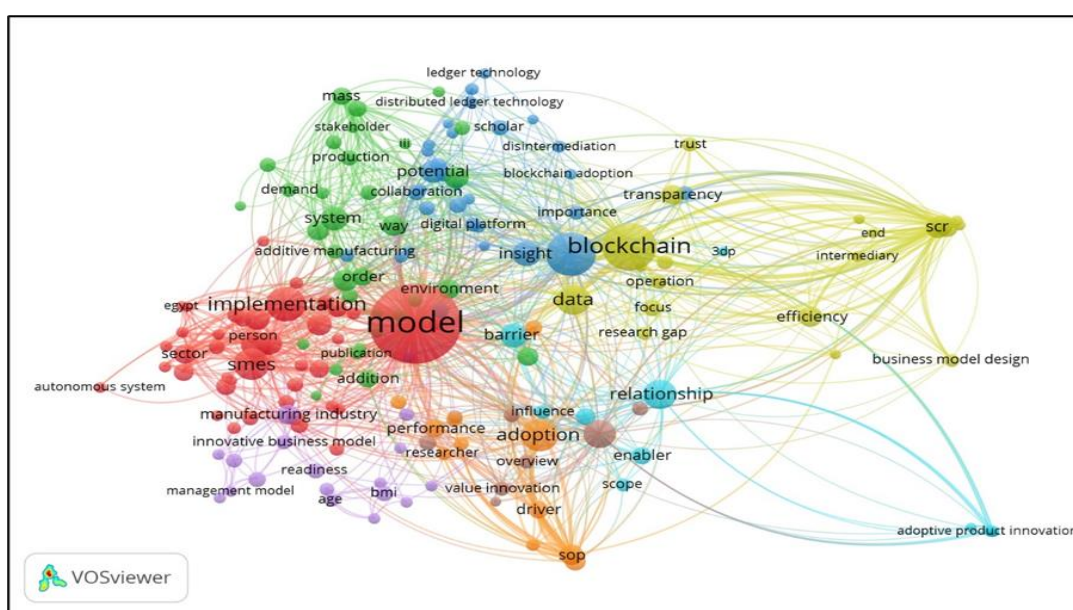


Figure 1.7: Co-occurrence network visualisation

Source: Author

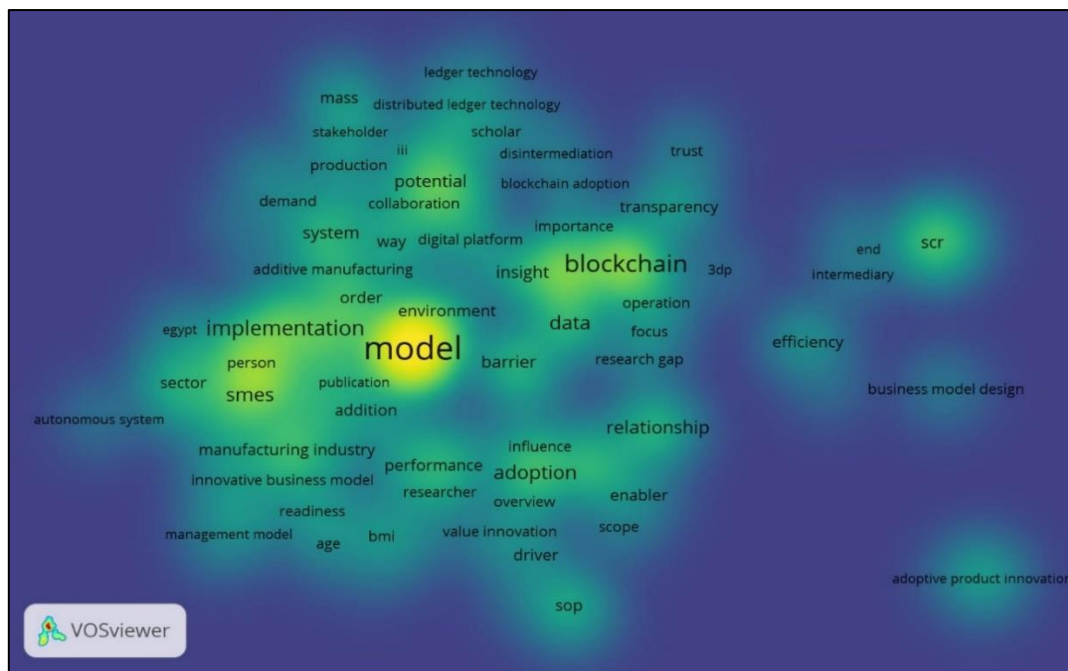


Figure 1.8: Indexed keywords density map

Source: Author

Table 1.16: Literature classification from co-occurrence analysis

Cluster	Themes	No. of keywords	Colour
1	Industry 4.0 key terms and strategic frameworks	40	Red
2	Industry 4.0 technologies in modern manufacturing	25	Green
3	Blockchain adoption in manufacturing operations	16	Blue
4	Exploring Business Models Utilising Blockchain Technology	17	Yellow
5	Role of business model in digital transformation	15	Purple
6	Challenges/ enablers of Industry 4.0 adoption	12	Brown
7	Understanding Business Models: A Multi-Dimensional Perspective	13	Aqua
8	Business model	10	Orange

The eight clusters identified from the bibliometric analysis are clubbed together and discussed further into four themes due to the interconnection between clusters as presented in Table 1.17. The first theme includes articles that discuss digital transformation in the context of Industry 4.0, challenges and barriers to digital transformation in manufacturing firms and maturity/readiness models. The second theme emphasises literature that discusses Industry 4.0 technologies in modern manufacturing. The third theme identified literature with a specific focus on Blockchain adoption in manufacturing operations which further includes Blockchain-based business models. The discussion on the business model is then

continued with literature emphasising Business models in digital transformation in the fourth theme. The clustering of research themes provides a useful framework for understanding the readiness factor across manufacturing operations in the context of Industry 4.0. The interconnectedness of the dominant clusters 1, 5 and 6 as shown in Table 1.17, suggests that there is a clear focus on exploring digital transformation in the context of Industry 4.0 across the manufacturing sector, particularly in terms of understanding the barriers and challenges to digital transformation. On the other hand, the peripheral clusters (Cluster 7 and 8 shown in Table 1.17) including business models in the digital transformation show a weaker connection to the dominant clusters, highlighting the need for further theoretical development in this area.

Table 1.17: Themes emerged from the identified clusters

Top terms	Total keywords identified in each cluster	No. of studies identified using keywords	Clusters	Themes	Authors
Digitisation, dimension, factor, I4.0, implementation, manufacturer, maturity model, SMEs, Barrier, enabler, relationship, readiness.	67	40	Clusters 1, 5 and 6.	Industry 4.0 key terms and strategic framework.	See Appendix 2
Customer, environment, fourth industrial revolution, information, mass, production.	25	14	Cluster 2.	Industry 4.0 technologies in modern manufacturing.	
Blockchain technology, collaboration, potential, visibility, platform Blockchain, BMD, data, efficiency, firm performance, SCR, transparency.	33	23	Clusters 3 and 4.	Blockchain adoption in manufacturing operations.	
Innovative business model, Servitisation business model, Product service system, model.	23	25	Clusters 7 and 8.	Role of business model in digital transformation.	

Appendix 2: Literature on Industry 4.0 (Themes identified in Chapter 2)

Authors	Title	Year	Themes	Size of company	Empirical or non empirical	Research Methodology	Research strategy	Research methods	Country
Müller, et al., (2018)	Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0	2018	1	SMEs	Empirical	Qualitative	Case study	Interviews	Germany
Konstantinidis, et al., (2022)	Assessment of Industry 4.0 for Modern Manufacturing Ecosystem: A Systematic Survey of Surveys	2022	1	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Savastano, et al., (2019)	Contextual Impacts on Industrial Processes Brought by the Digital Transformation of Manufacturing: A Systematic Review	2019	1	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Herceg et al., (2020)	Challenges and Driving Forces for Industry 4.0 Implementation	2020	1	SMEs	Empirical	Quantitative	Survey	Questionnaire	Serbia
Giudice et al., (2021)	A Self-Tuning Model for Smart Manufacturing SMEs: Effects on Digital Innovation	2021	1	SMEs	Empirical	Quantitative	Survey	Questionnaire	Italy
G. et al., (2019)	Industry 4.0: key findings and analysis from the literature arena	2019	1	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Fernández-Miranda, et al., (2017)	The challenge of integrating Industry 4.0 in the degree of Mechanical Engineering	2017	1	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	

Korner, et al., (2020)	Systematic literature review: Integration of additive manufacturing and industry 4.0	2020	1	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Chonsawat & Sopadang, (2020)	Defining SMEs' 4.0 Readiness Indicators	2020	1	Small enterprise	Empirical	Quantitative	Case study	Interviews	Thailand
Pozzi et al. (2021)	Industry 4.0 technologies: critical success factors for implementation and improvements in manufacturing companies	2021	1	Large Scale Enterprises	Empirical	Qualitative	Case study	Interviews	Italy
Crešnar et al. (2020)	Speeding Up the Implementation of Industry 4.0 with Management Tools: Empirical Investigations in Manufacturing Organizations	2020	1	Micro, Small, Medium and Large Enterprises	Empirical	Quantitative	Survey	Questionnaire	Slovenia
Kiraz et al., (2020)	Analysis of the factors affecting the Industry 4.0 tendency with the structural equation model and an application	2020	1	Small, Medium, and Large Enterprises	Empirical	Quantitative	Survey	Questionnaire	Turkey
Simetinger and Zhang, 2020	Deriving secondary traits of industry 4.0: A comparative analysis of significant maturity models	2020	1	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	
Paiola et al. (2021)	Prior knowledge, industry 4.0 and digital servitization. An inductive framework	2021	1	Medium Sized Enterprises	Empirical	Qualitative	Case study	Interviews	Italy
Stornelli et al., 2021	Advanced manufacturing technology adoption and innovation: A systematic literature review on barriers, enablers, and innovation types	2021	1	Not applicable	Non Empirical	Conceptual	Systematic literature review	Systematic literature review	

Jesus and Lima, 2020	Literature search of key factors for the development of generic and specific maturity models for industry 4.0	2020	1	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Botha et al., (2020)	A framework for digital transformation and business model innovation	2020	1	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	
Rübel et al., (2018)	A maturity model for business model management in industry 4.0	2018	1	Not applicable	Non Empirical	Conceptual	Literature review	Literature review	
Sütöová et al., (2020)	Learning needs determination for industry 4.0 maturity development in automotive organisations in Slovakia	2020	1	Large Scale Enterprises	Empirical	Quantitative	Survey	Questionnaire	Slovakia
Moica et al., (2018)	Change made in shop floor management to transform a conventional production system into an "Industry 4.0": Case studies in SME automotive production manufacturing	2018	1	SMEs	Empirical	Qualitative	Case study	Interviews	Romania
Cruzara, et al., (2021)	The value at the industry 4.0 and the digital transformation process: evidence from brazilian small enterprises	2021	1	SMEs	Empirical	Qualitative	Case study	Interviews	Brazil
King and Grobbelaar, (2020)	Industry 4.0 and Business Model Innovation: A Scoping Review	2020	1	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Bordeleau and Felden, (2019)	Digitally transforming organisations: A review of change models of industry 4.0	2020	1	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	

Paiola, et al., (2021)	The process of business model innovation driven by IoT: Exploring the case of incumbent SMEs	2022	1	SMEs	Empirical	Qualitative	Case study	Interviews	Italy
Alcácer et al., (2021)	Tracking the maturity of industry 4.0: the perspective of a real scenario	2021	1	Micro, Small, Medium and Large Enterprises	Empirical	Mixed Methodology	Survey	Questionnaire/ Interviews	Portugal
Ericson et al., 2020	Challenges of Industry 4.0 in SME businesses	2020	1	SMEs	Empirical	Qualitative	Survey	Interviews	Sweden
Müller and Voigt, (2017)	Industry 4.0 - Integration strategies for SMEs	2020	1	SMEs	Empirical	Qualitative	Case study	Interviews	Germany
Trstenjak et al., (2022)	Industry 4.0 Readiness Calculation-Transitional Strategy Definition by Decision Support Systems.	2022	1	Small, Medium, and Large Enterprises	Empirical	Quantitative	Case study	Interviews	Croatia
Črešnar et al. (2022)	It takes two to tango: technological and non-technological factors of Industry 4.0 implementation in manufacturing firms	2022	1	Large Scale Enterprises	Empirical	Quantitative	Survey	Questionnaire	Slovenia
Schroderus et al., (2022)	Towards a Pay-Per-X Maturity Model for Equipment Manufacturing Companies	2022	1	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	
Spaltini, et al., (2022)	Defining the Roadmap towards Industry 4.0: The 6Ps Maturity Model for Manufacturing SMEs	2022	1	SMEs	Empirical	Qualitative	Survey	Interviews	Europe
Ávila-Bohórquez and Gil-Herrera (2022)	Proposal and Validation of an Industry 4.0 Maturity Model for SMEs	2022	1	SMEs	Empirical	Quantitative	Survey	Questionnaire	Latin America
Núñez-Merino, et al., (2022)	Industry 4.0 and supply chain. A Systematic Science Mapping analysis	2022	1	Not relevant	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	

Parente et al., (2022)	Digital technologies review for manufacturing processes	2022	1	Not relevant	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Imbar, et al., (2022)	Digital Transformation Framework: A Review	2022	1	not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Bhatt and Kumar (2022)	Reindustrialization Using Industry 4.0 Maturity Models in Msmes and Tenets of Digital Transformation Phases	2022	1	Micro, Small, Medium and Large Enterprises	Non Empirical	Literature Review	Literature review	Literature review	
Khourshed et al., (2023)	Investigating the Readiness Factors for Industry 4.0 Implementation for Manufacturing Industry in Egypt	2023	1	Large and Medium Enterprises	Empirical	Quantitative	Survey	Questionnaire	Egypt
Leso et al., (2023)	The contribution of organizational culture, structure, and leadership factors in the digital transformation of SMEs: a mixed-methods approach	2023	1	SMEs	Empirical	Mixed Methodology	Survey	Questionnaire/ Interviews	Europe
Hajoary et al., (2023)	Industry 4.0 maturity assessment: a multi-dimensional indicator approach	2023	1	Large Scale Enterprises	Empirical	Quantitative	Case study	Questionnaire	India
Hu et al., (2024)	Navigating Digital Transformation and Knowledge Structures: Insights for Small and Medium-Sized Enterprises	2024	1	Not applicable	Non Empirical	Systematic Literature review	Systematic literature review	Systematic literature review	
Pérez-Lara, et al., (2018)	Vertical and horizontal integration systems in Industry 4.0	2020	1 and 3	Not mentioned	Empirical	Conceptual	Survey	Questionnaire	Mexico

Arnold et al., (2018)	What drives industry 4.0 adoption? An examination of technological, organizational, and environmental determinants	2018	1 and 2	Small, Medium, and Large Enterprises	Empirical	Quantitative	Survey	Questionnaire	German
Ivanov et al., (2022)	Cloud supply chain: Integrating Industry 4.0 and digital platforms in the “Supply Chain-as-a-Service”	2022	1 and 2	Not applicable	Non Empirical	Conceptual	Literature review	Literature review	
Lee, et al., (2021)	Understanding digital transformation in advanced manufacturing and engineering: A bibliometric analysis, topic modeling and research trend discovery	2021	1 and 4	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Favoretto et al., (2021)	Digital transformation of business model in manufacturing companies: challenges and research agenda	2022	1 and 4	Not applicable	Non Empirical	Conceptual	Systematic literature review	Systematic literature review	
Patrucco et al., (2022)	How Do Industry 4.0 Technologies Boost Collaborations in Buyer-Supplier Relationships? In assessing Industry 4.0 technologies, this study found that buyer-supplier visibility and buyer-supplier integration matters more than the digital technologies used.	2021	1 and 2	Small, Medium, and Large Enterprises	Empirical	Mixed Methodology	Survey	Interviews/ Questionnaire	Europe, North and South America
Teixeira & Tavares-Lehmann, (2021)	The confluence of I.4.0 technologies and new business models: a systematic literature review	2021	1 and 4	not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	

Gadekar et al., (2022)	Investigating the relationship among Industry 4.0 drivers, adoption, risks reduction, and sustainable organizational performance in manufacturing industries: An empirical study	2022	1 and 2	Large and Medium Enterprises	Empirical	Quantitative	Survey	Questionnaire	India
Ratte, et al., (2022)	Design or Redesign Business Models' Innovation in the Digital Transformation Context	2022	1 and 4	Not relevant	Non Empirical	Conceptual	Literature review	Literature review	
Boffa & Maffei, (2023)	Development and application of an Integrated Business Model framework to describe the digital transformation of manufacturing-a bibliometric analysis	2023	1 and 4	not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Zhang, et al., (2021)	The impact of digital transformation of manufacturing on corporate performance-The mediating effect of business model innovation and the moderating effect of innovation capability	2023	1 and 4	Micro, Small, Medium and Large Enterprises	Empirical	Quantitative	Survey	Questionnaire	China
Hopkins, (2021)	An investigation into emerging industry 4.0 technologies as drivers of supply chain innovation in Australia	2021	2	Small and Large Enterprises	Empirical	Quantitative	Survey	Questionnaire	Australia
Zulu, et al., (2022)	Strategy as a key driver of the Fourth Industrial Revolution transformation journey	2022	2	Medium Sized Enterprises	Empirical	Qualitative	Case study	Interviews	Brazil
Dalmarco et al., (2019)	Providing industry 4.0 technologies: The case of a	2019	2	Large Scale Enterprises	Empirical	Qualitative	Case study	Interviews	Portugal

	production technology cluster								
Chatterjee et al., (2021)	Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model	2021	2	Small, Medium, and Large Enterprises	Empirical	Quantitative	Survey	Questionnaire	India
Bogner et al., (2016)	Study Based Analysis on the Current Digitalization Degree in the Manufacturing Industry in Germany	2016	2	Large and Medium Enterprises	Empirical	Quantitative	Survey	Questionnaire	Germany
Botha, (2019)	Innovating for market adoption in the fourth industrial revolution	2019	2	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Maalmi et al., (2021)	Innovative and Sustainable Supply Chain Model in Industry 4.0 Based on Moroccan Industrial Field	2021	2	Medium Sized Enterprises	Empirical	Quantitative	Survey	Questionnaire	Morocco
Taghipour, et al., (2022)	The impact of digitalization on supply chain management: A literature review	2022	2	not applicable	Non Empirical	Literature Review	Literature review	Literature review	
Zulu, et al., (2022)	Strategy as a key driver of the Fourth Industrial Revolution transformation journey	2022	2	not applicable	Non Empirical	Conceptual	Literature review	Literature review	
Bansal et al., (2023)	Understanding the Role of Digital Technologies in Supply Chain Management of SMEs	2023	2	SMEs	Empirical	Qualitative	Interviews	Questionnaire	India
Safar et al., (2018)	Concept of SME Business Model for Industry 4.0 Environment	2018	2 and 4	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	

Guo et al., (2020)	A framework for personalized production based on digital twin, blockchain and additive manufacturing in the context of Industry 4.0	2020	2 and 3	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	
Pérez et al., (2022)	Mass customized/personalized manufacturing in Industry 4.0 and blockchain: Research challenges, main problems, and the design of an information architecture	2022	2 and 3	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Grabowska & Saniuk, (2022)	Business Models in the Industry 4.0 Environment—Results of Web of Science Bibliometric Analysis	2022	2 and 4	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Morkunas, et al., (2019)	How blockchain technologies impact your business model	2019	3	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	
Nowiński & Kozma, (2017)	How can blockchain technology disrupt the existing business models?	2017	3	Not applicable	Non Empirical	Conceptual	Literature review	Literature review	
Weking et al., (2020)	Leveraging industry 4.0-A business model pattern framework	2020	3	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Weking et al., (2020)	The impact of blockchain technology on business models – a taxonomy and archetypal patterns	2020	3	Not applicable	Non Empirical	Conceptual	Literature Review	Literature review	
Lohmer and Lasch, (2020)	Blockchain in operations management and manufacturing: Potential and barriers	2020	3	Start ups	Empirical	Qualitative	Case study	Interviews	Europe
Olvera & Mora, (2019)	A Comprehensive Framework for the Analysis	2019	3	Not applicable	Non Empirical	Conceptual	Literature review	Literature review	

	of Industry 4.0 Value Domains								
Schlecht, et al., (2021)	The prospective value creation potential of Blockchain in business models: A delphi study	2021	3	Not mentioned	Empirical	Quantitative	Survey	Questionnaire	Germany
Rückeshäuser & Ostern, (2017)	Typology of distributed ledger based business models	2017	3	SMEs	Empirical	Qualitative	Case study	Questionnaire	UK, USA, Singapore, China
Li, et al., (2022)	Blockchain-supported business model design, supply chain resilience, and firm performance	2022	3	Small, Medium, and Large Enterprises	Empirical	Quantitative	Survey	Questionnaire	China
Momo, et al., (2019)	Business models and blockchain: What can change?	2018	3	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Christopher et al., (2022)	Capabilities of digital servitization: Evidence from the socio-technical systems theory	2022	3	Large Scale Enterprises	Empirical	Qualitative	Case study	Interviews	Germany
Schuh (2019)	Monetizing Industry 4.0: Design Principles for Subscription Business in the Manufacturing Industry	2019	3	Small, Medium, and Large Enterprises	Empirical	Traingulation	Case study/Survey	Interviews/ Questionnaire	Germany
Levis, et al., (2021)	A look into the future of blockchain technology	2021	3	Not specified	Empirical	Traingulation	Survey	Interviews	Europe
Mayer, et al., (2021)	How Distributed Ledger Technologies affect business models of manufacturing companies	2021	3	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	
Marikyan et al., (2022)	Blockchain: A business model innovation analysis	2022	3	Not applicable	Non Empirical	Conceptual	Literature review	Literature review	
Sun et al., (2022)	Blockchain as a cutting-edge technology impacting business: A systematic literature review perspective	2022	3	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	

Xu et al., (2020)	On the impact of blockchain technology on business models and supply chain management	2020	3	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Papanikolaou, et al., (2021)	Implicit business model effects of DLT adoption	2021	3	Large Scale Enterprises	Empirical	Qualitative	Case study	Interviews	Europe
Chen et al., (2022)	A transaction cost perspective on blockchain governance in global value chains	2022	3	Others (marketplace)	Non Empirical	Qualitative	Case study	Netnography	
Balachander & Murugan, (2022)	Assessing the feasibility of Blockchain Technology in Automotive Industry	2022	3	not applicable	Non Empirical	Literature Review	Literature review	Literature review	
Zhu et al., (2022)	Blockchain technology and supply chains: The paradox of the atheoretical research discourse	2022	3	not applicable	Non Empirical	Systematic Literature review	Systematic literature review	Systematic literature review	
Sun et al., (2022)	Potential Requirements and Opportunities of Blockchain-Based Industrial IoT in Supply Chain: A Survey	2022	3	not applicable	Empirical	Mixed Methodology	Survey	Interviews	Shanghai
Perrelet, et al., (2022)	A Modeling Approach for Blockchain-inspired Business Models: An Extension of the e3-Value Method	2022	3	Not relevant	Non Empirical	Conceptual	Literature Review	Literature Review	
Nuerk & Dařena, (2023)	Activating supply chain business models' value potentials through Systems Engineering	2023	3	Not applicable	Non Empirical	Conceptual	Literature review	Literature review	
Kohtamäki, et al., (2019)	Digital servitization business models in ecosystems: A theory of the firm	2019	4	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	

Ibarra et al., (2018)	Business model innovation through Industry 4.0: A review	2018	4	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Müller et al., (2021)	The role of absorptive capacity and innovation strategy in the design of industry 4.0 business Models-A comparison between SMEs and large enterprises	2021	4	Small, Medium, and Large Enterprises	Empirical	Quantitative	Survey	Questionnaire	Germany
Gerlitz, (2016)	Design management as a domain of smart and sustainable enterprise: business modelling for innovation and smart growth in Industry 4.0	2016	4	Small enterprise	Empirical	Qualitative	Case study	Interviews	Germany
Culot et al., (2020)	The future of manufacturing: A Delphi-based scenario analysis on Industry 4.0	2020	4	Large and Medium Enterprises	Empirical	Qualitative	Survey	Focus group	Germany, Italy and USA
Gaiardelli et al., (2021)	Product-service systems evolution in the era of Industry 4.0	2021	4	University	Empirical	Qualitative	Focus Group	Interviews	Europe and North America
Müller et al., (2019)	Business model innovation in small- and medium-sized enterprises Strategies for industry 4.0 providers and users	2019	4	SMEs	Empirical	Qualitative	Case study	Interviews	Germany
Weking et al., (2018)	Archetypes for industry 4.0 business model innovations	2018	4	Not applicable	Non Empirical	Qualitative	Case study	Literature review	
Paschou et al., (2018)	Towards Service 4.0: a new framework and research priorities	2018	4	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Linde et al., (2021)	Evaluation of Digital Business Model Opportunities: A Framework	2020	4	Not mentioned	Empirical	Qualitative	Survey	Interviews	Sweden

	for Avoiding Digitalization Traps								
Budler et al., (2021)	The development of business model research: A bibliometric review	2021	4	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Zheng et al., (2021)	Product innovation in entrepreneurial firms: How business model design influences disruptive and adoptive innovation	2021	4	Not mentioned	Empirical	Quantitative	Survey	Questionnaire	China
Montes (2016)	Impacts of 3D printing on the development of new business models	2016	4	Small and Large Enterprises	Empirical	Qualitative	Case study	Interviews	Canada
Schaefer, et al., (2017)	A data-driven business model framework for value capture in Industry 4.0	2017	4	MNC	Non Empirical	Literature Review	Literature review	Literature review	
Agostini & Nosella, (2021)	Industry 4.0 and business models: a bibliometric literature review	2021	4	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Riesener, et al., (2020)	Methodology for the implementation of subscription models in machinery and plant engineering	2020	4	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	
Pietrewicz, (2019)	Technology, Business Models and Competitive Advantage in the Age of Industry 4.0	2019	4	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	
Schuh (2020)	Outcome economy: Subscription business models in machinery and plant engineering	2020	4	Small, Medium, and Large Enterprises	Empirical	Traingulation	Case study	Interviews	Germany
Averina et al., (2021)	Impact of digital technologies on the company's business model	2021	4	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	

Florén, et al., (2021)	Additive manufacturing technologies and business models – a systematic literature review	2021	4	Not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Ahmad, et al., (2020)	Behind the Blackbox of digital business models	2020	4	not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Arnold et al., (2020)	Innovative business models for the industrial internet of things	2020	4	not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Reis et al., (2022)	Business Models for the Internet of Services: State of the Art and Research Agenda	2022	4	not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Grabowska & Saniuk, (2022)	Development of Business Models in the Fourth Industrial Revolution: Conditions in the Context of Empirical Research on Worldwide Scope Companies Located in Poland	2022	4	Small, Medium, and Large Enterprises	Empirical	Quantitative	Survey	Questionnaire	Poland
Boßlau, (2021)	Business Model Engineering for Smart Product-Service Systems	2021	4	Not applicable	Non Empirical	Conceptual	Literature review	Literature review	
Simões et al., (2021)	Impacts on business models resulting from digitalization	2021	4	SMEs	Empirical	Qualitative	Case study	Interviews	Portuguese
Westphal, et al., (2016)	Evaluating potential Business Models for innovative Product Service Systems : Transparency regarding the relation to existing business	2016	4	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	
Armengaud et al., (2021)	DDI: A novel technology and innovation model for dependable, collaborative and autonomous systems	2021	4	Not applicable	Non Empirical	Literature Review	Literature review	Literature review	

Schuh et al., (2022)	Methodology for the Development of Value Propositions within Subscription Models	2022	4	Not applicable	Non Empirical	Conceptual	Literature review	Literature review	
Elhazmiri et al., (2022)	The role of additive manufacturing in industry 4.0: An exploration of different business models	2022	4	SMEs	Empirical	Quantitative	Survey	Questionnaire	UK, Europe America
van Tonder, et al., (2021)	Business model innovation success in the fourth industrial revolution	2021	4	SMEs	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Musara & Nieuwenhuizen, (2019)	Development of an integrative business model innovation framework	2019	4	not applicable	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Torre and Sanchez (2022)	Evolution of Servitization: New Business Model Opportunities	2022	4	Not relevant	Non Empirical	Systematic literature review	Systematic literature review	Systematic literature review	
Richnák, (2022)	Current Trend of Industry 4.0 in Logistics and Transformation of Logistics Processes Using Digital Technologies: An Empirical Study in the Slovak Republic	2022	4	Small, Medium, and Large Enterprises	Empirical	Quantitative	Survey	Questionnaire	Slovakia
Ferrigno, et al., (2023)	Industry 4.0 base technologies and business models: a bibliometric analysis	2023	4	Not applicable	Non Empirical	Systematic Literature Review	Systematic literature review	Systematic literature review	

Appendix 3: Thematic Analysis (Chapter 6)

	Second order themes	Supporting statements
Automation	Manual	<i>we have manual machinery so workers have to supervise all the machines</i>
	Partially automated	<i>We have a machine maintenance schedule for the whole year, maintenance department checks it from time to time irrespective of any failure. Another thing is we have a daily check sheet, we check the machinery daily, operators check the machine daily and production starts only after it is approved by the operator</i>
	Highly automated	<i>We mainly rely on pneumatic presses. These presses are all controlled by a Programmable machine control system. Then automation progressive tools are capable of doing high production with high consistency</i>
	No integration	<i>we communicate with the machine operator, informing them that the particular part was manufactured using specific machinery and that their inspection was inadequate</i>
	some coordination and communication between the machine and the computer	<i>Manufacturing is based on a proper system, and we have the latest machinery, all computer-based machines. to make a specific part we have to make the program on the machine then it works automatically. Manual inspection is required for tool wear</i>
	Integrated with room for further improvement	<i>Machines and ICT are not integrated for all lines, but we are gradually getting there, that is known as SCADA (supervisory control and data acquisition system) where we are recording all the data online so what it means is it will become integrated to the manufacturing process altogether</i>
Inventory management	Manual Inventory Control	<i>As such there is no software for managing inventory, it is all manual, in some cases, we are maintaining Excel</i>
	Partially Automated Inventory Control	<i>We are determined to operate on a just-in-time inventory system, We have software, we implemented research software, and we just have to review it. It demands sensing as the customer's data moves and adjust the inventory level. The counting is manual</i>
	Highly Automated Inventory Control	<i>It is cloud-based and I can check inventory record anywhere which gets updates as per requirement of customer</i>
Communication with buyers and suppliers	Manual - relying on traditional methods such as emails, phone calls	<i>The main communication channel is phone, WhatsApp, and email. We communicate with suppliers via email for raw material orders instead of issuing purchase orders due to fluctuating rates" (Case F)</i>
	sharing only fundamental details such as order details	<i>user-friendly software it takes hardly 2-3 minutes we have the supplier fixed, we have the material fixed, we know the quantity only three or four entries in the system in the software purchase order will be there all other terms and conditions are already existing so he has to fill the details and everything is mentioned there</i>
	Data transfer, such as inventory levels, demand forecasting	<i>We have software, we implemented research software that senses demand as the customer's data moves.</i>

Integration between suppliers and customers	no integration with suppliers or customers Visibility of site locations, capacities, and inventory levels between first-tier and customers Visibility of site locations, capacities, and inventory throughout the supply chain	<i>No scanning or RFID system. Just a code. Which is moving when he is releasing material from store to production and then from production to dispatch</i> <i>We know the quantity only three or four entries in the system in the software purchase order will be there all other terms and conditions already exist so he has to fill in the details and everything is mentioned there</i> <i>One way to simplify this process is by sharing the origin, alternating between Ghaziabad and the other site on different days. Whatever the reason or site status, it's acceptable to me</i>
Data-driven decision making	Top management utilizes the data coming from operators Plant managers and supervisors analyze historical and real-time data leverages big data analytics to gain valuable insights across multiple stakeholders	<i>the lower staff informed me about the requirement, so I addressed that issue</i> <i>Then there are common interfaces from the customer side, the plant side, and the purchase side and then we have the plant leadership the monitoring teams, production teams. So based on that, we issue certain targets and then a tracking mechanism</i> <i>Extrapolating data from various sources to strike the right balance between customer needs and supplier performance</i>
Real-time tracking	Limited product tracking Tracking with the involvement of third-party Tracking between manufacturer and seller without involvement of third party	<i>We use the traceability code though which is ingrained in the components. It's like the identification code of the company and packing slip as well, but we don't have any internal system</i> <i>The tracking system is already in place and consistent throughout the entire supply chain. However, for the "last mile" of the supply chain, which involves distribution, we rely on other entities</i> <i>By utilising real-time data from GPS and automation systems, along with the computing power of quantum systems</i>
Collaboration within organisation	departments operate in silos limited interaction between departments high level of interaction between departments	<i>it is managed by the company owners. We get schedules from buyers, then we plan our production, and then we communicate to our production staff like the foreman for the changeover of the production. It's a small company so it's direct communication and nothing is in writing, it's all verbal</i> <i>We have established a specialized forum called ATM (Active Task Management) where we focus on discussing critical points and urgent matters</i> <i>For collaboration, we have well-structured systems in place. One of them is the development process, which is cross-functional and allows for flexibility.</i>
Collaboration with technology experts	No involvement Foundational level of support	<i>The participant responded "No"</i> <i>we reached out to some consultants to understand the ways we can do so. It is for new technology for which we don't have people internally. Therefore, we are using some support from outside</i>

	Redesigning the manufacturing process and integrating technologies in collaboration	<i>We have tied up with the IIT Delhi, we have incubators, taken space for working around engines, electric vehicle, motor controllers for other legacy parts. We have companies, like Honda company and companies in Germany, these are all technical collaborators</i>
Leadership	lacks recognition of Industry 4.0 but is positive towards technology adoption exploring the potential benefits in the process of formulating investment plans	<i>Technology has always been useful, to adopt the technology and how the adopt the technology is the only issue</i> <i>Many times, it happens I'm not able to capture the real percentage first-time-through (FTD) percentage. For example, what is my scrap rate? All those things can be calculated through IoT itself as we are exploring the benefits.</i> <i>In terms of adopting advanced technology like say using Blockchain technology for our payment processing, that is one area, where we have already adopted this technology. We are currently working to integrate this into other processes</i>

Appendix 4: Ethics Approval



Faculty of Business, Law & Social Sciences Research Office
Curzon Building, 4 Cardigan Street
Birmingham
B4 7BD

BLSSethics@bcu.ac.uk;

14/Feb/2023

Miss Kokil Talan

kokil.talan@mail.bcu.ac.uk

Dear Kokil ,

Re: Talan /#10873 /sub1 /R(A) /2023 /Jan /BLSS FAEC - Industry 4.0 and Blockchain: Digital Transformation model of competitive performance for the automotive supply chain in SMEs in India

Thank you for your application and documentation regarding the above activity. I am pleased to take Chair's Action and approve this activity.

Provided that you are granted Permission of Access by relevant parties (meeting requirements as laid out by them), you may begin your activity.

I can also confirm that any person participating in the project is covered under the University's insurance arrangements.

Please note that ethics approval only covers your activity as it has been detailed in your ethics application. If you wish to make any changes to the activity, then you must submit an Amendment application for approval of the proposed changes.

Examples of changes include (but are not limited to) adding a new study site, a new method of participant recruitment, adding a new method of data collection and/or change of Project Lead.

Please also note that the Business, Law and Social Sciences Faculty Academic Ethics Committee should be notified of any serious adverse effects arising as a result of this activity.

If for any reason the Committee feels that the activity is no longer ethically sound, it reserves the right to withdraw its approval. In the unlikely event of issues arising which would lead to this, you will be consulted.

Keep a copy of this letter along with the corresponding application for your records as evidence of approval.

If you have any queries, please contact BLSSethics@bcu.ac.uk;

If you would like to provide feedback on the ethics process, please complete the feedback form using [this link](#).

I wish you every success with your activity.

Yours Sincerely,

Dr Stefania Paladini

On behalf of the Business, Law and Social Sciences Faculty Academic Ethics Committee

Appendix 5: Interview Guide

Questions
Company's current business model/practices
What is the current strategy followed by the company across raw materials, processes, and network structure?
What is the monitoring system in place to oversee these activities? - Inventory management – manual/ software ➤ If manual what are the consequences of inaccurate or incomplete raw material calculation? ➤ What other processes get affected. - sourcing raw materials and parts (procurement time which affects the production process, if all parties are not having access to the status of raw materials; delay in the production process affects the production schedule and output) - manufacturing and assembly (KPIs – cycle time, defect rate, downtime, and on-time delivery; how any lag in these indicators further impacts inventory levels, order fulfilment, lead time) - warehousing and inventory tracking (bar codes, RFID, GPS, QR codes) (inventory visibility at supplier, in transit, in warehouse, at customer; facilitate demand forecasting, managing inventory levels, improving delayed deliveries) - order entry and order management (purchase order, advanced shipment notice from supplier, BOL, BOM) - distribution across all channels, and - delivery to the customers. Establishing forecast accuracies which improves decision making across procurement and production – determining required inventory levels – impacts inventory carrying cost, inventory investment Lead times – cycle time of all processes, transportation mode, sourcing, automation Transaction cost - setting up or changing over the production line – cost, time (production) Purchasing – time, communication, planning and execution of purchase order Supply chain transactions: setup cost, changeover cost, purchase order cost, freight bill payment, transportation setup cost Lack of visibility results in ordering excess inventory or shortage of inventory Excess inventory – increases inventory carrying cost
The company's operations and processes involved in delivering the value - Operations across manufacturing processes - operations across procurement processes - operations across logistics processes
How do you ensure coordination of activities with supply chain partners, such as departments, suppliers, third-party companies, customers, and trading partners?
What are the organization's internal and external processes? - Internal processes in terms of technology, infrastructure, and customer management - External processes in terms of partners and stakeholders, suppliers, customers
Stakeholders' involvement
What are the key stakeholders involved?
Key internal and external processes in terms of involvement of suppliers, manufacturers, distributors, customers
What is the level of complexity involved across these processes, what are those complexities, and how company tackles them?
How do you ensure effective communication and collaboration among all parties in a value chain?

- What communication channels do you use to facilitate collaboration and communication among all parties in a value chain? - How do you ensure that all parties in the value chain have access to the necessary information and resources to collaborate effectively? - How do you manage and resolve conflicts or disagreements that may arise among parties in a value chain?	
Value creation	
The company's strategy involved delivering the value - Strategy across manufacturing processes - Strategy across procurement processes - Strategy across logistics processes	
How each of these strategies creates value across different processes?	
Is the company practicing any product differentiation strategy, if yes what's that strategy?	
Technology	
Any level of automation involved across 1, 2, 3	
Is the company using any technology for optimizing the operations and processes	
No: What is the reason for not using any technology?	
Yes: How do you integrate any technological changes in the existing manufacturing processes - What is the process for identifying and evaluating new technological changes to be integrated into existing manufacturing processes? - How do you determine which technological changes will provide the greatest benefits to the manufacturing processes? - What is the process for testing and validating new technological changes before integrating them into the manufacturing processes? - How do you ensure that new technological changes are compatible with existing manufacturing processes and equipment? - How do you monitor and measure the effectiveness of new technological changes once they have been integrated into the manufacturing processes?	
What are the company's Internal and external capabilities - Internal capabilities: Sharing of knowledge, internal communication, culture - External capabilities: new key partners, open innovation, external expertise/ consultation	
Is there any real-time monitoring or any kind of system in place to trace the processes?	
Do you believe adding a technological aspect can change that value, if yes how and what could be the challenges of adopting that technology?	

Appendix 6: Access Request Letter

Respected Sir/ Madam

I am writing to introduce myself in the capacity of Doctorate researcher. As part of ***“Research to Ph.D. (Business)”*** I am undertaking a research project titled ***“Industry 4.0 and Blockchain: Digital Transformation model of competitive performance for the automotive supply chain in SMEs in India”***.

My name is Kokil Talan and I’m a doctoral researcher in business at Birmingham City University (United Kingdom). My research intends to design a business model by focusing on Industry 4.0 and Blockchain technology. To achieve this objective, the research involves ascertaining the current business models, industrial strategies, processes, and industries’ responses toward digital transformation by automotive SMEs. The research will use the case study research approach where your organization will be identified as a single case and information will be obtained by using a semi-structured questionnaire. The questionnaire is designed to consider the motivation of top-level management in transforming the business models and business practices adopted so far within strategic settings. Semi-structured interviews will be conducted in understanding the phenomenon of value creation within your organization. The guided conversation with participants will help in understanding this with a greater depth for informed decision-making with the assistance of experts’ intuitive insight and judgment. The conversation will start with the opening question for idea generation which will serve as a basis for further questions. I’ll have to interact with the expert from your organization within the field of supply chain management, business operations, business strategy, and IT holding the strategic role (Product planning, customer solution, product and segment management, product manager, IT, and business architecture (Manager), service portfolio manager) and operational role (technology planning manager, Business planner, project manager) and spend a reasonable amount of time. A considerable number of questions will be asked to obtain enough information about how the organization operates across business competencies, processes, and functions for creating value. The informal conversations and observations will also be used in the research and will be recorded as field notes. For now, it is estimated that the participant will be interviewed once initially, and the interview will last for an hour. Though, the interviewee might be contacted again to obtain any further information, if required.

I would like to emphasize the potential for mutual benefits that my project will possess for your organization. Core examples include consultancy work through the sharing of findings chapter after the successful submission of the thesis.

Please be informed that participants have the right to withdraw the data anytime up until February 2024 but after that, they would not be able to withdraw as all data will have been coded, anonymized, and woven into the findings chapter and thesis submission.

I hope you understand the need for the project and how the process including discussions, recording the data, and dissemination of the findings to participants will be carried out to meet the objective of the research. I warmly invite you to meet me face-to-face or through MS teams for answering any further questions.

Warm regards

Kokil

Kokil Talan

Kokil.Talan@mail.bcu.ac.uk

PhD Researcher in Business

Birmingham City University's Faculty of Business, Law, and Social Sciences.

Contact details and further information

If you have any questions or concerns about this research project, please email one of the following contacts:

- Primary Researcher: Miss Kokil Talan – Kokil.Talan@mail.bcu.ac.uk
- Doctoral Supervisor: Dr Shishank Shishank – Shishank.Shishank@bcu.ac.uk
- Doctoral Supervisor: Dr Di Li – dili.sophia@outlook.com

If you remain unhappy with this process or if there is a problem, please contact Birmingham City University's Faculty of Business, Law and Social Sciences Ethics Committee at: blssethics@bcu.ac.uk

Appendix 7: Participant Information Sheet

Project Title: Industry 4.0 and Blockchain: Digital Transformation model of competitive performance for the automotive supply chain in SMEs in India.

Dear potential participants,

As part of “Research to Ph.D. (Business)” I am undertaking a research project which is aimed at proposing a transformative business model which will provide the theoretical and practical framework to Indian SMEs to speed up the adoption of Industry 4.0. The purpose of the research is to examine the current business model of SMEs and assess the potential challenges faced by the enterprises in changing their business model to involve I4.0 and blockchain technology within the manufacturing ecosystem. Further, the objective of the research is to design a business model with Industry 4.0 and blockchain as key components for achieving digital transformation. The research will address the need of Indian SMEs to shift from traditional industrial processes which are ruled by the center-oriented production process towards network-oriented production processes for product variety and customization managed by smart technologies enabled by I4.0. The research is intended to provide SMEs with an integrated manufacturing business model which can combat the industry 4.0 transition for approaching new technologies in new ways for making the manufacturing process more flexible, dynamic, agile, and adaptive. To achieve this aim, the research focus on answering the following questions:

1. What are the prevailing I4.0 elements practiced by your organization?
2. Adoption of any I4.0 technologies in the organizations so far from a strategic perspective.
3. What potential challenges were faced concerning the adoption?
4. Identifying the current business model.

Further, based on the research aims, the selection criteria is designed which includes the SMEs located within the Northern region of India and operating in automotive manufacturing as characterized by:

Manufacturing SMEs with investment in Plant & machinery and the annual turnover as follows:

Classification	Small	Medium
Manufacturing Enterprises	Investment in Plant and Machinery or Equipment: Not more than Rs.10 crore and Annual Turnover; not more than Rs. 50 crores	Investment in Plant and Machinery or Equipment: Not more than Rs.50 crore and Annual Turnover; not more than Rs. 250 crores

The research requires the participation of experts from the field of supply chain management, business operations, business strategy, and IT within Indian SMEs. To answer these questions, the knowledge, and experience of the people having the operational and strategic roles will be required to understand the business methods, management practices, activities, and processes. Discussions around the level of awareness of industry 4.0 within the organization and the findings regarding the current business models, industrial strategies, and industries’ response toward digital transformation for value creation will be utilized to verify the framework which is already designed at this stage using the available literature in the field.

The information will be obtained through semi-structured interviews in understanding the phenomenon of value creation within your organization and the functions and processes involved thereof for creating that value. The guided conversation with participants will help in understanding this with a greater depth for informed decision-making with the assistance of experts' intuitive insight and judgment. The conversation will start with the opening question for idea generation which will serve as a basis for further questions. The researcher will have to interact with the expert from your organization within the field of supply chain management, business operations, business strategy, and IT holding the strategic role (Product planning, customer solution, product and segment management, product manager, IT, and business architecture (Manager), service portfolio manager) and operational role (technology planning manager, Business planner, project manager) and spend a reasonable amount of time. A considerable number of questions will be asked to obtain enough information about how the organization operates across business competencies, processes, and functions for creating value. The informal conversations and observations will also be used in the research and will be recorded as field notes. For now, it is estimated that the participant will be interviewed once initially, and the interview will last for an hour. Though, the interviewee might be contacted again to obtain any further information, if required.

You are therefore invited to participate in the research. Participation will be completely voluntary without any obligation or social pressure to assist the research and there will be no negative consequences for not taking part in the research. It will be ensured that the research does not harm any participant psychologically, financially, or socially and participants will be given the right to withdraw from the research at any time. This information guide will assist you in understanding the requirement of the project so that you can decide if you want to take part in the research or not.

Potential risks of participation

The research seems not to have any identified physical risk. The psychological risk is minimal as the research does not include any sensitive topics which might cause distress.

Right to informed consent and to withdraw

You will have every right to withdraw from the research at any time without giving any further explanation or stating the reason for doing so. The data collected from you up to that stage will be immediately destroyed in the situation where you request not to use your data. Otherwise, data will form part of the analysis and discussion. Also, when the research commences, you will be asked to declare the initials of the first name and surname of your favorite celebrity and then the date of the day of your birthday. For example, a participant called Kokil Talan (myself) would be codified as HP28 (Harry Potter) 28th September).

Right to confidentiality and anonymity

The responses that are discussed within the open (Round 1) and close-ended questionnaire (Round 2) will be kept strictly anonymous and confidential and comments will never have their name mentioned. Moreover, all research interview transcripts will be codified. Interviews will be recorded using an audio recording tool and all data and transcripts will be stored securely on BCU's One Drive Account. This is to ensure the protection of all data.

In guidance with General data protection regulation (GDPR) compliance, data will be stored on BCUs One Drive for 10 years after the completion of the research. However, you can withdraw your data anytime up until February 2024. After February 2024 you will not be able to withdraw any data as all data will have been coded, anonymized, and woven into the findings chapter and thesis submission. You can further contact BCU's Data Protection Officer at informationmanagement@bcu.ac.uk or

alternatively telephone +44 (0) 121 331-5288 in case you have any concerns about how your data is stored.

Contact details and further information

If you have any questions or concerns about this research project, please email one of the following contacts:

- Primary Researcher: Miss Kokil Talan – Kokil.Talan@mail.bcu.ac.uk
- Doctoral Supervisor: Dr Shishank Shishank – Shishank.Shishank@bcu.ac.uk
- Doctoral Supervisor: Dr Di Li – dili.sophia@outlook.com

If you have any complaints concerning how research is conducted, please contact BCU_Ethics@bcu.ac.uk

Moving forward, if you have understood the information provided and would like to participate in the research, please sign the consent form which is attached below this document.

Thank you for your valuable time and for considering your participation in the study.

Appendix 8: Consent Form

The purpose of the study is to design a transformative business model which will assist the Indian automotive SMEs and manufacturing industry in the application of Industry 4.0 by demonstrating the strategy for the adoption of business models in the I4.0 related areas. The research identifies the field of action for Indian SMEs by designing a business model which uses the combination of a theoretical and practical framework for I4.0 application within Indian SMEs. The research examines the readiness level of disruptive technologies like industry 4.0 and Blockchain in small and medium enterprises in the Indian manufacturing industry and thus provides solutions to the enterprises which recognize the need for adoption of this technology but lack the approach and a framework model for embracing digitalization.

The research will use the case study research approach where your organization will be identified as a single case and information will be obtained by using a semi-structured questionnaire. The questionnaire is designed to consider the motivation of top-level management in transforming the business models and business practices adopted so far within strategic settings. Semi-structured interviews will be conducted in understanding the phenomenon of value creation within your organization. The conversation will start with the opening question for idea generation which will serve as a basis for further questions. I'll have to interact with the expert from your organization within the field of supply chain management, business operations, business strategy, and IT holding the strategic role (Product planning, customer solution, product and segment management, product manager, IT, and business architecture (Manager), service portfolio manager) and operational role (technology planning manager, Business planner, project manager) and spend a reasonable amount of time. A considerable number of questions will be asked to obtain enough information about how the organization operates across business competencies, processes, and functions for creating value. The informal conversations and observations will also be used in the research and will be recorded as field notes. For now, it is estimated that the participant will be interviewed once initially, and the interview will last for an hour. Though, the interviewee might be contacted again to obtain any further information, if required.

This document is used to check that you have understood the objective of the project and what is expected from you as a participant and that you are willing to participate in the research. A checklist is available for you at the end of this form which will help in understanding your role and your rights as a participant.

If you wish to withdraw from the research, you will have every right to withdraw from the research at any time without giving any further explanation or stating a reason for doing so. The data collected from you up to that stage will be immediately destroyed except in the situation where you willingly give consent and permission to use the data. In the case where you lose the ability because of unforeseen events to consent, the data will be automatically destroyed. Please be aware that you can withdraw the data anytime up until February 2024 but after that, you would not be able to withdraw as all data will have been coded, anonymized, and woven into the findings chapter and thesis submission. Also, your identity will be kept strictly confidential, and any data collected during the research will be stored in a password-protected file. Also, your name will be kept anonymous, and the data will be stored using a pseudonym which will guarantee confidentiality.

Questions	Responses
You have read and fully understand the participant information sheet	Yes/No
You have had the opportunity to ask questions	Yes/No
You understand that participation is entirely voluntary	Yes/No
You agree to take part in a semi-structured interview whereby the interview will be audio recorded using a Dictaphone.	Yes/No
You understand that you have the right to withdraw at any time and for your data to be destroyed at any time up until February 2024	Yes/No
You understand that your data will be destroyed if you ask to be removed from the study?	Yes/No
You always understand your right to anonymity/confidentiality?	Yes/No
Do you consent for your data to be included in public engagement and dissemination events?	
Yes/ No	

Signature/mark of participant: _____

Signature/mark of researcher: _____

Date:

Appendix 9: Survey Questionnaire

Evaluating Industry 4.0 Readiness and manufacturing operational efficiency

Hello!

Thank you for agreeing to participate in this survey. The survey is a part of Ph.D. research that examines the readiness level of disruptive technologies like Industry 4.0 and Blockchain in the Indian manufacturing industry and thus provides solutions to the enterprises which recognize the need for adoption of this technology but lack the approach and a framework model for embracing digital transformation.

The survey should not take more than 4-5 minutes to complete, and information obtained through it will be analyzed as a part of the Researcher's Ph.D. project. By completing this survey, you are agreeing to the use of information provided by you for the above research. The responses will be kept strictly anonymous and confidential. If you have any complaints concerning how research is conducted, please contact BCU_Ethics@bcu.ac.uk

Thank you for your valuable time and for considering your participation in the study.

If you have any questions or concerns about this research project, please contact the researcher at Kokil.talan@mail.bcu.ac.uk

There are three sections in this survey. The first section covers the demographic information. The second section evaluates the level of readiness for Industry 4.0 within the manufacturing sector and the third section examines the efficiencies and inefficiencies resulting from the current practices. Kindly respond to all questions.

Part I

1. Job Title -----
2. Years of experience
3. What best describes your role?
 - a) Senior Manager/ Specialist
 - b) Associate
 - c) Vice president
 - d) C-Level executive (CEO, CMO)
 - e) Director
 - f) Others
4. Turnover of the company during the last financial year
 - a) 0-10 crores
 - b) 10-50 crores
 - c) 50-100 crores
 - d) 100-250 crores
 - e) More than 250 crores

5. What industry within the manufacturing sector best describes your company?
 - a) Automobile manufacturing
 - b) Machinery manufacturing
 - c) Consumer electronics manufacturing
 - d) Medical devices manufacturing
 - e) Other
6. Field of expertise
 - a) Manufacturing technology and innovation
 - b) Supply chain management
 - c) Production and operations management
 - d) Process engineering
 - e) Project manager
 - f) Technology planning manager
 - g) Other

Part II: Assessment of readiness level

7. What is the extent of automation in the production field, and how is it typically categorized based on the level of automation?

L1: Manual - Signifying that the production process is predominantly carried out by human operators without significant automation.

L2: Partially automated - Indicating that some aspects of the production process involve automation, but substantial manual intervention is still required.

L3: Highly automated - Reflecting a production process where a significant portion of tasks are automated, reducing the need for constant manual involvement.

L4: Self-regulating - Denoting an advanced level of automation where the production system can autonomously monitor and adjust its operations without continuous human intervention, optimizing efficiency and minimizing errors.
8. What describes best the level of integration between the production machines and operating system in your organization's operations where Integration refers to the coordination between the hardware and software components?

L1: No integration: The machines are not at all connected to the operating system, with limited coordination between hardware and software components, requiring significant manual intervention.

L2: The production machines and operating system possess information exchange capabilities allowing for some coordination and communication between two

L3: Machines and systems are partially integrated with communication and coordination being limited with room for further improvement to achieve better synchronization between the two.

L4: Machines and operating systems are highly integrated facilitating seamless coordination and communication between hardware and software components with real-time data exchange capability.

9. What is the current method of data collection utilized across the procurement process in your organization where the procurement process involves purchase requests, vendor selection, purchase orders, and record-keeping?

L1: The procurement process is carried out by human involvement where purchase requests and purchase orders are generated and approved through paperwork or emails

L2: Data is collected digitally in certain areas: Data is collected through a combination of manual and automated methods. It means that some data is gathered through manual processes involving human input, while other data is collected using automated systems and digital tools (SAP-ERP).

L3: Data collected digitally in multiple areas: This scenario describes the data collection in various aspects of the procurement process is done digitally. It specifies that multiple areas, including requesting, vendor selection, purchase orders, and record-keeping, rely on digital methods for data collection.

L4: automated digital data collection across the entire process with the use of digital tools and technologies to collect and manage data at every stage of the procurement lifecycle (procurement software, e-procurement, electronic data interchange, cloud-based solutions).

10. Which among the following best describes the procurement practices in terms of supplier evaluation and the selection of suppliers based on factors such as quality, delivery timelines, and cost-effectiveness?

L1: Non-integrated: Supplier selection is ad hoc driven by convenience rather than a structured evaluation process.

L2: Somewhat integrated: Supplier evaluation is conducted with the further requirement of data integration and analysis for decision-making.

L3: Moderately integrated: The supplier evaluation process is well structured and designed and selection is conducted with an emphasis on aligning business objectives and operational requirements involving cost competitiveness, material quality, and delivery timelines.

L4: Fully integrated: Automated supplier evaluation process with the use of digital tools for collecting and transmitting real-time data to gain a constant stream of insights into supplier's performance allowing the company to maintain the balance between the supplier's performance and customer satisfaction.

11. Which level of inventory control best describes the scenario in your organization, considering the use of computer databases, smart devices, and real-time data updates for managing inventory levels?

L1: Manual Inventory Control - Inventory levels are updated through human intervention and physical counting methods.

L2: Partially Automated Inventory Control - A computer database is utilized to track inventory levels.

L3: Highly Automated Inventory Control - Inventory levels are constantly monitored and promptly updated through a real-time database integrated with smart devices, ensuring efficient and accurate inventory management.

L4: Self-Regulating Inventory Control - An advanced, autonomous system continuously monitors and dynamically adjusts inventory levels in real-time, leveraging smart devices and real-time databases for seamless and precise inventory management, minimising human intervention.

12. To what extent is the supply chain effectively integrated in terms of communication with both suppliers and customers? Please carefully evaluate the current state of integration and select the option that best describes the level of communication

L1: Communication with suppliers and customers is primarily manual, relying on traditional methods such as emails, phone calls, and paper-based documentation for informal responsive communication

L2: the supply chain relies on straightforward means of communication to fulfill immediate requirements with external partners by sharing only fundamental details such as order details, shipment status, basic product specifications, and payment updates.

L3: Data transfer between key strategic suppliers and customers including the exchange of essential information, such as inventory levels, demand forecasting, price and cost details, and quality data.

L4: Fully integrated system with every party having access to the real-time flow of information allowing stakeholders to have access to the most up-to-date data for example real-time visibility into levels across all parties.

13. How would you describe the current level of supply chain visibility in your organization, where it allows you to gain insights into product status, location, and condition at various points for effectively tracking shipments, monitoring inventory levels, analyzing production processes, and sharing data with supply chain partners?

L1: There is no integration with suppliers or customers in terms of data sharing from both sides and the organization operates independently without any interconnected system in place.

L2: Visibility of site locations, capacities, inventory levels, and operations is maintained between the first-tier suppliers and customers.

L3: Visibility of site locations, capacities, inventory, and operations extends throughout the entire supply chain.

L4: Real-time visibility of site locations, capacities, inventory, and operations where data is actively used for monitoring and optimizations of operations and processes throughout the supply chain.

14. How would you describe the prevailing lead time situation within your organization considering factors such as procurement time, material availability, and production scheduling and timeline?

L1: Long material lead time affects other production operations creating chaotic situations during demand fluctuations.

L2: The company is looking for improvements to reduce the lead time aiming to mitigate the risk of buyer rejection due to delayed deliveries.

L3: Some improvements have been implemented like dynamic safety stock management, just in time inventory management to reduce lead time.

L4: Differentiated stock policies have been implemented by quickly responding to fluctuating customer demands through stocked sub-components. Further, advanced production scheduling including demand forecasting, and real-time adjustments in production scheduling has been adopted. Real-time data integration through sensors on machines, RFID tags, and data collected from operations further facilitated the adjustments in reducing lead time.

15. What level of data-driven decision-making best described the scenario in your organization

L1 - Operational Decision-Making: Top management utilizes the data coming from operators on the factory floor to manage production, ensuring smooth operations and a rapid response to machine issues, while operators diligently follow the given instructions and orders.

L2 - Tactical Decision-Making: Plant managers and supervisors analyze historical and real-time data to optimize production processes and improve overall quality.

L3 - Strategic Decision-Making: Top management leverages big data analytics to gain valuable insights across multiple stakeholders and departments, enabling them to guide production efficiency and drive advancements within the organization without direct involvement in daily operations.

L4 - Executive Decision-Making: Executives and board members leverage internal (intra-organizational) and external (suppliers, buyers, stakeholders) data to make critical decisions about the company's direction, partnerships, and growth.

16. To what extent is the product can be tracked across the supply chain as it moves from the supplier to the final buyer (OEMs)

L1: Limited product tracking

L2: Product can be tracked as it moves within the organization across the manufacturing process.

L3: The product can be tracked as it reaches the company manufacturing site until it reaches the final buyer without the involvement of any third party.

L4: Product can be tracked throughout the supply chain comprising supplier, manufacturing unit, and buyers distribution center.

17. Which among the following describes the strategy employed by the company in co-creating products with customers for managing product customization

L1: No individualization as the company is manufacturing the same product as manufactured by other suppliers in the industry.

L2: The company manufactures products in large quantities or batches with limited late differentiations which includes modifying the product at a later stage in the production process (for example shifting production from Internal combustion engines to electric motors or battery management)

L3: The company manufactures products in close collaboration with its customers and conducts market research for product improvements (customized products) with a standardized base.

L4: Make-to-order manufacturing that combines personalized customization with an efficient production process.

18. How would you describe the level of partnership and collaboration with external experts and consultants to drive innovation and advancing processes within the organization?

L1: External engagements are minimal in the organization without the involvement of any external experts.

L2: Partnership and collaboration with external experts and consultants provide a foundational level of support in terms of introducing novel ideas and best practices.

L3: Partnership and collaboration with external experts and consultants form a vital part of the organization and play a significant role in shaping innovation by redesigning the manufacturing process and integrating technologies in existing processes (for instance strategies required for the smooth execution of a technological plan, strategies for reducing stockouts, minimizing excess inventory, redesigning procurement, and distribution process, etc.)

L4: Partnership and collaboration with external experts and consultants form an integral part of the company's strategy which are not only involved in redesigning processes and technology implementation but digitally transforming business through overhaul of processes, technologies, and business models.

19. How would you describe the level of collaboration across various departments within the organizations in terms of sharing information for decision-making? Collaboration refers to the extent to which departments actively share data and insights, work together, and collaborate on decision-making processes to achieve organizational goals.

L1: departments operate in silos, with limited communication and sharing of information. Each department primarily focuses on its own goals and objectives, resulting in isolated decision-making processes.

L2: There is limited interaction between departments, there might be occasional exchanges of data and insights, but it is not a systematic and consistent practice.

L3: There is a high level of interaction between departments and engaged in sharing knowledge, insights, and best practices, contributing to a more comprehensive understanding of organizational processes.

L4: The company actively participates in cross-company collaboration, forming partnerships with external parties to drive continuous improvements.

20. To what extent does the leadership team recognize the value of Industry 4.0 investments encompassing technologies like Artificial intelligence, Internet of Things, Blockchain, Robotics, Additive manufacturing (3D printing), and cloud computing in the organization's growth and operational improvements?

L1: The leadership team lacks recognition of the value associated with Industry 4.0 investments in operational processes

L2: The leadership team is currently exploring the potential benefits of Industry 4.0

L3: The leadership team acknowledges the benefits that can be attained through Industry 4.0 within operational processes and is in the process of formulating investment plans

L4: The adoption of these technologies is embraced positively by the leadership team and employees with a collaborative mindset, showcasing a strong commitment to leveraging them for the organization's success and growth.

Part III: Operational efficiency/ inefficiency

21. Please rate the level of importance or significance of the following core operational areas within the organization's production process on a scale of 1 to 5, where 1 indicates not important and 5 indicates extremely important:

- Buyer's order processing
- Production planning and scheduling
- Procurement/purchasing.
- Goods Receiving
- Incoming inspection
- Demand forecasting
- Warehousing
- Production
- Research and development

- Ancillary services (heat treatment)
 - Assembly
 - Quality control/ packaging
 - Inbound Logistics
 - Outbound logistics
 - Inventory management
22. Please indicate the occurrence of the following problem within the network structure on a scale of 1 to 5, where 1 indicates no occurrence and 5 indicates high occurrence:
- Information loss
 - Lack of transparency
 - Miscommunication and misalignment
 - Inefficient production planning and scheduling
 - Misalignment with OEM's production schedule on account of delayed decision-making.
 - Supplier-associated material and quality issues
23. Please rate the occurrence of the following problem in the production process for the following aspects on a scale of 1 to 5, where 1 indicates no occurrence and 5 indicates high occurrence:
- *discrepancies and mismanagement related to inventory.*
 - *Rescheduling the production process*
 - *Buyer's alternative sourcing in case of production disruption or inventory shortage*
 - *Limited visibility into inventory levels to address fluctuating customer demand.*
 - *No integration in terms of integrating other processes like procurement, production, order fulfillment, and responding to market changes.*
 - *Quality control gaps*
24. On a scale of 1 to 5, please rate your level of agreement with the given statement: Suppliers experience significant pressure from OEMs to consistently enhance their manufacturing processes, upgrade machinery, enhance capabilities, and adopt advanced technologies, where 1 indicates strongly disagree and 5 indicates strongly agree.
25. On a scale of 1 to 5, please rate your level of agreement with the given statement: Suppliers encounter considerable cost pressure including quality control costs, variable material costs, and unpredictable fluctuations in OEMs demand, where 1 indicates strongly disagree and 5 indicates strongly agree.
26. Has your company acknowledged Industry 4.0 at the organizational level and integrated it into the business model?
- a) Yes
 - b) No

27. Are you aware of blockchain technology in terms of its application in the supply chain?

- a) Yes
- b) No

28. Is your company involved in the ongoing developments and transition toward the current Electric Vehicle (EV) market?

- a) Yes
- b) No