Exploring the Adoption Intention of Artificial Intelligence in Human Resource Management

A PhD Thesis

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Submission Date: 31st October 2024

This thesis submitted in partially fulfilment of the requirements of Birmingham City University for the degree of Doctor of Philosophy

Faculty of Business, Law and Social Science (BLSS), Birmingham City University

BCU RESEARCH ETHICS APPROVAL LETTER

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Dear Anh,

Re: Phan /#9609 /sub2 /R(A) /2021 /Oct /BLSS FAEC **-** The Use and Acceptance of Artificial Intelligence in Human Resource Management

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I wish you every success with your activity.

Yours Sincerely,

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On behalf of the Business, Law and Social Sciences Faculty Academic Ethics Committee

Abstract

Artificial Intelligence (AI) is increasingly reshaping Human Resource Management (HRM) through the automation of HR processes and the enhancement of decision-making capabilities. Despite its potential, the adoption of AI in HRM remains uneven, with persistent challenges related to organisational readiness, professional acceptance, and uncertainty surrounding AI-enabled systems.

This thesis investigates the key determinants influencing HR professionals' intention to adopt AI technologies within HRM. Anchored in the Unified Theory of Acceptance and Use of Technology (UTAUT), the study extends existing technology adoption frameworks by incorporating the psychological factors of Perceived Risk (PR) and Status Quo Bias (SQB) to capture the socio-cognitive complexities of AI adoption in HR contexts. The research also addresses a recurring conceptual conflation between HR analytics, automation, and AI-powered HRM, which shapes HR professionals' perceptions and adoption intentions.

A mixed-methods research design was employed across two sequential phases. Phase 1 involved qualitative research using thematic analysis of eighteen semi-structured interviews with HR professionals engaged with AI-enabled HR practices in the West Midlands, England. This phase confirmed the relevance of core UTAUT constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—while identifying perceived risk, status quo bias, and conceptual ambiguity surrounding AI as salient influences on adoption intention. Phase 2 comprised a quantitative study analysing 146 survey responses from HR professionals using SPSS. The quantitative findings refined the qualitative insights, demonstrating that social influence and status quo bias significantly influence AI adoption intention, whereas effort expectancy and facilitating conditions did not demonstrate statistical significance.

The findings indicate that performance expectancy and social influence are primary drivers of AI adoption in HRM, while heightened perceived risks, status quo bias, and the misinterpretation of AI as conventional HR analytics act as key barriers. Based on these results, the study proposes a context-specific AI adoption framework for HRM that integrates technological, social, and psychological dimensions of adoption. This research contributes empirical and conceptual insights to academic debates on AI adoption in HRM and provides practical guidance for policymakers, AI vendors, and HR practitioners seeking to support sustainable and responsible AI implementation.

Acknowledgement

First, I am grateful to the Almighty for endowing the strength and resilience for me to complete this PhD project.

Next, I would like to express my sincere gratitude to Dr Bruce Philp (my director of study) and Professor Dr Cindy Millman (my second supervisor) for their tremendous support and sagacious guidance throughout my PhD. Without knowing them in this research journey, I would not have progressed and built my confidence to become a genuine researcher and pursue this research till its final stage. Thanks to their advice, patience, trust and relentless encouragement, I had had a phenomenal, transformational and developmental PhD experience. I was extremely fortunate to have met them not only due to the help academically but also because they cared so much about my mental health and well-being during the research process, which is beyond their job's duty and my expectation. For that, I am always indebted to them. I would also like to thank my Master's lecturer and HR Specialist: Mr Harry Allen (Chartered Member MCIPD) and Dr Paul Turner for assisting me in building connections with HR professionals; Mrs Farzana Choudhury for mentally supporting and advising me when I was confronting difficulties; my line manager, Dr Michalis Kourtidis, for kind supports academically and professionally. Unreservedly, I am grateful to Birmingham City University for the generous tenure and opportunities provided during my research journey in England.

Especially, I would like to extend my gratitude to my family (mom, dad and my sister) and my aunt who consistently love, support and pray for me in every step of my life. And last but not least, my partner, Long Pham, for your kind companion and perpetual encouragement for me throughout all the hurdles I confronted during this journey.

Finally, I thank many colleagues, students, friends and research participants for being part of my PhD journey and making this research happen.

Accomplishments from this research

Phan, A., Hawela, M., Ahmed, W., (2022). **Exploring the Impact of Artificial Intelligence technologies in Human Resource Management (Developmental Track).** Accepted to be presented at *British Academy of Management Conference (BAM) 36th*, University of Manchester, Manchester, England, between 31st August to 2nd September 2021. *BAM2022 Proceedings.* ISBN: 978-0-9956413-5-8.

*(*Note: the contents of this conference paper were extracted from Chapter 1, 2 and 3 of this thesis)*

Phan, A., Philp, B., Millman, C., (2022). **Exploring the Use and Acceptance of Artificial Intelligence in Human Resource Management**. Achieved the 2nd Up- Runner Award (£1000), PhD 3-min Pitch Contest, *Innovation Fest 2022* by BCU STEAMHouse and Santander Universities, Birmingham City University, Birmingham, England, between 10th May to 23rd May 2022.

Phan, A., Philp, B., Millman, C., (2023). **The Use and Acceptance of Artificial Intelligence in Human Resource Management – The first phase: Qualitative Research (Developmental Track).** Accepted to be presented at *British Academy of Management Conference (BAM) 37th*, University of Sussex, Brighton, England, between 4th September to 6th September 2023. *BAM2023 Proceedings*. ISBN: 978-0-9956413-6-5.

*(*Note: the contents of this conference paper were extracted from Chapter 1, 2, 3 and 4 of this thesis)*

Phan, A., (2024). **The Use and Acceptance of Artificial Intelligence (AI) in Human Resource Management (HRM) – Comprehensive Findings from Mixed-Method Research (Full track).** Accepted to be presented at *British Academy of Management Conference (BAM) 38th*, Nottingham Trent University, Nottingham, England, between 3rd September to 6th September 2024. *BAM2024 Proceedings*. ISBN: 978-9-9956413-7-2.

*(*Note: the contents of this conference paper were extracted from Chapter 1, 2, 3, 4, 6 and 7 of this thesis.)*

The content for the conference papers was extracted from the thesis drafts and the supervisors supported to craft it into an acceptable format for the conferences. They had provided support and feedback at the research design phase, but the essential elements of the research design and the operationalisation of the research itself was undertaken by me in its entirety)

Abbreviation (Abb)

Abb	Full Term	Abb	Full Term
AI	Artificial Intelligence	MM	Motivational Model
ANNs	Artificial Neural Networks	MMR	Mixed-Method Research
ATS	Applicant Tracking System	MPCU	Model of PC Utilisation
BC	Bias Concern	NLP	Natural Language Processing
BCU	Birmingham City University	PC	Perceived Cost
CBR	Case-Based Reasoning	PE	Performance Expectancy
CE	Cost Effectiveness	PR	Perceived Risk
CIPD	Chartered Institute of Personnel and Development	PRC	Privacy Concern
CM	Cognitive Misperception	PU	Perceived Unemployment
DL	Deep Learning	PYC	Psychology Commitment
DNN	Deep Neural Networks	QUAL-quant	QUALITATIVE-quantitative
DOI	Diffusion of Innovation	RQ	Research Question
EE	Effort Expectancy	ROI	Return on Investment
EFA	Exploratory Factor Analysis	SHRM	Strategic Human Resource Management
EB	Employer Branding	SHR4.0	Smart Human Resource 4.0
EOU	Ease of Use	SI	Social Influence
FC	Facilitating Condition	SCT	Social Cognitive Theory
FOTU	Fear of the Unknown	SME	Small Medium Enterprise
GAs	Genetic Algorithms	SN	Subjective Norm
GDPR	General Data Protection Regulation	SQB	Status Quo Bias
HRM	Human Resource Management	TAM	Technology Acceptance Model
ID	Innovation Driven	TMS	Top Management Support
ILP	Inductive Logic Programming	TPB	Theory of Planned Behaviour
IS	Information System	TRA	Theory of Reasoned Action
JC	Job Compatibility	TV	Task Versatility
KSA	Knowledge, Skills, and Attitudes	UTAUT	Unified Theory of Acceptance and Use of Technology
LR	Literature Review	SQB	Status Quo Bias
LS	Leadership Support	TAM	Technology Acceptance Model
ML	Machine Learning	TMS	Top Management Support

Key concepts

Artificial Intelligence (AI): The capacity of machines to deliver multidisciplinary advanced and human cognitive tasks such as memorising, creating, speaking, and making decisions based on the ability to imitate and learn from experiences.
Traditional HRM: Within the context of the research, the concept refers to the manual and conventional methods (primarily paper-based and intuition-relied) in managing manpower resources.
HR Analytics: the enhancement in HR ability and capacity in managing human resource by involving analytics attributes from the assistance of advanced technologies.
AI-powered HRM: The enhancement in HR ability and capacity in managing human resource by involving various algorithms powered by AI technologies.
Big Data Analytics: The process of extracting and deploying big data to discover underlying patterns/results with the purpose of drawing meaningful findings.
Machine Learning (ML): One of the main functions of AI which concentrates on deploying data by applying different algorithms to draw meaningful findings.
Deep Learning (DL): A subset of ML whose function concentrates on processing and extracting values from data based on artificial neural networks.
Data Mining: The data analysis process which concentrates on discovering anomalies and potential correlations from data input to draw meaningful findings.

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CHAPTER 1: INTRODUCTION

1.1 Introduction

Artificial Intelligence (AI) and Human Resource Management (HRM) have become pervasively spreading words, which have been recently discussed among businesses regarding a novel HR capacity. This is due to its ability to become more agile in responding to customers, generate prompt solutions and create more innovative ways of working (Cantoni and Mangia, 2020). The novel concept of AI-HR collaboration is argued to significantly contribute insightful and analytical values to business success within the thrive of the digital era. Baabdullah (2024) further reports that adopting AI to enhance organisational decision-making and functional performance is essential for maintaining competitiveness. With the new normal established in the middle of the 4.0 Industrial Revolution after the pandemic, the ability of HR professionals to contextualise data has become paramount in guiding ongoing decisions and ensuring the value of data collection for decision foundation (Cantoni and Mangia, 2020). By virtue of the above-mentioned reasons, the HR realm is not immune to the advent of AI disruptions to become agile in multi-aspects of the organisation.

Since the Covid-19 pandemic, there has been a shifting concentration of the recruitment team in building the candidate pipeline by scheduling virtual interviews to stay connected with potential candidates. This could be considered as an illustration of agile culture from organisations for talent attraction and management. In fact, the traditional HRM is undergoing a staggering digital transformation to adapt with the culture of agility fostered by digital transformation. AI is argued to significantly cultivate advanced attributes into the conventional HR bundles of practices and satisfy the agile learning needed for employees (Panda et al., 2025). In a broader context, constant changes occurring in the dynamic market such as globalisation, pandemic, and economic crisis have accentuated the agility factor to become ultimately essential for HRM to keep pace with the evolving needs of employees, maintain employee connection and facilitate a two-way communication. Since the business environment will continuously incline towards fierce competitions, the investment in advanced technologies for long-term sustainability is essential for long-term survival of businesses. The HR functions were promised to be streamlined and connected within AI foundation (Zirar et al., 2023). Interestingly, despite the growing interest in the concept of AI-augmented HRM, the adoption rate of the AI technologies in HRM till date is not significant.

Echoing the mentioned discussion, the current situation poses a theoretical and practical gap between AI and HR field in terms of adoption and usage acceptance. Hence, this research aims to shed a light on this understudied area of AI adoption intention in the lens of HR professionals in the manpower management field. This chapter presents the fundamental landscape of this research nature and presents the contemporary contexts of AI adoption in the field of HR.

1.2 Research Background

1.2.1 Overview of the Context

The agile germinations of advanced technology over the past few decades have tremendously impacted various industries. It is evinced with the predominant occurrence of Artificial Intelligence (AI) as a pivotal driver for innovation across business sectors. In practice, the AI taxonomy has recently become more ubiquitous. This is due to the diversity of AI functionalities and categorisations applied in different professions, industries, and business practices. Particularly, AI is defined as an overarching terminology used to describe the ability of human-cognitive replication of machines (Singh and Pandey, 2023). It is an umbrella theme which covers a large class of digital technologies. The advanced technologies are asserted to possess the capability of imitating certain human behaviours and abilities such as analytical, cognitive, human-replicated and even emotional (Miller, 2019). Recent studies also indicate a colossal disruption of AI across organisations, which generates a foundation for staggering transformation in organisational decision-making process and employee and customer management (Arslan et al., 2022; Budhwar et al., 2022).

Historically, human beings have been experiencing crucial transformations through different eras. Each remarkable milestone requires the adoption of new skills, strategies and working styles to adapt to the dynamics agilely and flexibly. The industrial revolutions have contributed to the dramatic changes in how effective management could be adjusted and conducted compatibly in businesses within divergent circumstances. To a considerable extent, the 4th Industrial Revolution has been eliciting and generating diverse technological features contributing to an advanced transformation in different disciplines (Skilton and Hovsepian, 2018). On closer inspection, from the steam-engine industry in the 18th century to the electric, gas and oil era, and from electronics and telecommunication to the contemporary industry 4.0, worldwide economics has been undergoing a staggering transformation. The process of replacing outdated approaches with more innovative and effective methods is vital for enhancing organisational effectiveness in business management (Teece, 2018). Current businesses are constantly making efforts to keep pace with the dynamics and ruthless changes of the surrounding business environment accelerated by the race of organisations' advanced technology adoption (Hacioglu, 2020). In a similar vein, AI technologies are providing existing businesses with potential tools to effectively optimise business performances and strategy formulation.

Indeed, contemporary organisations has demonstrated a growing interest in AI adoption within HRM practices. The mechanism is owing to the uninterrupted innovations produced by AI vendors to generate AI-based HR solutions into the business market. Several AI-powered applications have been produced and increasingly penetrating the HR market from popular vendors such as IBM, Ceridian, Oracle, SAP, Ultimate, Workday and small-medium vendors such as HiBob, Sage, Zenefits, Gusto, BambooHR, Zoho, Namely, Paycom, Paychex, Paycor, PeopleStrong, and Darwinbox (Bersin, 2019). The HR bundles of practices have been deployed either by using public AI applications and platforms or self-designed AI products requested exclusively by certain organisations. Singh and Pandey (2023) claim that organisations deploying AI applications in commensurate fields can augment business performance and enhance strategic approaches. In a similar vein, AI adoption will lead to staggering transformation of business models and performance which requests a resharpening and innovating overall business processes (Jatobá et al., 2019). The situation would possibly generate a significant impact on how businesses construct their management and assign manpower sources. In fact, Brynjolfsson and McAfee (2014) argue that organisations that do not adapt to new technological trends risk becoming obsolete in an increasingly digital and automated world.

The capacity of AI has experienced significant fluctuations in terms of interests and practical deployments. In the extant context, due to the increase in the dynamics, competitiveness, and uncertain nature of the business market, promising values of AI are critically examined and applied to multidisciplinary areas. In addition, the occurrence of the Covid-19 pandemic has initiated novel working notions and triggered advanced technology deployments such as hybrid working, cloud-based platforms, cognitive learning, and automation (Harney and Collings, 2021). In fact, the pandemic has been arguably considered as a hastening factor for the digital transformation process of all levels (Akinjiyan, 2020). Those concepts are significantly articulated with AI functionalities and performances, which generates a mechanism for AI frenzy to be coined to illustrate its precipitous growth (Baryannis et al., 2019). Indeed, the pandemic could be considered as an epitome of how data make sense and turn into valuable sources for business to conduct market analysis without physical human interaction due to the virus spread (Akinjiyan, 2020). By the virtue of the pandemic, there are issues related to digital adoption which need to be envisaged by business leaders. Apparently, the buzzword of AI has captured the attention of businesses as several organisations have started to explore how AI technologies can perform at work while the others are concentrating on building approaches to work with it. Hence, the above-mentioned facts have profoundly generated a foundation for digital transformation in the realm of HRM.

1.2.2 The field of Artificial Intelligence in Human Resource Management

The COVID-19 pandemic, which first emerged in Wuhan, China, eventually spread across the globe. Its onset significantly disrupted traditional HR practices across various sectors worldwide, including business, services, and education (Böhmer and Schinnenburg, 2023). In fact, there had been multiple elements facilitating and promoting the adoption of AI in different sectors within this period such as agile HR concept, business models transformation and the availability of digital supports in the market since the Covid-19 incident (Fenwick et al., 2023). Since then, there have been a continuously growing number of journals and articles in various forums and academic journals on the topics regarding AI-cognate themes including AI solutions, blockchain, cloud and virtual assistant (Amar et al., 2023). AI has played a transformative role in reshaping the field of HRM. Specifically, IBM was considered as a pioneer in adopting AI in their HR practices and successfully secured 107 million dollars from HR operation costs, which directed the company towards the investment and technology development of AI in the HR realm (Guenole and Feinzig, 2018). In practice, organisations are heading to ramp up remote-working training and investment, preparing themselves to transform to a new normal (Teo, 2012). A strategic competitive edge could be sharpened if HRM practices could adapt and create a more flexible working environment while redesigning jobs and retaining employees for the future of the work. In the long-run, advanced AI technologies are becoming a critical and indispensable tool for business management (Haefner et al., 2021). Kiron and Schrage (2019) further posit that AI will not simply be a trend to follow suit but a powerful tool to enhance the formulation and execution of strategy. Hmoud and Várallyai (2020) also echo a similar sentiment in acknowledging the promising applications of AI in various use cases in HRM. In effect, a recent study of Fenwick et al. (2023) outlined the three domains in HRM in which AI could penetrate and generate values: people management, culture and compliance. **Figure 1.1** illustrates the key HR layers proposed for AI adoption.

Figure 1.1: Three core HR-functional categorisations for AI deployments (Fenwick et al., 2023)

Organisational value within the 4th Industrial Revolution is potentially altered by the strong emphasis on AI, which results in the thriving of the data science sector (George and Thomas, 2019). The incremental demand of innovation and technology adoption gravitates to the direction of strengthening strategic HRM (SHRM). The technology can augment analytical tasks and would eventually evolve to perform more intuitive and empathetic tasks (Huang and Rust, 2018). Indeed, the significant growth of digital-supported networks has brought more considerations to business operational models in terms of how to deploy effectively and efficiently the availability of those assistant networks to maximise business success (Skilton and Hovsepian, 2018). The Internet of things (IoT) and the new introduction of the 5G network recently in the market have allowed AI adoptions to expand to potential consumers. According to Ahmad et al. (2023) study regarding digital care network in next generation, AI and 5G networks will be the combo of the future of work which augment communications while maintaining the users' privacy. The 5G networks can transmit data speedier and in much greater amounts, which is considered the fuel for the growth of AI in many aspects of the work (Drew and Tysiac, 2020). Businesses are exploring the ability of the networks to optimise their operations so that AI could be built upon these digital-supported networks as a strong foundation. The concept of the International Communication Union (ITU) has been recently mentioned as a matter of this trend. It is standardisation to assist Machine Learning (ML) to bring more automation and intelligence in network design and management.

AI adoption in HRM, therefore, is not considered as a radical departure from the previous digital innovations but rather as an inventible progression of technical development within business world. In practice, HRM department has long applied digital tools such as Human Resource Information System (HRIS), E-recruitment platforms and self-service to streamline administrative tasks, enhance decision and workforce planning (Bondarouk et al., 2017). This shift paved the necessary way for the progression of predictive HR analytics which enables data-driven insights into sharpening strategic HRM (Marler and Boudreau, 2017; Leicht-Deobald et al., 2019. Therefore, AI represents the continuous phase of this evolution which builds on the data infrastructure and algorithmics from earlier technologies. Particularly, AI-powered applications augment and enrich the capabilities of HR analytics by enabling automation and adaptive learning to support a wide range of HR functions.

The scenario has urged HR professionals to reconsider their conventional way of work. In fact, AI investments have triggered a flatter approach for HRM and generated a new path to rethink on the degree of vertical integration (Heukamp and Canals, 2020). As a result, the concept of Smart Human Resource 4.0 (SHR 4.0) has been coined as an evolving part of the 4.0 Industrial Revolution formed by internet of things (IoT), big data analytics, artificial intelligence (AI). The fast data networks such as 4G and 5G for the effective management of next-generation employees (Ahmad et al., 2019). **Figure 1.2** briefly illustrates HRM transformation through four industrial revolutions.

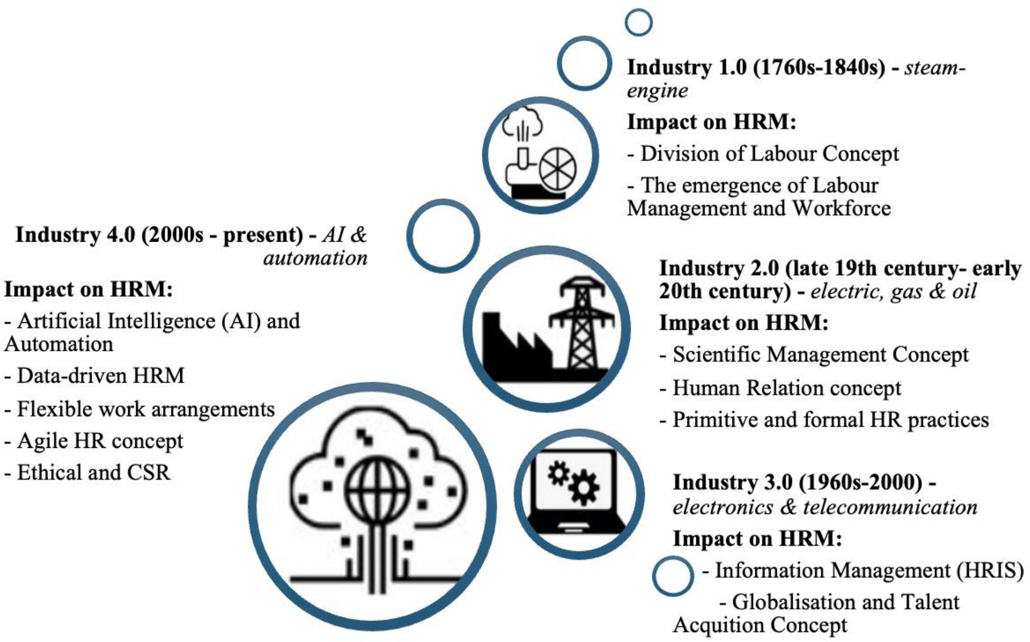

Figure 1.2: HRM transformations through the industrial revolutions (designed by researcher)

The application of Artificial Intelligence (AI) in Human Resource Management (HRM) represents not a radical rupture but a significant development within a continuum of digital transformation. Over the past two decades, organisations have progressively adopted HR Information Systems (HRIS), electronic recruitment platforms, and self-service portals to streamline administrative tasks and enhance service delivery (Bondarouk et al., 2017). This shift paved the way for the emergence of predictive HR analytics, enabling data-driven insights into workforce trends, performance forecasting, and strategic planning (Marler and Boudreau, 2017; Leicht-Deobald et al., 2019). More recently, AI has extended these capabilities through advanced machine learning algorithms, natural language processing, and intelligent automation — tools that build directly upon the data infrastructures and practices developed through earlier digital systems (Jarrahi et al., 2021; Meijerink et al., 2021).

The traditional HRM therefore, is required to shift accordingly to generate competitive advantages based on AI advanced technologies. Since Covid, HR has been recommended to pioneer in AI adoption due to its strategic roles of engaging, training, and sharpening employees' mindsets to be able to familiarise with the new way of hybrid work in the digital era (Fenwick et al., 2023). Furtherance, The World Economic Forum has also recognised the dramatic development of advanced technology over the past decades and emphasised the rise of the technology adoption and applications in HRM as agile as the previous industrial revolutions of steam, mass production, and electronics (Tursunbayeva, 2019). In effect, there have been growing discussions in forums, research and articles regarding the broad influence of AI adoption in the HR realm (Schmidpeter, 2023). From this vein, AI is not an isolated innovation but a continuum of relentless efforts to harness digital technologies into strategic HRM. As a result, the adoption of AI is examined not only through the perspectives of novelty in technology but a logical pathway of evolving digital HRM landscape. **Figure 1.3** illustrates the progression of Digitalisation in HRM.

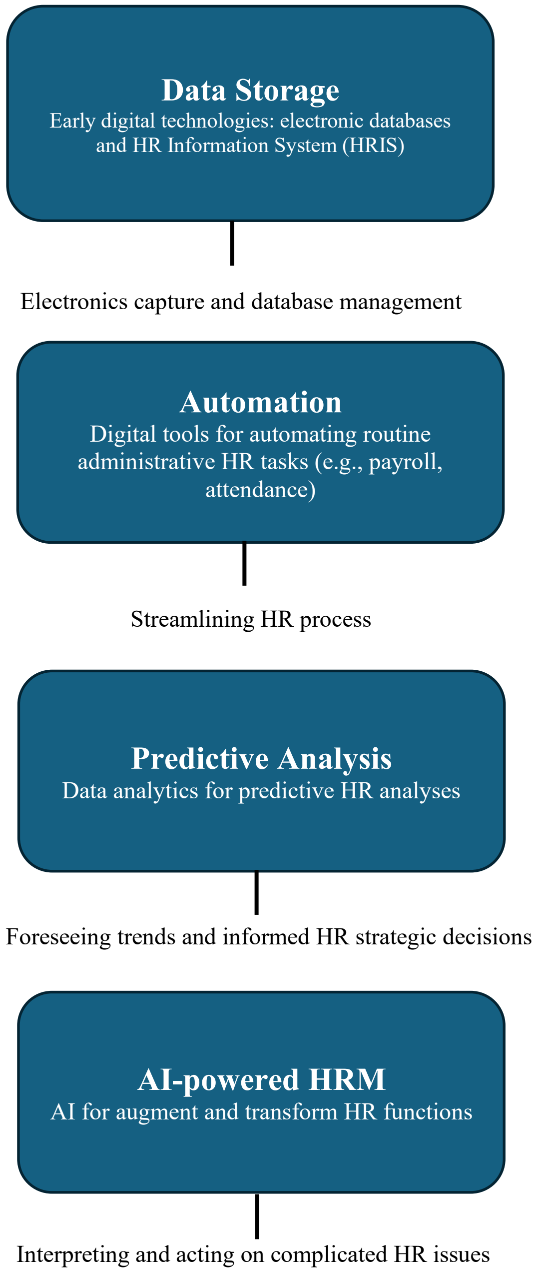

Figure 1.3: The progression of Digitalisation in HRM

This study, therefore, situates AI adoption within a progression of technological advancement in HR field. It recognises an extension of digital transformation underway in organisations. By tailoring this research in this development context, the study responds to calls for more integrated strategies to AI-HR adoption. It also enhances the practical perspectives for HR professionals navigating digital transformation. Hence, at this turning point, the research scope and interests from this study centred on the emerging factors currently impacting the adoption intention of AI in HRM within the dynamic context of the business world. With an attempt to illuminate the current AI development in intervention in the HRM field, it is suggested for empirical research to examine the emerging issue, especially in the aspect of adoption and deployment of AI advanced technologies. This would generate a concrete foundation to efficiently assist HR to digitally transform and augment the business performance. The research findings contribute to understanding how organisations from data-facilitated HR systems to AI-augmented practices, ensuring the alignment with broader organisational strategies while addressing the determinants of AI adoption in HRM. As such, the adoption of AI must be examined not only through the lens of technological novelty but also as a logical next step in an evolving digital HRM landscape. This research builds on that trajectory by focusing on the human and organisational dimensions of AI adoption in HR. It responds to recent calls for research that integrates technological affordances with behavioural and cultural readiness in the workplace (Kaplan and Haenlein, 2020; van Esch et al., 2021).

1.3 Problem Statement

The mechanism for this study was established to the exploration of the emerging factors currently impacting the adoption of AI in HRM in businesses. At this turning point, the practical scope and interests of this research were navigated based on the issues embedded in the context of AI and HRM evolution through three angles represented in the problem statements of this study.

1.3.1 Existing Impediments in traditional HRM

Budhwar et al. (2022) argued that the adoption of AI will not only revolutionise the workplace but also transform HRM by authorising more freedom for humans in mundane and manual tasks. AI technologies have the capacity to disrupt almost every industry as their costs decline and become increasingly accessible to both large organisations and SMEs (Agrawal et al., 2018). However, there are numerous HRM practices in organisations that are mainly conducted in manual and traditional approaches (Eubanks, 2019). The traditional HR practices such as recruitment, selection and employee performance management remain well-controlled by human factors. The practices raise concerns relating to human error, efficiency, and the optimal utilisation of human resources, which has prompted growing interest in artificial intelligence (AI) as a potential enabler within HRM (Risna and Omar, 2019). Advanced AI technologies allow organisations to process large volumes of data, enhance value-adding HR practices, and augment human roles (Akerkar, 2019). In contrast, traditional manual HR practices continue to face challenges in managing workforce administration and performance effectively, often resulting in inefficiencies, increased operational costs, and unintended budgetary losses (Pandey et al., 2023). Against this backdrop, the adoption of AI in HRM is increasingly viewed as a means of mitigating such limitations. By supporting data-driven decision-making and automating routine administrative tasks, AI enables HR professionals to focus more effectively on strategic, analytical, and judgement-based activities, thereby strengthening HR's strategic contribution to organisational performance (Cardon, 2018).

Notably, the pandemic has been escalating and challenging the resilience of many business models struggling to compete against centric companies that can leverage data and apply machine learning to generate essential insights and improve capacity (Napier et al., 2020). In practice, large organisations including Google, Microsoft and Amazon are applying diverse AI applications into HR practices aiming at creating an ecosystem in managing employees' information flow, storage, and development. In particular, Microsoft has successfully created and deployed the Phenom People AI application to assist HR managers in succession planning by ranking top performers after analysing their interview data (Kambur and Akar, 2022). The discussions above emphasise the significant role of preparing for changes in employees' skills and job designs to be able to adapt and maintain organisational resilience in operation and practices in the post-pandemic era (Akinjiyan, 2020). The present incident has become the accelerator for the new HR working-pattern transformation, which brings both challenges and opportunities for businesses to plausibly adjust the procedures of HRM. In line with it, the situation generates a pressure on the HR realm which requires a cautious scrutiny on digital transformation. This is to establish a novel manpower management approach to prepare for the dynamics such as hybrid working, contract management, and novel approaches for employee engagement and retention (Akinjiyan, 2020).

1.3.2 Low AI adoption rate in HRM

Despite the advantages of AI technologies, low AI adoption rate has remained a dilemma, and the progression is at trivial pace (Michelman, 2020). In fact, Chowdhury et al. (2023) argues that the adoption of AI in HRM confronts major impediments in terms of data capacity and employee resistances. When cloud technologies were first introduced, organisations expressed concerns around data security, loss of control, system reliability, and the displacement of established IT roles. These concerns were compounded by uncertainty about regulatory compliance and a lack of organisational readiness to migrate legacy systems to new technological infrastructures (Arslan et al., 2022). Over time, cloud computing became normalised as organisations developed governance frameworks, invested in skills development, and gained confidence through incremental adoption and demonstrated performance benefits. A similar pattern appears to be emerging in the context of AI adoption in HRM. Concerns around data governance, algorithmic bias, transparency, and the perceived threat to professional judgement mirror earlier anxieties associated with cloud technologies.

In practice, the majority of organisations are not ready to embrace the shifting mindset partly ascribed to the current infrastructures which are tied closely to the old economy thinking (Hudson, 2018). As a matter of fact, McKinsey's (2024) recent annual management report continues to reveal a stagnancy in AI adoption in the field of HR. **Figure 1.4** presented the top adoptions of AI in business functions in 2024.

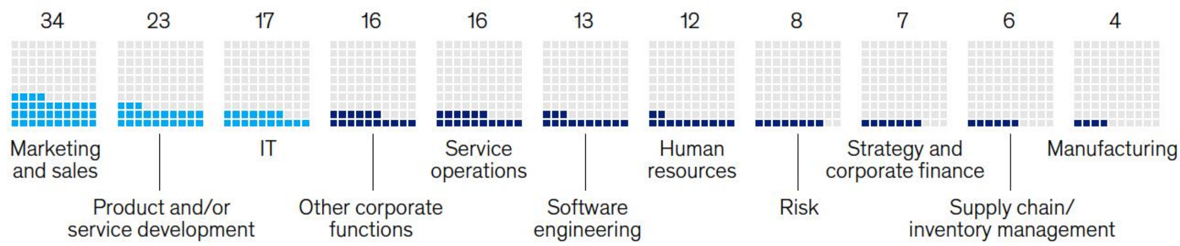

Figure 1.4: AI current adoption rate across business functions (Mckinsey, 2024)

As can be seen from above figure, AI technologies are dominantly adopted in the areas of marketing, product/service development and IT while HR captivated a much smaller proportion in the total percentage. This is in line with the assertion of Pan et al. (2022) that AI adoption has been widely occurring in numerous non-HR disciplines, with a concentration predominantly on IT techniques. Therefore, critical concerns on whether organisations are yet to prepare for the adoption of AI in the HR field are worth examining to contribute to the empirical literature for the future of HR. Skilton and Hovsepian (2018) posited that the adoption of AI would generate significant disruptiveness in business performance, however, the decision of whether to become early birds in the market or to adapt by becoming fast followers is still under discussion within organisations. In sum, AI has demonstrated to be a crucially disruptive factor significantly intervening the HRM practices. It is stated that the deployment of AI is still in its infancy in terms of impact, however, its development pace is evolving rapidly (Hutchinson, 2021).

1.3.3 Scarcity of the empirical review in AI and HRM

Regardless of the agile development and incremental prevalence of AI technologies across business sectors, it is claimed that there are notably finite empirical studies particularly examining the adoption of AI in HR principle. Indeed, Horodyski (2023) highlighted that despite the potential AI deployments in HRM are substantial, the limitation of empirical investigation poses a gap for integrating the real-world applications to the manpower management field. Interestingly, there is an increasing body of literature in recent time focusing on the advantages and challenges relevant to AI and HR (Strohmeier, 2022). However, Budhwar et al. (2022) posits that a number of studies anchors to anecdotal foundations in evidence which lacks solid evidence extracted from rigorous practical examinations and methodologies. This is in line with Böhmer and Schinnenburg's (2023) assertion that existing scientific HR literatures provide too little support on the adoption of AI technologies in organisations to date. A recent study also pointed out that the actual impact of AI on the HR realm is in absence of empirical findings as scholarly studies on the field was function-based and sporadic in themes (Eftimov and Kitanavikj, 2023). Consequently, the dearth of empirical AI-HR studies can hinder organisations in effectively generating corresponding strategies to leverage AI in augmenting HR functions. Anchored to the mechanism, this research centres on enriching the extant literature due to under-researched topics of AI and HRM in the existing literature. Particularly, this research explored the adoption of AI in HRM in the lens of HR professionals. A mixed research method (QUAL-quant) was applied and later presented in this research to discover the AI-HR adoption dilemma. In particular, the QUAL research results significantly assisted the researcher to obtain the insights of the AI adoption factors in HRM. Subsequently, quant results in this study revealed another layer of the actual correlation of the discovered adoption factors to HR professional's adoption intention. The results from this study promise to reveal the actual and contemporary adoption context of AI in HRM practices.

1.4 Research Aims and Importance

The adoption of Artificial Intelligence (AI) in Human Resource Management (HRM) represents more than a technological evolution—it signals a fundamental shift in how HR functions are conceived, executed, and evaluated. For HR practitioners, understanding the enablers and barriers to AI adoption is crucial for improving strategic workforce planning, enhancing recruitment processes, optimising employee engagement, and enabling data-driven decision-making. Despite AI's potential to augment HR capabilities, many organisations still face significant uncertainty, resistance, and capability gaps that hinder effective implementation.

This research addresses these practical challenges by identifying the key psychological and organisational factors influencing AI adoption intention within HR contexts. In doing so, it offers HR professionals empirically grounded insights to support change management, upskilling initiatives, policy design, and the strategic integration of AI into routine HR operations. As such, this study responds directly to the need for evidence-based guidance tailored to the lived realities and decision-making contexts of HR practitioners.

While academic interest in AI adoption has grown in areas like supply chain management, logistics, and marketing, its application in HR remains under-researched and undertheorised. This study helps to fill that gap by investigating AI adoption through the lens of HR professionals, with the aim of developing a more nuanced and practice-oriented understanding of how AI can transform traditional HR processes. It highlights how AI can reduce human bias, minimise manual errors, and improve operational efficiency, while also uncovering the human-centred and contextual dynamics that either support or obstruct this transformation.

By measuring and analysing the degree of influence of each adoption factor, the study offers a foundation for HR practitioners and organisations to craft context-specific strategies and policies. These insights can inform the development of a robust adoption framework grounded in the diffusion of innovation theory, helping organisations navigate the digital transformation journey more effectively. Ultimately, this research contributes to both scholarship and practice by bridging the gap between technological innovation and the human realities of HR work, equipping HR leaders with the knowledge needed to build resilient, competitive, and future-ready people strategies in the era of Industry 4.0.

1.5 Research Objectives

The research will be conducted with specific objectives to achieve the aim of the research:

Objective 1: To explore and accumulate scientific evidence of the critical context based on the current stage of AI applications in HRM with the purpose of formulating a congruent conceptual framework for empirical analysis.

Objective 2: To synthesise the possibility and feasibility of AI technologies in HRM by measuring the impact degree of each AI adoption construct determined from the first phase of exploratory research.

Objective 3: To discover the underlying opportunities and challenges brought by AI technologies in the transitions from manual HR practices to AI-powered HR practices.

Objective 4: To critically evaluate the future of AI implications in HRM and make the inference on how AI technologies could be conflated to augment HR functions.

Objective 5: To potentially establish a theoretical foundation and adoption framework for AI applications to be feasibly transferred into HRM practices.

1.6 Research Questions

There are three research questions that the researcher aims to clarify in researching the field of this emerging issue. The listed questions will encompass the directions of the research together with identifying potential findings on the novel area of AI in HRM:

Research Question 1: To what extent does the use and acceptance of AI in HRM generate opportunities and challenges for businesses?

Research Question 2: How do HR Professionals perceive and relate to the use and acceptance of AI in HRM?

Research Question 3: To what extent do the explored determinants relate to the intention to adopt AI in HRM?

1.7 Research Scope and Delimitation

1.7.1 Study Scope

Upon the discussion regarding the research background and problem statements, the research scope is now presented. By assessing the issues named in the research scope, the research attempts to identify influencing factors for AI adoption in HRM. According to the highlighting gaps indicated in the previous sections, this study attempts to provide insights regarding the following aspects:

- Identifying the key determinants driving AI adoption in the HR field.
- Assessing the current impact of AI on organisational performance and management
- Investigate technological preparedness degree and AI adoption readiness in HRM
- Examine the influence of HR professionals' perception and attitudes on AI adoption
- Investigating exogenous factors potentially impacting AI adoption intention in HRM

In essence, the research foci are on discovering the key determinants influencing the adoption of intentional behaviour of HR professionals with the presented contexts of digital transformation across business sectors. Further to the above, the study explores the emerging impact of the AI concepts on business operations and human management. In this vein, the scope of this study expands to assess the technological maturity and AI adoption readiness in HRM. This could be investigated through examining the current attitudes and perceptions of the HR professionals regarding AI adoption and deployment. Ultimately, the research also attempts to explore possible external pressures influencing the adoption intention of HR professionals towards AI technologies. To effectively accommodate the research investigation, the theoretical lenses are concurrently examined. Specifically, the technology adoption theories such as TAM, TRA, DOI, UTAUT and some others were taken into consideration. The proposed theories are argued to possess the fundamental base for the relevant studies examining technological adoption in organisations. Notably, this study does not examine all the adoption models in the context of AI in HRM. Rather, it centres on exploring the most relevant variables based on the context and investigating how the adoption determinants associate to the adoption intention of HR professionals.

1.7.2 Study Limitation

To comprehensively apprehend and interpret the findings of this study, certain delimitations of this study are navigated as presented in three aspects.

Geographic Scope: The data collected from this research will be obtained primarily on a particular geographic (West Midlands, England) to ensure the consistency and comparability of the data.

Data Collection and Analysis Method: This study relies on specific data collection and analysis methods (discussed in Chapter 3) depending on the research objectives and available resource.

Research Timeframe: The study was conducted within a specific timeframe (2020-2024), which potentially hinders the ability to captivate an exhaustive and long-run trends of AI technologies and adoption intention in HRM.

1.8 Significance of the research

The influence of advanced technology on different human tasks enables optimism as well as pessimism. The findings of the research contribute to further research centring on extending the exploratory scope of AI and HRM. In addition, it reveals updated and valuable insights to current studies on relevant fields regarding digitalisation transformation and impacts on businesses' performance, strategies, and AI deployment in the field of HRM. In this thesis, the researcher has bestowed the literature review on the nature of HRM practices with the intervention of AI within businesses. Additionally, organisations could access and fathom the current context of AI applications in HRM by acknowledging the factors influencing the adoption of AI in HRM. By that means, strategic approaches could be established accordingly to assist employees to become well-equipped in the advent of HR transformation. Finally, broader concerns of the government in the aspect of AI in organisations' HRM could be enhanced and accelerated in terms of enacting supportive laws on the utilisation of AI to protect AI's users (employers) and consumers (employees).

1.9 Research Structure

This study is designed into eight chapters namely Introduction, Literature Review, Methodology, Qualitative Research (QUAL), Refined Conceptual Framework and Hypotheses Establishment, Quantitative Research (quant), Research Discussion, Research Conclusion and Future Orientation. **Figure 1.5** illustrates the overall research structure of this study.

To narrate the research structure, Chapter 1 presents the overall background of the research foci of AI and HRM with research aims, objectives and key research questions for the whole thesis. Next, in Chapter 2, the research delves into key parts (as outlined in **Figure 1.5**) which reflect the theoretical and conceptual reviews of AI application in business, HRM and technology adoption theories. The structure of Chapter 2 is to accommodate and provide readers with discrete pictures of the incumbent contexts and the theoretical foundation for the preliminary conceptual framework of the research. In Chapter 3, the research methodology applied to explore the adoption intention of AI in HRM will be closely discussed. The research approaches, strategies, paradigm, and overarching approaches for data collection of the thesis will be meticulously explained. Within this chapter, the two phases of the research (qualitative and quantitative) are also showcased to accommodate the direction of investigating the adoption factors of AI in HRM. Proceeding to Chapter 4, the qualitative research (QUAL) will be presented with the overview of Phase 1 of the research and the establishment of the A priori codebook. The empirical findings of the QUAL research and discussion of the initial findings are also provided in this chapter. Chapter 5 comprises the key contents of model refinement, research constructs, hypotheses establishment and construct measurement establishment. In Chapter 5, the correlations between main testing constructs are established. The key purpose of Chapter 5 is to refine the initial conceptual framework and establish testable hypotheses among the variables in the research model. Hence, the preliminary conceptual framework proposed in Chapter 2 is refined in this chapter. Subsequently, Chapter 6 presents the quantitative research of this thesis. Specifically, the sampling overview and research quality examinations for quantitative research is closely discussed. The statistical test and findings for the quantitative research are communicated in this chapter. Chapter 7 of this thesis is dedicated to communicating the primary outputs of the QUAL-quant research delved on the extant milieu and literature within the digitalisation era. Finally, Chapter 8 summarises the thesis by revisiting all the research's chapters and providing a synthesis in research objectives to the core research questions. In addition, the research's contributions in theoretical, political and practical lens are discussed in this conclusion chapter.

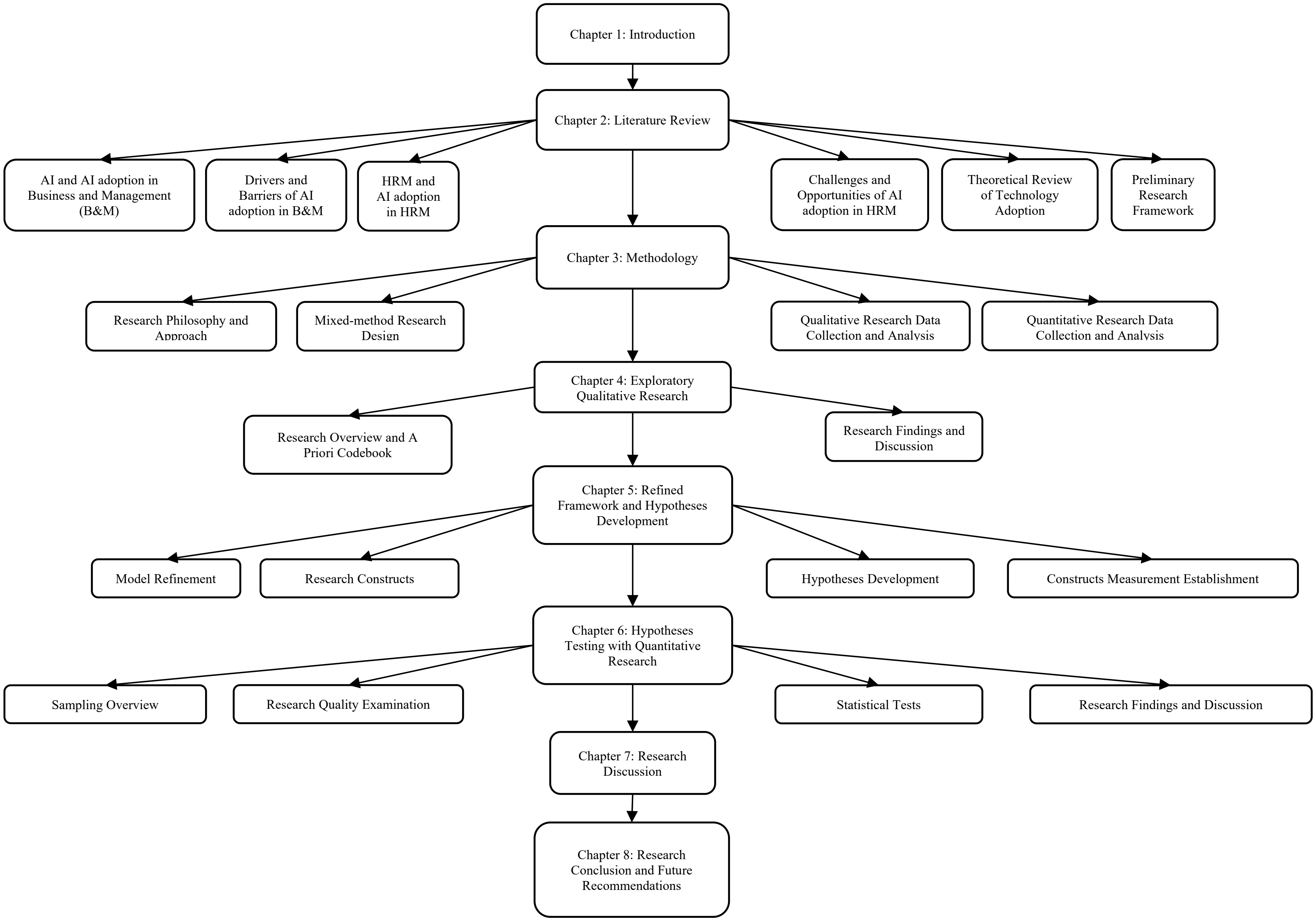

Figure 1.5: Research Structure

1.10 Chapter Summary

The phenomenon of AI disruptions and transformation has engendered an opportunity for the researcher to investigate the impact of AI applications and explore the adoption potentials to maximise business performance and productivity. In the context of this research, the exploration will lie on the field of Human Resource Management (HRM). Although the applications of AI technologies have been discussed in alternative business disciplines majorly in supply chain (Toorajipour et al., 2021) or marketing (Mariani et al., 2022) due to its straightforward outputs on business performance, the integration of AI and HRM poses an emerging frontier warranting an exhaustive exploration to apprehend the adoption determinants. Anchored to this motive, this research was conceived to excavate this under-researched premise. The mentioned lacuna necessitates empirical research to bridge the AI capacity and potentials and the HR functions.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter illuminates fundamental concepts, theories and models which are used as a critical foundation for research direction in both qualitative and quantitative studies This serves as a cornerstone for developing and clarifying a broader perspective on the critical knowledge within the fields of AI and HRM. The secondary data is used to support, compare, contrast, and discuss the research findings to facilitate broader understandings and outcomes of the research. This chapter is sectioned into several key parts which reflect the theoretical and conceptual reviews of the research foci. The structure of the chapter is designed to offer readers a clear understanding of the current context and theoretical foundations, leading to the development of a conceptual framework for the research.

This chapter starts with the conceptual introduction where principal research concepts were proposed and reflected in the contemporary settings. The conceptual review introduced key ideas related to Artificial Intelligence (AI) and Human Resource Management (HRM), covering AI's background, structure, uses, HRM functions, and how AI is being used and intepreted in HRM, to build a solid understanding of the research topic. The discussion subsequently progresses on how AI technologies are currently applied in business management and further extends to the HR context, where the applications of the technologies are fragmented in individual HR practice. In this sort of orientation, readers' perceptions about the recent collaboration level of AI in HRM could be enhanced.

This chapter next introduces the theoretical review where academic theories, models and previous related studies associated with the research were discussed and analysed to illustrate the possible correlations and reinforce the preliminary conceptual framework. A variety of concepts and models were introduced including Technology Acceptance Model (TAM), Theory of Reason Action (TRA), Theory of Planned Behaviour (TPB), Diffusion of Innovation (DOI), Social Cognitive Theory (SCT), and The Unified theory of Acceptance and Use of Technology (UTAUT). The Chapter ends with a preliminary working conceptual framework illustrates the potential constructs affecting the adoption intention of AI in HRM. The framework provided a significant mechanism for the researcher in shaping research methods and approaches to identify main influential factors of AI adoption. Artificial Intelligence (AI).

2.1.1 Definition of Artificial Intelligence

Artificial Intelligence (AI) is a branch of computer science that looks to establish machines with capabilities of simulation human cognitive functions, such as learning, problem-solving and decision-making (Armenia et al., 2024). Research about Artificial Intelligence (AI) was first captured at the Dartmouth University conference in the US in 1956. Since then, this domain has witnessed a downfall in research interest as demonstrated by the number of historical accounts (Hajkowicz et al., 2023). However, the topic of AI in recent years have exploded in academia with remarkable investment, research, training and publications such as AI and machine learning (Bratanova et al., 2022). Artificial Intelligence (AI) has been tailored to one of the current emerging realms in the business world. It has been the current propensity to be used in different technology-related research fields. However, there is not yet a universal consensus on coining definitions on the term (Kirsh, 1991).

The letter "A" has gained and is globally seconded as Artificial and therefore does not need defining (Bringsjord and Schimanski, 2003). However, there have been arguments on the letter "I" within the definition of "Intelligence". The term refers to potential tasks to be performed by machine or program with relevant human activities namely planning, problem-solving, reasoning, analysing and manipulation that generates creativity and social intelligence to a lesser extent (Guenole and Feinzig, 2018). Collectively, the AI definition is not simply to be discussed as computer intelligence or machine intelligence and therefore, the well-completed definition is unlikely to be obtained (Wang, 2019). According to Thorisson and Talbot (2018), the term intelligence has empirical and emerging content and therefore the concept is a barely stable one. The subject includes complicated terms to be followed, and its definition has been evolving. AI used to be constructed as "machines that can think like humans, reason and make decisions" which formed a perspective to be considered as general human-level AI" (Russell, 2010, p.28).

Previous studies have suggested numerous definitions of AI, embracing the key concepts of non-human intelligence designed to execute the tasks. For instance, Russell and Norvig (2016) referred to AI as systems that imitate cognitive functions normally associated with human beings, such as learning and problem-solving. Kaplan and Haenlein (2019) provided a more detailed attribute of AI in the context of its ability to autonomously interpret and learn from external resources to accomplish specific outcomes. The common among these definitions is the robust capabilities of physical entities to take roles and autonomously fulfil tasks which are currently performed by humans in the society (Dwivedi et al., 2021).

2.1.2 History of Artificial Intelligence

The idea in which a machine can think and conduct human tasks is not truly a new term established in recent decades when human civilisation is experiencing and observing the remarkable progression of technology development. Although the concept of AI was formed in 1956, the primary root of the advanced machine was back to 1940s and until 1950, when Alan Turing proposed his seminal question of whether or not a machine can think in computer machinery and intelligence journal (Bundy, 2017). The term AI was officially coined in 1956 when John McCarthy first operated his academic conference titled the concept (Ekmekci and Arda, 2020). The first AI applications were manifested during this period of 1956 with the most popular introduction of automatic chess playing which is based on “logic theorems and chess game” (Mijiwel, 2015, p.2). The programme developed at that time had enlightened the idea that intelligence could be applied in machines and computers.

The later period between 1965 and 1970 was considered as the dark time for AI development and research. The reason was due to the acknowledgement that intelligence machines were at an infant stage where very few tests and developments were conducted to satisfy the proposed expectations in advancing human tasks (Mijwel, 2015). In the ensuing decades, AI application and its practical implementation remained unclear as AI research issues proved more challenges than predicted and it was not compatible with the development pace of technology and information flow at the time. AI-realm research started to bloom again in 1990 since AI researchers concentrated more on sub-issues of AI and its possible applications in conversions, translate languages, interpret pictures. Since the 2010s, AI applications have been proving the potential of a new era of advanced technology and intelligence machinery when achievements. AI advanced products such as IBM self-driving cars or Asimo Robot applied Mindpower, have been starting to imprint technology advancement in the real world (Thakur et al., 2024).

In recent years, AI, robotics and big data have become popular and key terms in related-technology fields and research (Thakur et al., 2024). AI has made huge progressions in transforming and creating novel human working approaches in diverse sectors such as business, engineering, education, and medication (Wang and Siau, 2017; Obschonka and Audretsch, 2020; Huang and Rust, 2018). Three paramount factors contribute to the thriving of the AI field in recent decades which are (1) the availability of big data and the feasible flow of information; (2) the improvements in machine learning approaches and algorithms; and (3) the enlarging of powerful computer fields (Bundy, 2017). AI has been delivering more influences in nowadays world and gradually transferring the traditional ways of human tasks, which emphasises the need for scrutinization and research on AI influences to be well-prepared for future dynamics.

2.1.3 Types of Artificial Intelligence

Automation has transformed the economy and the way of working in the sense that manual and repetitive tasks have been largely taken over by machines. In response to that movement, labour forces started focusing on thinking tasks which mechanical devices cannot do better than humans, such as analysing and evaluating information (Huang et al., 2019). With the introduction and development of AI in the last decade, smart machines have been advanced to increase thinking capabilities, pushing labour to a new economy called The Feeling Economy, where the feeling tasks (e.g. communicating with others and establishing interpersonal relationships) become more critical than the mechanical tasks. Huang et al. (2019) conducted impactful research about AI to prepare employees, managers, businesses, researchers and educators for the transitions between different economic eras (**Table 2.1**)

Table 2.1: Types of Economy

Type of Economy	Characteristics
Mechanical Economy	Occupational features and employee benefits were more attributable to physical and repetitive tasks, such as inspecting material, performing physical activities, repairing and maintaining.
Thinking Economy	Occupational features and employee benefits are more attributable to thinking tasks, such as analysing and interpreting information, solving problems and making decisions. Thinking Economy is still with us today; however, it is being taken over by the Feeling Economy.
Feeling Economy	This economy treasures the values that new technologies have not yet reached, such as communicating with people both internal and external to the organisations, establishing and maintaining interpersonal relationships and influencing others. These feeling tasks are indicated to be more critical than previous mechanical and thinking tasks for both employees and customers.

Drawing upon the above three types of economy, Huang et al. (2019) categorised Artificial Intelligence into three types of intelligences: Mechanical intelligence, Thinking intelligence and Feeling intelligence (**Figure 2.1)**. In specific terms, Mechanical intelligence refers to the ability to execute mechanical and repetitive tasks with a limitation of learning and adaptation. For example, autonomous robots in factories are utilised to improve the output performance whilst their learning algorithms are programmed to update periodically. Thinking intelligence refers to the ability to analyse and make rational decisions, involving the autonomous adaptation and learning from system databases. An example for this type of intelligence is the current market of business intelligence (BI) software offered for organisations. These BI tools with embedded AI can provide analytical insights based on the data drawn from the system and offer predictive actions tailored for the sake of top management. Finally, Feeling intelligence refers to the ability to recognise and respond appropriately to human emotions. Such AI techniques can learn from the historical experience characterised by contextual data and adapt themselves for future interactions (Huang et al., 2019). Current AI systems, such as Siri, Alexa, and Google Gemini, are presented through virtual interfaces and rely on natural language processing to interpret human language. However, the development of true-recognised emotional AI proves difficult to achieve and is currently a work-in-process, thereby it seems to be a decade more before AI comprehensively mimics what humans can do.

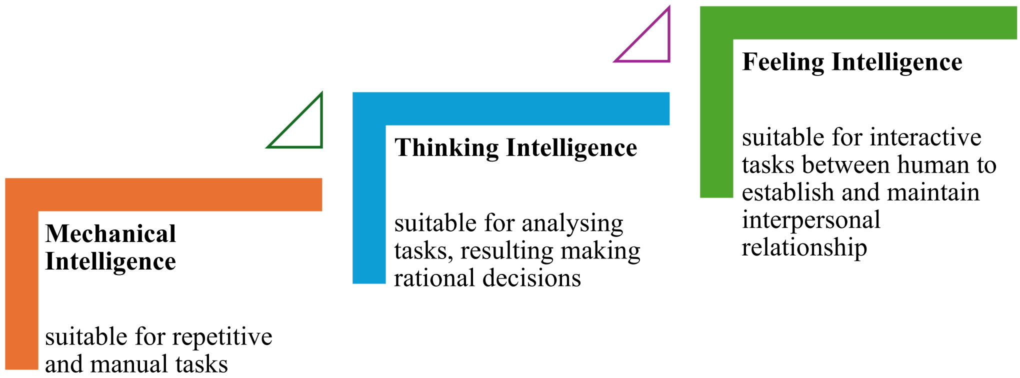

Figure 2.1: Types of AI

Since AI applications are applied in diverse circumstances with divergent problem-solution elements, it is complicated to label the constitution of AI. Other authors categorised AI along two dimensions, which are Narrow AI and Artificial General Intelligence (AGI). The first type of AI is considered as "Weak AI" which is defined as limited-context AI operations whose functions are mostly simulated human intelligence (Thakur et al., 2024). Particularly, Narrow AI is designed to concentrate and complete specific tasks with the assistance of machine learning and deep learning (the two concepts will be later clarified in the following sections). The technology has been utilised and applied in different economical aspects of human life such as search engines and other digital personal assistants (Alexa or Siri). The second type of AI is considered as "Strong AI" which is described as a machine with human intelligence. Its ability can be exploited to assist humans with difficult situations or conundrums (Thakur et al. (2024). Russel and Norvig (2016) state that this type of AI applies a universal algorithm for learning and acting in any environment. Building on the advancement of AI, Thakur et al. (2024) also states that AI will be continuing to shape the features of cognitive intelligence.

However, drawing upon the work of Hintze (2021), Geisel classified AI into four different types **(Figure 2.2)** subjective to their functions, abilities, and intelligent levels to perform assigned tasks (Geisel, 2018). Specifically, Type I of AI was characterised as the intelligence feature is performed with no memories and experience recorded in the system (e.g. automated machines in factories). Type II of AI was described as an upgraded version of type I. Particularly; decisions will be generated with limited memories and internal concept analysis (e.g. self-driving vehicles). Type III is the theory of mind where the machine possesses the ability to absorb general information of the surroundings such as people and objects. This will be later processed to generate its thoughts and emotions and behaviours will be accordingly generated (Hintze, 2021). Type IV of AI is elaborated as the highest state of intelligence where self-awareness is included, which means self-understanding is generated from the machine to establish different behaviours rooted in the machine's choice (Hintze, 2021). By delving deeply into the types of AI, technological users and applicators could perceive critical approaches to utilise and control the capacity of AI. In that way, predictive risks brought by AI can be envisaged to avoid unexpected outcomes related to data and legislations' breach (Geisel, 2018).

Figure 2.2: The four types of AI

2.1.4 Artificial Intelligence Technologies

Artificial Intelligence applications in business are growing at a fast pace to satisfy the demands of businesses in a fierce global market. Due to the blooming of technology inflows into the business market, the term business intelligence (BI) is generated to describe some specific fields that AI could potentially give impacts. According to Geisel (2018), BI applications possess the ability to imply trends and discover businesses' insights stemming from the organisations' database or external inputs by using installed algorithms (Geisel, 2018). Since there are scores of AI approaches to be applied in each realm, it is essential to narrow down the approaches used in businesses as a core concentration. AI is visualised in concept as an umbrella that envelopes and embraces diverse sets of computational technologies galvanised by human intelligence such as sensing, learning, reasoning, and acting (Banafa, 2025). For each AI approach, specialised aspects are applied compatible with human's demands. It is argued that there are two main AI approaches in recent years which are Machine Learning and Deep Learning (Hu et al., 2019). In the next part, the researcher will illustrate the relationship among AI, machine learning and deep learning as three different layers of an onion with respective arrangement.

2.1.4.1 Machine Learning

Machine Learning (ML) is scrutinised as the most potential AI approach thanks to its performance capacity (Brynjolfsson and Mcafee, 2017). ML is defined as the automated detection of patterns that give meanings for data analysing the demand of users (Kulkarni, 2017). It is the study of calculation methods applied to automate the process from knowledge accumulations from previous confronted incidents (Langley and Simon, 1995). As maintained by Hu et al. (2019), ML is an important sub-realm of AI with its foundation is on the statistical methods or numerical optimization techniques. To elaborate, ML will generate models which are extracted from the data input without processing calculating steps or model parameters. A widely used strategy in ML is to discover a pattern in large datasets. It represents an alternative approach to generate software where a machine learns through examples rather than being programmed for expected results. Therefore, ML has opened a new area of advanced technology since codification of knowledge and procedures and embedding of the coded data in the machine have been applied mostly for over 50 years (Brynjolfsson and Mcafee, 2017). An example of the ML use case could be perceived in the Wal-Mart organisation. Wal-Mart business also applies ML to capture numerous of the company's transactions through each retailer. From the transactions recorded, purchasing patterns of individual customers, patrons, customer groups are analysed based on derived models generated by ML to establish appropriate business strategies accordingly (Bose and Mahapatra, 2001).

As proposed by Bose and Mahapatra (2001), there are five paramount ML techniques which are rule induction, neural network, case-based reasoning, genetic algorithms and inductive logic programming. These domains of ML are continuously cultivated in the current business world to maximise organisational performances by improving the decision-making process of human beings.

Rule induction is a ML technique that is defined as a set of decision rules generated based on training examples (classifications) and the outputs will be presented as a decision tree. It is essential for users to learn how to read decision-making tree and to translate them into rule sets (Maruster, 2003) since the presentation of the outcomes could potentially be sophisticated to read. This technique has been used in detecting fraud or delinquencies in the banking industry.

Neural Network (NN) is the second ML technique, and it has been applied mainly in Deep Learning with a more advanced version. It is described as a collection of input nodes linked to output nodes through hidden node sets to create a multi-layered network (Medsker, 1995). The applications of NN are still under discovery and exploring symbolic rules to increase the obviousness to applicants.

The Case-Based Reasoning Approach (CBR) is a ML technique where examples of each case will be in place to be ready to work when receiving input datasets. In particular, each case is installed with a case description and according to solutions by applying appropriate algorithms. When an issue is put into the process, the CBR function is to match the case with the examples stored to provide solutions.

Genetic Algorithms (GAs) is the ML technique buried in natural selections and evolution theories which are applied in the prediction or classification work (Medsker, 1995). Based on the three fundamental elements of selection, crossover and mutation, the technique is used best with “noisy data”. Noisy data is defined as meaningless data which generate hindrances for a system to understand and interpret input information (Gupta and Gupta, 2019).

The Inductive Logic Programming technique (ILP) is described to be the crossing point between ML and Logic Programming (Kakas et al., 1992). The technique used to confirm the logic to identify the concept relied on positive and negative examples. This technique offers advantages of simplifying the illustration of the relationship between two elements and the domain knowledge will be expressed easily to enhance the effectiveness of the system (Medsker, 1995).

2.1.4.2 Deep Learning

Deep Learning (DL) is a class of Machine Learning developed to establish and utilise Deep Neural Network (DNN) for machine learning tasks (Mathew et al., 2021). The term deep is based on the multilayers used to analyse inputs in the system. The technique has become prevalent due to the higher ability in learning and analysing the information from numerous unstructured inputs, which contributes significantly to Big Data Analysis where unlabelled raw data are appearing massively in the digital world. DNN is a type of Artificial Neural Networks (ANNs) in which its constitution includes various hidden layers laid between inputs and outputs. Neurons are contained in each layer to receive inputs from previous layers and create for next layers a non-linear output (Medsker, 1995). Its outstanding performance has been recognised with the ability to process unlabelled datasets, learning features at various levels, extracting complicated patterns from big data, semantic indexing, data tagging and decreasing the complex level of discriminative tasks (Najafabadi et al., 2015). In recent decades, DL methods have been applied in different fields in multiple industries. With the ability to apply multiple layers to extract high features from raw information, there are currently seven important applications of DL namely Image Recognition, Automatic Speech Recognition, Natural Language Processing, Customer Relationship Management, Drug Discovery and Toxicology, Bioinformatics and Recommendation Systems (Hordri et al., 2016). DL has been proliferating in more fields, which stimulates the process of altering the traditional working process of humans in the workplace. Large tech-organisations such as Google, YouTube or Microsoft have been applying the technique to be able to analyse and detect possible issues to assist and upgrade the functions of their products and services (Najafabadi et al., 2015). The advanced technology also brings chances and challenges for researchers or practitioners to measure the working pace and give correct predictions for the future workplace and manpower.

2.2 AI adoption in Business and Management

2.2.1 Overview of AI adoption landscape based on sectors

Of all industry and economic sectors, the science and research sector are believed to be the earliest employers of AI technology which can help to improve efficiency, speed and quality of research (Hajkowicz et al., 2022). Understanding research trends of AI can help scholars to navigate potential avenues of this domain and wisely allocate the resources to uplift future studies. There are several articles using bibliometric analysis and relevant approaches to examine the AI adoption in various contexts, picturing a holistic view about this domain (Hajkowicz et al., 2023). For example, Bianchini et al. (2022) conducted a study to examine the diffusion of a subset of AI (neural networks) during 1990-2018 across six research fields of technology, physical sciences, biomedicine, health sciences, social sciences, as well as the arts and humanities. They suggested that AI would reshape and change the ways of doing sciences. Another study investigated by Frank et al. (2019) using bibliometric analysis to identify which major fields were cited within AI research. The authors found that mathematics and computer science were the most cited, whereas philosophy, geography and arts received less attention (Frank et al., 2019). Additionally, they also argued that AI research should shift the focus into social sciences, the arts and humanities, to ensure their usefulness for policy makers and society at large (Frank et al., 2019).

Responding to that call, Hajkowicz et al. (2022) conducted a thorough bibliometric study by reviewing 3.1 million peer-reviewed publications (between 1960 and 2020) to provide a holistic view of AI adoption across different fields of research. The authors revealed that the adoption of AI beyond computer science has increased rapidly to cover half of all research fields by 1972, over 80% by 1986 and over 98% at the present time. A closer look into the second level of research fields, **Figure 2.3** notably indicates that physical sciences are leading the largest adopter of AI research, and the following sectors have slight increases in AI publications between 2020 and 2021 (Hajkowicz et al., 2022). Specifically, AI-related publications have increased in certain fields, such as dentistry (by 1.9 times); arts and humanities (by 1.4 times); economics and finance (increased by 1.3 times); healthcare (increased by 1.3 times); and social sciences with same increasing rate (Hajkowicz et al., 2022). These findings suggest opportunities for future research within these domains to extend the current body of research. In this paper, given researchers' disciplinary backgrounds, they primarily paid attention to the field of social science, with specific concentration on Business and Management.

Business and Management is a large-scale discipline that encompasses the administration and operation of an organisation. It consists of organising, planning, setting objectives, directing and analysing business activities irrespective of the firms' size (Kamugisha, 2017). Given that AI applications have been employed in various business function, Cubric (2020) argued that most of reviews emphasise on a particular sector (e.g. healthcare, engineering, and hotel); or a specific business function (e.g. marketing, supply chain or system managements). There has been a paucity of literature aiming to synthesise and categorise the adoption of AI within the business and management domain. **Table 2.2** briefly reviews some representative literature researching the adoption of this advanced technology in Business and Management. Artificial Intelligence is currently employed under two primary reorientations (either virtual or physical agents) across business sectors and functions.

Fields of Research (Second-Level ASJC)	1970	1980	1990	2000	2010	2015	2020	2021
Agricultural and Biological Sciences	0.1	0.1	0.3	0.7	1.2	1.5	2.5	2.8
Arts and Humanities	0.0	0.1	0.3	0.4	0.6	0.7	2.3	3.2
Biochemistry Genetics and Molecular Biology	0.1	0.1	0.2	0.4	1.3	1.9	3.2	3.8
Business Management and Accounting	0.5	0.5	0.9	1.3	2.2	2.6	4.8	5.0
Chemical Engineering	0.1	0.0	0.2	0.7	1.0	1.1	4.1	4.8
Chemistry	0.0	0.1	0.2	0.4	0.6	1.0	2.7	3.2
Computer Science	3.7	1.9	6.9	12.4	16.0	17.1	22.7	25.7
Decision Sciences	2.3	1.4	2.1	4.5	7.1	8.5	9.8	11.3
Dentistry	0.0	0.0	0.1	0.3	0.3	0.3	0.9	1.7
Earth and Planetary Sciences	0.1	0.2	0.5	0.9	1.7	2.5	4.4	5.5
Economics Econometrics and Finance	0.0	0.1	0.3	0.8	0.9	1.1	2.7	3.5
Energy	0.1	0.2	0.3	0.8	1.5	2.1	4.5	5.2
Engineering	0.3	0.4	1.6	3.0	4.4	5.2	10.1	11.3
Environmental Science	0.1	0.2	0.3	0.7	1.3	1.7	2.9	3.3
Health Professions	0.1	0.2	0.4	1.1	1.4	2.2	3.2	4.1
Immunology and Microbiology	0.1	0.1	0.1	0.3	0.7	1.4	1.9	2.3
Materials Science	0.1	0.1	0.3	0.5	0.7	0.9	4.2	4.1
Mathematics	0.6	0.8	1.9	4.9	7.9	9.0	12.7	14.1
Medicine	0.0	0.1	0.2	0.3	0.8	1.1	2.2	2.7
Neuroscience	0.1	0.1	0.5	1.1	2.3	3.5	5.1	6.1
Nursing	0.0	0.0	0.1	0.2	0.3	0.5	1.1	1.2
Pharmacology Toxicology and Pharmaceutics	0.0	0.0	0.1	0.3	0.6	0.9	1.7	2.0
Physics and Astronomy	0.1	0.2	0.6	0.8	1.2	1.7	5.6	7.0
Psychology	0.2	0.4	0.7	1.2	1.7	2.2	2.7	2.9
Social Sciences	0.1	0.1	0.3	0.4	0.8	1.2	2.8	3.6
Veterinary	0.0	0.0	0.1	0.1	0.2	0.4	1.0	1.1

Figure 2.3: Artificial Intelligence publishing intensity in second-level research fields (Hajkowicz et al., 2022)

For instance, logistics provider DHL is using virtual AI agents to enhance the performance of its logistics function, such as AI-powered inventory management or AI-based safety control. Regarding the manufacturing sector, beverage company – Coca Cola is deploying virtual AI agents (ChatGPT) to assist its marketing functions in terms of crafting customised adverts and advertising campaigns (Brown et al., 2024). In the financing sector, most retail banks are using virtual AI called Robo-advisor to better handle customer needs and offer personalised recommendations (Zhang et al., 2021). In the healthcare sector, AI-equipped devices, such as Pearl, Care-O-bot and Paro; provide mobility support and therapeutic treatments to elderly and disabled people (Kuo et al., 2009; Cantone et al., 2023). In the restaurant and dining sector, AI-humanoid robots can execute both front-of-house and back-of-house tasks. For example, Chinese restaurant – Claypot in Calgary majorly use AI-robot to welcome guests, take orders and serve the tables (Zhang et al., 2022), whereas Café X in San Francisco International Airport utilised a physical AI bartender to mix cocktails and mocktails for the passengers (Choi et al., 2023). In the same manner, several hotels have been adopting AI-robots to optimise their operations. A prime example is the Henn-na Hotel in Japan which stands out as the world's first robot-operated hotel by deploying advanced technologies for their frontline services, such as welcoming, luggage handling and room assistance (Cakar and Aykol, 2021).

Table 2.2: AI adoption in Business and Management

Business sector	Business Function/ Area	AI Representation	AI Description	Sources
Supply Chain	Logistic	Virtual	AI-powered inventory management AI-powered safety management	(Brown et al., 2024)
Retail	Various	Virtual	AI-powered image search AI-based storage management AI-powered security platform	(Cao, 2021)
Production	Marketing	Virtual	Crafting customised ad and advertising campaign	(Brown et al., 2024)
Hotel	Customer Service	Physical Virtual	Concierge robots Chatbot	(Prentice and Nguyen, 2020)
Hotel	Frontline Service	Physical	Humanoid assistant robot	(Kong et al., 2021)
General	Human Resource	Virtual	E-recruitment Automation of job offers	(Pillai and Sivathanu, 2020)
General	Human Resource	Virtual	Chatbot Automated Assessment	(Kambur and Akar, 2022)
Finance	Customer Service	Virtual	Chatbot to enhance handling customer needs and offer personalised recommendations	(Zhang et al., 2021)
Finance	Customer Service	Virtual	Robo-advisors	(Zhang et al., 2021)
Transportation	System Management	Physical	Autonomous vehicles	(Namazi et al., 2019)
Healthcare	Treatment/ Therapy	Physical	Pearl, Care-O-bot – aids with elderly people	(Cantone et al., 2023)

Healthcare	Treatment/ Therapy	Physical	Paro – provides therapeutic treatments	(Kuo et al., 2009)
Restaurant	Front-of-house service	Physical	Welcoming guests, take orders	(Zhang et al., 2022)
Restaurant	Back-of-house service	Physical	humanoid AI-powered bartender to make drink	(Choi et al., 2023)
Tourism	Tour leading	Physical	Tour guide	(Parvez et al., 2024)
Tourism	Tour leading	Physical	Tour guide	(Wong and Wong, 2024)
Hotel	Customer Service	Physical	AI-powered butler	(Cakar and Aykol, 2021)
Hotel	Customer Service	Physical	AI-powered robots fully operated hotel	(Yörük et al., 2023)
Retail	Customer Service	Physical	Sales assistant	(Guido et al., 2024)
Retail	Customer Service	Physical	Sales assistant	(Roozen et al., 2023)

2.2.2 Drivers and Barriers of AI adoption in Business and Management

The summary and classification of the main drivers for the AI adoption in business and management are illustrated in **Table 2.3**. The motivations for the AI adoption in Business and Management are mainly related to economic and social improvements. Drawing upon the troubleshooting complexities in the heal monitoring systems, AI techniques have helped to improve the downtime and cost implications. These effective implementations are rooted in the designing algorithms for processing and the computing architectures called deep learning. AI Deep Learning has been successfully applied in various domains, generating pathways for potential innovations and cost efficiency for businesses (Khan and Yairi, 2018). Another subset of AI – machine learning (ML), is suggested as a useful technology for supporting Decision Support System which refers to the practice of using computers to assist decision-makers. Applying machine learning techniques can increase efficiency in the decision-making process and AI power can continue to learn from those decisions and provide predictive capabilities (Merkert et al., 2015). Nevertheless, artificial intelligence technology is also suitable for analysing medical data, providing detailed diagnosis and assisting healthcare practitioners during consultations (Laranjo et al., 2018; Shahid et al., 2019). Some other factors contribute to the consistent urges for AI adoption are needs for more comprehensive understanding of consumers' behaviour (Shahid et al., 2019; Kaartemo and Helkkula, 2018), maintaining customer satisfaction and supporting their behavioural changes (Kaartemo and Helkkula, 2018; Laranjo et al., 2018), reducing uncertainties and enhancing flexibilities in production planning and control (Guo et al., 2011; Merkert et al., 2015) , alleviate traffic congestion with AI-powered traffic management (Namazi et al., 2019), reduce human errors and increase accuracy in the quality assessment process (Parvez at el., 2024; Khan and Yairi, 2018).

Table 2.3: Drivers of AI adoption in Business and Management

Category	Drivers for AI Adoption	Descriptions	Sources
Economic Dimension	Innovation	Pathways for potential deep learning-based innovation.	(Khan and Yairi, 2018)
	Cost Efficiency	AI-technique can autonomously operate, requiring less human intervention.	(Khan and Yairi, 2018)
		Potentially reduce the cost for healthcare providers in long-term	(Parvez at el., 2024)
	Customer Satisfaction	Integrate resources between service providers and users. Support customer behavioural changes.	(Kaartemo and Helkkula, 2018; Laranjo et al., 2018)

	Accuracy	Reduce human errors in quality assessment process	(Parvez at el., 2024; Khan and Yairi, 2018)
	Productivity	Alleviate traffic congestion with AI-based control systems	(Namazi et al., 2019)
		Reduce uncertainties and enhance flexibilities	(Guo et al., 2011; Merkert et al., 2015)
	Decision Support System	Enhance efficiency in decision making process, learn from the decisions to provide predictive capabilities.	(Merkert et al., 2015)
		Comprehend customer behaviours.	(Shahid et al., 2019; Kaartemo and Helkkula, 2018)
		Provide details of medical diagnosis and assist clinicians during the consultation.	(Laranjo et al., 2018; Shahid et al., 2019)
Social Dimension	Well-being	Decrease workload for caregivers and enhance elderly well-being	(Kachouie et al., 2017)

However, there are a few barriers (illustrated in **Table 2.4**) influencing the adoption of AI in Business and Management. Prior systematic review about this domain suggested that those barriers usually revolve around following dimensions, such as economic (cost and infrastructure), technical (database and model standardisation), and social (knowledge requirement, safety and trust and fear of unknown).

Table 2.4: Barriers of AI adoption in Business and Management

Category	Barriers for AI Adoption	Descriptions	Sources
Economic dimension	Cost	Manual labelling expert knowledge is usually an expensive practice.	(Khan and Yairi, 2018)
	Infrastructure	Require decent investments in infrastructure for large-scale implementation.	(Shahid et al., 2019)
Technical dimension	Database	Unable to comprehend unstructured information.	(Shahid et al., 2019)
		Require frequent maintenance and data training to avoid performance degradation.	(Memeti et al., 2019)
	Model Standardisation	Some bespoke AI-models may not apply to other areas.	(Guo et al., 2011)
Social dimension	Knowledge requirement	Require comprehensive knowledge to explore full potential of AI techniques	(Baryannis et al., 2019)

	Safety and Trust	Potential leak of confidential information.	(Wen et al., 2012)
	Fear of Unknown	People's resistance to use new technologies. Being threatened with job losses.	(Broadbent et al., 2009; Maalouf et al., 2018)

2.2.3 The importance of AI adoption in Business and HRM

The integration of AI into business and management practices has increasingly shifted from experimental innovation to mainstream strategic implementation. AI applications are ranging from predictive analytics and robotic process automation to conversational agents and generative tools. They are now used across sectors to enhance productivity, enable real-time decision-making, and automate previously human-led functions. For HR functions, this promise translates into applications such as talent acquisition, workforce planning, performance management, and learning and development, where AI-enabled systems are expected to enhance efficiency and insight. However, recent scholarship warns against adopting a purely techno-optimistic narrative (Danaher, 2022). Instead, a growing body of critical literature has interrogated the nuanced implications of AI for the future of work, particularly within the realm of HRM, where the deployment of AI has direct consequences on job roles, organisational justice, and employee autonomy.

In the wider business context, AI has been recognised for its transformative potential. As Dima et al., (2024) state, AI impacts business activities in at least five key areas: the automation of tasks, enhanced data usage, augmentation of decision-making, redefinition of work structures, and transformation of social and relational dynamics within organisations. These changes present both strategic opportunities and challenges for business leaders. For instance, while AI can streamline routine administrative processes, reduce cost, and deliver data-driven insights to inform strategy, it simultaneously demands new forms of managerial oversight and ethical governance (Mujtaba and Mahapatra, 2024). Without these, the technology may reinforce existing biases or exacerbate inequalities.

The strategic value of AI lies in its ability to enable organisations to become more agile and responsive. Yet, such value does not exist in a vacuum. AI relies heavily on historical data and the assumptions embedded within algorithmic design—both of which can reflect and amplify social inequities (Zajko, 2022). Deranty and Corbin (2024), in a sociologically grounded review, highlight that current AI research often underestimates the social, political, and organisational contexts in which such technologies are deployed. They caution that AI in the workplace is frequently framed as a neutral efficiency tool, ignoring its role in shaping power dynamics, intensifying surveillance, and reinforcing managerial control under the guise of technological rationality.

In HRM, AI systems are increasingly used to screen job applicants, monitor employee performance, and even predict turnover or engagement (Madanchian, 2024). While these systems promise increased objectivity and efficiency, they also raise serious concerns about fairness, accountability, and the erosion of human judgment. Mujtaba and Mahapatra (2024) discuss the pressing challenge of fairness in AI-driven recruitment, noting that current algorithmic models often inherit bias from historical data and may unintentionally discriminate against marginalised groups. For instance, large-language-model resume-screening tools have been found to favour white-sounding names in 85% of cases and entirely overlook black candidates in certain roles (Wilson and Caliskan, 2024). This calls for more transparent fairness metrics and greater emphasis on inclusive data practices.

The critical lens offered by Narayanan and Kapoor (2024) further reinforces these concerns. The authors argue that AI tools, especially in domains such as hiring and education, often fail to deliver on their claims. Their analysis challenges the stance that AI is universally workable and instead reveals that multiple applications serve as black boxes with questionable validity as well as limited empirical evidence supporting the use. For HR professionals, this critique is significantly relevant, where decisions often involve ethical judgment, contextual interpretation, and human discretion. High-ranking journal research has raised concerns that AI-driven HR systems risk reproducing historical biases, narrowing definitions of performance, and shifting accountability away from human decision-makers (Kellogg et al., 2020; Meijerink et al., 2021; Jarrahi et al., 2023). The scenario demands a reassessment of the assumptions behind AI-powered tools and a commitment to evidence-based adoption grounded in both technological capability and ethical responsibility. Rather than replacing human judgment, AI may reconfigure power relations and intensify managerial control, reshaping employees' experience of work through surveillance, standardisation, and algorithmic evaluation.

Moreover, recent study by Shao et al. (2025) provides a forward-looking perspective by introducing a framework to evaluate whether specific workplace tasks should be automated, augmented, or preserved as human led. Their study finds that the optimal integration of AI into the workforce requires a redefinition of human roles, emphasising creativity, empathy, and complex judgment over routine execution. This reframing aligns with broader calls for augmented intelligence rather than wholesale automation. In business contexts, De Cremer and Kasparov (2021) suggest that AI should be used to support, not replace, practitioners in decision-making, enabling a shift towards more strategic and human-centred practices.

Through these recent studies, a more complex picture of AI in business and management is visualised. While AI undoubtedly provides significant advantages in terms of operational efficiency and strategic agility, its integration into the workplace must be approached critically and ethically. AI represents both a continuation of digital innovation and a critical juncture in how work is organised and experienced. The challenge is not merely to implement AI but to do so in a way that upholds the values of fairness, dignity, and human flourishing. This entails a shift from viewing AI as a universal solution to understanding it as a socially embedded technology with profound implications for the future of work.

Hence, the contemporary literature suggests that AI is important for business and HR not because it guarantees superior outcomes, but because it forces organisations to confront fundamental questions about judgment, expertise, and the future experience of work. For HR practitioners in particular, AI adoption represents a strategic and ethical challenge rather than a purely technical one. This reframing underpins the present study, which examines not only whether HR professionals intend to adopt AI, but how their expectations, concerns, and sensemaking reflect broader tensions identified in critical business-HR-AI scholarship.

2.3 Human Resource Management (HRM)

The above discussions shed light regarding the construction of AI, its impact as well as providing a landscape of AI technologies that are invading in business management. The next part continues to introduce the subsequent key concept of this study: Human Resource Management and its key functions.

2.3.1 The view about Traditional Human Resource Management

Previous research elucidated how HRM functions contribute to the long-term success of organisational development. Early studies on traditional HRM stated that the activities should involve “staffing, training, reward and job design” (Chaturvedi and Joshi, 2018, p.38). The scope of HRM has since expanded beyond core administrative tasks to encompass strategic communication of organisational goals, leadership alignment, targeted training, and employee autonomy—reflecting its evolving role as a driver of organisational performance and culture (Husen et al., 2024).

To support conceptual clarity and analytical consistency, this study adopts the term *Traditional HRM* to refer to forms of human resource management that rely primarily on human judgement, interpersonal interaction, and rule-based or administrative digital systems. Traditional HRM, as defined here, includes practices such as recruitment, performance management, and employee relations conducted through human decision-making, supported by conventional HRIS, workflow automation, and descriptive or reporting-based HR analytics. While such systems may be digital, they do not involve adaptive learning, probabilistic inference, or algorithmic decision support.

In its early form, traditional HRM was largely administrative and operational, involving a high degree of manual paperwork**,** physical data storage, and labour-intensive record-keeping (Kambur and Yildirim, 2023). Main activities including recruitment, onboarding, attendance tracking, and performance appraisal—were executed through repetitive and standardised procedures, often relying on human judgment and subjective interpretation (Yusoff, 2025). This conventional approach, though foundational, was frequently constrained by inefficiencies, prone to human error, and lacked real-time decision support (Ashrafuzzaman et al., 2024).

Traditional HR departments operated in siloed systems with limited integration across business functions. Personnel files were typically stored in filing cabinets or spreadsheets, and decisions regarding hiring, promotion, or performance evaluation were based on qualitative impressions rather than empirical data. In addition, many organisations still operate HR functions separately, leading to fragmented systems often referred to as HR data silos. These disconnected systems limit the strategic integration of HR functions, reduce the visibility of critical insights, and negatively affect the overall employee experience (Ng et al., 2025). As a result, HRM functioned reactively rather than strategically, focusing on maintaining compliance, managing contracts, and resolving workplace issues with minimal predictive insight. While this model provided structure and process discipline, it often struggled to scale with growing workforce complexity and the increasing demand for agility.

In fact, HRM integrates a wide range of decision-making processes such as workforce planning and employee engagement. Hence, the structure and design of effective HR practices have significant ripple effects across the organisation. The effective HRM systems link positively to business performance, including employee productivity, organisational climate, and cost-efficiency (Bakator et al., 2019). Empirical research shows that organisations with strong employer branding and aligned HR practices are more successful at drawing high-calibre candidates and building a resilient talent pipeline (Joyce et al., 2024). This strategic reputation benefit translates into sustained competitive advantage by reinforcing employer appeal and customer trust.

Traditional HRM is on the path of technology evolution, especially the intervention of AI in HRM is considered a ground-breaking field. The emergence of AI-powered HRM represents a shift toward digitisation, integration, and strategic enablement. Rather than positioning Traditional HRM and AI-powered HRM as mutually exclusive categories, this study conceptualises HRM practices along a continuum of technological engagement. At one end of the spectrum are predominantly human-centred HR practices supported by basic digital systems; at the other are HR functions where AI systems play a more prominent role in analysis and decision support. Most organisations occupy intermediate positions on this continuum, combining elements of traditional, analytical, and AI-enabled HR practices to varying degrees.

This continuum-based framing is analytically important for two reasons. First, it avoids a reductive opposition between “manual” and “AI-driven” HRM, recognising that adoption is incremental, uneven, and context dependent. Second, it provides a conceptual foundation for interpreting empirical findings in this study, particularly participants’ tendency to conflate AI with analytics or automation. By viewing AI-powered HRM as an extension of existing HR technologies, the study is able to explain adoption factors as historically grounded responses to evolving HR practices.

2.3.2 HR Functions in traditional HRM

Following the discussion on traditional HRM, this section explores the core HR functions and how they have evolved in response to contemporary organisational demands. HRM comprises a broad range of interconnected activities, including recruitment and selection, training and development, performance management, and employee retention (Breaugh and Starke, 2000). These functions, while often implemented individually in traditional models, have increasingly shifted toward integrated and strategic frameworks. One influential model capturing this integration is the People Performance Model developed by Boxall and Purcell (2022), which emphasises the synergistic effect of coherent HR practices. According to this model, when HR activities are strategically aligned and mutually reinforcing, they can enhance employees’ ability, motivation, and opportunities—ultimately fostering greater job satisfaction, commitment, and organisational performance. The subsequent discussions will explore the key human resource functions within the context of current HRM practices.

2.3.2.1 Recruitment

Recruitment is defined as the practice where organisations conduct an activity of finding the candidates in the employment market to fulfil an open job vacancy (Stoilkovska et al., 2015). Recruitment activity used to be narrowed in the aspect where organisations were solely concerned with ensuring to supply sufficient numbers of workers to meet the businesses' objectives. Effective recruitment is vital for organisational success. It includes organisational ability and capacity to search for the right candidate for the right role at the right time. It also assists businesses to form a foundation for long-term organisational success. Nowadays, recruitment remains a cornerstone of HRM, encompassing activities that identify, attract, and select candidates with the requisite knowledge, skills, and attitudes (KSAs) to fit organisational needs (Al-Ayed, 2021). The **Figure 2.4** illustrates a 5-step recruitment model, and it is considered as a basic framework for effective recruitment (Breaugh and Starke, 2000).

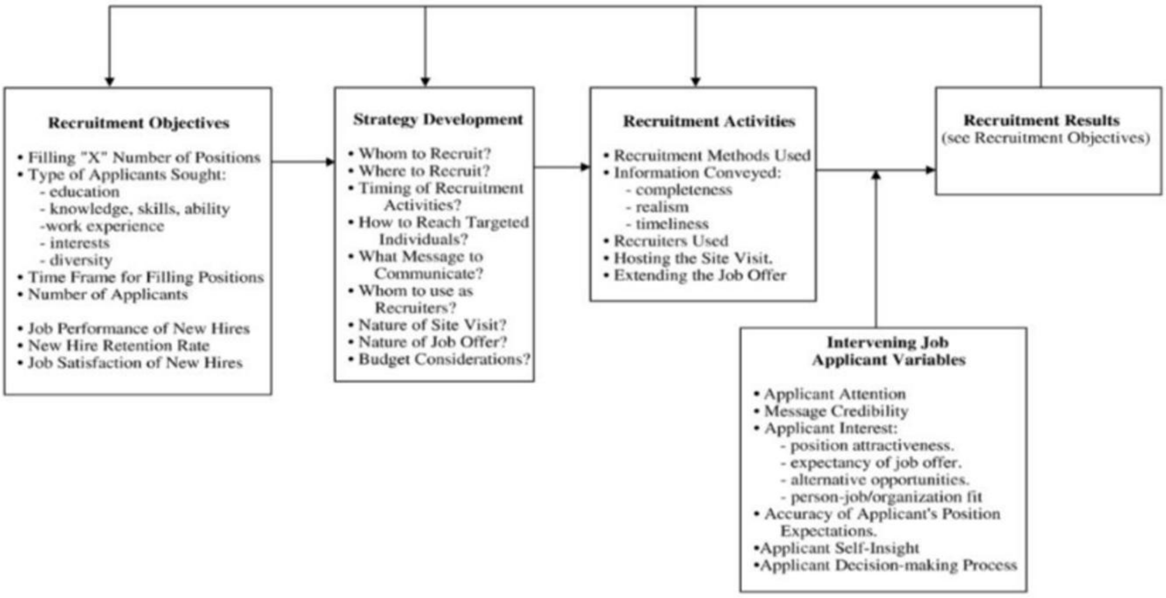

Figure 2.4: Steps in Recruitment (Breaugh and Starke, 2000)

Recent scholarship underscores how recruitment intersects with broader HRM functions in the age of AI. It is emphasised that effective recruitment requires robust fairness mechanisms alongside competence assessment to prevent the reinforcement of existing inequalities and ensuring equal access to opportunities for job applicants (Rigotti and Fosch-Villaronga, 2024). Joseph and Anantharaman (2024) also argue that algorithmic systems may perpetuate existing biases in recruitment process unless carefully governed. Hence, incorporating ethical safeguards like fairness metrics, transparent algorithms, and inclusive design practices becomes essential for equitable and effective hiring—particularly when recruitment acts as the gateway to other HR functions such as development, compensation, and retention.

2.3.2.2 Selection

Selection activity is where a company plays a jigsaw to figure out the correct pieces among other splinters to complete the comprehensive picture (Boxall and Purcell, 2022). Conventional methods such as interviewing, or company-designed tests are where the selection processing is being conducted. The most paramount factor in selection is candidate equality, which remains a critical issue in HRM when considering human biases (Stoilkovska et al., 2015). Selection remains a cornerstone of effective HRM, aimed at finding the ideal candidates whose competencies and cultural fit align with organisational needs. In traditional settings, companies relied on tools such as resumes, structured interviews, and assessment centres to make hiring decisions. The mentioned process is often criticised for limited efficiency and a reliance on subjective human judgment (Cook, 2016). While structured interviews and tests provide a degree of standardisation, they still leave room for bias (Cai and Zhang, 2024). In the age of AI, the selection practice must be carefully revised. A recent study shows that AI-powered recruitment tools significantly accelerate CV screening and interview scheduling while maintaining or improving candidate match quality, albeit requiring caution around ethical implementation (Oman et al., 2024). However, a grounded theory study by Rigotti and Fosch-Villaronga (2025) highlights that AI algorithms applied selection often embed hidden biases learned from historical data, underlining the importance of fairness-aware design and auditability capabilities.

2.3.2.3 Talent Acquisition

Talent Acquisition is the process of identifying and acquiring employees whose KSAs are stronger to potentially outperform at work. The activity implies an efficient process where candidates are centred on future-oriented needs. Strategic activities to assist talent acquisition consist of sourcing strategy, effective staffing plan, diversifying the organisational workforce and establishing a robust pipeline for potential candidates (Boxall and Purcell, 2022). These mentioned activities are paramount to delivering the culture of organisations to create an attractive pattern for candidates. Nowadays, talent acquisition has evolved into a strategic imperative, essential for securing high-performing candidates whose knowledge, skills, and attributes (KSAs) align with organisational goals (Opada et al., 2024). The function now centres on anticipating future talent needs and building long-term workforce capabilities (Silva, 2025). With the accessibility to big data, the function also plays an essential part of the success of recruitment process by deploying predictive analytics to source and fuel talent pools. In this evolved framework, organisations conduct comprehensive job and person analysis, then employ technological tools such as ATS, AI resume filters and chatbots alongside strategic employer branding to build robust candidate pipelines aligned with long-term workforce goals (Nalla, 2024). The activity is relentlessly contributing to the organisational success where there is a need for an extreme work to be filled (Ferrer et al., 2024).

2.3.2.4 Performance Management

Performance management function has long been regarded as a critical driver of employee development and organisational effectiveness (Mone et al., 2011). It is argued that the function serves to align individual efforts with organisational objectives through activities such as goal setting, ongoing feedback, performance evaluation, and review cycles (Rajapakshe, 2024). This alignment cultivates clarity of expectation and consensus, enhancing employee engagement and productivity. The absence of Performance Management could lead to potential inequality in organisational reward systems, which might eventually engender employee disengagement. Businesses nowadays are trying to optimise performance management systems since there are available hindrances occurred in the process. The difficulties that could be mentioned are poor-designed tools and processes or there is a potential threat of human biases since the activity is a highly personal intervention.

However, digital transformation has elevated the strategic importance of performance management systems. A recent study by Lackhamraju (2025) highlights how digital HR tools such as cloud-based performance dashboards and continuous feedback platforms, enable real-time insights and agile performance controls. The tools are claimed to overcome the limitations of static annual appraisal systems. Despite the positive impact, Carter and Liu (2025) highlight in their recent study about the potential of anchoring bias, where line managers exhibit the bias by leaning heavily on performance data —particularly when supported by AI-generated insights. Since there remain defects of human biases in the processes, it entails HR practitioners to be skilfully trained and adopt technological innovations to reduce available biases (Budhwar and Aryee, 2008).

2.3.2.5 Learning and Development (L&D)

Learning and Development (L&D) has been mentioned in recent research to be a crucial tactic to enhance employees' job satisfaction levels. The term is defined as the process for organisations to develop their manpower in terms of capacities, skills, and competencies, which encourages the competitive aspects of the business in the market (MacKenzie et al., 2011). It must rely on the organisation value and culture. Top companies nowadays recognise the important role of investments in employee learning as a method to secure competitive advantages (Porter, 1990). Investment in L&D is potential for the sustainability and exclusiveness of the business. L&D focuses on transferring KSAs which are needed for businesses' operation and development. Learning and Development (L&D) initiatives are essential for equipping employees with new KSAs while ensuring these competencies are effectively embedded to support career progression and enhance organisational competitiveness. Perkins and Robinson (2025) highlight that well-structured L&D programmes not only upskill employees but also integrate these newly acquired capabilities into everyday work, aligning individual development with organisational objectives. The expectations of the workforce, especially among younger generations, pose challenges for organisations, as these employees seek continuous learning opportunities and engaging tasks, making Learning and Development (L&D) essential for promoting job satisfaction. A similar viewpoint is presented by Andrade (2024), who suggest that the increasing demand for skill development and meaningful work among younger workers underscores the importance of L&D in enhancing employee engagement and satisfaction. Additionally, with the dynamics and fierce competitiveness in the global market, L&D investments would be the ideal method to help businesses to keep up with the fast business pace, requiring businesses to continuously upgrade and respond frequently to changes. Herzberg' two factor theory emphasises the important role of providing opportunities for growth and progress as a tool for motivation and retention (Herzberg, 1966). The investment in L&D, therefore, becomes pivotal to the thriving and surviving of businesses.

2.4 Data-driven HRM: from HR Analytics to AI in HRM

Although contemporary discourse often frames AI as a novel and disruptive force in the workplace, it is important to situate AI within a longer history of technological change. From this perspective, AI can be understood not as a radical break from the past, but as the latest phase in a series of technological developments that have progressively reshaped work, management, and organisational control since the industrial revolution. Hence, this section critically reviews the evolution of HR Analytics and its integration with AI technologies, drawing on academic debates and commercial developments to position HRM within contemporary digital transformation discourses. It establishes the relevance of this literature for understanding the drivers and implications of AI adoption in HRM.

2.4.1 HR Analytics in HRM

HR Analytics refers to the use of data analysis techniques to improve HR decision-making (Marler and Boudreau, 2017). Initially focused on descriptive reporting, HR analytics has evolved to include diagnostic, predictive, and prescriptive applications aimed at improving talent management, workforce planning, and organisational performance (Isson and Harriott, 2016; Bahuguna et al., 2024). This progression reflects increasing analytical sophistication, enabled by advancements in digital infrastructure and data availability within HR functions.

The value proposition of HR analytics lies in its potential to align workforce management with organisational objectives. Indeed, Rasmussen and Ulrich (2024) emphasise the need to move from insight generation to demonstrable impact, while earlier studies highlight how digital systems have automated administrative HR tasks and expanded access to workforce data through self-service platforms (Lawler et al., 2004; Boudreau, 2010). Tasks once managed solely by HR personnel such as salary administration, job postings, address and family changes, and benefits enrolment—can now be executed through self-service platforms accessible to employees and line managers. Enabled by cloud computing and mobile technologies, these HR systems are not only more efficient but also allow seamless access from virtually anywhere. Contemporary HR information systems (HRIS) facilitate the integration, and analysis of vast amounts of employee-related data (Roul et al., 2024), supporting evidence-based decisions in recruitment, development, retention, and succession planning (Boudreau and Ramstad, 2007; Lawler et al., 2004a). The capacity also allows HR professionals to monitor key HR outcomes such as turnover, employee engagement, leadership pipeline strength, and performance trends.

Despite these advances, the adoption of HR analytics remains uneven. Challenges persist around data quality, fragmented systems, ethical concerns, and limited analytical capability among HR professionals (Suri and Lakhanpal, 2024; Karmańska, 2020). Research has also raised concerns regarding employee agency, psychological safety, and the scientific validity of analytics-driven HR practices (Van den Heuvel and Bondarouk, 2017; Larsson and Edwards, 2022; Yoon, 2024). These limitations suggest that the potential of HR analytics is often constrained by organisational readiness and governance rather than technological availability alone.

2.4.2 The transition from HR Analytics to AI-powered HRM

AI is widely presented as the next stage in the evolution of data-driven HRM, extending the analytical foundations established by HR analytics. Rather than displacing existing systems, AI is layered onto earlier technologies, including ERP systems, HRIS, and predictive analytics platforms. Each wave of digitalisation has incrementally enhanced HR's decision-support capabilities, with AI introducing automation, pattern recognition, adaptive and continuous learning into HR processes (Stone et al., 2015). AI applications in HR now span recruitment, virtual interviewing, chatbots, learning personalisation, performance management, and predictive attrition modelling (Rai and Singh, 2023). Scholars describe AI as a transformative force that reconfigures HR roles and decision-making by augmenting human judgement with data-driven insights (Ghatak, 2022; Stankevičiūtė, 2024; Kambur and Yildirim, 2023). This convergence of big data, analytics and strategic HRM potentially enables a shift from reactive administration towards proactive value creation (Boudreau and Jesuthasan, 2011).

Despite that, the adoption of AI in HR is accompanied by significant ethical, operational, and infrastructural challenges. Concerns relating to algorithmic opacity, bias, fairness, and accountability remain prominent, particularly in the absence of clear regulatory frameworks (Bar-Gil et al., 2024). Moreover, organisations' ability to implement AI effectively depends heavily on leadership support, digital maturity, and pre-existing analytics capability (Suri and Lakhanpal, 2024). Long-standing critiques suggest that HR functions often lack the strategic positioning and analytical orientation required to fully leverage data-driven technologies (Lawler, 1995; Boudreau and Ramstad, 2007; Lawler and Boudreau, 2015). In many cases, HR remains primarily an administrative function, led by individuals whose responsibilities are centred on managing costs and performing routine administrative tasks (Ulrich, 1997; Lawler and Mohrman 2003; Boudreau and Ramstad 2005; Lawler and Boudreau, 2015).

However, the transition of AI analytics to AI-powered HRM has become more evident. AI technologies are asserted to be pervasively evolving and become a buzzword in the 21st century (Mehrotra, 2022). The relation map below illustrates a connection of overarching research regarding AI in HRM through time.

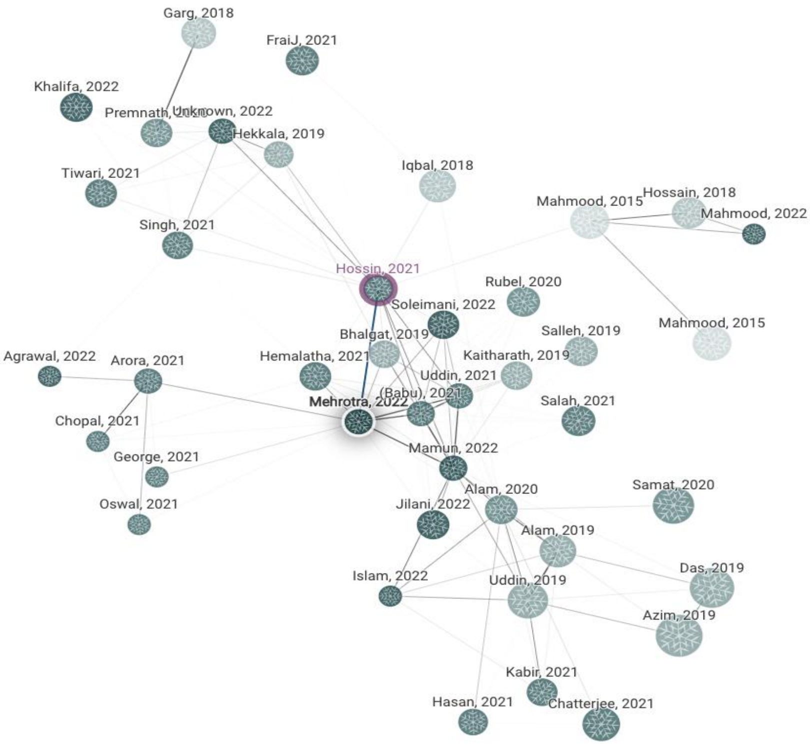

Figure 2.5: Interconnection network of research about Artificial Intelligence in Human Resource – Connected Paper Platform powered by (Microsoft Azure, 2022)

As can be seen from the **Figure 2.5**, research regarding AI applications within the field of HR was initiated in 2015 with two research conducted by the same scholar (Microsoft Azure, 2022). The accretion of interest in the realm has perceived a surge starting since 2019. This could be reasonably explained due to the unexpected emergence of the global pandemic of Covid-19 with its challenges on universal business performance management. Indeed, according to Cross and Swart (2022), the HR professionals are indicated to be critically impacted by the surge of digital transformation due to their substantial role in providing ingenious approaches to maintain business performance in the current dynamic context.

To conclude, AI adoption in HRM exhibits strong parallels with these earlier transitions. Many of the concerns expressed by HR professionals such as loss of control, diminished human judgement, transparency, and fairness. These concerns had been occurring during the adoption of computerised HR systems and HR analytics. Resistance is, therefore, not unique to AI, but reflects a recurring organisational response to technologies. Understanding AI as part of an evolutionary trajectory rather than a singular disruption provides a more nuanced foundation for analysing adoption behaviour. It allows resistance, status quo bias, and social influence to be identified as dominant factors in this study. It is interpreted as historically grounded responses to technological change, rather than as irrational or purely individual barriers.

2.4.3 Commercial HR Analytics and AI products

Parallel to academic developments, a growing commercial market promotes HR Analytics and AI solutions as essential tools for contemporary HRM (Marler and Boudreau, 2017; Boudreau and Jesuthasan, 2011). Major vendors such as SAP, Oracle, and AI-focused platforms such as HireVue claim to enhance efficiency, objectivity, and predictive accuracy across HR functions, reflecting a broader commercial narrative that positions AI as a strategic necessity for workforce management (Charlwood and Guenole, 2022). Commercial narratives often portray AI as a superior decision-maker capable of reducing bias and improving HR outcomes. However, such claims conceal the underlying mechanisms of these systems. Many of which primarily rely on conventional predictive analytics and decision-support tools rather than autonomous, explainable, or self-learning AI (Jarrahi, 2018; Kellogg et al., 2020). This marketing-driven use of the term "AI" risks overstating technological capability while underplaying challenges related to data quality, contextual judgement, bias replication, and governance (Raghavan et al., 2020; Charlwood and Guenole, 2022). Thus, critical review of vendor discourse reveals a frequent conflation of HR analytics, automation, and AI, with these concepts often used interchangeably without clear conceptual distinction (Marler and Boudreau, 2017; Raisch and Krakowski, 2021). Furthermore, vendor language tends to normalise AI adoption as an inevitable progression, marginalising ethical concerns such as employee surveillance, consent, transparency, and accountability

This review demonstrates that AI in HRM represents an emergent extension of data-driven HR practices rather than a discrete technological shift. The persistent conflation of HR analytics and AI in both academic and commercial discourses complicates adoption decisions and obscures underlying ethical and organisational challenges. These insights reinforce the need for a contextualised examination of AI adoption intention in HRM that accounts for technological capability, perceived risks, organisational readiness, and the influence of commercial narratives. Accordingly, this study investigates the drivers and barriers shaping HR professionals' intentions to adopt AI, contributing to a more nuanced understanding of data-driven innovation in HRM. It offers insights into how digital innovation can be strategically integrated into people management to improve organisational outcomes. The following section reviews recent literature on AI adoption and examines current and emerging AI applications within HRM.

2.4.4 Research Scope of AI technologies in HRM

Given the conceptual ambiguity surrounding AI in organisational practice, it is necessary to clearly define what is meant by AI for HRM for the purposes of this research. While practitioner discourse and software vendor narratives often use AI as an umbrella term for a wide range of digital HR technologies, this research adopts a more precise and analytically grounded definition.

In this study, AI for HRM refers to systems that employ advanced computational techniques such as machine learning, natural language processing, or algorithmic pattern recognition. The mentioned AI techniques tare o analyse data, generate predictions, or support decision-making in ways that go beyond rule-based automation or static analytics. These systems typically involve some degree of adaptability, probabilistic reasoning, or inference, enabling them to identify patterns and generate insights that are not explicitly programmed in advance. Examples include AI-driven candidate screening tools using machine learning models, predictive systems for workforce planning or turnover risk, and conversational agents that use natural language processing to interact with employees. The explanation of the mentioned AI techniques is subsequently discussed in the upcoming **Section 2.6. Challenges and Opportunities of AI adoption in HRM**.

By contrast, this study explicitly excludes from its definition of AI for HRM those technologies that rely primarily on predefined rules, simple automation, or traditional reporting and dashboard analytics. Human Resource Information Systems (HRIS), self-service portals, workflow automation tools, and descriptive HR analytics are therefore treated as enabling digital technologies rather than AI in their own right. While such systems may incorporate data processing or automation, they do not exhibit the adaptive or inferential characteristics central to contemporary AI.

This distinction is analytically important, particularly given evidence that HR professionals often conflate AI with broader digitalisation or HR analytics. Although participants in this study frequently referred to automation, predictive analytics, or self-service systems as AI, this divergence between practitioner understanding and academic definition is treated as an empirical finding rather than a limitation. By establishing a clear conceptual boundary in the literature review, the study is able to critically examine how HR professionals' perceptions of AI are shaped by limited exposure and prior experience with analytics-led HR systems. Positioning AI for HRM in this way also enables a clearer practical contribution.

2.5 Extant studies about AI adoption in HRM

The extant literature on AI adoption in HRM has grown rapidly in recent years, largely reflecting the increasing penetration of AI-enabled systems across core HR functions. Existing empirical studies primarily focuses on identifying the antecedent, drivers and barriers influencing AI adoption in HRM context (Qahtani and Alsmairat, 2023; Yadav and Kapoor, 2024; Goswami et al., 2023; Islam et al., 2022). Other strands of research have examined the assimilation and institutionalisation of AI within HRM processes (Prikshat et al., 2023) or explored HR professionals' behavioural intentions toward adopting AI technologies (Hmoud and Várallyai, 2020; Horodyski, 2023; Xu et al., 2024; Rukadikar and Khandelwal, 2024). Collectively, this body of work has provided important insights into how AI is introduced and evaluated within HRM functions.

In practical terms, AI adoption in HRM has been studied across applications such as e-recruitment platforms, algorithmic CV screening, virtual interview analytics, performance management systems, personalised learning and development platforms, and AI-enabled compensation and benchmarking tools. To examine the adoption behaviour, scholars have commonly relied on established technology acceptance and socio-technical frameworks, including the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology–Organisation–Environment (TOE) framework, the Technology–Organisation–People (TOP) framework, and the Stimulus–Organism–Response (SOR) model. These approaches have enabled researchers to identify a wide range of determinants associated with AI adoption in HRM. Synthesising the literature, prior reviews have identified many antecedents — over 40 in total — which have been grouped into several overarching dimensions. As illustrated in **Figure 2.6**, these dimensions include leadership, human resource readiness, environmental context, technology context, organisational context, user perception of technology and AI characteristics. Each category comprises multiple related factors that collectively shape organisations and individual's intentions to adopt AI in HRM practices. However, while this categorisation provides a useful structure, the empirical findings (as summarised in **Table 2.5)** associated with these determinants remain highly inconsistent across studies.

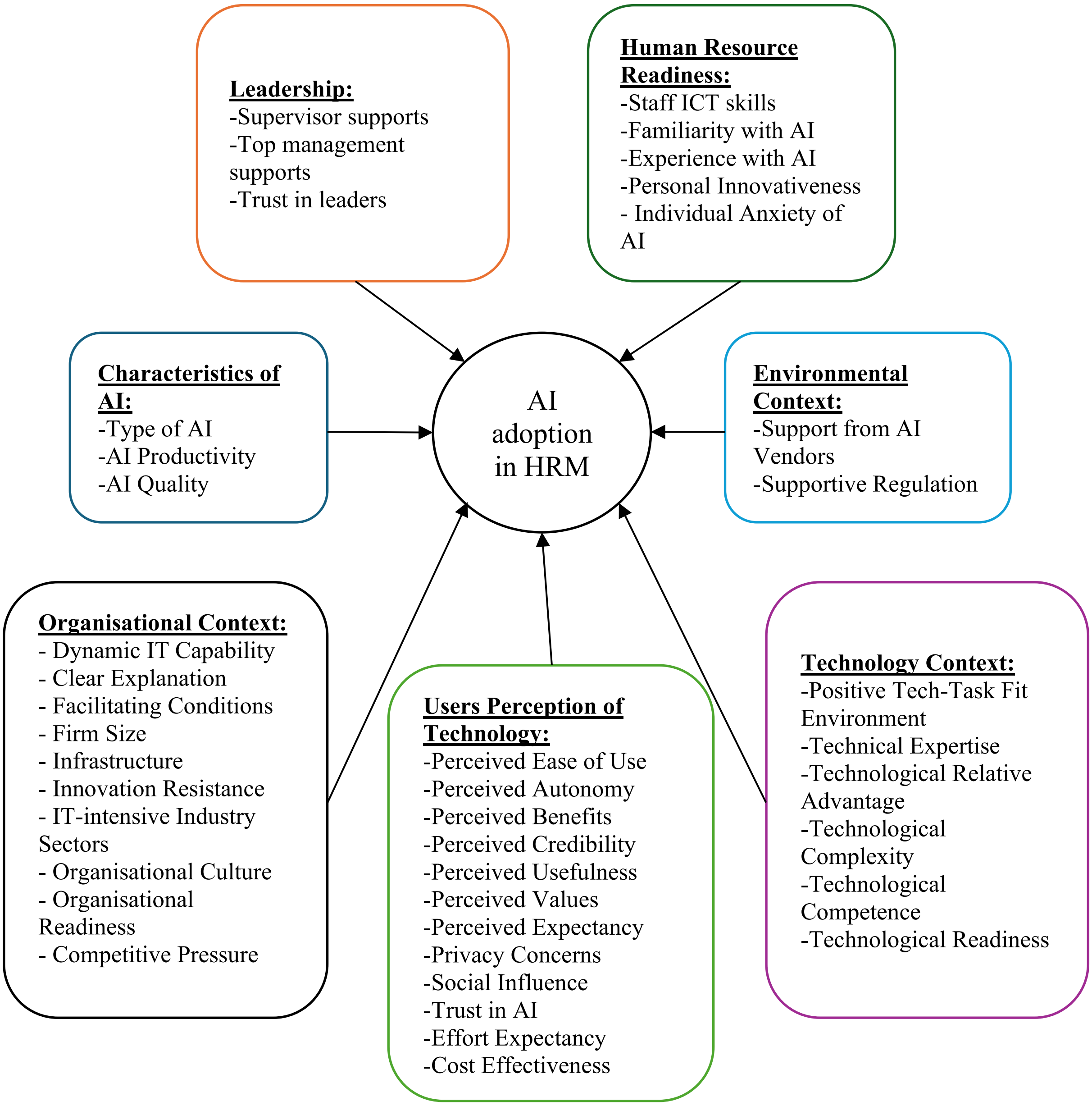

Figure 2.6: Determinants of AI adoption in HRM

As can be seen in **Figure 2.6**, each of the categories includes related factors that contribute to the formation of the overall influencing themes. Constructs associated with user perceptions of technology have produced mixed and sometimes contradictory results. For example, Islam et al. (2022) demonstrated that performance expectancy and social influence exert a significant positive effect on behavioural intention to use AI-based HR technologies. In contrast, Horodyski (2023) found that effort expectancy and social influence did not have statistically significant relationships with behavioural intention to use AI in HRM. Similarly, Islam et al. (2024) reported non-significant effects of these variables on intention to adopt AI in HRM practices. These inconsistencies suggest that the explanatory power of traditional acceptance constructs may be contingent on contextual factors that are not fully theorised within existing models.

Beyond individual-level perceptions, organisational and environmental determinants of AI adoption in HRM have also produced contested findings. Pillai and Sivathanu (2020) drawing on data from 562 HR managers, found that top management support positively influenced the adoption of AI technologies in HRM. However, Hmoud and Várallyai (2023), based on a sample of 389 HR managers from Middle Eastern countries, rejected the significance of top management support in shaping HR leaders' attitudes toward AI adoption. Similarly, competitive pressure was shown to positively influence AI adoption in HRM practices in Pillai and Sivathanu's (2020) study, whereas Goswami et al. (2023) reported that competitive pressure had no positive relationship with AI adoption and instead exerted a negative influence on effective HRM. Likewise, Hmoud and Várallyai (2023) found no significant relationship between competitive pressure and HR managers' attitudes toward AI implementation. Comparable contradictions are evident in the relationship between technological relative advantage and AI adoption, which exhibited positive effects in Pillai and Sivathanu (2020) but no significant influence in studies by Pan et al. (2022) and Yadav and Kapoor (2024).

Recent scholarship in leading HRM journals has begun to challenge the assumption that AI adoption in HRM can be adequately explained through linear acceptance models alone. Charlwood and Guenole (2022), for instance, argue that AI introduces enduring paradoxes for HR functions, such as efficiency versus fairness, standardisation versus contextual judgement, transparency versus algorithmic opacity, and innovation versus risk control. From this perspective, AI adoption is not merely a technical or attitudinal decision but a continuous process of managing tensions that shape HR legitimacy, professional judgement, and governance arrangements. Additionally, the emergence of generative AI has further amplified these challenges. Budhwar et al. (2023) contend that generative AI systems differ fundamentally from earlier HR technologies due to their capacity to generate seemingly authoritative outputs that are probabilistic, difficult to audit, and potentially biased. This raises new concerns related to data confidentiality, accountability, ethical compliance, and the boundaries between human and algorithmic decision-making in HRM. The following section will discuss about the challenges and opportunities of popular AI approaches in HRM.

Table 2.5: Relevant studies about AI adoption factors in HRM

Sources	Research purpose	AI representation	HRM functions	Theory/ Framework	Influencing factors	Effects
(Ramesh et al., 2024)	Determine the impact of perceived benefits and sacrifices derived from the AI adoption in TA	Virtual agent	Talent Acquisition	Value-based Adoption Model	Advantages of AI	Positive
					Cost effectiveness	Positive
					Innovation resistance	Negative
					Lack of trust in vendors	Negative
					Security and privacy issues	Negative
					Usefulness of AI	Positive
(Prikshat et al., 2023)	Develop theoretical framework of HRM-AI assimilation	Virtual agent	Multifunctional	Technology – Organisation - People	Dynamic IT capability	Positive
					Organisational readiness	Positive
					Personal Innovativeness	Positive
					Positive TTF environment	Positive
					Staff ICT skills	Positive
					Supervisor supports	Positive
					Technological infrastructure	Positive
					Top management support	Positive
(Agarwal, 2023)	Examine AI adoption in HRM	Virtual agent	Multifunctional	Technology – Organisation - Environment	Organisational preparedness	Positive
					Perceived benefits	Positive
					Technical expertise	Positive

(Rukadikar and Khandelwal, 2024)	Examine HR professionals' experiences and challenges of adopting chatbot in hiring process	Virtual agent	Recruitment	Organisational Culture Theory	Organisational culture integration	
				Resistance To Change Theory	Employee resistance	
				Technology Acceptance Model	Privacy Concerns	
				Trust theory	Trust and perceived credibility	
(Xu et al., 2024)	Examine initial trust formation in AI adoption	Virtual agent	Multifunctional	Social Exchange Theory	Explanation	Negative
					Familiarity with AI	Positive
					Organisational collectivism	Positive
					Trust in leader	Positive
(Horodyski, 2023)	Examine recruiters' intention to use AI	Virtual agent	Recruitment	UTAUT	Effort Expectancy	Neutral
					Experience use of AI	Neutral
					Frequency of AI use	Positive
					Performance Expectancy	Positive
					Social Influence	Neutral
(Arora and Mittal, 2024)	Examine the change in. perception of AI in HR functions	Virtual agent	Multifunctional	Stimulus – Organism - Response	Perception of change that AI create in PA	Positive
					Perception of change that AI create in PR	Positive
					Perception of change that AI create in TA	Positive
					Perception of change that AI create in TD	Positive
(Suseno et al., 2022)	Examine the change readiness for AI adoption in HR managers	Virtual agent	Multifunctional	Social Cognitive Theory	Individuals' AI anxiety	Negative

				Tripartite Model of Attitudes	Beliefs about AI	Positive
(Kot et al., 2021)	Examine the impact of AI recruitment and quality on Employer reputation through AI adoption	Virtual agent	Recruitment		AI Quality	Positive
					AI Recruitment	Positive
(Hmoud and Varallyai, 2023)	Explore attitude of HR managers toward the adoption of AI	Virtual agent	Multifunctional	Technology – Organisation - Environment	Competitive Pressure	Negative
					Firm Size	Negative
					Technological readiness	Negative
					Top management support	Negative
(Tanantong and Wongras, 2024)	Explore factors influencing intention to adopt AI in recruitment	Virtual agent	Recruitment	UTAUT	Effort Expectancy	Negative
					Facilitation Conditions	Positive
					Perceived Autonomy	Positive
					Perceived Values	Positive
					Performance Expectancy	Negative
					Privacy and Security	Negative
					Social Influence	Negative
					Trust in AI	Negative
(Islam et al., 2022)	Identify main antecedents of AI adoption in recruitment	Virtual agent	Recruitment	UTAUT	Effort Expectancy	Positive
					Facilitation Conditions	Positive
					Perceived credibility	Negative
					Performance Expectancy	Positive
					Social Influence	Positive

(Qahtani and Alsmairat, 2023)	Investigate AI adoption drivers in HRM	Virtual agent	Multifunctional	Technology Acceptance Model	Ease of Use	Positive
					Infrastructure	Negative
					Perceived Usefulness	Positive
(Goswami et al., 2023)	Investigate factors that facilitate AI adoption in HRM	Virtual agent	Multifunctional	Task-Technology Fit	Competitive Pressure	Negative
					Organisational culture	Positive
					Organisational preparedness	Positive
					Perceived benefits	Positive
					Technological readiness	Negative
(Pan et al., 2022)	Investigate the adoption of AI in employee recruitment	Virtual agent	Multifunctional	Technology – Organisation - Environment	IT-intensive industry sectors	Neutral
					Large company size	Neutral
					Supportive regulatory environment	Positive
					Technological relative advantage	Neutral
					Technological complexity	Negative
					Technology competence	Positive
(Pillai and Sivathanu, 2020)	Investigate the adoption of AI technology for TA	Virtual agent	Talent Acquisition	Technology – Organisation - Environment	Competitive Pressure	Positive
					Cost effectiveness	Positive
					HR readiness	Positive
					Relative advantage	Positive
					Security and privacy issues	Negative
					Support from AI Vendors	Positive

					Top management support	Positive
(Del Giudice et al., 2022)	Investigate the relationship between humanoid robot adoption and labour productivity	Physical agent	Multifunctional	Service Robot Deployment (SRD)	Labour productivity	Neutral
(Yadav and Kapoor, 2024)	Understanding factors that promote the adoption of AI in recruitment	Virtual agent	Recruitment	Technology – Organisation - Environment	IT-intensive industry sectors	Neutral
					Large company size	Neutral
					Supportive regulatory environment	Positive
					Technological relative advantage	Neutral
					Technological complexity	Negative
					Technology competence	Positive
(Islam et al., 2024)	Unpack the intention and actual use of AI among hiring professionals	Virtual agent	Recruitment	UTAUT	Effort Expectancy	Neutral
					Facilitation Conditions	Positive
					Hedonic motivation	Positive
					Performance Expectancy	Positive
					Social Influence	Neutral
					Technological complexity	Neutral

2.6 Challenges and Opportunities of AI adoption in HRM

Due to its multifunctional ability, AI can be used in various fields to assist manual tasks with analytical and logical work. Recent research has shown an increase in AI applications in HRM thanks to the data-driven aspects brought by AI to offer more insights to HR functions (Minbaeva, 2020). The empowerment of data-driven AI to augment business performance has been recently recognised in HR field (Chaturvedi and Joshi, 2018). It is stated that the transformation encourages "people to communicate across geographic boundaries and share information" and therefore, it enhances the strategic role of HR in supporting the organisation in achieving its business strategy (Parry and Tyson, 2011). In reality, the prevalent AI applications in business include big data analytics, virtual agent, machine learning, deep learning and data mining (Soori et al., 2023). The following part illustrates the current opportunities and obstacles of AI deployment, its critical applications and potential applications in HR practices. In particular, the popular AI approaches such as big data analytics, virtual agents, machine learning, deep learning and data mining will be discussed.

To begin with, **big data analytics** is one of the dominant applications when mentioning AI capability. Big data analytics is an overarching term to describe the ability to analyse a large amount of information applying different AI algorithms (Singh and El-Kassar, 2019). The capacity of processing high volumes of data allows AI users to extract potential patterns for decision making and planning. There are a wide range of opportunities and challenges embedded in the deployment of big data analytics, specifically through technical applications such as rule induction and case-based reasoning (CBR). In practice, rule induction refers to a set of decision rules generated based on training examples (classifications) and the outputs will be presented as a decision tree. It is essential for users to learn how to read decision-making trees and to translate it into rule sets (Maruster, 2006). The application in the technique can be highly useful in HR payroll and succession planning. On the other hand, it is worth noting that CBR approach functions based on collected cases to match new inflowed dataset and create appropriate solutions. Therefore, the technique is considered to be applied in several HR functions such as staffing, reward management, planning and budgeting. This is due to the solutions that the approach can generate based on the comparison between empirical and historical cases.

However, there are several challenges related to its application in practice. In fact, it is claimed that the deployment of big data analytics requires a high degree of technical expertise for data interpretation and analysis. In addition, the readiness of IT infrastructure and facilities are demanded for data storage and processing. This is due to the requirement of a large amount of data to generate enough fuel for AI technologies to process. In addition, certain IT systems must be installed and collaborated as a foundation for AI to build upon. The investment costs, therefore, can be a challenge depending on the scale of AI applications in organisations. The technical applications can potentially generate a black box issue, where the decision-making procedures are not transparent enough for the users (Cheng and Hackett, 2021). In addition, some technical issues such as overfitting: the situation where the models are too specific and fail to generalise the contexts (Zhang, 2021); or noisy data: the collected data that is corrupted and meaningless to interpret the contexts (Cheng and Hackett, 2021).

Virtual Agent is another powerful AI application supporting businesses by answering enquiries from users using Natural Language Processing (NLP) or Machine Learning algorithms. The capability of the virtual assistants, such as cobot/chatbot, is to analyse and respond to users based on given contexts and learning ability through training data (Vrontis et al., 2021). Within this AI approach, NLP is the main domain of analysing, extracting and articulating information from conversations. In practice, the application of virtual agents has become more complex in their abilities in terms of personalising responses and handling more sophisticated conversations to enrich users' interaction experience. In HR realm, the use of cobot/chatbot has been becoming increasingly strategic in streamlining HR practices and reducing HR workload. Some of the examples can be found in certain practical HR cases such as humanoid strategy interaction applied in on-boarding and recruitment (Majumder and Mondal, 2021); detecting and classifying multimodal conversations and social signals applied in HR conflict/frauds detecting (Lubbe and Ngoma, 2021); diverse communication channel through various dimensions (such as speech, intonation, gesture, and facial recognition) applied in employee engagement and retention (Rahman et al., 2018); and measuring engagement by gathering feedback in real time applied in employee engagement and performance evaluation (Thorat and Jadhav, 2020).

Despite the above-mentioned opportunities, the deployment of virtual assistants also presents significant impediments. One of the primary concerns lies on data privacy and security of users. This is due to the requirement of the virtual agents to assess users' information in order to optimise the human interaction and simulation. In addition, cost infrastructures and IT investments are also required a high consideration based on the degree of advancement provided from the deployed virtual assistants. The complexity level depends upon the demand of cobot/chatbot in according to special or customised offers from organisations to AI vendors such as the availability of customised dialogues and interactions (Rosruen and Samanchuen, 2019). It is also worth noting that several technical issues including mistaken interpretations (Majumder and Mondal, 2021), unnatural conversations (Rahman et al., 2018), or wrong case/pattern detection (Thorat and Jadhav, 2020) can impact negatively HR performance and limit the effectiveness in processing sensitive and intricate HR cases.

Machine learning (ML) and deep learning (DL) are the two dominant subsets of AI taxonomy. Specifically, ML is defined as automated detection of patterns that give meanings for data analysing the demand of users (Kulkarni, 2017). The machine learns from recorded data from the past of its users and absorbs the knowledge to function for the future when the same incidents occur. On the other hand, DL is a class of ML. The term deep is founded based on the multilayers used to analyse inputs in the system. DL is developed to establish and utilise Deep Neural Network (DNN) for advanced machine learning tasks (Mathew et al., 2021).

In essence, Machine Learning (ML) obtains three rudimentary algorithms which are supervised, unsupervised and semi-supervised learnings (alternatively called as reinforcement learning) (Chaturvedi et al., 2017). To begin with, supervised learning entails data that are labelled to have a computational model trained. It is stated that the potential applications of the approach in HR are diverse such as succession planning, HR planning and staffing. In contrast, unsupervised learning will analyse unlabelled data to extract patterns. It does not require labelled data to function and is used in recognising patterns and clustering. It is also claimed that HR professionals can benefit from this approach in managing Conflict and employee well-being. Finally, semi-supervised learning trains a computational model to learn by applying reward or punishment as feedback and notifies when unlabelled data is received. The HR functions such as training and development or coaching could be beneficial in applying this technical approach.

On the other hand, deep learning (DL) uses deep neural network (DNN) as a foundation for processing data. DNN is a type of artificial neuron networks (ANNs) in which its constitution includes various hidden layers laid between inputs and outputs. Neurons are contained in each layer to receive inputs from previous layers and create for next layers a non-linear output (Medsker, 1995). DL has the ability to process unlabelled datasets, learn features at various levels, extract complicated patterns from big data, semantic indexing, data tagging and decrease the complex level of the discriminative tasks (Najafabadi et al., 2015). The potential applications of this AI approach include performance evaluation, learning and development, or training and coaching. Nevertheless, the application of the ML and DL also confronts several challenges. On of the primary disadvantages of using ML and DL algorithms is the potential biases inherited from organisation's historical data. For instance, uncontrolled biases from organisation's historical data can amplify the discrimination tendency (e.g. in recruitment) and falsifying decisions (e.g. in selection). In addition, privacy and security matters related to the data collected from employees to function ML and DL also pose significant challenges for HR professionals when applying the AI techniques. This is due to the high degree of sensitive and personal characteristics of information embedded in HRM, which potentially leads to the data breach and legal regulation regarding General Data Protection Regulation (GDPR). Furthermore, there are several technical issues could potentially occur in the application of ML and DL such as black-box circumstances (Cheng and Hackett, 2021), overfitting data (Zhang, 2021), noisy data (Gupta and Gupta, 2019).

Finally, **data mining (DM)** is defined as a process of detecting useful and valid patterns in the collected data (Strohmeier and Piazza, 2013). In HR field, this AI approach is considered as prominent is presenting valuable data to drive decision making and optimise business management. Specifically, DM can extract unnoticed value information from large amounts of random input using well-known data mining algorithms such as decision tree, spatial clustering and statistical analysis. Hence, this technical application could be deployed in several HR functions such as recruitment management, talent acquisition, performance evaluation and retention (Zhang, 2021). The historical recruitment or performance data can significantly allow HR professionals to identify critical factors leading to employee attrition and enable accurate prediction on employee-organisation fits.

Nevertheless, one of the challenges in implementing of this AI approach is that it requires intermediate to high investments in IT infrastructure due to the entail of a large amount of data to function appropriately. In addition, because of the sophisticated patterns or relationships generated by DM approach, the technical expertise to plausibly interpret the data is demanded. This approach also confronts several technical issues such as black-box circumstances (Cheng and Hackett, 2021), overfitting data (Zhang, 2021). It is also worth mentioning that for SMEs which obtain small HR departments, front cost can be a prohibitive factor since the return on investment (ROI) cannot always be measured instantly.

2.7 The Darkside of Artificial Intelligence in HRM

While the previous section explored the advantages and various applications of AI, it is equally important to examine its dark side of AI applications, which potentially poses hindrances on the actual adoption. This section delves into the key impediments in AI research and applications in HRM, highlighting the ethical dilemmas, biases, security risks, and resistance that shape its development and implementation.

2.7.1 Bias and Fairness Issues in AI-Driven HRM

AI has been increasingly adopted in HRM to enhance efficiency in recruitment, performance evaluation, and talent management. However, one of the most pressing concerns is the issue of bias and fairness. While AI is often perceived as objective, it is only as unbiased as the data used to train it (Raghavan et al., 2020). If historical data reflects societal prejudices, AI systems can inherit and even amplify these biases, leading to discriminatory hiring practices and unfair performance assessments (Mehrabi et al., 2021). AI-driven recruitment systems have demonstrated racial and gender biases in multiple case studies. For instance, Amazon's hiring algorithm, trained on past hiring data, was found to systematically favour male candidates over female ones due to historical male dominance in technical roles (Andrews and Bucher, 2022). Similarly, facial recognition tools used in video interviews have shown lower accuracy for individuals from minority ethnic backgrounds, leading to concerns about unequal opportunities (Ajunwa, 2021). These biases can inadvertently reinforce systemic discrimination, undermining diversity and inclusion efforts within organisations. In effect, Maryland in the US enacted legislation in 2020 prohibiting the use of facial recognition technology in job interviews without explicit consent from candidates (Spivack and Garvie, 2020). Additionally, Portland, Oregon, implemented a comprehensive ban on facial recognition technology in both public and private sectors, including during hiring processes (Richardson, 2022). Eventually, HireVue, a major provider of video interviewing services, also discontinued the use of facial analysis tools in 2021, following public concern and internal assessments of alternative, more effective methods (Ajunwa, 2021).

Another critical issue is the lack of transparency in AI decision-making, often referred to as the "black box" problem (Brkan and Bonnet, 2020). HR professionals and job applicants may not fully understand how AI-driven decisions are made, making it difficult to challenge unfair outcomes. The lack of explainability in AI models can erode trust in AI-driven HR processes and potentially lead to legal ramifications if organisations fail to demonstrate fairness in their decision-making (Yanamala, 2023). Addressing these issues requires a multi-faceted approach, including diverse training datasets, algorithmic audits, and regulatory frameworks to ensure accountability in AI-driven HRM.

2.7.2 Loss of Human Touch and Employee Engagement

A fundamental aspect of HRM is the human-centred approach that emphasises empathy, communication, and interpersonal relationships. However, the increasing automation of HR functions, such as employee onboarding, performance reviews, and grievance handling, raises concerns about the loss of human touch in HR processes (Brougham and Haar, 2020). Employees may perceive AI-driven HR interactions as impersonal and lacking emotional intelligence, which can negatively impact job satisfaction and workplace engagement (Singh and Chouhan, 2023). For example, chatbots are increasingly integrated into recruitment processes, assisting with tasks such as initial candidate screening and interview scheduling (Koivunen et at., 2022). While these technologies improve efficiency, they often fail to provide the nuanced understanding and empathetic responses that HR professionals offer (Chhabra and Malhotra, 2024). A study by Malik et al. (2023) found that employees who interacted with AI-driven HR systems reported feeling less valued and engaged than those who received support from human HR representatives. Furthermore, AI-driven performance evaluations may lack the contextual understanding needed to fairly assess employee contributions (Nyathani, 2023). Employees may feel dehumanised if they believe that their performance is being judged solely by an algorithm, rather than through a more holistic evaluation that includes human judgement. As a result, organisations must strike a balance between automation and human oversight, ensuring that AI is used to augment rather than replace human in HR functions (Chaudhry, 2024).

2.7.3 Privacy and Data Security Concerns

The integration of AI into HRM also raises significant concerns about privacy and data security. In truth, AI systems in HRM often process vast amounts of sensitive employee data, including personal details, behavioural analytics, and biometric information (Ajunwa, 2021). The storage and analysis of such data pose risks related to data breaches, unauthorised access, and unethical surveillance practices (Ikwuanusi et al., 2023). One particular concern is the use of AI-powered monitoring tools to track employee productivity. Some organisations have implemented AI systems that analyse keystrokes and sentiment analysis in emails to assess employee engagement and productivity (Majumder and Misra, 2025). While these tools can provide valuable insights for performance management, they also raise ethical questions about employee autonomy and workplace surveillance. Employees may feel that their privacy is being invaded, leading to increased stress and dissatisfaction (Malik et al., 2022). Additionally, there are risks associated with data storage and cybersecurity. AI-driven HR systems often rely on cloud-based platforms, making them vulnerable to cyberattacks (Min-Jun and Ji-Eun, 2020). A major data breach in an AI-powered HR system could expose sensitive employee information, leading to reputational damage and legal consequences for organisations. Therefore, it is crucial for companies to implement stringent data protection policies, ensure compliance with privacy regulations such as the GDPR, and adopt ethical AI governance frameworks to safeguard employee data.

2.7.4 Job Displacement and Resistance to AI Adoption

AI's role in HRM extends beyond recruitment and analytics; it is increasingly being used for decision-making processes that were traditionally managed by HR professionals. While automation can improve efficiency, it also raises concerns about job displacement within HR departments (Tambe and Yakubovich, 2019). As AI automates routine tasks such as resume screening, payroll management, and compliance tracking, there is growing apprehension that HR roles will become obsolete or significantly altered. Brougham and Haar (2020) indicate that HR professionals express resistance to AI adoption due to fears of job loss and concerns about AI's ability to handle complex, human-centric tasks. This resistance can create implementation challenges for organisations seeking to integrate AI into their HRM strategies. It is suggested that AI should be positioned as a tool to assist HR professionals rather than replace them entirely (Sakka et al., 2022). For example, AI can be leveraged to automate administrative tasks, allowing HR personnel to focus on strategic initiatives such as employee well-being, leadership development, and organisational culture. Moreover, AI adoption may lead to the emergence of new HR roles that focus on AI ethics, compliance, and human-AI collaboration (Tenakwah and Watson, 2025). Organisations should invest in reskilling and upskilling HR professionals to ensure that they can work effectively alongside AI systems. By fostering a culture of digital adaptability, companies can mitigate resistance and create a more seamless transition to AI-driven HRM.

2.8 Conceptual Review Conclusion:

This conceptual review of HRM progression, tracing the evolution from HR analytics to AI-enabled HRM, highlights both the expanding strategic ambitions and the persistent conceptual ambiguities surrounding the use of data and intelligent technologies in HR practice. While HR analytics has primarily focused on descriptive and predictive insights to support decision-making, the increasing incorporation of AI introduces more autonomous and consequential forms of intervention in HR processes. The literature reveals not only heightened expectations regarding efficiency, objectivity, and strategic value, but also enduring concerns related to trust, transparency, ethical governance, and organisational readiness.

These tensions are directly relevant to the present study, which seeks to move beyond technological capability alone and examine the factors shaping organisational adoption intentions toward AI in HRM. In particular, the distinction between HR analytics and AI in HRM informed the study's conceptual framing, ensuring that AI adoption was examined as a socio-technical and organisational phenomenon rather than a purely analytical advancement. Insights from this literature guided the formulation of the research objectives and questions by foregrounding issues of perceived value, risk, social influence, and resistance to change, all of which emerged as critical in understanding how organisations interpret and respond to AI-enabled HR innovations. As such, this section provides a critical foundation for the empirical investigation that follows, linking developments in data-driven HRM to the study's focus on AI adoption intention in HRM contexts.

2.9 Theoretical review on technology adoption models

Regarding approaches used to understand the acceptance level of technology, multiple proposed frameworks have been deployed in the research world. Over time, the models have been evolving with additional factors added to fulfil the measurement instrument of technology acceptance. To establish an appropriate justification conceptual model for AI in HRM, preferred models were collectively mentioned in the thesis. In this section, a whole range of models and theories about the research area and subjects were briefly and chronologically taken into consideration. **Table 2.6** provides an overview landscape of the key adoption technology models considered and used in this research.

2.9.1 Theory of Reasoned Action (TRA)

Developed by Fishbein and Ajzen (1975), the Theory of Reasoned Action (TRA) has been introduced and deployed in several related research fields in testing an individual's behavioural intention. The nature of the TRA Model specifies two paramount factors forming an individual's intention which are Attitude toward Behaviour and Subjective Norm (Fishbein and Ajzen, 1975). The former element is attached to one's belief which describes one's personal nature while the latter component reflects social influences (Lada et al., 2009). Reviewing the content of the TRA framework illustrates that a person's actual behaviour is shaped by his/her behavioural intention (Wu and Liao, 2011). In support of this orientation, a range of different research has been applied TRA to investigate customers' behavioural intentions towards specific products or incidents (Muñoz-Silva et al., 2007; Hsu and Lin, 2008; Paul et al., 2016; Lada et al., 2009; Lishomwa and Phiri, 2020). The model has been successfully used in divergent fields including social psychology, knowledge management, medical studies, and IT adoption (Chow and Chan, 2008).

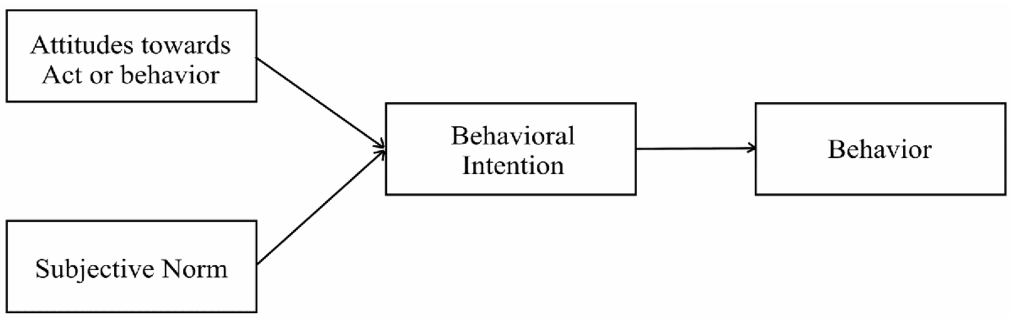

Figure 2.7: Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975)

Table 2.6: Summary of Adoption models and factors impacting the behavioural intention

Theory Model	Key Constructs and Characteristics	Main Contents	Studies applied the theory
Theory of Reasoned Action (TRA) (Ajzen, 1991)	Attitudes towards behaviour; Subjective Norm; Behavioural Intention, Behaviour	Examine people's behaviour intention	(Hsu and Lin, 2008; Lada et al., 2009; Lishomwa and Phiri, 2020; Muñoz-Silva et al., 2007; Paul et al., 2016).
Theory of Planned Behaviour (TPB) (Ajzen, 1991)	Attitudes towards behaviour; Subjective Norm; Perceived Behavioural Control; Intention; Behaviour	Examine people's behaviour intention and impact on behaviour	(AL Ziadat, 2015; Hsieh, 2015; Kumar, 2017; Nadlifatin et al., 2020)
Technology Acceptance Model (TAM) (Davis, 1989)	External Variables; Perceived Usefulness; Perceived Ease of Use; Attitude towards Use; Intention to Use; Actual Usage	Established to examine employees' computer usage behaviours	(Sánchez-Prieto et al., 2017; Mazuri Abd Ghani, Samar Rahi, 2017; Biucky et al., 2017; Ramaswamy et al., 2015)
Diffusion of Innovation Theory (DOI) (Rogers, 1962)	5-stage Diffusion Model (Innovators, Early Adopters, Early Majority, Late Majority and Laggards) Relative Advantage; Compatibility; Observability; Trialability; Complexity. Observability	Model of diffusion of technology in the market Examine people's adoption intention towards innovations	(Frei-Landau et al., 2022; Mohammadi et al., 2018; Menzli et al., 2022; Völlink et al., 2002; Cheng et al., 2004)
Social Cognitive theory (SCT) (Bandura, 1986)	Personal Determinants, Behavioural Determinants; Environmental Determinants	Examine people's behaviours and intentions	(Lent et al., 2018; Kim and Baylor, 2006)
The Unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003)	Performance Expectancy; Effort Expectancy; Social Influence; Facilitating Condition	Examine people's behaviours and intentions	(Cody-Alen and Kishore, 2006; Alwahaishi and Snášel, 2013; Yu, 2012; Wrycza et al., 2017; Lee et al., 2017; Chen et al., 2021)

Regardless, further investigations on the model have documented several key issues when researchers consider applying TRA. In essence, it is yielded that The RA model solely centres on "volitional personal" which generates a defect as in certain contexts, non-volitional factors would rigorously make an impact on a person's decision (Lin, 2005, p56). For instance, pricing issues and additional expenses were listed as essential hindrances for adopting the green-hotel approach on ordinary hotel service, stated in a study of Han in testing the deployment of environmental-friendly activities considering the TRA model (Han et al., 2010). In addition, it is important to highlight that the model is inclusive, and it does not illustrate beliefs about specific behaviours, which requires researchers to pay more attention to salient beliefs when applying the model (Hsu and Lin, 2008). These analyses found evidence for a promising aspect of discovering additional elements influencing the user's intention to be deliberated in future research.

2.9.2 Theory of Planned Behaviour (TPB)

To mitigate limitation in the TRA model, Ajzen continued further investigations on behavioural intention and introduced the Theory of Planned Behaviour in the 1991 (Ajzen, 1991). The model is postulated to be the extension of the TRA model, which is marked as a maturity of the preceding TRA model, to be able to provide a more profound mechanism for human's behaviours (Liao et al., 2017). Particularly, an individual's actual behaviour is controlled by behavioural intentions and perceived behavioural controls. Simultaneously, attitude towards the behaviour, subjective norm, and perceived behavioural control are key determinants of behaviour intention (Liao et al., 2007). In general, attitude towards the behaviour, subjective norm, and perceived behavioural control are directly proportional to behaviour intention which will generate a higher probability of conversion into direct behaviour.

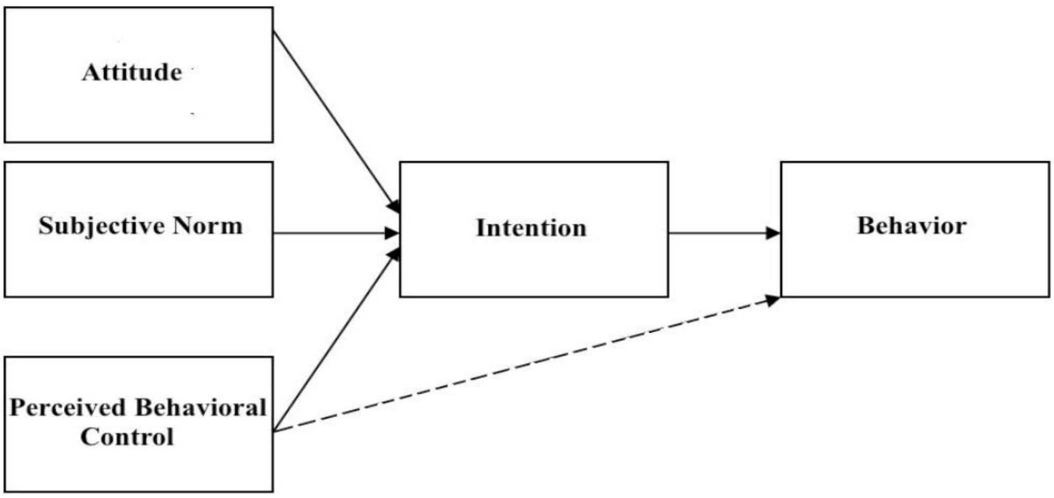

Figure 2.8: Theory of Planned Behaviour Model (TPB) (Ajzen, 1991)

Ajzen (1991) also emphasises the important role of examining correspondingly alternative dimensions and measurement variables to reinforce explanatory ability in different research's applied context. In part, although the model has been broadly adopted and gained significant supports from the foregoing research findings (Hsieh, 2015; AL Ziadat, 2015; Kumar, 2017; Nadlifatin et al., 2020), it is postulated that exogenous elements generated from the complicatedly individual case could potentially affect the conceptual framework (Haro, 2016). In effect, it is tailored that the framework is inherently subjective and would change based on "personalised perception of human behaviour" (Oluka et al., 2014). Discernibly, future investigations are necessary to validate the kind of conclusions that can be drawn from predominantly preceding studies in akin fields.

2.9.3 Technology Acceptance Model (TAM)

The Technology Acceptance Model is a prevalent framework that has gained global consensus on its use to project user acceptance of novel technology. Developed by Davis (1989), the model has been recognised as a validated framework by postulating influential components impacting a company's decision to adopt the information technology (Davis, 1989). It is stated that the TAM model is the extension in accordance with the previous TRA model which explains the determinants of technology adoption originated from the cognitive process and the purpose to "satisfy the wearer or maximise the usefulness of the technology" (Harryanto et al., 2018, p.78).

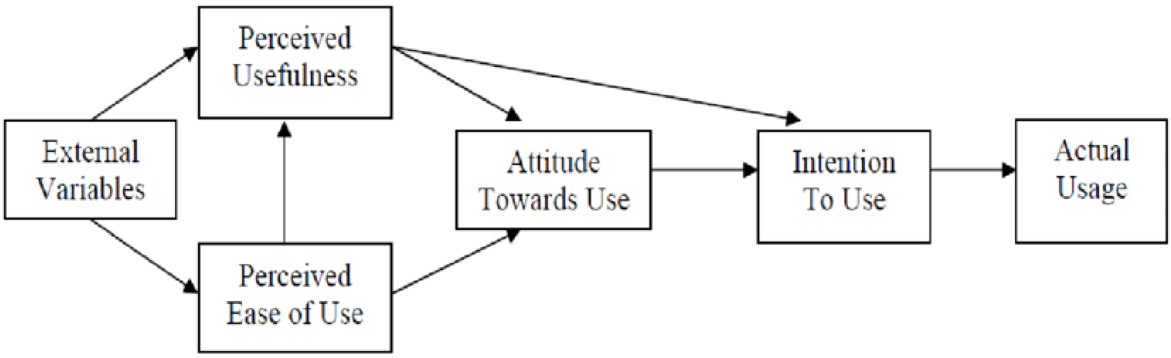

Figure 2.9: Technology Acceptance Model (TAM) (Davis, 1989)

In essence, the model suggests the two dominant determinants, perceived usefulness and perceived ease of use, which are substantially influenced by an individual's behaviour intention (Nura et al., 2012). Perceived usefulness refers to which degree a person believes that job performance would be enhanced by deploying a specific system or procedure, while perceived ease of use describes an individual belief in free mental effort when using the system (Davis, 1989). It is speculated that perceived usefulness is potentially impacted by perceived ease of use since, stating in equal conditions, “the easier the system is to use the more useful it can be” (Venkatesh and Davis, 2000, p.242). In time, intensive literature has developed on examining new technologies and innovations adoption by deploying the TAM model. Examinations of TAM model on investing the intention of use in M-learning (Sánchez-Prieto et al., 2017), internet banking (Mazuri Abd Ghani, Samar Rahi, 2017), social commerce (Biucky et al., 2017) or cloud-computing (Ramaswamy et al., 2015) have been conducting through multiple of research. By running the gamut of myriad empirical tests of TAM, perceived usefulness has been consistently considered as a vital determinant of usage intention. Presumably, the mentioned factor is a rudimentary driver for the intention of use.

It is notable that the adoption of a new system or innovation generates alterable-constructed components over time through changes (Venkatesh and Davis, 2000). In effect, a study of Infusion of Innovation Adoption conducted by Meister depicted that the TAM model speculates around 40% and 30% variance of usage intention and system usage respectively (Meister and Compeau, 2002). From this standpoint, Davis (1993) also pinpointed the necessity to uphold to examine the role of external variables to enhance the facilitators of technology adoption in the future. This implies that there should be a critical consideration on further validations of potentially external variables such as “cognitive, personality, demographic, and situational variables” (Zmud, 1979, p.178) due to their vitally-driver roles (Legris et al., 2003).

2.9.4 Diffusion of Innovation Theory (DOI)

Diffusion of Innovation Theory (DOI) is the prevalent framework that has been applied in multiple studies to perceive the essence of innovation and its affiliated factors affecting adoption. Formulated by Rogers (1962), the model acquires rich traditions of deployment in myriad realms including “sociology, anthropology, geography, economics, advertising and market research, and communication” (Ravichandran, 1999, p.245). The framework is considered as a comprehensive instrument to apprehend the widespread of innovation and its driving forces (Chang, 2010). DOI is defined as “the process by which an innovation is communicated through certain channels over time among the members of a social system” (Rogers, 1962, p.341).

As maintained by Roger (1962), the decision on innovation adoption is principally modified by five primary elements: compatibility, trialability, observability, relative advantage, and complexity. In time, the theory has gained its recognition in different research fields by successfully providing an efficient instrument to understand how people translate novel ideas and how ideas are phase-disseminating and circulating fields (Neo and Calvert, 2012).

According to Roger's study, compatibility is described as "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and the needs of potential" (Rogers, 1962; Mahler and Rogers, 1999, p.367). In simple terms, the factor is appraised based on individuals' belief of social and cultural values on the introduced ideas and the need to potentially possess the innovation. Relative advantage is the subsequent factor that refers to the exclusivity need value and the financial return (Rogers, 1962; Rogers et al., 2003). To clarify the term, the component describes the adopter's entailment on scrutinising potential costs and benefits of deploying the innovation. Notably, the mentioned factor is also deemed to be analogous with the element of perceived usefulness in the TAM model (Valente and Davis, 1999).

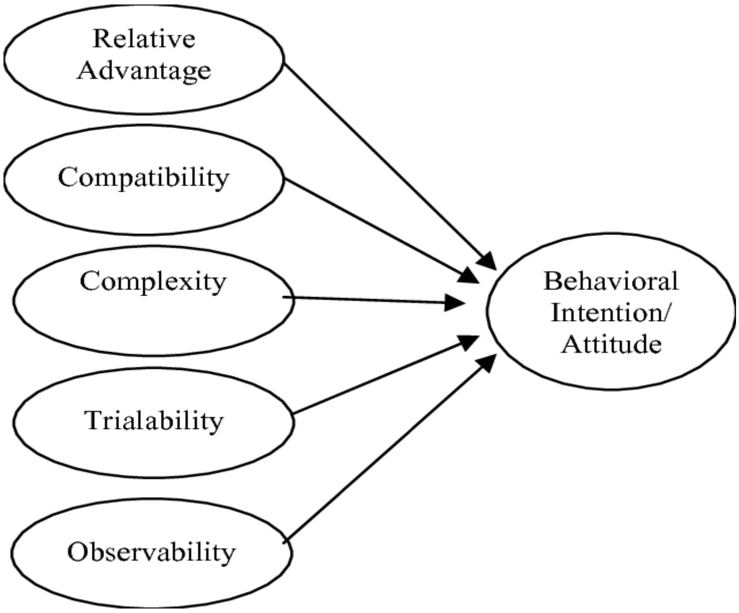

Figure 2.10: Adoption Factors in Innovation Theory (DOI) (Rogers, 1962)

Complexity is the third factor used in DOI which is defined as "the degree to which an innovation is perceived as relatively difficult to understand and use" (Rogers, 1962; Rogers et al., 2003, p.356). Fundamentally, the factor describes various strata of an individual's necessary effort, physically and mentally, applied to functionate the innovation. The factor is also considered as antagonistic with "ease of use" in the TAM model (Valente and Davis, 1999, p.89). Trialability is yielded to be the factor described as "the degree to which an innovation may be experimented with on a limited basis" (Rogers, 1962; Rogers et al., 2003, p.439). In particular, the foreshadowed attribute enables adopters to test drive to deliver the meaning of using actual innovation (Md et al., 2010). Eventually, observability refers to "the degree to which the results of an innovation are visible to others" (Rogers et al., 2003, p.232).

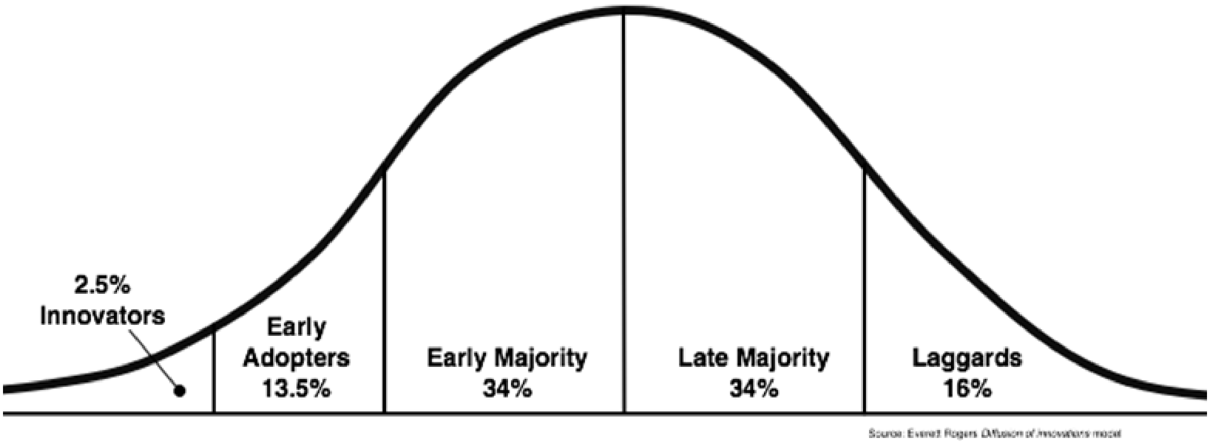

Figure 2.11: Diffusion of Innovation Theory (DOI) (Rogers, 1962)

Based on Roger's DOI proposal, there are five categories of adopters toward the introduction of an innovation namely innovators, early adopters, early majority, late majority, and laggards (Rogers et al., 2003). Depending on individual needs and motivation, the adoption rate among individuals varies accordingly. In effect, Innovators accounted for 2.5% in the diffusion diagram. They are called pioneers or information seekers who attain a certain confidence level on obtaining novel ideas (Lien and Jiang, 2017). This group is exposed to a higher level of uncertainty compared to the other groups due to the lack of existing subjective evaluations on the innovation. Early adopter is the second group to be presented in the adoption curve who are seeking advice and acceptance behaviours from innovators before innovation adoption. The adapters are stakeholders in the social system who enable them to lead people toward possible alternatives (MacVaugh and Schiavone, 2010).

Early majority is the third group which is described to have broad interest and full concern on innovation during the introduction of it. However, the innovation adoption process of this group could only occur when recognising the successful deployment of innovation from the preceding groups. The focal learning of the innovation is heavily leaned on "close associates" and "personal communication channels" to promulgate innovation information (Lien and Jiang, 2017, p224). The fourth group is called the Late majority referring to adopters who are more cautious and conservative toward innovation adoption. The lack of resources and inadequate information supplies are reported to become the driving forces of uncertainty causing the delay of adoption in this group (Deb et al., 2017). Ultimately, Laggards are the last group to adopt innovation due to vulnerability and conservation attributes shaped by finite information and shortage of social support (Lien and Jiang, 2017). It is also speculated that the sixth group of non-adopters is existing (Kaminski, 2011), whose characteristic is pessimistic toward changes.

It is argued that the most significant attribute of empirical research of innovation is the tremendous variance of instability among studies' results (Downs and Mohr, 1976). Although for most of the predominant research deploying DOI, the results appear consistent with prior studies examining similar influential factors, several finiteness pertaining to its predictive power tend to consequently exist (Chang, 2010). To elaborate, a study could find a potential factor to be significant for organisational innovation while the mentioned element, in another research, is concluded to be less crucial and even perceiving adverse effects (Dibra, 2015). In fact, the diversity of genes of innovations and the complexities emerging during the preface of innovation contribute significantly to constitute the potential driving forces of adoption. It is suggested that future research must investigate deeper in exogenous factors influencing the organisational innovation-adoption decision to understand potential contradictions from research findings (Damanpour, 1991).

2.9.5 Social Cognitive Theory (SCT)

Social Cognitive Theory is one of the significant models in providing an informative precept explaining human behaviours and intentions anchored to three dominant premises of personal, behavioural, and social factors (Bandura, 1986). This psychological theory has been explicitly used to understand human behaviour in studies in multiple fields such as business, education, and health (Lin, 2020; Wood and Bandura, 1989; Devi et al., 2017). It is argued that the fundamental mechanism of human behaviour tailors to the triadic complementary propositions determined by individual perceptions and beliefs absorbed through personal cognition and the external environment (Boateng et al., 2016). It is postulated that the theory emphasises the crucial foundation of the external environment as a stimulant for individual motivation, learning and adapting to novel knowledge (Bandura, 2011). In essence, the personal attribute is promoted as individual knowledge, expectation, and attitude; social attribute is entrenched in the external environment such as social norms; eventually, the behavioural element is regulated by overt behaviour including skills, practices, and self-efficacy.

According to (Bandura, 1986), the individual cognitive process is expressly articulated with the person's behaviour intention reinforced by the self-establishment of his ability, knowledge, and skills. In other words, the engagement towards specific actions is rooted in the accumulated formation of the mentioned factors. The triadic competencies are delineated to be obtained through the observational learning (McCormick, 2001). Technically, former event observations acquired by an individual initiate cognitive constructs; in accordance with the causality principle; which will direct forthcoming behaviours. The individual herein retains the modelled behaviour and is motivated to conduct the identified behaviour (Ratten and Ratten, 2007). This process is called “triadic reciprocal determinism” which aims to elaborate on the collaborative relationship among social, individual, and behavioural factors (Devi et al., 2017; Wood and Bandura, 1989, p.20-30).

In elaborate, the environment competence refers to the externally social and physical factors impacting individual behaviour (Bandura, 2005). The physical elements are constituted by natural or artificial entities surrounding the individual while the social elements centre on cultural milieus affected by social circles such as family, friends, or colleagues. The next competence is Individual competence, which refers to the origin of human behaviours shaped by personal introspective triggered by perceptions, goals, feelings, and other motivational elements. Finally, the behavioural competence refers to skills, practices and knowledge enabling a person to perform a certain behaviour.

The thesis centres on the behavioural motivation generated by social influences regulated by social norms. This exogenous motivation is a prominent feature in innovation diffusion theories formulated by how peer pressures or social trends internally engender the motive of adoption (Lent et al., 2018; Kim and Baylor, 2006). SCT provides the approach to enhance the understanding of consumers’ behaviours toward technological innovations (Ratten, 2015). In practice, AI is a novel concept that has been recently introduced into the business market which potentially involves sophisticated processes to pursue a comprehensive understanding. In response to this reason, SCT incorporates exogenous and endogenous environmental elements allowing the researcher to investigate individual motivators to endorse certain behaviours.

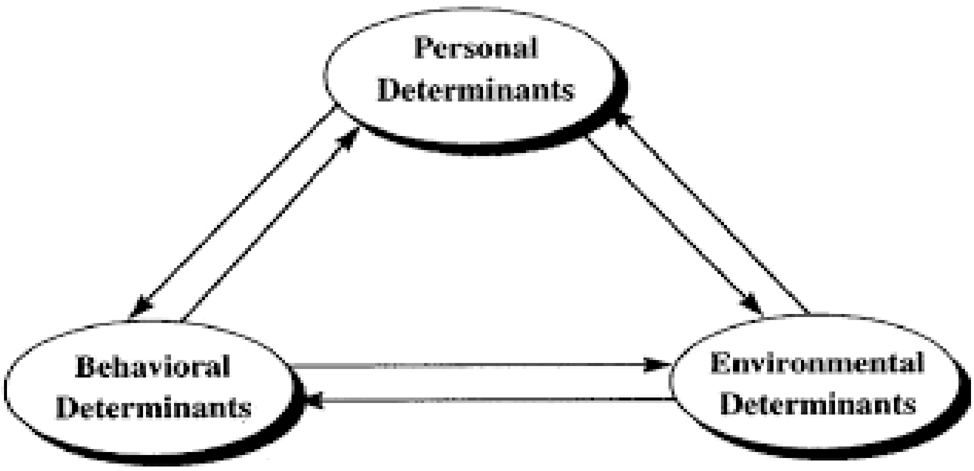

Figure 2.12: Social Cognitive Theory (Bandura, 1986)

2.9.6 The Unified Theory of Acceptance and Use of Technology (UTAUT)

The unified theory of acceptance and use of technology (UTAUT) has been considered as a comprehensive and profound framework by virtue of its high explanatory power and greater projective capacity of technology acceptance and use (Barrane et al., 2018; Palau-Saumell et al., 2019). Developed in 2003, Venkatesh successfully introduced the UTAUT framework by integrating and refining eight predominant models in the affiliated field to formulate the final model selecting cardinal elements from the preceding dominant model's (Venkatesh et al., 2003). The eight examined models constituting UTAUT include Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), Theory of Acceptance Model (TAM) (Davis, 1989), Motivational Model (MM) (Davis et al., 1992), Theory of Planned Behaviour (TPB) (Ajzen, 1991), Combined TAM and TPB (C-TAM-TPB) (Taylor and Todd, 1995), Model of Personal Computer Utilisation (MPCU) (Thompson et al., 1991), Diffusion of Innovation Theory (DOI) (Rogers, 1962), and Social Cognitive Theory (SCT) (Compeau and Higgins, 1995).

The nature of the model is to effectively describe the acceptance of IT service in its introduction phase. By dint of the framework's versatility, multitudes of research have been established on the foundation of UTAUT to examine technological factors' use and acceptance presenting in various realms (Cody-Alen and Kishore, 2006; Alwahaishi and Snášel, 2013; Yu, 2012; Wrycza et al., 2017; Lee et al., 2017; Chen et al., 2021). Additionally, the UTAUT framework is posited to be likely to rectify potential limitations presented in previous affiliating models. In fact, by the virtue of its prevalence, the model is suggested to be an effective instrument for the management board to measure the presence of novel technology in the market while also explaining and envisaging adopters' behaviours on technology acceptance. The explanatory power of UTAUT is scrutinised to be higher than TAM (20%-30%), increasing the explanation of adopter's intention-and-behaviour likelihood up to 40%–50% (Barrane et al., 2018).

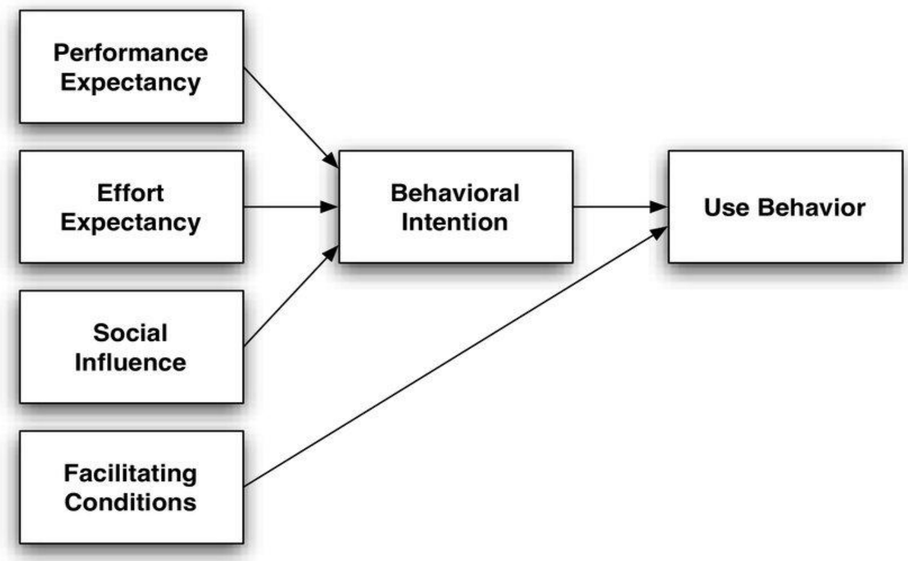

Figure 2.13: The Unified theory of acceptance and use of technology Model (UTAUT) (Venkatesh et al., 2003)

According to the framework, there are four fundamental variables to be determinants leading to technology adoption: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). Among the facilitators, PE, EE, and SI are the elements affecting Behavioural Intention (BI) while FC and BI are components that directly affect the adopter's actual behaviour. PE refers to the degree to which an individual has a belief that using the new system will improve the current performance. EE is described as similar to perceived usefulness in the TAM model. SI is defined as the degree to which an individual perceives the significance of other people's beliefs that one should adopt the technology. Ultimately, FC is the factor describing the degree to which the existing infrastructure could support the technology. Through empirical analysis, Venkatesh had also equipped the model with four moderators extracted from social psychological perspective namely gender, age, experience, and voluntariness of use (Venkatesh et al., 2003; Lee et al., 2019).

Since UTAUT has been deployed in multiple research projects in analogous technology fields such as online mobile banking payment (Lee et al., 2019), blockchain (Christopher, 2019) or cloud computing (Rastogi et al., 2018), the findings provide a potential mechanism for the applied context of AI. Regardless of possessing greater explanatory power compared to the others', limited studies have applied this model to AI adoption research. This could be simply explained by the emerging context of AI deployment in a business scenario, which will henceforth require further persistent validation and investigation in future studies. From this orientation, the researcher aims at driving the further development of UTAUT on the current dynamic of AI in HRM with a modified UTAUT framework. The preliminarily conceptual framework and thesis preconceptions were followingly introduced based on two key drivers. The researcher chose the work preconception due to its preliminary nature of hypotheses at this research stage. The first driver was shaped based on the original UTAUT model dovetailing with potential key variables established from consonant study fields. The second driver was found centring on the first phase of the research where data of potential variables affecting users' adoption intention were collected and extracted from AI vendors' perspectives.

2.10 Preliminary Research Framework

To the best of researcher's knowledge, studies conducted in the field of AI in HRM are at the infant stage and it is starting to attract scholars to delve into the realm. Several studies have recently started to examine AI applications in certain fields (Pradhan and Chawla, 2020; Kushwaha et al., 2020; Sanchez et al., 2020; Simeone et al., 2021; Kurade and Latpate, 2020; Chi-Hsien and Nagasawa, 2019; Lu, 2019; Tkachenko et al., 2019; Li et al., 2019; Wang and

Siau, 2017; Yang and Siau, 2018). Regardless of the continuous growth in AI-related fields, there is a minority of research applied in the context of AI adoption at the organisational level, especially when narrowing down to the area of HRM functions. In line with previous studies in the IS field, publications regarding the subject related to AI are yet to achieve the maturity stage (Chen et al., 2021). Consequently, the popular growth of AI in the market and the lack of research on AI adoption have impeded the establishment of research construction on existing theories straightforwardly. At this junction, the scenario requires the researcher to go through a series of research examinations' refinement to identify the factors influencing the adoption of AI and subsequently formulate a compatible conceptual framework.

The core purpose of the research is to measure AI adoption intention from organisations in the HRM field, and therefore factors and related models affecting individuals' adoption behaviours will be considered. From a theoretical standpoint, the UTAUT framework has successfully summoned critical determinants of predicting users' adoption intention. In comparison with other research frameworks, UTAUT has become the most predominant model due to its comprehensive aspects involved in measuring adopters' intention and the willingness to prolong the utilisation (Cody-Alen and Kishore, 2006). In recent decades, with the ubiquity and growing interest of AI adoption in the dynamic market, it is suggested that researchers consider other potential factors which are likely to emerge influencing the technology adoption. The UTAUT model has been deployed in a variety of studies addressing rapid changes and emergence of technology products and service (Lee et al., 2019). By the virtue of the mentioned reasons, the thesis was designed to considerably utilise the variables in the original UTAUT framework combined with emerging exogenous factors directly affecting AI adoption in HRM.

While reviewing the current context, a recent study about AI adoption intention within organisations delivered by Chen et al. (2021) depicts two important themes for AI adoption based on AI attributes and organisational capacity. The critical attributes applied in the research of AI adoption could be categorised in the PP, PE, SI and FC indicators of users' adoption intention in UTAUT. In line with the results of technology adoption's intention from salient previous research utilised UTAUT (Liza, 2017; Udo et al., 2016; Alrawashdeh et al., 2012; Jo and Lee, 2019; Palau-Saumell et al., 2019; Alwahaishi and Snášel, 2013; Wrycza et al., 2017; Lee et al., 2017; Rodrigues et al., 2016; Chen et al., 2021; Hou, 2014), PE, EE, SI and FC are envisaged to be paramount elements in the prediction of adopters' behaviours in innovation technology adoption.

Performance Expectancy (PE)

Performance expectancy refers to "the degree to which an individual believes that using the system will help him or her to attain gain in job performance" (Venkatesh et al., 2003, p.447). In his research, this factor was found to be the strongest predictor of intention and consistent with all previous tests conducted by other intellectuals. The essence of this factor was supported by another study of Ronaghi and Forouharfar (2020) in Middle East countries, performance expectancy was proved to have a positive influence on the propensity to use IoTs in smart farming. With respect to other literature reviews within this area, performance expectancy was depicted to be a crucial factor to influence the intention of deploying new technology (Shiferaw and Mehari, 2019). Therefore, preconception 1 was developed as follow.

Preconception 1: The adoption of AI in HRM is influenced by PE

Effort Expectancy (EE)

Venkatesh and Davis (2000) defined effort expectancy as the degree of ease associated with the use of the system which was expected to be more noticeable in the early stages of a new behaviour. In their studies, effort expectancy was demonstrated to be among the critical success factors in adopting new technology despite some controversy against this. According to findings from the study of Dwivedi. et al. (2011), effort expectancy was indicated to have a weak influence on the intention to use technology. On the contrary, many intellectuals suggested that EE influences the behavioural intention of using new technology fields (Dennis, 2016; Michael, 2013). Therefore, preconception 2 was developed as follow.

Preconception 2: The adoption of AI in HRM is influenced by EE

Social Influence (SI)

Social influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Udo et al., 2010, p.481). The name of this factor varied across the research where authors used the term social norms to originate from the TRA model in investigating their constructs. Despite the different names, this concept looked at an individual's perception about how his or her close-knit relationships think he or she should or should not perform the behaviour. It is indicated in the study of Shiferaw and Mehari (2019) that social impact has a significant influence on an individual's propensity to accept technology. This is supported by the study of Ronaghi and Forouharfar (2020) who also spotted the importance of social influence on the propensity to adopt new technology. Therefore, preconception 3 was developed as follow.

Preconception 3: The adoption of AI in HRM is influenced by SI

Facilitating Conditions (FC)

Venkatesh et al. (2003) defined facilitating conditions as "the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system" (p.452). Some intellectuals suggested that this element consists of two aspects: resource facilitating conditions and technological conditions (Taylor and Todd, 1995). Investigations that examined these factors have found a positive relationship with the successful implementation of the computerised systems (Aggelidis and Chatzoglou, 2009). However, there was an argument that FC does not play an important role in predicting intentions; on the other hand, there is a significant relationship between FC and the actual usage of the technology (Venkatesh et al., 2003). Nevertheless, there are plenty of papers conducted on technology adoption indicating that FC is one of the critical success factors of intention to use technology (Yi et al., 2006; Tosuntaş et al., 2015). For that reason, preconception 4 was developed as follow.

Preconception 4: The adoption of AI in HRM is influenced by FC

Perceived Risks (PR)

The proliferation of AI in the last decades has assisted enterprises with all kinds of tools and techniques to make the business more efficient. However, as AI development accelerates, specialists in the industry have alerted firms to be aware of its potential risks. This factor is proven to be significantly impacted on the users' perceptions toward the intention to adopt AI (Seo and Lee, 2021). For instance, Flikkema and Cambou (2017) investigated the privacy issues relating to the use of IoT environments in Arizona and came up with the finding that cloud intelligent tools are capturing our data and manipulating our daily lives. Additionally, it is indicated that AI is typically a software advancement and easily exposed to vulnerabilities, which raises the question of trustworthiness (Hurlburt, 2017). Johnson (2017) also illustrated three science fiction prototypes to explain the negative outcomes of ignoring threats associated with AI, which could lead to the destruction and death of the human world. Given those scenarios from the literature review, preconception 5 was developed as follow.

Preconception 5: The adoption of AI in HRM is influenced by PR

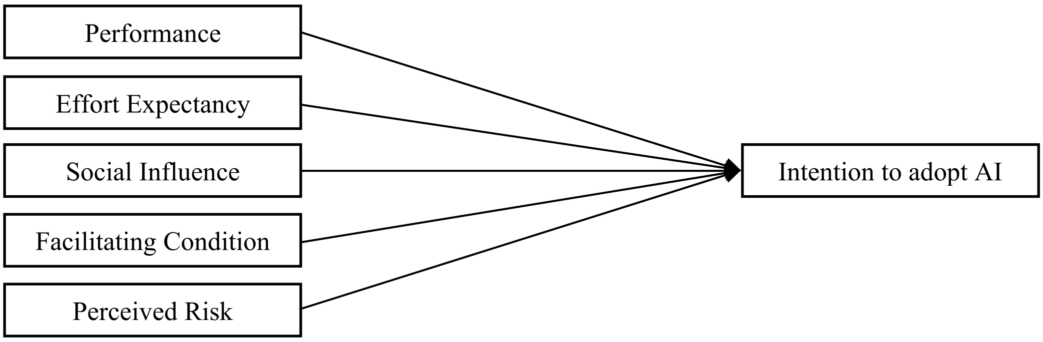

Figure 2.14: Preliminary Conceptual Framework

2.11 Chapter Summary

This chapter illustrated the primary keystone through affiliated theories, concepts, models, and knowledge which regulates the research direction and the design of research methods. The contribution of this chapter inherently facilitated the fundamental research strategy when progressing to practically collect the primary data. This chapter presented the key concepts of HRM and AI as well as clarified the related aspects of fundamental HR functions and AI techniques. In addition, critical AI adoption factors in business management and HRM were discussed to outline the orientation of the AI-HR phenomenon. In addition, this chapter equipped the researcher with sufficient basis from both theoretical standpoints and contemporary contexts of the research subjects. Specifically, a diversity of technology adoption models (such as TRA, TPB, TAM, DOI, SCT and, UTAUT) was presented and considered. As a result, a preliminary conceptual framework was established in the Chapter aiding to the assumed directions of AI adoption factors in HRM. On the strength of the LR discussion, the following Chapter 3 will elaborate the research methodology applied to explore, detect, and examine potential constructs which impact the adoption intention of AI in HRM.

CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter discusses the research methodology applied to explore the use and acceptance of AI in HRM. The research approaches, strategies, paradigm, and overarching approaches for the thesis will be indicated and explained for reasons of adoption. The method for gathering primary data was discussed and justified to provide a transparent research analysis picture. The research was conducted in two phases. Initially, Phase 1 (QUAL) was executed by applying a qualitative approach to explore the novel concept of AI within the current business context by collecting knowledge and perceptions from professionals working in HR and AI fields. Sequentially, Phase 2 (quant) was conducted quantitatively to test the extracted constructs from the first phase to detect the level of correlations among the factors. Within this chapter, the two phases of the research were explained in detail with the purpose of generating a solid research method to accommodate the direction of investigating the adoption factors of AI in HRM.

3.2 Research Philosophy

According to Saunders et al. (2018, p.123), research philosophy is defined to be the "system of beliefs and assumptions about the development of knowledge". The concept seems to be broad and unspecific; however, it is a significant foundation of how research is constituted. In the purview of research philosophy, it is the embarkment of knowledge development of the researcher onto the research paper during the research journey. This research adopts a pragmatic philosophical stance, reflecting a problem-centred view that emphasises practical consequences and pluralistic approaches. Research philosophy refers to the system of beliefs and assumptions guiding the development of knowledge (Saunders et al., 2018). In this study, the selection of pragmatism reflects the researcher's intention to investigate both the contextual understanding and measurable patterns of AI adoption in HRM.

3.2.1 Ontology

Ontological perspectives address the nature of reality, influencing researchers' assumptions of how the world operates. In social science research, if scholars are interested in understanding reality, ontology matters because it shapes how scholars define that reality (Clark et al., 2021). From an ontological perspective, this research recognises that social reality is complex and constructed by individuals but also acknowledges the existence of observable organisational patterns. This aligns with pragmatism's middle-ground approach between objectivism and subjectivism (Clark et al., 2021). The study examines how AI is perceived and adopted by HR professionals within their organisational contexts (subjectivist lens), while also exploring generalisable patterns in adoption behaviours (objectivist lens).

3.2.2 Epistemology

Epistemology is the second aspect of philosophical underpinnings that asserts the concerns of what constitutes knowledge in a field of study, especially regarding the validation and methods of obtaining social reality knowledge (Saunders et al., 2009; Grix, 2002). In social sciences, it is indicated by Clark et al. (2021) that a central issue is whether or not a social phenomenon can or should be examined in accordance with the same principles, procedures, and ethos as natural sciences. Hence, epistemology branches into two distinct positions: positivism and interpretivism. Epistemologically, the study is guided by the view that knowledge is both constructed and tested through experience, interaction, and empirical observation. It rejects the rigidity of a purely positivist or interpretivist stance, instead employing both qualitative exploration and quantitative validation. As Crotty (2013) and Alvesson and Sköldberg (2017) suggest, this reflexive approach supports methodological flexibility while maintaining coherence with the research objectives.

3.2.3 The philosophical stance of the research

This study will primarily be predicated upon the epistemological stance of pragmatism to investigate the social phenomenon, namely “Artificial Intelligence’s Adoption in HRM”. This is rational and aligned with the previous definition of epistemological position because the research on AI’s adoption in HRM will concentrate on how organisations and their stakeholders acquire knowledge about AI, how they evaluate its benefits and their willingness to integrate AI into their processes. While ontology may seem less relevant, it is not entirely absent. One part of this study is understanding the nature of AI technology, its role within organisations and the antecedents of AI adoption, which will all fall under the ontological dimensions. However, the core focus of this study is on the knowledge and understanding of AI adoption from the perspective of social actors (e.g. HR professionals), making it predominantly a pragmatism of epistemological stance. By adopting a pragmatic paradigm, the study integrates different methods to address both exploratory and explanatory aspects of the research questions. This philosophical alignment enables the use of mixed methods, where qualitative inquiry uncovers key factors of AI adoption and quantitative analysis tests their significance and relationships.

3.3 Research Approach

The research approach refers to the concerns with the relationship between theory and research in terms of how theory and data are being used (Bell et al., 2022). Three ubiquitous research approaches in social sciences are deductive, inductive, and abductive (Saunders et al., 2009; Bell et al., 2022). In social research, the approaches contribute to clarify research objectives and orientate research direction based on its execution nature of approaching the research problems. **Table 3.1** summarises some key features of the three reasoning approaches in scientific research (Barrett and Younas, 2024).

Table 3.1: Key features of research approach

	Inductive	Deductive	Abductive
Key features	Specific observation to logical inferences	General rules to a specific conclusion	Starts with general observations toward the likeliest explanation
Use of theory	Generally, not using existing theories or models	General rules are drawn upon existing theories and models	May or may not use theory-base premises
Research methodology	Primarily used in qualitative methods	Primarily used in quantitative methods	Mainly used in mixed methods
Primary focus of outcome	Theoretical or conceptual development	Theory and hypotheses testing	Develop most plausible inferences about observations

This study follows an **abductive research approach**, consistent with the pragmatic paradigm. Saunders et al. (2009) and Bell et al. (2022) outline, abduction combines inductive exploration and deductive confirmation, making it particularly suitable for studies seeking both theoretical development and empirical validation. The research approach is deployed to make logical inferences and build theories about social reality. In particular, the abductive approach first allows researchers to recognise themes and explicate patterns and then either develop a new theory or alter an already existing theory that is examined based on the collected data (Kennedy et al., 2021). This kind of reasoning can overcome the limitations associated with the two former positions (Barrett and Younas, 2024).

In Phase 1, qualitative data were collected through semi-structured interviews to explore perceptions, barriers, and enablers of AI adoption in HRM. The initial coding and thematic analysis allowed new insights to emerge, which contributed to the construction of a conceptual framework. This process reflects inductive reasoning, enabling the researcher to ground emerging concepts in participants' lived experiences.

Phase 2 involved the design and distribution of a survey instrument, informed by themes from Phase 1 and the literature. Quantitative data were then analysed using statistical methods to test the relationships between identified constructs. This represents deductive reasoning, aligning with the goal of validating theoretical assumptions with measurable data.

The iterative nature of abduction allowed the study to revise and refine the conceptual framework throughout the research process. This approach supports theoretical flexibility and aligns with the dynamic and evolving nature of AI adoption in organisations.

3.4 Research Strategy

Research strategies are techniques adopted by scholars to achieve the research objectives and find answers to research questions. Researchers have different approaches when classifying research strategies. For instance, Saunders et al. (2009) specified seven distinct strategies in their research onion, such as experiment, survey, case study, action research, grounded theory, ethnography, archival research. In contrast, Bell et al. (2022) has different perspectives depicting only two main strategies: qualitative and quantitative. Irrespective of the classification, this research adopts a mixed-method approach, including both qualitative and quantitative methodologies to leverage the strengths of both approaches. Given the philosophical and methodological orientation of the study, a mixed-methods research strategy was employed. The combination of qualitative and quantitative methods enabled the researcher to address the research questions comprehensively, enhancing the validity and robustness of the findings (Doyle et al., 2009).

The qualitative phase provided rich, contextual insights into how HR professionals perceive and interact with AI technologies. It allowed for an in-depth understanding of the social and organisational factors that influence adoption. These findings informed the development of a structured survey used in the quantitative phase. The quantitative phase facilitated the statistical testing of the conceptual framework developed from the qualitative insights. Using a survey administered via Qualtrics, the study collected responses from a broader sample, enabling the identification of significant relationships among adoption factors. This two-phase design aligns with the QUAL-quant sequencing of the research, where qualitative insights guided the subsequent quantitative instrument. The strategy supported methodological triangulation, enhancing both the depth and generalisability of the findings (Shorten and Smith, 2017).

3.4.1 Advantage of Mixed-Methods Research (MMR)

MMR enables scholars to harness the strengths and compensate for the weakness of both quantitative and qualitative research. For instance, quantitative research is often criticised to be weak regarding the efforts to understand the investigated contexts or circumstances where participants' voices are overlooked (Azer et al., 2022). Fortunately, with the adoption of MMR, these weaknesses will be offset at the qualitative research phase. On the other hand, it is noteworthy that the qualitative also has its limitations, such as bias stemmed from the researchers' interpretations and the insufficient generalisability of findings (Azer et al., 2022). Thus, the advantages of one approach can compensate for the flaws of the other (Doyle et al., 2009). Employing MMR allows scholars to flexibly use different data collection instruments, unconstrained by the typical boundaries connected with qualitative or quantitative research. In this sense, MMR can bridge the gaps between these two main approaches, proving its usefulness for social, behavioural, and human science research (Azer et al., 2022). Importantly, MMR offers researchers a greater chance to produce diverse outputs (e.g. a quantitative article, a qualitative article, and a methodological article) from a single study (Azer et al., 2022; Doyle et al., 2009).

In fact, the MMR provides an effective methodological triangulation for the researcher to synthesise and interpret contextual data from the AI-HR adoption phenomenon. Further discussions in this Chapter will enlighten each research phase in greater details. In brief, this research employed a methodological triangulation approach in which the combination of QUAL and quant data was expected to assist the researcher to obtain a broader perspective regarding the research foci. The discovered themes, through semi-structured interviews with research participants in Phase 1, provided the contexts and insightful rationales about AI adoption factors in HRM. Meanwhile, Phase 2 of statistical analysis provided validation for the conceptual framework of AI adoption intention. The triangulation approach enriched the reliability of the research's findings and offered a comprehensive assessment on the research focus: AI adoption and HRM.

3.4.2 Types of mixed methods design

The arrangement of how data is gathered in the mixed-method application is considered critical. When concluding with the selected mixed methodology, the method design to ideally gather valuable data extraction must be determined to maintain the consistency and logical data-collection path. Due to the significant role of having purposeful data, types of mixed methods must be deliberated carefully before being applied in this research. In practice, there are four core mixed-method designs including convergent parallel, sequential explanatory, sequential exploratory and embedded/ nested. As presented in **Table 3.2**, there are four main types of mixed research method including convergent parallel (Qual-Quant), sequential explanatory (QUANT-qual), sequential exploratory (QUAL-quant) and embedded nested (Qual(quant) or Quant(qual)) (Halcomb and Hickman, 2015).

Table 3.2: Mixed research method design (Halcomb and Hickman, 2015)

Research Design	Process	Purpose	Level of Interaction	Priority	Example from Literature
Convergent parallel (concurrent)	Qual Quant	To obtain different but complementary data to answer a single research question	Data collected & analysed independently	Equal	Peters and Cotton (2013) collected both mailed surveys and undertook unstructured interviews with women with physical disability in order to gain a broad understanding of the barriers and facilitating factors associated with in accessing and experiencing breast and cervical cancer screening services.
Sequential explanatory	QUANT → qual	Qualitative data are collected to explain the quantitative findings	Quant data frames qualitative data collection	Quantitative dominant	Pfaff et al. (2014) used a mailed survey to measure perceived confidence in interprofessional collaboration amongst new graduate nurses. Following analysis of the survey data they conducted interviews with 16 new graduate nurses to explain and expand upon the quantitative findings.
Sequential exploratory	QUAL → quant	Quant data builds on qualitative findings to provide generalizability	Qualitative data frames quant data collection	Qualitative dominant	Hamshire, Willgoss and Wibberley (2013) conducted a series of interviews with nursing students to explore their experiences and expectations of their nursing course. These interview findings informed the development of an online survey that was administered to 1080 students across nine UK universities.
Embedded / Nested	Qual (quant) Or Quant (qual)	To obtain different data to answer a complementary research question	Embedded dataset provides answers to a complementary research question.	Can be either Qualitative or Quantitative dominant	Kinser et al. (2013) conducted a randomised controlled trial of an 8 week yoga intervention for women with major depression. Outcomes included depression severity, stress, anxiety an rumination. Qualitative interviews were embedded in the trial to explore the feasibility and acceptability of the intervention.

This study adopted a sequential exploratory mixed-methods design (QUAL → quant) to comprehensively explore the phenomenon of AI adoption in HRM. This design was selected based on the nature and aim of the research—to first explore participants' perspectives and experiences in-depth (qualitative phase) and subsequently test emerging themes and constructs empirically through a quantitative survey. As outlined by Halcomb and Hickman (2015), sequential exploratory designs are particularly useful when the initial aim is to understand phenomena through open-ended exploration, before building and validating conceptual frameworks through statistical generalisation. In the context of this study, this meant conducting qualitative semi-structured interviews with HR professionals during Phase 1 to uncover factors influencing the adoption of AI technologies. These findings informed the development of a quantitative instrument, administered in Phase 2, to test the strength and relationships of these identified factors across a broader population. The selected design aligns with the pragmatist research philosophy adopted in this thesis, which supports the combination of inductive and deductive reasoning to generate actionable and context-rich findings. It also reflects the qualitative priority of the study, wherein rich, contextual insight was needed to guide meaningful quantitative validation. This design enabled triangulation of methods, enhancing the validity and robustness of the overall findings.

3.5 Research Design

Anchored to the above discussion, this research employed a sequential exploratory design as the most appropriate framework to investigate the adoption of Artificial Intelligence (AI) in Human Resource Management (HRM). This choice was informed by the exploratory nature of the research questions, which first required in-depth exploration to identify key influencing factors before testing and generalising those insights. **Figure 3.1** illustrates the research strategy to address the research questions.

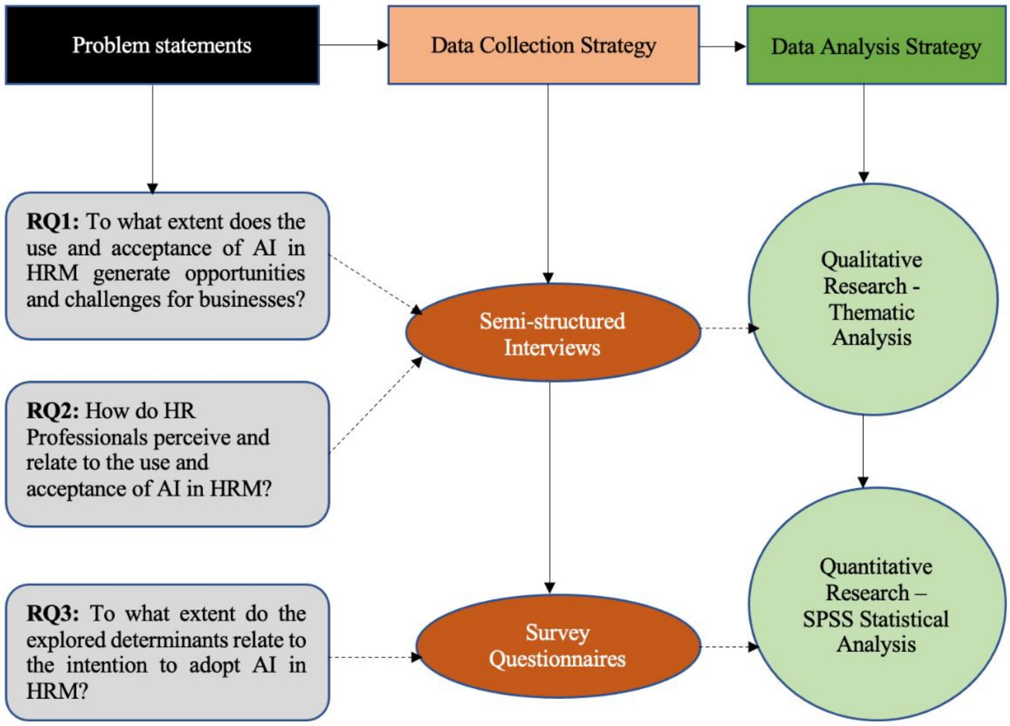

Figure 3.1: Designed Integration Strategy of Research Approaches and Research Questions

The study was conducted in two distinct phases. In Phase 1, a qualitative approach was applied through semi-structured interviews with AI-HR professionals. The aim was to gain rich, contextual insights into how AI technologies are currently used in HRM and to identify key antecedents that influence their adoption. This phase also considers data from professional AI events and forums, such as Think IBM 2021 and the SAP AI Summit, where participants' discussions and perspectives contributed to theme generation. All qualitative data were analysed using NVivo software, with a thematic analysis guiding the identification of patterns and new factors relevant to AI adoption decisions. These emergent themes informed the subsequent development of the quantitative instrument.

Phase 2 followed with a quantitative survey, developed directly from the findings of Phase 1 and aligned with the UTAUT (Unified Theory of Acceptance and Use of Technology) model. The survey was distributed to a broader sample of HR professionals across West Midlands England using the Qualtrics online platform, with participation preceded by informed consent. The purpose of this phase was to test the correlations between the key themes identified earlier and the intention to adopt AI technologies in HRM. Demographic variables were also included to contextualise and support the interpretation of findings.

The overall design enabled the research to transition from exploration to explanation, combining rich qualitative insights with empirical generalisation. This approach supports the study's pragmatist philosophical stance and reflects the use of abductive reasoning—moving iteratively between theory, data, and interpretation. **Table 3.3** summarised the two phases of conducting the mixed method research (QUAL-quant).

Table 3.3: Two main phases of the research

Phase 1	AI-HR Professionals (QUAL research)	Deep understanding about the current use and acceptance of AI in the market for the establishment potential themes
Phase 2	HR Professionals (quant research)	Examine the correlations among the projected influential factors affecting adoption intention

3.6 Sampling techniques

Sampling techniques refers to the method or procedure that the researcher would employ in selecting a sample from a given population (Kothari, 2004). The population is the entire group of subjects that the researcher would like to gain information on, whilst a sample is a subset which can represent the entire population (Stockemer, 2019). It is realistic and challenging for the researcher to obtain data from the whole population, therefore it is critical to adopt appropriate sampling techniques to optimise the amount of collected data while ensuring its quality for the research. In alignment with the sequential exploratory design of this study, two distinct sampling techniques were employed across the qualitative and quantitative phases to ensure methodological rigour, appropriateness for the research context, and relevance to the study aims (Creswell, 2017; Saunders et al., 2018).

3.6.1 Qualitative Phase Sampling

For Phase 1, which involved qualitative data collection through semi-structured interviews, a non-probability snowball sampling technique was adopted. This technique was chosen due to the exploratory nature of the phase and the challenge of identifying a specialised population with direct experience in AI adoption within HRM. Snowball sampling is recognised as a practical and purposive strategy when the research population is hard to access, especially in emerging fields or where a sampling frame is unavailable (Noy, 2008; Etikan et al., 2016). Initial participants were identified via professional networks and were then asked to refer other AI-HR professionals who met the inclusion criteria. This approach supported the recruitment of informed participants who could offer rich, contextualised insights into AI implementation and attitudes within HR contexts (Given, 2008). The use of snowball sampling in qualitative inquiry is appropriate for capturing expert perspectives where generalisability is not the primary aim but rather the depth and richness of data (Patton, 1980).

The recruitment process began with a small number of initial participants identified through the researcher's existing professional network, which included contacts from academic-practitioner events, HRM forums, and LinkedIn communities (**Appendix 3.10**). These participants were selected using convenience sampling based on accessibility, willingness to participate, and relevance to the study criteria: AI technologies in HRM practices. Following the initial interviews, participants were asked to recommend colleagues or professional contacts who also had relevant knowledge or experience in AI-HR applications. This referral process constituted the snowballing aspect, enabling the sample to grow through social and professional networks.

The researcher initially contacted five individuals known to be engaged in AI-HR practice or research. These included professional acquaintances, former HR colleagues, and academic contacts, representing a form of convenience sampling in the initial wave. These initial participants were then asked to recommend additional individuals who met the eligibility criteria. This process continued through multiple waves until the target number of participants was reached. In total, 18 out of 20 participants were successfully recruited through this method. This approach was essential given the limited visibility and concentration of AI-related roles within HR departments at the time of data collection, particularly during and after the COVID-19 pandemic when direct access to organisations was restricted. The use of convenience sampling in the initial stage, followed by snowball sampling, provided a practical and context-sensitive method to access informed participants. While this strategy does not allow for statistical generalisability, it is well-suited to the research objectives of the first research phase, which prioritised depth, insight, and thematic development over representativeness (Saunders et al., 2018; Given, 2008).

3.6.2 Quantitative Phase Sampling

In Phase 2, a probability-based simple random sampling strategy was implemented to ensure representativeness and statistical validity in the broader population of HR professionals in England. Probability sampling is widely endorsed in quantitative research for its capacity to reduce selection bias and increase the generalisability of findings (Bryman, 2016; Taherdoost, 2016). Participants were selected from a compiled sampling frame of HR professionals through academic-industry networks, CIPD directories, and online professional platforms. The application of simple random sampling ensured that every individual in the defined population had an equal and independent chance of being selected (Saunders et al., 2018). This sampling approach was particularly appropriate for this phase, which aimed to test relationships among constructs and validate the conceptual framework developed in Phase 1. The combination of snowball sampling in the exploratory phase and random sampling in the explanatory phase reflects the pragmatist foundation of the study. This dual strategy supports abductive reasoning, enabling a comprehensive and flexible inquiry while maintaining methodological coherence (Morgan, 2007; Teddlie and Tashakkori, 2009). In this study, out of the 225 responses initially collected through the survey, only 146 cases were deemed valid for quantitative analysis following a data screening process. A total of 79 responses were excluded due to various issues, including incomplete answers (n = 42), straight lining or patterned responses (n = 21), and failure to meet the screening criteria such as no relevant HR work experience nor geographical location within England (n = 16). These exclusions were essential to maintain the integrity, reliability, and relevance of the dataset in alignment with the research objectives.

3.7 Data Collection and Analysis Approaches

The research was divided in two main phases to effectively deploy a sequential mixed research method. To maintain the consistency of data collection and analysis, a concrete research process was established as illustrated in **Figure 3.2**. As presented in the figure, the literature review was the foundation for the initial direction of the overall research. The decision on research strategy approaches was subsequently established upon the preliminary conceptual framework sieved from the research literature. More specifically, this study had the Primary Research Approach conducted into two main phases: Phase 1 (QUAL) and Phase 2 (quant) in order to serve the exploratory nature of this research. The research procedure of each phase will be explained in the next section.

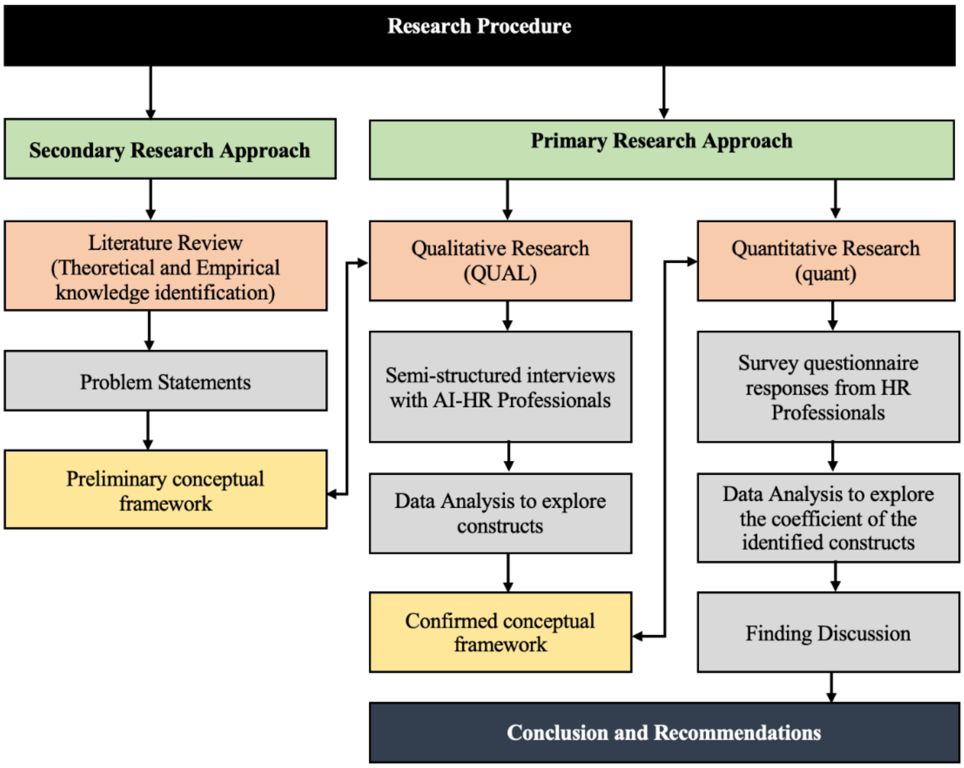

Figure 3.2: Comprehensive Research Process

3.7.1 Phase One: Qualitative Research

3.7.1.1 Qualitative Data Collection

As declared in QUAL-quant research, the nature of exploratory aspects must be prioritised in order to address the core issues undercovering in the research phenomena in qualitative research. Indeed, Bell et al. (2019) emphasised the importance of addressing the research questions by applying the appropriate methodological choice and interview design. Therein, this study gathered data at Phase 1 using a semi-structured interview method. The mechanism for semi-structured interviews is due to its capacity in providing in-depth stances, meanings and interpretations of concepts within the discourses with participants (Kallio et al., 2016). This approach enabled a flexible yet focused exploration of AI adoption in HRM, allowing new concepts to emerge while maintaining alignment with the research objectives. The semi-structured format was deemed particularly appropriate for technology-related research where user experiences and organisational contexts may vary significantly (Venkatesh et al., 2013; Yin, 2014). Interviews were conducted virtually using either face-to-face or Microsoft Teams between February and June 2022, each lasting between 50 and 90 minutes. An interview guide was developed based on existing literature and refined through consultation with supervisors and a small pilot group. Ethical approval was obtained prior to participant recruitment. The interview protocol was designed to elicit views on perceived benefits, challenges, organisational readiness, and individual perceptions toward AI in HRM. A total of 18 out of

20 participants took part in this phase, and recruitment continued until the point of thematic saturation was reached, meaning no new significant codes or categories emerged during the final interviews (Guest et al., 2006; Braun and Clarke, 2021). The data collection procedure is described as follow.

Interview Procedure:

As a nature of exploratory research, the process to organise and design a well-structured interview protocol is crucial in order to capture the essential insights from the participants. In line with this, the research interview was designed as illustrated in **Appendix 3.1** and was divided into four parts. Specifically, the participant was initially introduced about the research and verbally consent to participate in the interview. Demographic and organisation backgrounds were also collected from the participants to apprehend and interpret the context accurately. Next, Part 1 was introduced with the purpose of understanding the current HR infrastructure and structure of the organisation as the first attempt to understand the current HR approach (either conventional or AI-intervention HRM). Subsequently, after capturing the current context of HR, Part 2 of the interview elicits the insights of a level of awareness of AI technologies in the realm of HR where participants would define the concept and assert the understanding and the contemporary applications in HRM. At this junction, possible comparison between AI-powered HRM and traditional HRM will be centred to navigate RQ1 regarding opportunities and challenges in AI adoption in HRM. Next, Part 3 of the interview centres on exploring the perceptions and attitudes to address RQ2 of this thesis. Ultimately, Part 4 of the research seeks the information to elicit the adoption intention from the participants and how they link with business performance, strategy and future plan.

The research aims to collect the rich data from semi-structured interviews with the participants, hence, the researcher attempted not to approach the participants with direct questioning. This allows the exposure of honest expression, meanings and explanation. This is suggested by Bell et al. (2019) that it would maximise the participants' experience and perspectives. The questions were also designed followings the instruction of which stresses on the eliminations of leading and bias natures potentially embedded in the question design (Creswell, 2017). Jargons and terminologies were avoided and further explained to the participants to ensure the correct understanding of the research interview questions. Before reaching the usage stage, the interview protocol was pilot tested with two HR professionals through audio calls for further feedback and refinement. In addition, an Interview Experience Log was also designed

(**Appendix 3.8**) as a reflection tool for the researcher in order to improve and extract key lessons from each interview conducted.

Access Request

The next step after designing the research interview questions was to gain access to the potential candidates. As acknowledged by Humphreys and Jacobs (2023), the process to obtain access in research is critically important to accurately address the research issues. Due to the scope and in-depth requirements of this exploratory study, it posed certain challenges in recruiting participants in the realm of HR. In fact, the occurrence of the Covid-19 pandemic had generated the impediments in recruiting participants due to organisational and operational disruptions in a large scale. HR professionals had shifted their focus on crisis management and hybrid working transitions, which hampered their availability and willingness to participate in the research. It, coupled with the fact that this study centres on HR professionals who usually tight schedules and workload, generating difficulty in securing interview slots. In addition, due to the nature of the HR discipline, principles regarding HR policies, confidentiality, and data privacy were considered sensitive topics for the participants. Hence, this imposed certain restrictions for the participants to explicitly share the company information, infrastructure or HR practices. As a result, some HR professionals were hesitant to participate or withdraw from the research. Due to the aforementioned challenges, the researcher strategically commenced the tasks by reaching out to the available HR network in Chartered Institute of Personnel and Development (CIPD). Specifically, the snowballing technique was applied due to the requirements of trust and closeness in the HR network to increase the chance to gain access (**Appendix 3.10**). Non-probability purposeful sampling technique was subsequently applied to choose the appropriate participants for this research. As AI adoption in HRM is a critical and strategic issue in England's firms, key information about the research purposes and aims was introduced and distributed through required individual and firm request access (**Appendix 3.5** and **Appendix 3.6**). Additionally, the procedure also adheres BCU ethical standards with required signatures from participants for the consent form the participant's information sheet (**Appendix 3.4** and **Appendix 3.3**), where the participant's withdrawal right and procedures were clearly explained and communicated.

The Interviewees

As previously described, the consent forms and participant's information sheets were distributed to the research's participants before the interview session. This is to ensure the participant could obtain an idea about the interview themes. Since this research does not bound within a particular industry, HR professionals from different sectors in West Midlands, England were approached with diverse organisational backgrounds, sizes and industry. This approach enabled a diversity of perspectives and organisational contexts, which is critical for understanding the nuanced application of AI in HRM. The selection process focused on individuals who were actively working in AI and HR realm, whose tasks either involve strategic decision-making, implementation, or operational HRM tasks. This included professionals from organisations of varying sizes and sectors. During analysis, further classification of the participants' organisational context (e.g. industry, organisation size, HR department structure) was undertaken to support a more context-sensitive interpretation of the findings. Recruitment was primarily conducted through snowball sampling, supplemented by convenience sampling in the early stages. Initial participants were identified through professional networks, and subsequent participants were recommended by those already interviewed. In total, 18 participants were successfully interviewed, offering diverse yet thematically convergent insights that supported the development of the quantitative phase. These professionals played roles ranging from HR managers and AI project leads to consultants specialising in HR tech adoption. Full demographic and organisational information about the interviewees are detailed in Chapter 4.

Data Sufficiency

The number of interviews was not arbitrarily determined but followed the principle of *data adequacy* (Vasileiou et al., 2018), where the goal is to collect sufficiently rich, relevant, and diverse data rather than achieving a fixed numerical target. Following the recommendation of Saunders et al. (2018), the researcher adopted a pragmatic approach to identify the point at which further interviews no longer contributed substantially new insights—commonly referred to as *code saturation*. At approximately the 16th interview, recurring themes and patterns became evident, and by the 18th interview, no substantially new codes or concepts were emerging. This was discussed with the supervisory team, and it was collectively agreed that the data gathered was adequate to address the exploratory aims of Phase 1. This supports the notion of *thematic saturation* as defined by Guest et al., (2006), who argue that saturation often occurs within the first 12–20 interviews in studies with a relatively homogenous group and focused research questions. However, as O'Reilly and Parker (2013) caution against using the term *saturation* without critical reflection, this study uses the term *data sufficiency* to reflect a more flexible and context-specific judgement of data adequacy. Hence, the decision to conclude data collection at 18 interviews is grounded in methodological rigour, informed supervision, and theoretical consistency. Details of participant backgrounds and roles are presented in **Chapter 4** to demonstrate the diversity and appropriateness of the sample for addressing the research objectives.

The interview

Ultimately, the interview session was confirmed with each participant upon their convenience and agreed time. Since the AI-HR participants were all recruited in England, there was no time zone adjustment required in the procedure. As stated in the Consent and Research Information sheets, the participants could choose face-to-face or MS Team video interviews due to certain Covid-19 restrictions applied for meetings and people gathering. The interview ensures the participants feel comfortable with no time pressure and can freely refuse to answer questions which they do not wish to expose. Additional notes were also taken while video or audio were recording the discussions to ensure the noticeable or intriguing parts were marked for later data analysis. A list of follow-up questions (**Appendix 3.2**) was precedingly prepared in case data collected from the participants were not rich enough to uncover the research questions. The summary of the discourse was subsequently communicated with the participants. In addition, the confirmation on the accuracy of the content of the discussion was requested from the participants via emails with the timeline of maximum two weeks to revise so the researcher could proceed with the analysis part.

3.7.1.2 Data Analysis of Qualitative Research

As asserted by Silverman (2004), thematic analysis was ideal to derive and extract the insights from the research phenomenon rooted from exploratory study. In practice, thematic analysis is indicated as one of the most popular approaches in qualitative research (Creswell, 2017). The method provides the flexibility in capturing and discovering emerging patterns hidden in the dataset. The fundamentals of this method lie on its ability to narrow down by drawing inferences and directions from the themes emerged during the analysis of data. To further assist this process, either manual analysis or available Qualitative Data Analysis Software such as NVivo could be deployed. Within this study, although both techniques were applied to analyse the dataset, NVivo version 12 was mainly utilised due to its convenience of recording data and navigating the connections of nodes and themes of the analysis.

Thematic Analysis

Thematic analysis refers to the identification, analysis and report of patterns within contextualised data (Braun and Clarke, 2008). The approach allows researchers to organise and concisely describe the data in rich detail while allowing the flexible interpretation of diverse perspectives of the research topic. The reduction of dominant patterns illustrating a set of dominant themes entails appropriate interpretation. Empirical results yielded from a field of study are constructed from themes. The foundation of the theme in research analysis generates a paramount feature to summarise a large data set into sufficient ones. Themes are stated to be shaped from an overarching layer of conceptualisation from participants' points of view where implicit meanings are extracted from the context (Vaismoradi et al., 2016). In essence, themes capture underlying opinions beneath the surface of data collected and they establish based on small meaning units called codes (Braun et al., 2019). In qualitative research, the establishment of themes is critical in exploring and discovering the meanings of the studied subjects (Krauss, 2015). Hence, based on the extent of the context of the research, this exploratory research applied thematic analysis to discover the important themes which were implemented to search for potential adoption factors in the current market. This research approach endows flexibility for researchers because there are no restrictions on the subscriptions to the theoretical commitment (Kiger and Varpio, 2020). This is to provide a concrete conceptual framework with discovered variables quantitatively examined in Phase 2.

Coding technique

In general, the main challenge for qualitative data analysis is owing to sophistication in drawing plausible inferences from the dataset. Patton (1980) suggested that a systematic data reduction approach averting the disposal of essential information is an effective way to handle the issues and enrich the accuracy of the analytical conclusions. In other words, an appropriate codifying technique must be applied to codify potential themes and patterns. During the process of code establishments, analytical memos noting, and contextual consideration were involved. Reflecting upon this study, the development of codes in data analysis was in line with the research questions and existing knowledge from the literature. To obtain the main constructs for the quantitative stage of the research, descriptive coding was applied. The coding and theme establishment followed the method described **Table 3.4**.

Table 3.4: The process of data coding and categorisation establishments

Conduction Phases	Descriptions
Data Familiarisation	Data transcription, reflective journals, recording initial ideas while practising the approach of spaced repetition in reading the collected data.
Manual initial coding	A comprehensive skimming, scanning, and codifying of crucial features identified from the data corpus.
Categories searching	The establishment of categories by grouping related codes

Categories grouping and theme establishment	Grouping the related categories to establish fundamental themes
Theme defining and reflections	Define themes based on existing theories and models reviewed from literature review
Findings formation	Drawing critical conclusions based on qualitative data analysis of theme establishment.

Specifically, descriptive coding was used to extract key data from the data corpus to form a precise foundation for the main themes to be established. According to Sutton and Austin (2015), descriptive coding includes the labelling the segment of information from the dataset which is considered to represent the topic or concept relevant to the research scope. This process assists the researcher to simplify the text clusters by encapsulating the key ideas of the discussion and turning them into manageable parts for further analysis. Once the rigorous coding system was established, thematic analysis was initially conducted manually for data familiarisation on NVivo software. Quotes from the interviewees were later extracted from the data corpus to present the findings of qualitative research in Chapter 4. As a result, the findings derived from thematic analysis linked with specific codes. More details about data analysis were discussed in the next chapter and subsequently extended and refined the proposed conceptual framework in Chapter 5.

3.7.2 Phase 2: Quantitative Research

The predetermined conceptual framework for this study was presented in Chapter 2. As previously explained in **section 3.7**, the qualitative research's outcomes in Chapter 4 were used as a refinement tool for the proposed conceptual framework in Chapter 5. The mechanism of this was to generate the synthesis between the conceptual framework with the context of AI development and existing HRM because of the scarcity of literature and knowledge in this field. Thus, the second phase of quantitative research targets the examination of the relations of the discovered adoption factors to HR professionals' behavioural intention, which matches with the RQ3 of this study. Hence, this part of the research outlines the discussions regarding quantitative data collection and analysis deployed in the Phase 2.

3.7.2.1 Quantitative Data Collection

As highlighted by Saunders et al. (2018), the appropriateness of data collection tools must be aligned with research aims, questions, philosophy, and the available resources. In this research, the aim of the second phase was to empirically test and validate the qualitative themes identified earlier, using a structured and statistically analysable format. Thus, the questionnaire survey was selected as the primary data collection tool for the quantitative phase. In fact, surveys are considered a dominant tool in deductive research, allowing for standardised data collection from a large sample within a relatively short timeframe (Bell et al., 2022). In line with the abductive reasoning process that informed the conceptual framework, the survey aimed to verify theoretical constructs derived from both literature and exploratory interview findings. The structured nature of questionnaires also facilitated subsequent quantitative analysis using SPSS, with potential for generalisability across broader populations (Creswell and Creswell, 2022).

To ensure methodological rigour, the questionnaire was designed using established measurement scales adapted from validated prior studies (e.g., Venkatesh et al., 2003; Palau-Saumell et al., 2019; Alam et al., 2020). Before full deployment, the survey instrument was piloted with two academic experts to refine clarity, wording, and flow. Following feedback, adjustments were made to several items to reduce ambiguity. The survey was distributed online using Qualtrics, targeting HR professionals across industries in the West Midlands, England. Convenience sampling was used to circulate the survey through professional networks, LinkedIn groups, CIPD forums, and alumni mailing lists. Over the course of three months, 225 responses were collected. After screening for incompleteness, response inconsistencies, and straight-lining**,** 146 valid responses were retained for analysis. The data cleaning process is further detailed in **Section 3.8**.

Building on the above, the research highlights the plausibility of data collection chosen in this study. The researcher was also fully aware of existing risks embedded in this method namely low response rate, data misinterpretation and potential bias (Williams et al., 2022). Despite the mentioned drawbacks, the issues could be mitigated by appropriately accommodating statistical research skills. In addition, the survey questionnaire has been declared to be a ubiquitous approach in business and management research. Hence, the above discussion justifies the selection of the survey questionnaires in this study. Specifically, the data collection procedure is described as follow.

The questionnaire type selection

At this junction, it is critical to select the appropriate type of questionnaires before designing and releasing them to the participants. Saunders et al. (2009) classified questionnaires into two types as illustrated in **Figure 3.3**.

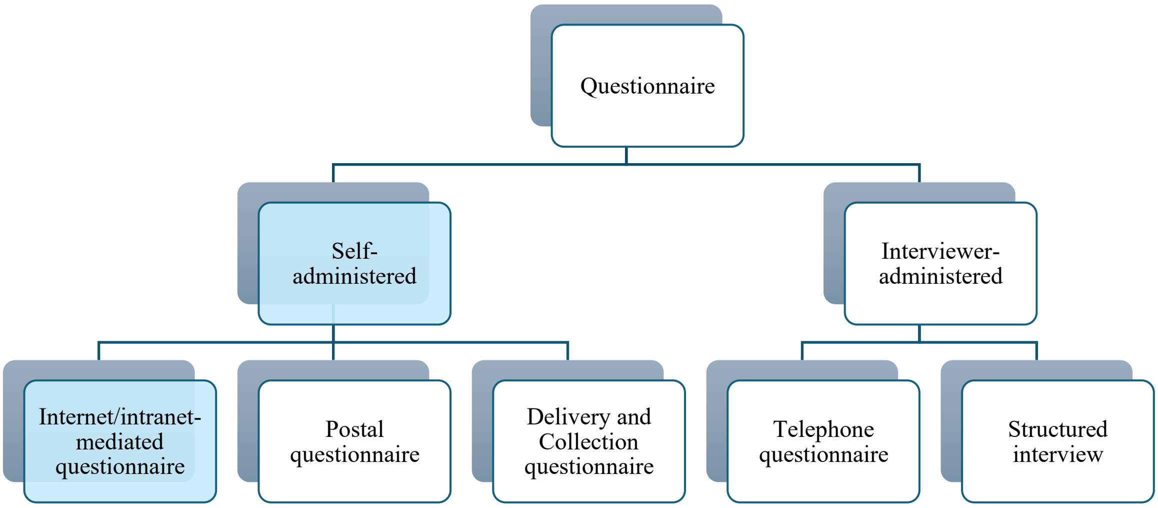

Figure 3.3: Research questionnaire's types (Saunders et al., 2009)

(**Note:* The highlighted boxes are the selected options in this research)

To further explain, the self-administration questionnaires type does not require the presence of the researcher due to the usage of different survey questionnaire platforms. The platforms could be identified as presented in Figure such as Internet/intranet, postal and delivery and connection. In contrast, the interviewer-administered type entails the availability of the researcher which is conducted through telephone or structured interview. In order to select the suitable type for the research, Saunders et al., (2009) considers six elementary factors including (1) data analysis' sample size; (2) quantity of questions and question type; (3) the essence and characteristics of the participants; (4) timeframe for data collection; (5) cost implications of data collection and (6) the automation possibility in data collection.

Tailored to the above suggestions, this research deployed the self-administered questionnaire type, specifically the internet-mediated questionnaires, to collect data for the second phase. Despite the manifest advantage of the remaining questionnaire type in terms of providing insightful content about the research foci, it is considered insufficient to reach a large sample size in the quantitative research (O'Dwyer and Bernauer, 2014). In relation to the above, Phase 1 of exploratory research has generated a rich substratum regarding the associated adoption constructs while the main aim of this phase is on identifying the relationship between dependent and independent variables. Therefore, Phase 2 of this research pursued the self-administered questionnaire type. Notably, this type is dominant for its convenience in terms of effective time and cost involved (Williams et al., 2022), which also made it suited with the nature of doctoral research.

Regarding the selection of internet-mediated questionnaires in this study, certain attributes and advantages of this type were considered. In particular, the successful deployment of this questionnaire type relied on two key components which are (1) internet access availability and (2) basic computer literacy of the respondents and the researcher. Reflecting upon these factors, this study secured the capacity of internet access due to its inevitable availability in the England area for both parties. Further, this technique also facilitates the distribution of the survey questionnaire to more relevant participants in the HR network. Notedly, the targeted participants are HR professionals who are required to possess certain computer literacy, internet and email resources to manage diurnal HR tasks. Further, the automation function of this type creates an ease of use for the researcher at both data collection and analysis stages. Hence, the proposed context provides a mechanism for the selection of this questionnaire type in this study.

The design of the questionnaire

The next step was to design the appropriate questionnaire to successfully obtain the expected outcomes of the research. According to Iacobucci and Churchill (2010), there are nine steps to consider when creating the questionnaire's content and structure. **Figure 3.4** illustrates the main steps of the questionnaire design.

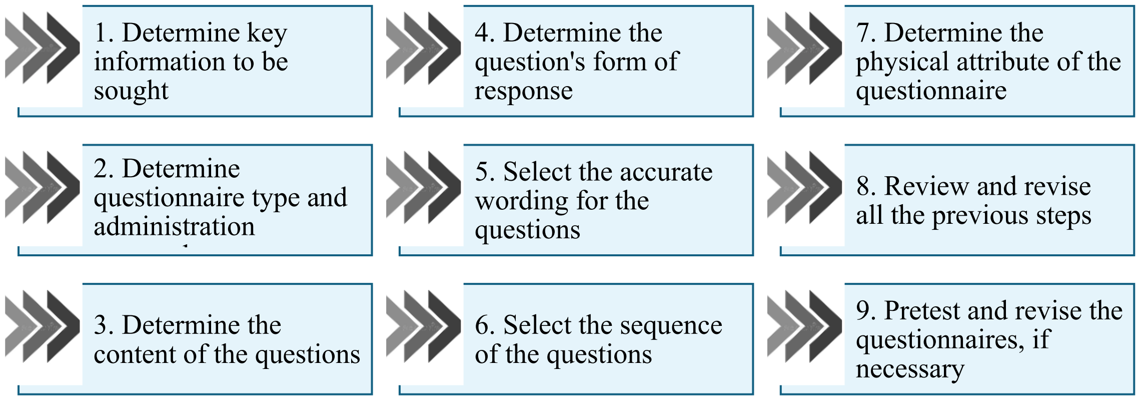

Figure 3.4: Questionnaire Design process (Iacobucci and Churchill, 2010)

As can be seen from the process, Step 1 has been fulfilled by anchoring to the research questions of this study. In addition, the justification on the usage of the survey questionnaire, specifically, self-administered and internet-mediated questionnaire was addressed in Step 2. Hence, the research therein continues to address the residue of the questionnaire design as follow.

Step 3: The content of the questionnaire

The main purpose of this step is to formulate the questions in this research while maintaining the content consistency and validity. It is suggested that an exhaustive literature review significantly assists researchers in justifying relevant questions for the research (White, 2009). Indeed, the content of the questionnaire obtained in this study was extracted from established literature (discussed in Chapter 5). Notably, Patton (1980) also claims the necessity of the establishments of the new questions or adaptation of the existing ones in case the relevant questions could not be found in the extant literature. Mirroring the above discussion, this study adapted the existing questions discovered in the literature review for generating the questionnaire.

Step 4: The question's form of response

According to Brace (2018), there are two types of questions in designing a questionnaire which will indicate the format of the response from the participants. **Figure 3.5** illustrates the types of questions in structuring the research questions.

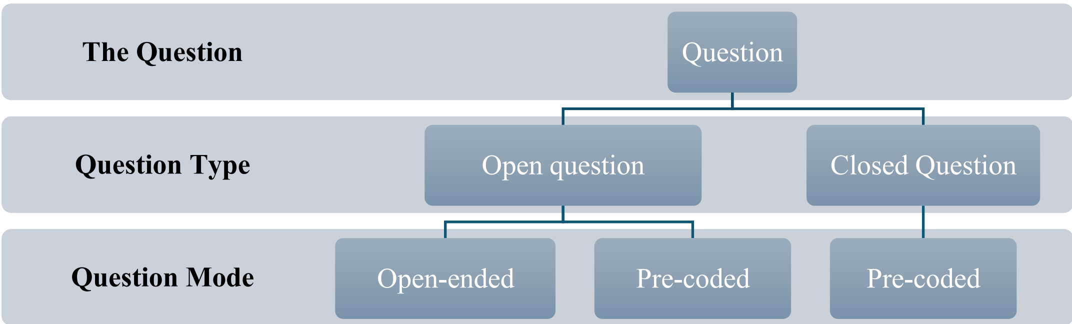

Figure 3.5: Types of questions in creating research questionnaire (Brace, 2018)

Open questions refer to unstructured or free response questions which are used when the researchers cannot predict the responses from the participants and attempt to explore the phenomenon rather than framing the results (Silverman, 2004). Within this type of question, open-ended questions operate in a way to facilitate non-directional answers which suit the nature of unstructured questionnaires. For this question type, there are no predetermined themes to be considered when approaching the participants for the research issues. On the other hand, pre-coded open questions will entail certain predetermined categorisations to be embedded in the questions, forcing the response to a certain direction but also allow the freedom for new information to be obtained. Therefore, this type of question will require a specific theme to be selected to formulate the questions.

For closed question types, it requires researchers to follow the pre-coded mode due to its nature of confirmatory based on the questions. A limited number of answers can be provided for the respondent for this type. Specifically, there are three types of pre-coded closed questions namely: dichotomous (yes/no question), single response (one answer required) and multiple response (more than one answer within a range of available answers) (Brace, 2018). Based on the above discussion, closed pre-coded questions (single response) were selected for Phase 2 of the research. At this stage, rather than exploring the phenomenon, the study focused on testing the relationship of the discovered constructs. In addition, the researcher adapted the questionnaires in the existing literature to gather the data from the participants. A 5-Point Likert scale was chosen in the questionnaire in which one response among five options was allowed from the participants. The options ranged from *Strongly Disagree* to *Strongly Agree* which assists the researcher to gather ratio-based data for further analysis. Fallon (2016) asserted that the 5-Point Likert scale is one of the ideal approaches to enhance the richness of data in statistical analysis.

Step 5: The question wording

McCall (2018) stressed the importance of selecting the right wording for the research to eliminate possible ambiguity embedded in the questionnaire since it would lead to the potential bias and distorted responses from the participants. Hence, wording in this research was perused and selected adhering to the principles of AI, HR and technology adoption in a simple, clear and straightforward manner. In fact, simplicity and clarity of the questionnaire were significantly improved after several attempts to review and revise the questions in the pilot testing sections. Each item was adapted to suit the context of AI use in HRM, drawing from well-established instruments such as UTAUT (Venkatesh et al., 2003) and TAM (Taylor and Todd, 1995). The aim was to ensure that the language was accessible to HR professionals, while accurately capturing constructs.

For example, the original item from Venkatesh et al. (2003), *"I find the system useful in my job"*, was revised to *"I believe the use of AI technologies in HRM will be useful in my job"* to directly anchor the statement in the AI–HRM application domain. Similarly, an item like *"The system enables me to accomplish tasks more quickly"* was contextualised as *"I believe the use of AI technologies in HRM saves me time"*, ensuring clarity and relevance to respondents' professional experience. During the pilot testing phase, several items were revised based on participant feedback. For instance, one early draft item—*"AI improves organisational* *performance"*—was considered too vague by participants and was subsequently reworded to *"The use of AI technologies in HRM will offer better value for the organisation"*, to improve specificity and interpretability. These refinements reflect a deliberate effort to align question phrasing with both the domain-specific terminology and the cognitive expectations of HR professionals. Multiple iterative reviews of the questionnaire were conducted prior to distribution, enhancing the validity and readability of the instrument.

Step 6: The question sequence

An appropriate flow for the questions presented in the questionnaire is to foster its logic and avoid potential confusion for the respondents (Brace, 2018). In line with this, the design of the questionnaire of this study also emphasised the logical flow of the questions. Related to that, this study was meticulously arranged concerning the participants' demographics and individual adoption constructs. Since the constructs were distinct and not dependent of each other, the chronological order was not necessary. However, the constructs' positions were presented in line with the refined conceptual framework, which facilitated the convenience in further stages of data analysis.

Step 7: The questionnaire's physical attributes

All of the questionnaire in Phase 2 was disseminated to the respondents online through Qualtrics Survey Platform (a required platform indicated by Birmingham City University). There was no hard copy used to collect data at Phase 2. The online version of Qualtrics was examined and pre-launched in the pilot-testing section to ensure the quality and the standardised format was presented to the respondents. It appeared that the online Qualtrics survey questionnaire was compatible with both mobile and desktop devices, which enhanced the flexibility and convenience for the respondents to approach the questionnaire. The survey design prioritised clarity and ease of use. A consistent layout was employed throughout, using Arial font at size 12, which supported readability and respondent engagement. The structured, user-friendly interface of the Qualtrics platform contributed to an efficient and standardised data collection process.

Step 8: The questionnaire Review and Revision

Patten (2017) emphasises the critical importance of thoroughly revising questionnaires prior to distribution, as a means of mitigating potential design errors that could compromise data quality and reliability. In this research, the questionnaire revision process was undertaken in parallel with the development of the instrument's content. This allowed for iterative refinement and immediate correction of semantic inaccuracies, typographical errors, and issues related to clarity and terminology. Such a practice ensures the professionalism, standardisation, and contextual appropriateness of the instrument, thereby supporting the rigour of the overall research design (Creswell and Creswell, 2022).

Notably, expert reviewers provided constructive feedback that led to specific modifications. For instance, in Part 1 of the demographic section, initial limitations in industry classification were addressed by incorporating Standard Industrial Classification (SIC) codes. This broadened the scope beyond the originally limited sectors of Business, Education, and Manufacturing, thereby improving inclusivity and representativeness. Moreover, the ranges for respondents' working experience were expanded into five categories: 0–5, 6–10, 11–15, 16–20, and 21+ years. This stratification facilitated more nuanced participant profiling and enhanced the diversity of the sample.

In the main survey (Part 2), terminological precision was improved by replacing generic references to "technology" with the more specific term "AI technologies," aligning with the research focus. Furthermore, the business function under study was explicitly identified as the Human Resources (HR) department to clarify the context in which AI adoption was being examined. These revisions contributed to improving the instrument's construct validity and contextual relevance (Bryman, 2016), ensuring that the questionnaire effectively captured the dynamics and specificities of AI implementation in HRM settings.

Step 9: Pre-examining questionnaire

Iacobucci and Churchill (2010) indicated that pre-testing is the final step to be considered in generating a questionnaire, which is also recognised as pilot testing. The process is to ensure the standard of the questionnaire through monitoring the research instrument on a small-scale with certain invited participants. To ensure the validity and clarity of the survey instrument prior to launch, two academic experts were invited to review the questionnaire. One expert from Birmingham City University has a background in Economics and extensive experience with research-informed Knowledge Transfer Partnership (KTP) projects focused on innovation and technology adoption in enterprise contexts. The second expert, from the University for the Creative Arts, has a background in Organisational Behaviour and also brings valuable experience from multiple KTP projects related to organisational development and behavioural change. Their combined expertise ensured a robust evaluation of both the theoretical framing and practical applicability of the survey items. Constructive feedback was provided on aspects such as question numbering, sentence structure, and typographical errors, which were subsequently addressed. Furthermore, both experts contributed to refining the language of the questionnaire by eliminating jargon and overlapping concepts, thereby improving clarity and coherence. This process resulted in a refined survey instrument suitable for the target population of HR professionals.

3.7.2.2 Data Analysis of Quantitative Research

The findings at Phase 1 allowed the researcher to refine the conceptual framework where certain discovered constructs were positioned to examine the causal correlations between the adoption influencing factors with the behavioural intention of HR professionals. Hence the statistical data analysis at this stage plays a role in supporting to validate the causality of each individual construct to the adoption intention. In line with that, the essence of the refined conceptual framework proposes that a multivariate analysis technique was the most appropriate method to assess the research model of this study. In fact, there are multiple multivariate techniques to be considered such as logistic, multiple regression or structural equation models. Nevertheless, within this study, exploratory factor analysis (EFA), Pearson correlation test and multiple regression were selected to assess the dataset.

EFA is a popular statistical analysis technique which is applied to explore the principal relationship between measured variables (Saunders et al., 2009). The technique also assists to identify the influencing constructs on the variables. Within the scope of this study, EFA simplifies the sophistication of the adoption determinants by clustering correlated variables into discrete factors (Williams et al., 2022). This particular method is helpful in assisting research focusing on exploring dimensionality of variables (O'Dwyer and Bernauer, 2014; Saunders et al., 2009). Reflecting upon the nature of QUAL-quant from this study, this technique helps the collected data to be manageable by reducing a large set of variables to a smaller one. In this orientation, theoretical understanding about the constructs and the measurement instruments applied in the study could also be enriched. As a result, this technique helps the researcher to gain significant understanding about the correlations to predict and explain the adoption factors of AI in the realm of HRM.

In a similar vein, Pearson correlation is another statistical technique which assesses the linear relationship between two variables in terms of strength and direction. This measure assisted in clarifying the degree of relation between multiple variables in the construct of AI adoption intention of HR professionals (Hair et al., 2019). The correlation coefficients are quantified in The Pearson test in order to determine the attributes of the tested factors (positive, negative or no relationship) with the adoption intention (Creswell, 2017). Following the above, the instrument facilitates the obtaining of primitive insights for further statistical investigations by identifying multicollinearity among the independent variables. This assists the legitimacy for further regression analysis.

Ultimately, multiple regression analysis is the final statistical method applied in this study to establish the relationship between each adoption factor to the adoption intention in the HR field. This technique allows the researcher to examine the impact of each adoption factor by integrating various predictors simultaneously (Uyanık and Güler, 2013). The process generates a nuanced picture of how individual factors contribute to the adoption intention. It quantifies the associated significance of the independent variables to illuminate how the factor interacts with each other. As a result, the researcher can anchor the result to identify underlying obstacles and enablers of AI adoption factors to facilitate AI adoption in HRM.

3.7.2.3 Instrument Reliability Assurance

To ensure internal consistency of the adopted survey constructs, Cronbach's alpha coefficients from the original validated sources were reviewed prior to their adaptation. The core constructs in this study were adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT) model and prior empirical research into technology acceptance (TAM and TPB) in organisational contexts. For instance, Venkatesh et al. (2003) reported high reliability for key constructs in the original UTAUT framework, with Cronbach's alpha values ranging between 0.86 and 0.94 across Performance Expectancy ($\alpha = 0.92$), Effort Expectancy ($\alpha = 0.91$), Social Influence ($\alpha = 0.86$), and Facilitating Conditions ($\alpha = 0.93$). Similarly, constructs adapted from more recent studies related to AI adoption also demonstrated strong reliability, exceeding the conventional threshold of 0.70 (Hair et al., 2019). In the current research, the internal reliability of each multi-item scale was re-assessed after data collection using SPSS. Cronbach's alpha values for all retained constructs exceeded 0.70, indicating acceptable to high levels of internal consistency (Tavakol and Dennick, 2011). These scores are reported in the **Chapter 6** and confirm that the scales are suitable for subsequent statistical analyses.

3.8 Ethical Consideration

Since this study applied a robust design and implementation on a mixed-method approach, it adhered to compulsory ethical procedure when collecting data from the participants. It is stated that the consideration of the ethics aspects when conducting research is significant in social research to ensure social responsibility and the integrity of the study (Saunders et al., 2009). Dannels (2018) indicated that all aspects of ethical issues must be addressed and notified to related parties of the research. Hence, standardised ethical guidelines required by Birmingham City University (BCU) were strictly conformed through the research. This includes the protection of privacy and confidentiality of the participants when participating in the research. In particular, all sensitive information, such as the companies' HR information system and employment data, was strictly protected and confidentially assessed by the agreed-involved parties. In addition, audio and video recordings of the interviews and transcripts were encrypted and securely stored on BCU One-Drive. This was required by BCU Ethics Committees. Finally, the required documentations such as request assessment form (**Appendix 3.5** and **Appendix 3.6**), informed consent form (**Appendix 3.4**), research information form (**Appendix 3.3**), the confirmation of anonymity and potential risks were clearly communicated to the participants. Thus, this research followed necessary ethical guidelines to ensure the ethical standards and research transparency necessary for all participants.

3.9 Comprehensive Navigation of the Research

In summary, in order to explore the adoption intention of AI in HRM, this study employed a mixed method approach (QUAL-quant) to satisfy the requirement of exploratory research. The previous sections equipped readers with essential phases to prepare for the empirical data collection. To portrait the progression and the development of the research into stages, **Table 3.5** provides a summary for the main phases of the research.

Table 3.5: Summary of the research procedure

Phases	Procedure	Product
Qualitative data collection	Individual in-depth MS Team or Face-to-face interview Email to follow up interviews Elicitation materials Documents	Sample (N=18) Video/audio recorded data Text data (interview transcript, documents, artefact description where needed)
Qualitative data analysis	Coding and thematic analysis Within case and across case theme development Cross thematic analysis	Codes and themes Visual models of cases analysis Similar and different themes and categories
Case selection, survey questionnaires development	Purposely selecting sample to test the variable extracted from discovered themes Developing survey questionnaires to examine the relationships of the dependent and independent variables	Sample (N=146) Questionnaire's dissemination
Quantitative data collection	Qualtrics web-based survey (N=146)	Numeric data

Quantitative data analysis	Data screening Factor analysis SPSS quantitative data analysis software	Descriptive statistics, missing data, normality, linearity Factors loadings Standardised and structure coefficients Correlations
Integration of the qualitative and quantitative results	Integrate and explanation of the qualitative and quantitative results	Discussion, implication, future research orientation suggestions

Figure 3.6 and **Table 3.6** below provide an overarching picture of the foundation of research theories and methodology.

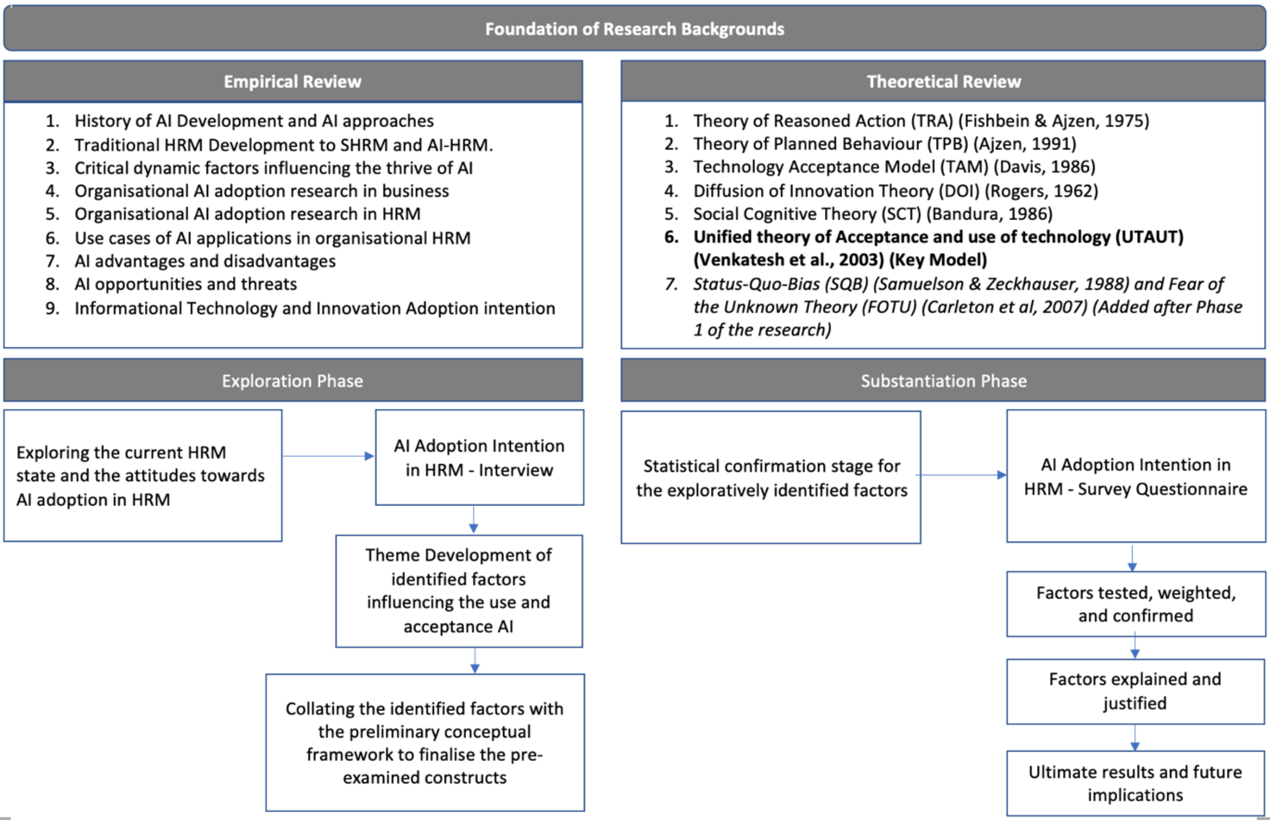

Figure 3.6: Foundation of Research Theoretical Background

Table 3.6: Summary of the research methodological approaches

Research philosophy	Research paradigm	Research Approach	Research Design	Research strategies
Epistemology	Pragmatism	Abductive	Sequential exploratory mixed method (QUAL - quant)	Interviews; Survey Questionnaire

3.10 Chapter Summary

In sum, the research methodology was transparently presented in this chapter of the study. This chapter presents the overall landscape for this research method commencing from the research philosophy, reviewing and deciding suitable options and clear justifications for each option. Pragmatism is anchored to this research philosophy. In addition, abductivism was discussed to be the ideal research approach to use in this sequential exploratory mixed method. Dovetailing to this, the exploratory study's findings were deemed to assist the revision and refinement of the research conceptual framework. In this process, measurement items for quantitative research will also be established based on the extant literature. The residue of this chapter illustrates the protocols of research sampling and survey of the participants. This chapter eventually summarises the two central research phases which are the foundations explaining how the subsequent chapters proceed.

CHAPTER 4: QUALITATIVE RESEARCH (QUAL)

4.1 Introduction

This chapter illustrates the first phase of the primary research in exploring and identifying the cornerstone factors of AI adoption in HRM. The data is gathered from semi-structured face-to-face and MS Team video-recording interviews with AI-HR professionals in England. The initial findings provided a concrete foundation to determine the direction of the quantitative research in phase two, and it aimed to confirm and elaborate on the related factors to AI adoption in HRM. In particular, the results from phase one inform and highlight a selective parameter in evaluating secondary data gained from the preliminary literature review. It was considered that the researcher's theoretical bias from pre-existing knowledge could be excluded with this orientation. In addition, practical knowledge could be enhanced and updated based on the collected incumbent erudition from professionals in the fields. This chapter presents the demographic of the participants and qualitative testing mechanism of the study. It also details the process of data collection and analysis with findings discussed. The finding is used as a refinement tool for finalising the research conceptual framework. The literature review is extended based on the identified key constructs.

4.2 Qualitative Research Overview

From a theoretical standpoint, Chapter 2 of the Literature Review pinpointed four constructs extracted majorly from the UTAUT Model and a significantly related factor of Perceived Risk (PR), which is psychologically linked with the motive of technology adoption in businesses. The other factors belong to the UTAUT model are Effort Expectancy (EE), Performance Expectancy (EE), Facilitating Condition (FC), and Social Influence (SI) (Venkatesh et al., 2003). Furthermore, Perceived Risk (PR) is the additional variable, not included in UTAUT, which is argued to potentially affect adoption behaviour (Hasan et al., 2021; Terblanche, 2020). The mentioned factors possess sub-categories that constituted the formation of the main themes. The articulation and classification of subthemes are based on the previously examined studies related to technology adoption and the integrated association tied to the connotation of each considered factor. Subsequently, the researcher will provide a detailed analysis formulated on the primary data collected through semi-structured AI-HR Professionals. The demographic data gathered was used to synthesise the overall characteristics of AI perceptions from the chosen sample. The rest of the primary data was used to examine, assemble, confirm, and establish central themes for the conceptual framework.

4.2.1 Demographic Information

The qualitative research was formulated on semi-structured interviews with a total of eighteen participants varying across industries and organisational scopes in West Midlands, England. Specifically, the participants were selected based on their expertise and experiences in HRM and AI which essentially serves the purpose of this phase of exploratory research. The interviews were either conducted via face-to-face or video recordings on MS Team so that the researcher could comprehensively capture the reactions, thoughts and feelings of the participants which assisted in reflections while conducting data analysis. The overall information of the research interviews can be viewed as follows. (More detailed demographic information can be viewed in **Appendix 4.1**)

Table 4.1: Demographic Information

Sample Characteristics	Frequency (n)	Proportion (%)
Total: (overall sample)	**18**	**100%**
Gender		
Male	6	33.33%
Female	12	66.67%
Working Experience		
>10 years	8	44.44%
5-10 years	3	16.67%
< 3 years	7	38.89%
Interview mode		
MS Team	16	88.89%
Face-to-Face	2	11.11%

Table 4.1 illustrates the attributes of the research participants selected to measure the perceptions of AI adoption within HRM. Since this stage of the research concentrates on exploring the emerging AI concepts in the HR market, the focal point is to reach the discursive understandings from different HR-related angles. Echoing that subtext, within the HR professionals recruited for the exploratory research, not only HR executives' opinions were taken into considerations, but an equal sample of HR practitioners was deployed to extract the insights from AI-HR contextualisation. It is argued that the evolution of learning organisations in recent years have contributed to enhance and facilitate flat-structured organisations where traditional top-down decisions could be flexibly altered with bottom-up decision-making processes (Kodama, 2018). Technically, the employees are endowed with more authorities and legal rights to voice opinions in organisational decision making. Distinctly, the disruptive intervention of AI in HRM has subsequently drawn attention of organisation management, especially the working employees due to the potential impacts of the advanced technologies on

their jobs (Basu et al., 2022). Since this phenomenon has proposed an institutional level of transformations, perceptions from HR professionals and AI-HR related professionals are significant for the comprehensive understanding of the research subjects.

To broaden the scope of perceptions, the AI-HR group of participants, involving four AI-HR professionals were invited to participate in the research. This is to provide ancillary angles as a reflective tool for the current perceptions of HR professionals towards AI applications. In addition, the research interview questions were designed not only to depict the main themes but the current awareness and perceptions of the participants about the emerging concept of AI. Therefore, the collaborations of the grouped participants will concede various points pertaining to behavioural adoption intention. This mechanism will provide a broad spectrum of this research orientation in terms of advanced technology maturity in the HRM field.

4.2.2 Thematic Establishment with NVivo

The researcher adopted NVivo 12 software to conduct qualitative research analysis. The analysis tool accommodates the researcher to obtain a flexible platform to analyse rich and wide ranges of data (Saunders et al., 2009). NVivo facilitates the use and organising information in terms of linking nodes, themes, and case studies to visualise the relationship of the empirical data (Edwards-Jones, 2014). Thanks to the discussed advantages, NVivo was employed to analyse the narrations of participants from collected interviews. By applying the software, themes were identified and linked with theoretical and empirical literature whilst answering the thesis' questions. Data progression with NVivo is illustrated in **Figure 4.1**.

Data familiarisation is a significant step required at the initial stage of thematic analysis. Through the act of familiarisation with empirical data from reading and re-reading the narrations from interview transcripts, the researcher could apprehend an insightful understanding of the contents and contexts from the collected responses. The cleaning process begins after the familiarisation stage to withdraw the irrelevant, corrupted, and unformatted data from the original transcripts (Chu and Ilyas, 2015). This assists in providing transparency for data synthesis and analysis. The interview transcripts were subsequently uploaded onto NVivo for further exploration, coding, and categorisation processes.

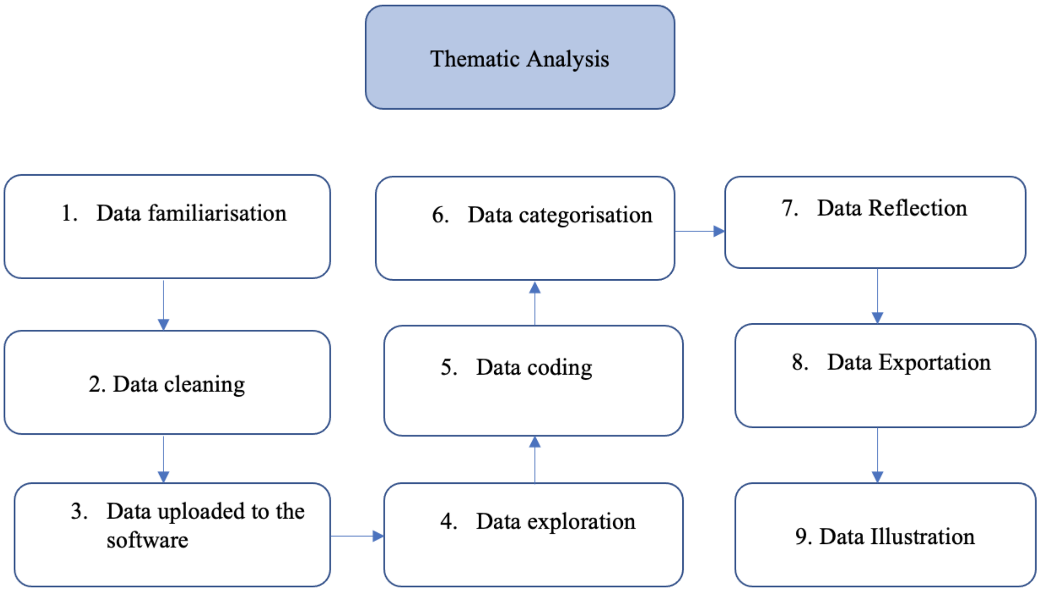

Figure 4.1: NVivo Thematic Analysis Procedure

Data coding was next deployed to anchor emerging collected information into a meaningful set of categories (Blair, 2015). It is the foundation of node generation from individual codes stemming from the observed data. This is a primary part of thematic analysis providing a concrete cornerstone for theme reasoning, classification, and establishment. The process facilitates a deeper understanding of the research phenomenon, which accelerates the process of data evaluation and sense-making. Descriptive coding was adopted which enables the classification of themes based on the *A priori* codebook when analysing and interpreting interview narrations (Roberts et al., 2019). The codebook for this research utilised knowledge retrieved from related theories based on the exploration research nature. In addition, the validation of established codes was ensured to be primarily data-driven and maintained throughout eighteen semi-structured interviews.

Table 4.2: Research A priori Codebook

Parent codes	Sub-codes
Perceptions on traditional HRM	Performance Expectancy of traditional HRM ● Current deployed Employee Management System ● Preferability of the current HR functions in manipulation and capacity
	Effort expectancy of traditional HRM ● Hindrances of the current HR functions in manipulation and capacity ● Dexterity and flexibility of traditional HRM application
Perceptions on AI-powered HRM	Performance Expectancy of AI-deployed HRM ● Applied or potentially applied AI-powered technologies in HRM ● Projected HR function of AI applications and justifications
	Effort expectancy of AI-deployed HRM ● Consideration on cost effectiveness ● Consideration on job dexterity and flexibility of AI-powered HRM application

Projections of AI adoption in HRM	Facilitating factors ● Organisational support for AI applications in HRM ● Innovation integration level in HRM
	Social Influence ● Employer branding concerns on AI adoption in HRM ● Competition pressure of AI adoption in HRM
Emerging Risks of AI Adoption	Fears and threats induced by AI deployment ● Potential biases in decision making ● Control level of personal information ● Job evolvement and replacement ● Lack of skills and deskills possibility

Table 4.2 illustrates the codebook with four parent codes sieved from the research literature and questions. The initial foundation of sub-codes was formulated on literature review and empirical data collection. In this vein, the codebook generates an integrating centre of articulating the research questions, related theories, and primary data. A concrete codification structure was applied to establish codenames with a high concentration on the possibility of forming affiliated themes. Collected data was subsequently uploaded and explored on NVivo software for coding, node generation, and theme establishment following the guidance of the *A priori* codebook.

To facilitate the nature of exploratory qualitative research, codes and nodes arrangement was deliberated following the data-driven positioning approach, which expedites the discovery of related and novel experiences from individual participants (Han et al., 1993). The approach significantly contributes to data synthesis and theoretical proposition, which clarified the gap between AI adoption factors in HRM functions, its drivers, and restraints. The novel emerging codes investigated at this later stage were further pigeonholed into new themes and sub-themes with the purpose of enriching research findings and analysis. Finally, data reflection and visualisation were applied to serve the sense-making process of the annotation from established themes, nodes, and codes. In particular, the relationship of parent themes and child nodes were visualised on a project map extracted on NVivo, which provides the potential hints for further data explanation. In effect, the visual findings extricated from NVivo provided a holistic picture of AI-adoption concerning factors. In the next part, the findings will be communicated to shape the outputs of this first phase of qualitative research.

4.3 Qualitative Research Findings

Through this qualitative study, the researcher synthesises the empirical data within the scope of the thesis into three sections. Each section comprises subcategories and themes used for quantitative research as a measurement tool at phase two of quantitative research. The research findings will be presented through three contradictory pairs of perceptions namely: ***Opportunity Vs Threat; Traditional HRM vs AI-powered HRM; and Theoretical Vs Practical Gap.*** By communicating the research findings, relationships among identified adoption factors will be reviewed, refined, and illustrated. Main findings of this research are depicted below.

4.3.1 Opportunity Vs Threat: The immaturity in AI understandings and use cases in accordance with the ubiquity diffusion of the concept

To comprehensively capture the overall perceptions of the participants, the questions were designed not only based on the *A priori* codebook, but it also centred on the colloquial understandings regarding the novel concept of AI. The participants were questioned about the initial relations of the AI by providing definitions for the concept. It could be indicated as a noun or an adjective for their answers. **Table 4.3** summarises the answers and perceptions of the participants who were questioned about AI opportunities, threats, and the potential for job replacements in HR. The arrangement of data is in response with chronological order.

Table 4.3: Participants' perceptions of AI

Interviewees	AI Concept relation	Threat or Opportunity	AI will replace human jobs
Participant 1	Future	Opportunity	Agreed
Participant 2	Advanced machine	Opportunity	Agreed
Participant 3	Advanced technology	Opportunity	Agreed
Participant 4	Advanced technology	Opportunity	Agreed
Participant 5	Automation	Neutral	Agreed
Participant 6	Advanced and smart object	Threat	Agreed
Participant 7	Siri, machine	Threat	Agreed
Participant 8	Robots, non-human	Threat	Agreed
Participant 9	Automation	Opportunity	Agreed
Participant 10	Technologies taking over	Threat	Agreed
Participant 11	Norms	Opportunity	Agreed
Participant 12	Self-service machine & robots	Opportunity	Agreed
Participant 13	Automation	Opportunity	Agreed
Participant 14	Robots	Opportunity	Agreed
Participant 15	Utopia	Opportunity	Disagreed
Participant 16	Robots	Neutral	Disagreed
Participant 17	Umbrella of innovative technologies	Opportunity	Disagreed
Participant 18	Robots and automation	Opportunity	Disagreed

According to the collected results, the concepts of AI were significantly separated pertaining to the HR professional participants' understandings of AI functions. As defined in Literature Review Chapter, AI is an umbrella technological term for diverse algorithm-based software serving multiple analytics' purposes (Braun et al., 2019). In this sort of orientation, it could be observed that the insights of AI technologies in HRM was not fully captured. The fundamental knowledge derived from HR professionals illustrated partial contributions and functions of AI as reflected in this research's Literature Review discussing AI technologies' capacities and deployments. Sporadic parts of AI functions were mentioned, and the answers were investigated to be corresponding with the amplification of ubiquitous conceptions related to AI. In particular, "robot", "automation" or "advanced technologies" were terms which were majorly used by the participants.

In addition, Aliman (2020) claimed that hybrid-working and alternative business approaches were effectively articulated with the support of advanced technologies during the pandemic period. The statement was proven to be aligned with the assertion of Participant 18, an HR Executive, in the interview: *"[...] regard to recruitment, again it is completely changed whenever I interview someone, one of the first questions asked is "how do you work? Are you all in the office? Are you hybrid? Are you remote?" So, I think the pandemic has changed a lot, not only in HR but within businesses alike"*

Anchoring to this perspective, a new mode of working characterised by closer collaboration between technology and human actors is increasingly being embedded within organisational operations. This context helps to explain why the functional potential of AI initially attracted the attention of HR professionals, even when conceptual understanding of AI remained limited. As a result, it is unsurprising that most participants struggled to clearly articulate the scope and nature of AI or its current applications in HR practice. An exception was Participant 17, an AI–HR leader, who described AI as an "umbrella of innovative technologies", indicating a comparatively higher level of strategic awareness. The qualitative findings therefore suggest a generally high level of awareness of AI within the HR field, while simultaneously revealing uneven depth of understanding across participants.

However, even in the case of Participant 17, the terminology used points to a degree of conceptual overlap between AI, HR analytics, and other digital technologies, highlighting the blurred boundaries that characterise organisational practice. For other participants, the use of generic expressions such as *"advanced technologies"*, *"advanced machines*", and "*smart objects"* reflects partial understanding, where AI is recognised as important but not clearly distinguished from existing information systems or analytical tools. This ambiguity is further illustrated by Participant 12, who appeared to misunderstand AI capabilities when describing expectations that the organisation would implement a self-service system for booking annual leave. Such functionality represents digital self-service or automation rather than AI-enabled decision-making, yet it was implicitly framed as an AI application:

"They (leaders) are currently in the process of developing a self-service app for employees to use […] to book their own annual leave and things like that. […] they're currently in the process of developing this and I believe this should be completed within eight months." - Participant 12

This distinction is particularly important in light of the literature review, which emphasises that predictive HR analytics and AI are closely related but not interchangeable. Predictive analytics typically relies on historical data, predefined variables, and human-designed statistical models to generate forecasts, whereas AI may involve adaptive algorithms, continuous learning, and greater autonomy in pattern recognition and decision support. The empirical findings demonstrate how the absence of clear conceptual differentiation between AI, HR analytics, and other digital HR technologies shapes HR professionals' perceptions, expectations, and adoption intentions.

Rather than representing a weakness, this conflation constitutes a significant empirical insight. It shows that AI adoption in HR is not only a technical challenge but also a cognitive and organisational one, requiring shared understanding, learning, and conceptual clarity within HR functions. This finding directly supports the study's contribution by highlighting that successful AI adoption depends as much on sensemaking and capability development among HR professionals as it does on the availability of advanced technologies.

Furthermore, while the majority of the participants evinced the potentials of AI by describing the novel element as Opportunity, only four participants out of eighteen participants fortified that applications of AI would be a threat in the HR Field. Two respondents expressed a neutral discernment about the application of the advanced technologies. This postulates that AI diffusion and recognition level is germinating and is under consideration of applications in the HR Field. In essence, multilateral aspects of HR functions are being analysed and found to be congruent with autonomous and algorithm-customised natures of AI (Bharati, 2020). Thereby, the empirical data revealed a relatively clear and consistent picture of a positive impact of AI within HR perspectives:
"Artificial intelligence has to be seen as an opportunity by companies and organisations, by HR leaders and HR departments. It has to be an opportunity to be more proactive."- Participant 2.

"It is an opportunity definitely. I think it's just identifying the right AI for the right thing, and I think it's very positive and certainly plays a part."- Participant 13.

Paradoxically to the above discussion, there is a high level of uncertainty when the discussion progressed to the acceptance of AI in HR Field. Notably, 75% participants who considered AI applications as Threat belongs to the HR Executives group. To exemplify, P7, P8 and P10, HR Executives confirmed that:

"For me, I wouldn't see it as an opportunity [...] It depends on which element [...] because they do have errors." – Participant 8.

"I think it's now becoming a threat [...] the companies don't treat their colleagues well and it's because they don't need them now because technology is replacing that. So, I do see it as a threat." – Participant 10.

"Yes. It is a threat [...] "because it's administered by humans." – Participant 7.

It could be indicated from the above statements that adoption-concerned foundation stems from Perceived Risk (PR) and Effort Expectancy (EE) factors as discussed in Chapter 2. In essence, humanitarian and functional issues are inferred from the HR perspectives, which appears to be consistent with Bias Concerns, Perceived Unemployment (sub-themes of PR) and Job Compatibility (sub-theme of EE). The respondent demonstrates reasonable fear assumptions regarding the novel technologies which is assimilated to the emerging factor of Fear of The Unknown (FOTU): this factor will be discussed in the upcoming section regarding ***Theoretical vs Practical Gap***. In fact, the growth of AI terminology and applications could be argued to be newly emerged and in the intersection of Innovator and Early Adopter. Due to the inchoate context, fear and doubtfulness are subconsciously unavoidable elements influencing the decision-making process.

Importantly, echoing the DOI theory discussed in Chapter 2, leaders contribute a critical role in becoming a foundation for behaviour changes in transition period (Rogers, 1962). In this vein, the circumstance demonstrates a potentially detrimental inclination on the adoption of AI elements in terms of leadership unfavourableness. Nevertheless, in the era of advanced technologies and changing markets, leadership roles are speculated to be actively testing potential hypotheses rather than solely concentrating on quantifiable values such as costs and profits (Schoemaker et al., 2018). The justification is in line with the earlier discussion regarding Leadership Support (sub-theme of Facilitating Condition (FC)) in determining adoption behaviours. However, according to the empirical data, the HR professionals simultaneously depicted a significant influence on leadership regarding adopting AI.

Table 4.4: Sample responses of positive adoption factors regarding LS and ID

(More sample responses can be found in Appendix 4.7)

Facilitating Condition	**Sample responses**
Leadership support	*"They [leaders] are thinking to do [AI technologies] soon because the workload is growing for all of us. So, one of their ways to improve that is creating new systems or improving the existing ones." - Participant 5* *"It's something we've (leaders) talked about so much in team meetings and what difference and value we think that could add if our systems were robust enough to allow us to do it. [...] I know that they (employees) would see that as positive because it's something we've talked about."- Participant 14*
Innovation Driven	*"I just see it is impacting broadly [...] I see it is impacting recruitment, selection, whether that the machine type or whether it be that the deep dive on Psychometrics, training and development."- Participant 6* *"we'll see a cautious but steady move to more people using it [...] AI then becomes an additional kind of entity"-Participant 1*

In this qualitative study, the questions were designed to weigh the degree of innovation importance in HRM. In practice, nearly 80% of the participants believed that AI would become a significant factor in future HR due to the requirement of continuous improvement and innovation transformation. The plethora of AI applications introduced in the HR market is deemed to be a facilitating condition of an adoption, which reinforces users' bargaining power overtime (Jia et al., 2022). As shown in **Table 4.4**, a variety of AI-powered HR functions were mentioned such as recruitment, selection, learning and development as a demonstration for an increasing AI diffusion level. As progressed further, the respondents expressed the recognition of AI positive influences not only on improving HR performance but also generating societal impressions regarding institutional branding and competitive edges. The table below exhibits the sample responses of the two evaluating factors of Employer Branding (EB) and Subjective Norms (SN) constituted in the broad theme of Social Influence (SI).

Table 4.5: Sample responses of positive adoption factors regarding EB and SN

(More sample responses can be found in Appendix 4.5)

Social Influence	Sample responses
Employer Branding	*"Because of the competition, once again everything is about competition. They will come up with a lot more advanced systems as well that they can use (to attract employees)"- Participant 9* *"It's all about measuring the weighing up the risk and opportunities of the equation to make sure you are moving just fast enough to innovate"- Participant 12*
Subjective norms	*"[…] eventually they must do it because if they want to stay on the game, we have an agreement on these technologies. Otherwise, they're not going to survive"- Participant 8* *"The main one that comes to mind is them being up to date with the technology. So […] big companies are growing constantly, you must adapt too"- Participant 4* *"I am pretty sure that if one or two started to go down that road, we would all want to follow up pretty quickly because broadly we all like to be in line"- Participant 5*

Seventeen of our eighteen participants agreed when being asked whether innovation is required in HR functions. In this realm, the majority of the participants acknowledged AI as an unavoidable factor for HRM in the future due to recognition of its competitive edge in building brand and staying relevant. **Table 4.5** illustrates some sample responses of EB and SN which are justified in LR to reinforce SI factor in AI adoption in HRM. This could be considered as an empirical validation of the interconnection between innovation transformation and competitive approach (Akter et al., 2021). This is in line with Black and Esch's (2021) proposition that SI is a crucial societal factor that generates a leveraging effect for innovation adoption. In fact, recent research centred on AI adoption in Recruitment confirmed the concrete relations between the use of novel technology with employer reputation (Kot et al., 2021).

Critically, it is argued that change impetus is rooted from individual rationality and formulated by self-interest (Kim, 2015). The endeavour of innovation transformation, to a certain extent, elicits when there is an impact on normative orientation to the preceding pattern (Johannsdottir, 2015). This illuminates the fact that, with respect to behavioural change, it is seminal to include the prospect of rehabilitation-approach influences on adoption behaviours in the individualism level. The above discussions strengthen the hypothesis of FC and SI factors critically involved in AI adoption behaviours of HR professionals. It also contributes to clarify RQ1 regarding the current favourableness of AI in HRM. The upcoming section will reveal more insights of the research issue regarding the current perceptions about AI applications in respected core HR functions under the lens of the AI-HR professionals.

4.3.2 Traditional HRM vs AI-powered HRM: The recognition of AI influences in HR functions

In this research, the inclination of AI applications is initially indicated by predetermined technology adoption related factors. The researcher made the effort in perusing and comparing associated literature to select the dominant antecedents for the study. Nonetheless, the factors were not arbitrarily selected but meticulously reflected upon recent research possessed familiar research subjects or philosophies. Furthermore, to comprehensively answer RQ2 of how HR professionals perceive and relate to the use of AI in HRM, exogenous and endogenous subtexts must be taken into account. It is argued that the transformation process within organisations is significantly triggered when recognising the demand to progress further (Albukhitan, 2020). The theoretical literature analysed in LR Chapter depicts the similar orientation for innovation, which emphasises on the ruthless digital transformation as a key in recent business operation (Verina and Titko, 2019).

Following this mechanism, the questions were subsequently designed to highlight the contradiction between the two main domains of Traditional HRM and AI-powered HRM. Extant studies suggest that traditional HRM is being constantly challenged due to the incongruence of features in the new economic world (Cross and Swart, 2022). It is posited that automatic and repetitive tasks are largely constituted in traditional HRM, which impedes organisational productivity (Mohamed et al., 2022). In addition, the impact of the global pandemic has generated a conundrum for HRM to rejuvenate the strategic HRM across core functions due to alternatives in working conditions and performance management (Hamouche, 2021). Anchoring in the orientation, the participants were asked to discuss their stances about the nature of traditional HRM with its advantages and disadvantages before approaching the main research theme. This is to investigate potential milieu triggering the intentional behaviours towards accepting AI technologies in HRM. **Table 4.6** presents the summarised stances of the participants towards the mentioned domains.

Table 4.6: Participants' opinions: Manual HRM vs AI-powered HRM

HR Related Fields	Related Questions	Summarised points from empirical data	Most concerns on the subject
Traditional HRM	Disadvantages in traditional HRM Process	Time-consuming Human errors Human Biases Paper-based Obsolete (Old fashion) Tediousness High human effort Long process Difficulty in managing large information Slow in decision making process Lack of historical reflection Cost inefficiency	**HR Professionals** Cost inefficiency Slow in decision making process Simplification Time-consuming Paper-based High human effort Tediousness Transparency
	Advantages in traditional HRM Process	Transparency Sympathy Simplification Human interaction	**AI-HR related professionals** Obsolete (Old fashion) Human errors Human Biases Lack of historical reflection
AI-powered HRM	Disadvantages in AI-powered HRM Process	Human Biases Complexity Lack of human interaction Costly Privacy concerns Trust matters Job insecurity	**HR Professionals** Costly Enhance Social Image Fast in decision making process Efficiency Speediness Less human efforts Large data storage Trust matters Job insecurity Human Biases Privacy concerns
	Advantages in AI-powered HRM Process	Efficiency Speediness Less human efforts Less human errors Consistency Large data storage Easy to use Fast in decision making process Cost saving Enhance Social Image	**AI-HR related professionals:** Cost saving Complexity

Table 4.6 illustrates the perceptions of HR professionals about traditional HRM in tandem with AI-powered HRM. By comparing two distinct angles of traditional HRM and AI-powered HRM, a parameter of AI demand in HR could be visualised and resonated. In essence, the literature discussed in Chapter 2 ascertained that agility is in line with organisational

effectiveness in responding towards dynamic changes in innovative economy (Heilmann et al., 2020). Hence, the absence of performance improvement to HRM could undermine business performance in the long run. Reflecting upon the collected data, twelve out of eighteen respondents indicated the extant downsides of traditional HRM while expressing their thoughts regarding manual HR practices. To exemplify, Participant 7 and Participant 15, HR Executives demonstrated their opinions about traditional HRM:

"So manual HR, my opinion is that it's time-consuming and it's not cost-effective and obviously it's introducing a level of increased risk because manual interventions are obvious off to my things go wrong so slow as the stone hints our processes, and I guess stops us from being able to spend time doing some of the more strategic stuff that we'd like today." – Participant 15.

"It's time-consuming and it's costly [...]. It's quite difficult in complete honesty here. I'm sure the machine would make it easier for workers without the mental repercussions afterwards." – Participant 7.

In this sort of orientation, traditional HRM was portrayed to presently obtain certain obstacles for HR professionals in terms of effectively and efficiently processing tasks. According to the collected data, over 76% of the participants encountered limitations and inconvenience in traditional HRM. The empirical context has pictured the high recognition of the downsides stem from the conventional HR practices. The scenario is argued to generate a leverage for HR evolvement to overcome the extant obstacles. Reflecting upon the discussed literature within this thesis, the AI-leverage factor could be argued to be the Innovation Driven (ID), a sub-theme of Facilitating Condition (FC), to positively influence adoption intentions from HR professionals.

Despite the aforementioned discussion, the feasibility to quantify HR functions confronts several disapprovals anchored to the supposition that human-touch attributes must not be detached from the core of HR operation (Craig, 2018). This is in line with the literature confirming that Psychology Commitment (PYC), sub-theme of SQB, is an important factor that negatively influences on adoption behaviours from users. This position is validated in HR professionals with a certain degree of favourableness in the conventional HR practices over technology awareness. The orientation triggers a hampering mechanism against innovative transformations despite the availability of beneficial aspects. The standpoint is also supported by a small number of HR professionals when being questioned about their opinions regarding traditional HRM. Four over eighteen participants exhibited their favours on traditional HRM.

“I think it's fair because there's a human touch in an element to it […] you get to have the interaction. I'd prefer it personally.” – Participant 8.

“Manual human resource management as human beings physically managing the HR processes […] that's how I define my more human resource management where each stage of the HR process is managed by actual people.”- Participant 12.

It is noteworthy that the literature indicates AI technologies introduce a powerful tool for HR professionals to augment their current performance and productivity. Multialgorithms software and platforms are created or customised to serve organisational operations’ purposes. This encourages a higher degree of expectations on current performance of HR functions. Indeed, HRM is deemed to be bewildered by the abundance of data and the increasing demand to perpetually optimise the processes (Radonjić et al., 2022). In line with this, the study further found that the awareness of AI-augmented HR functions was highly reflected in participants’ expressions towards the questions regarding AI technologies. In fact, when being questioned about AI applications in HRM, sixteen out of eighteen participants could depict some substantial AI applications currently available within the HR field.

“The advantages of artificial intelligence could help us predict employees’ retention, employees’ behaviour. What kind of employees stay with us? […] if we start making records of those as well, then we can predict that “what's the next steps that our employees going to take?” “How they navigate their decisions within our company?” […] So, there are a lot of things that can be taken out from the data if we are linking it with artificial intelligence or if we are utilising it in a more appropriate manner to make or to take useful information out of it.”. - Participant 3

Although the participant explicitly frames these capabilities as AI, the practices described align more closely with predictive HR analytics rather than with all conceptualisations of AI articulated in the literature. Specifically, the emphasis on collecting historical data, identifying patterns, and forecasting future outcomes reflects analytics-driven decision support, which has been embedded in HR functions through workforce analytics and statistical modelling (Boudreau and Cascio, 2017; Marler and Boudreau, 2017). That is in line with the previous discussion regarding the current blurred line distinction of HR Analytic and AI-powered HRM. Importantly, Participant 3’s framing highlights the role of *Performance Expectancy* in shaping perceptions of AI. The participant focuses on the perceived benefits of improved prediction, insight generation, and decision support, rather than on the underlying technological mechanisms. This aligns with technology adoption research, which suggests that users prioritise perceived usefulness and performance outcomes over technical accuracy when evaluating new systems (Venkatesh et al., 2003). Consequently, predictive analytics capabilities are readily labelled as AI because they deliver outcomes that practitioners associate with intelligence, foresight, and strategic value.

In practice, the amplifications of AI applications in certain HR functions such as recruitment, selections and onboarding have recently attracted and challenged HR professionals (Pan and Froese, 2022). From this standpoint, it is logical to observe a high level of awareness of AI-powered technologies in the HR field as alternatives for the shortcomings of the current performances. The extant HRM obstacles were subsequently compared with AI-powered HRM to capture the insights of the participants regarding the emerging AI factor. Based on the empirical data, Cost-effectiveness (CE), Task Versatility (TV), Job Compatible (JC) and Ease of Use (EOU) were identified to be prominent variables extracted from respondents' answers regarding AI capacities in HRM. The factors were discussed in the LR chapter as positive components influencing adoption behaviour from HR professionals. **Table 4.7** illustrates the sample responses from the participants regarding the dominant advantages toward AI applications in HRM.

Table 4.7: Sample responses of positive adoption factors regarding CV, TV, JC and EOU

(More sample responses can be found in Appendix 4.4)

Themes	**Sample responses**
Job Compatibility	*"[…] instead of someone putting or adding the details of the new joiner into the system. Instead of manually doing this, like taking a photo, straight away from the card."- Participant 15* *"We create a virtual world like the game SIM (psychometric tests), so candidates come with a character and come to talk to us like this."- Participant 2*
Ease of Use	*"Adoption of AI will be best beneficial like a lot of the admin tasks like inserting details into the database. Instead of having a human being do that […] an AI can identify all the details from a client or to input all those data in."- Participant 4* *"It's less time consuming and it's quicker to do things, get tasked done […] we were adopting new AI systems, and it meant that there was a self-service type of system where employees could input information and it would come straight through to HR rather than just having to fill out forms and then having to wait for them to give it into us."- Participant 14*
Themes	Sample responses
Cost Effectiveness	*"[…] it might require a major investment upfront in the technology, but over time over months and years ahead that that cost pays off and the efficiency savings come through. So, manual will almost always be more expensive in the long term"- Participant 5*

	"There would be significant cost saving because it would make us more efficient, and it would free up time to do the more meaningful things that could make a difference to wiser people in the organisation."- Participant 7
Task Versality	*"[…] (in hiring) you know that there's not going to be someone who's been left in the dark or they've had their interview that haven't been contacted. It makes sure that we keep that communication" – Participant 15* *"(decision making) The advantages of it (AI) are allowing you to do things productively […] provides insight, deep learning, intuitive thinking around creating that data diagnostic approach, which then a human can interpret."- Participant 7* *"Rather than going to wait on the call for an hour, at least, an AI chatbot can put you through to different departments straight away or help you to answer the questions that it's in the AI system itself."- Participant 18*

Following the conceptualisation by Kim (2022), this thesis defines Cost Effectiveness, Task Versality, Job Compatibility and Ease of Use as primary components of Performance Expectancy (PE) and Effort Expectancy (EE). Particularly, Cost Effectiveness and Task Versality are two proposed variables of PE while Job Compatibility and Ease of Use are the sub-themes of EE as entrenched in the *A priori* codebook. In this junction, the empirical evidence reinforces the literature extracted from the UTAUT model since PE and EE were the two primary factors critically directing users' intention toward technological transformation (Venkatesh et al., 2003). Sixteen out of eighteen participants in this research cited the augmented performance in HR practices through the listed PE and EE features presented in **Table 4.7**. Only two participants showed hesitation and uncertainty in sharing the opinions about AI in HRM. This could be reasonably assumed to be the lack of awareness of the emerging issue.

It is worth indicating that there were three HR professionals (Participant 1, Participant 5 and Participant 10) whose organisations have been applying AI technologies within some HR functions. The three participants specifically indicated significant ameliorations in the HR functions.

"Cost-saving, you save a lot of costs […] You don't have to pay salaries to workers every single month. So, you can downsize your organisation, help the business to save more costs and then just use one system to sort of run the business.". – Participant 5.

"So, recruitment […] because we have the X system, it cuts down a lot a lot of time instead of doing the right to work checks […] the technology where we pick out highlights or special words from CVs. And then we shortlist them and then they get interviewed. So, the managers don't see the CV […] we have thousands of CVs, and it will take a lot of time to go through.". – Participant 10

"We create a virtual world like the game SIM (psychometric tests), so candidates come with a character and come to talk to us like this. Candidates apply then they go through to the assessment, no one is going to take their course […] you need to pass a specific course if you wish this position, and it will go automatically.". – Participant 1.

In line with Figueroa-Armijos et al. (2022), the practical views undergird the argument that EE and PE positively facilitate AI adoption in HRM. The above analysis has highlighted the emerging motives for AI-powered HRM transformation by comparing the distinct conceptions of traditional and AI-powered HRM. Within this section, the findings also strengthen the proposed hypotheses that FC, PE, and EE are the influential factors in behavioural intention, which contributes to elaborate RQ2. In the next section, the researcher aims to provide more insights regarding opportunity and challenges concerns based on participants' propositions about AI in HR functions.

4.3.3 Theoretical Vs Practical Gap: A realistic picture of opportunities and challenges regarding AI adoption in HR functions

The study progresses further to explore the main issues of the extant AI applications within the HR market by excavating the gap between theoretical and practical applications. Dovetailing on this orientation, the interview questions were successively designed to elaborate the diffusion of AI technologies and the intention of adoption in specific HR functions. Technically, the participants were examined their insights while discussing the potential opportunities and challenges of AI applications in HR functions. This provides a potential mechanism for the researcher to articulate AI capacities with HR functions and capture AI pervasion scope. In addition, the intention to apply or expand AI applications in the future were questioned to measure the gravitation of AI and its maturity in the HR field. The table below summarises the discussion with respect to AI-augmented HR functions and future intention of applications.

Table 4.8: AI-powered HR functions in HRM

HR Related Fields	Related Questions	Summarised points from empirical data	Most concerns on the subject
AI-powered HRM functions	Most applicable HR function for AI	Recruitment Payrolls Employee Relation Reward Performance Management Employee engagement Onboarding Psychometric Test Learning and Development (L&D) Administration (Transactional process)	**HR Professionals** Recruitment Administration Onboarding Employee Relation Payrolls **AI-HR related professionals:**

	Recruitment Administration

Table 4.8 illustrates the emerging HR functions which are identified by the participants to be compatible with the demand of performance augmentation. Data analysis reveals that primary HR bundles of practices were considered across eighteen participants. There were a variety of HR functions aligning with AI technologies listed by the participants including Recruitment, Learning and Development and Administration tasks. Notably, eight out of eighteen respondents considered recruitment to be the most congruent function involved with AI technologies. In practice, recruitment is envisaged to be contemporarily the most ubiquitous functions integrating with AI capacities. It is depicted that there is a proliferation of interest reflected on recent studies regarding AI in Recruitment owing to its applicational germination. This recognition is in line with discussions regarding used cases of AI in Recruitment reflected in the LR chapter. It is argued that with the plethora of data and the accession of tasks rooted from recruitment functions such as AI-powered CV screening and selection, HR professionals are challenged to operate proactively and enhance productivity (Gupta and Mishra, 2022).

"The recruitment process certainly if you're a large employer with a high volume of applicant." – Participant 7

"So recruitment […] because some of the times will have thousands of CVs and it will take a lot of time to go through. We pick out as much as we can find that it's all recorded and logged.". – Participant 10

"Probably recruitment. It would probably be the best area because I think it's full of assumptions, predictions, data, the need for good technology […] the speed at which that's needed, I think the challenges that every business has even right now are recruiting and finding great people and that would be the area that I would focus on AI." – Participant 13.

It is also noteworthy that Administration tasks such as (answering common employment enquiries or managing leaves) were deemed to be in high demand of AI-augmentation. Above 50% of the participants expressed their approval of adopting AI technologies to erode inefficiency and counter-productivity features in administrative tasks.

"Admin tasks [...] AI will identify all the details from a client or to input all those data in [...] the majority of the admin work *but should require AI because it's also faster and it's accurate and it's less human error.". – Participant 5*

The remaining HR functions listed in **Table 4.8** captured a small proportion of favourableness of AI applications across participants. Next, **Figure 4.2** represented the percentages of depicted AI-powered HR functions from the participants.

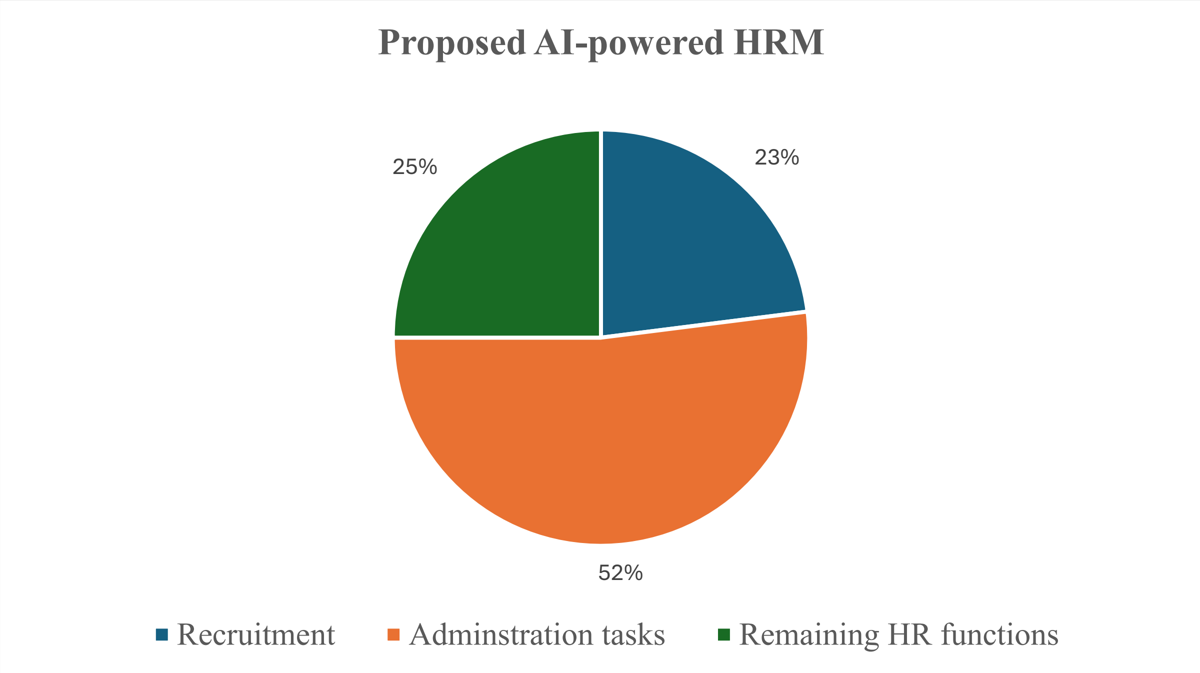

Figure 4.2: Proposed AI-powered HRM

Figure 4.2 exhibits a variety of expected AI-powered HRM across distinct functions extracted from the participants. In nature, there are two prominent spectrums constituted HRM, which profoundly orient and summarise this business function's activities: operational and decisional. In this study, the researcher defines the operational spectrum to be HR functions which could deal with quantifiable or transactional HR aspects such as payrolls or administrations. In contrast, the decisional spectrum is illustrated in the form of fusion between quantifiable and situational factors. Particularly, training and development requires the inspection of quantifiable features from goal-based accomplishments and relational features from employees' performance at work. The former factor is easily devolved to transactional attributes by its ability to quantify the number of tasks assigned. On the contrary, the latter factor requires the inclusion of the perusal of employees' strengths, weaknesses, and the deliberation of contextual elements such as working and environmental conditions.

Table 4.9: Operational and Decisional Spectrums embedded in HRM

Operational spectrum related functions **Quantifiable** (Examples of performed tasks)	Decisional spectrum related functions **Quantifiable + Situational** (Examples of performed tasks)
Sick Leave Management	Training and Development
Employment Contract	Job Mobility
Personal Employment Data Management	Recruitment and Selection
Pay Rolls	Performance Management
Attendance Management	Succession Planning
General Data Support (GDPR)	Retention

Table 4.9 presents the categorisations based on functions of the two discussed spectrums in HRM. The researcher's purpose is not to concretely divide HR functions into each category but to demonstrate the dominant features of individual HR tasks. As can be seen from the table, a number of HR tasks are highly constituted with quantifiable attributes. The tasks are envisaged to be transactional-based and obtain a high proportion of human efforts. The abeyance of mundane and repetitive natures embedded in traditional HRM is coherent with the discussion in LR chapter in terms of its inefficiency characteristics. In effect, it is delineated that HR manager's role is experiencing the shifting from operational control to human-focused coaching approach thanks to the introduction of AI advancement (Drent, 2022).

Reflecting upon the empirical data, HR professionals perceived a high expectation to eliminate repetitiveness constituted from HR tasks, which significantly links with quantifiable aspects. As illustrated in **Figure 4.2,** Administration tasks captured the highest proportion compared to other functions. Although recruitment is placed at the second echelon, there are components within the function that could be quantified based on the previous argument. The expectations in AI-powered HRM appear compatible with main AI capacities discussed in the LR chapter. The discussed AI functions serve multilateral HR functions where the functional concentrations are on logic, numeric and pattern of AI learning capacities (Jarrahi, 2018). The relation map presented in **Figure 4.3** represents the potential interconnections of five main AI capacities: computer vision, natural language processing, knowledge mining, machine learning and anomaly detection with HR functions.

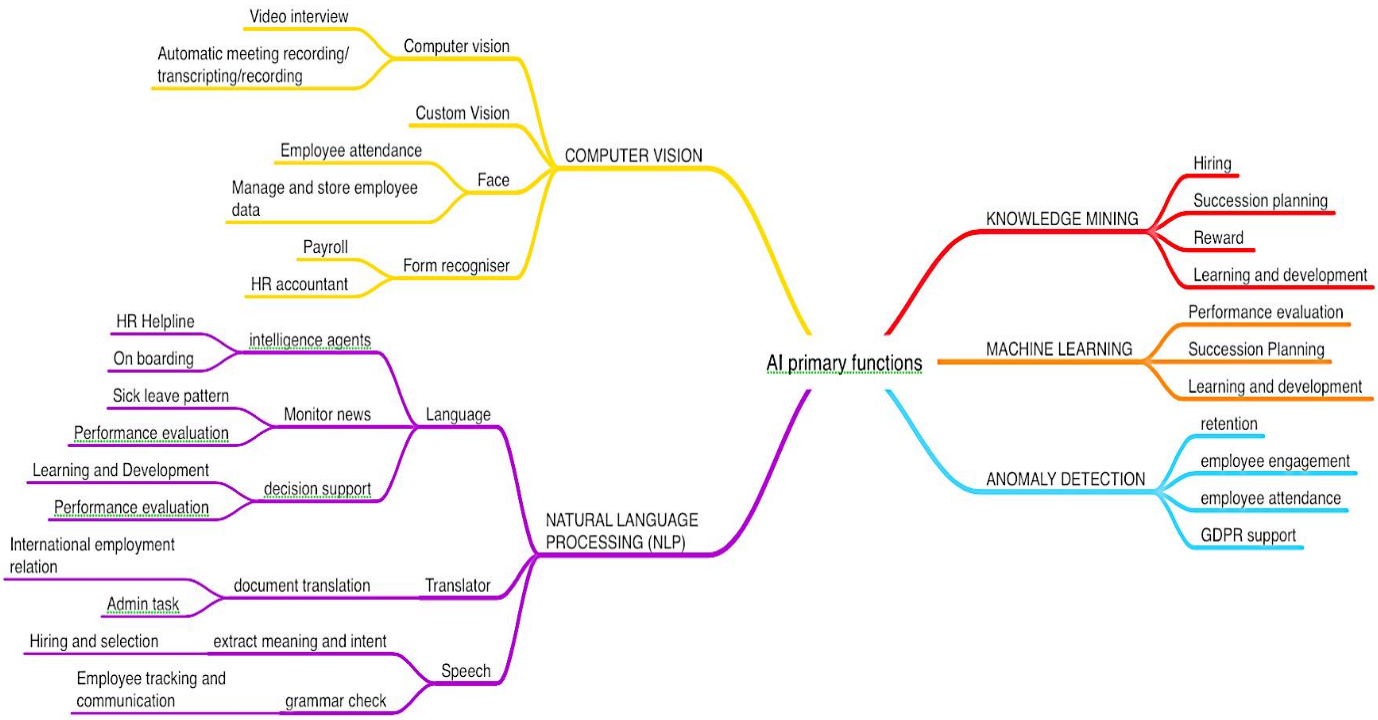

Figure 4.3: AI-Powered HR functions map based on core AI Capacities

Theoretically, AI technologies herein could be considered as an ultimate key to penetrate and upgrade current HR processes with a variety of technical solutions. The thriving of studies regarding AI in HRM and the high awareness and diffusion of its terminology in the HR market has also been confirmed in the previous arguments within this study (Hmoud and Várallyai, 2020; Basu et al., 2022; Arslan et al., 2022). Conversely, the empirical data continues to reveal significant influential factors of adoption decision on AI-powered HRM. In effect, to measure the practical scope of application, participants were subsequently questioned about their adoption intention in the future. The collected data from this research communicates three groups of answers from the participant: *will apply, will consider* and *will not consider*.

Ostensibly, the number of participants who ascertained about the decision in application was around 50%, which indicates a positive trend of AI adoption in HRM to enhance the performance. Initially, all participants asserted that AI technologies will have a significant impact across HR practices.

"I believe that due to Covid-19, a lot of us are moving forward in technology, I believe that that would be the push for […] new AI in.". – Participant 9.

"But now the pandemic happened […] a lot of organizations have adopted hybrid working and I feel like likewise AI and HRM, you know things will change in the future […] we need to adapt to those changes.". – Participant 12

There is a significant number of participants expressing uncertainty in the application decision. Around 23% of the participants stated that they would consider AI in the future while 27% of the respondents did not wish to apply the technology. As identified in LR, the adoption factors will be influenced not only on the positives but also accommodating concerns related to the novel subject (Carleton, 2016). In this study, the participants were also asked to discuss their critical concerns regarding the preventions of AI adoption in HRM. Despite the positive assertions regarding the high demand in AI adoption, the empirical data reveals several factors which impact on participants' decision in accepting AI technologies in HRM. In fact, thematic analysis confirms four types of risks highlighted by the participants in this research as presented in **Table 4.10**:

Table 4.10: Sample responses of emerging risks of AI-powered application in HRM

(More sample responses can be found in Appendix 4.9)

Perceived Risk	Sample responses
Bias Concern	*"There is debate around things like subconscious bias because the person whose programme these things got subconscious bias that then feeds through into the programmes"- Participant 11* *"I think there's something about fairness and bias. […] the data used to train these models often has got bias embedded within it, and […] it can amplify and extend and genuinely cause real-world harm and poor outcomes to people"- Participant 3*
Privacy concern	*"People might perceive any risk […] about the level of information and ways in which data and information are held in relation to those solutions. I think people will always have ongoing challenges with that."- Participant 13* *"I think privacy concern is increasing. There are a lot more cases where I suppose the media have made that fear amplified because there's always new stories that certain details have been leaked, a firewall has been breached and data is in the public domain."- Participant 8*
Fear of the unknown	*"I think without knowing exactly what it means and what it entails […] probably a bit of a threat in my mind because I just don't know that" – Participant 12* *"I do see artificial intelligence can be a scary concept for some [..] it's more about being scared of the unknown rather than actually having any real basis for the fear."- Participant 8*
Perceived Unemployment	*"Artificial intelligence, I believe it's something that's meant to be smarter than us. And like I said earlier, something that will replace us slowly."- Participant 4* *"The fear I think is on the part of HR practitioners. […] if you are introducing technology that replaces what you can currently do, then you will have a natural fear that your job is going to be eroded and eventually you'll be redundant."- Participant 10*

As presented in **Table 4.10**, there are several concerns regarding the adoption of AI in HRM despite the insistence on improving manual HR performance. In essence, these findings appear to be consistent with the projected themes in literature review that BC, PRC, FU and PU are associated obstacles when approaching technology transformation. This proposition is also in line with the position that certain perception regarding risks is triggered when the users are introduced with novel technological subjective (Pitardi and Marriott, 2021). The participants acknowledged the possible threats delivered by AI in terms of unemployment, privacy data exposure, potential bias from machine and human; and general fear in terms of the unknown matter due to the uncertainty nature as shown in the above table. This visualises a practical gap between the proposed benefits of AI technologies and the hindrance of application owing to the factor of PR. Therein, the collected evidence reinforces the literature, and projected antecedents stated in *A priori* codebook.

Significantly, an emerging factor of Status Quo Bias was explored within this study as a converse adoption mechanism toward AI advancements. Samuelson and Zeckhauser (1988) first coined the concept of SQB which refers to the bias triggered in individual decision making by remaining the current status quo as a mechanism towards changes. Paramount to this definition is the assertion that this is a psychological construct illustrated the typical hindrance of technology adoption (Eidelman and Crandall, 2012). The issue posed by the existence of an inertia tendency which facilitates the maintenance of status quo despite the pressure to alter the status (Polites and Karahanna, 2012). This concept was supplementarily adjoined in LR as it is validated within this section. In effect, thematic analysis results explored in this thesis established a new realm of AI influential adoption factor, which is not envisaged within the preceding framework.

Table 4.11: Sample responses of Status Quo Bias's factors influencing AI-HRM collaboration

(More sample responses can be found in Appendix 4.8)

Status Quo Bias	Sample responses
Psychology Commitment	*"I also refer that interaction. It's a lot better and sometimes you get the problem resolved a lot quicker and [...] when you're speaking to a human, you feel more valued, which is what I prefer."- Participant 10* *"I must admit, last year we did put together a spreadsheet. That we felt probably better to manage it and we're not having to deal the machine all the time"- Participant 11* *"Everything is working fine, so I don't necessarily see that needs to be improved. [...] I believe everything seems to be working just fine now about that."- Participant 5*
Cognitive Misperception	*"I'm thinking of something smarter than us up then as humans. [...] that was very scary to me because [...] artificial intelligence, I believe it's something that's meant to be smarter than us."- Participant 8* *"The first thing that comes to my mind is the movie The Matrix. And Tesla Self-service machines and robots. That's the first thing that comes to mind when I think about artificial intelligence [...] there are also people that could use AI for bad reasons."- Participant 17*

Perceived cost	*"[…] I implemented was a career development portal which was quite expensive and obviously, I do have a training budget, and I have to weigh up the losing majority of my training budget to implement this […] for the company and cost-wise."- Participant 8* *"Also because of cost, because to adopt AI, first thing it will cost […] it will be huge cost upfront, although long term it might be better because you're not going to pay salary to […] hundred people using AI."- Participant 4*

Psychology Commitment (PYC) is a theme that scholars have been emphasising in technological adoption studies. Within this study, the factor represents the implication of psychological attachment with the current HR functions. **Table 4.11** illustrates several sample responses supporting the mechanism such as the preference of human touch and the extant performance. This concept is challenged by the Innovation Driven factor constituted in FC, which was discussed in the previous section. Considering that AI is an emerging subject in the HR market, the appearance of PYC is unavoidable while measuring the impact of adoption factors.

Cognitive Misperception (CM): within this research, this theme is described as incorrect interpretations and understandings of AI applications in HRM leading to adoption stagnancy. As further supplemented in LR, this concept entrenches the distortion understanding formulated by the prevailing value and belief (Hsieh and Lin, 2018). **Table 4.11** illustrates several sample responses supporting the mechanism. It is posited that CM relies on users' perceived value and cognitive inertia toward changes (Gao and Zhou, 2024). The expressions highlight the participants' ambiguity about AI concept, and therefore CM is yielded to amplify the effects of SQB due to risk-averse concerns (Shankar and Kumari, 2019).

Perceived Cost (PC): Notably, finance is a significant factor for implementing AI-powered HRM. In this study, PC represents the costs of exhibit investments and commitments, which accelerates SQB (Hsieh and Lin, 2020). **Table 4.11** illustrates several sample responses supporting the mechanism. This phenomenon is criticised to generate inertia to the status quo where users exert the enjoyment and safety to maintain the existing state while weighting money and efforts invested (Balakrishnan et al., 2021).

In fact, the empirical results from this study are not surprising as AI-powered HRM is a new concept which will confront a diversity of potentially psychological impacts. The above-discussed features provide further evidence to Samuelson and Zeckhauser's (1988) assertions for SQB as a negative psychological element in intentional behaviours. Particularly, it is argued that SQB were manifested in influences of rational decision making, psychology commitment, and cognitive misperceptions to the status quo position (discussed in detail in Chapter 5). With the provided findings, the thesis broadens the existing conceptual framework on the addition of SQB as an impacting factor on AI adoption in HRM. Within this section, the empirical data also strengthen the factor of PR to be a critical factor in measuring intentional behaviours. The findings from this section contributes to clarify RQ2 and provides a critical foundation to orient the direction of RQ3 regarding the extent of AI-powered HRM adoption in businesses.

4.4 Qualitative Research Discussion

Anchoring the theoretical literature and *A priori* codebook as shown in **Table 4.2**, the thematic analysis conducted through eighteen semi-structured interviews with AI-HR Professionals reveals a high degree of AI advancements' awareness in the HR field across businesses. The empirical results demonstrate a profound picture of how AI is penetrating and impacting HRM as presented in three critical angles distilled from this qualitative research. The nexus between AI and HRM is presented as follow.

Opportunity Vs Threat: By examining the participants' evaluations on AI factor in HRM over the lens of Opportunity and Threat, the research confirms a positive inclination in AI-HRM collaboration. The empirical data in this section addressed a high recognition of AI terminology diffusion after the global incident of the Covid-19 pandemic, which triggers a mechanism for alternative working patterns. Critical adoption factors including FC (supported by LS and ID), and SI (supported by EB and SN) were confirmed within this section to positively influence AI-powered HRM to be executed. These findings are consistent with theoretical literature and *A priori* codebook discussed in this research.

Traditional HRM vs AI-powered HRM: By extracting the participants' perceptions regarding the two-opposing concept of traditional and AI-powered HRM, the research confirms a positive expectation in AI-HRM collaboration. The empirical data in this sphere addressed the contemporary limitations in traditional HRM whilst asserting the expectations in higher productivity with AI-augmented HRM. In this vein, critical adoption factors comprising PE (supported by CE and TV) and EE (supported by EOU and JC) were strengthened to positively influence AI-powered HRM to be executed. These findings are consistent with theoretical literature and *A priori* codebook discussed in this research.

Theoretical vs Practical Gap: By examining the adoption intention, the research elaborates the AI-HRM adoption issues between theory and practice. The empirical results in this stance addressed the emerging risks associated with AI-powered HRM implementation. The critical counter-adoption factor of PR (supported by BC, FU, PRC, and PU) was reinforced to negatively AI-HRM collaboration**.** These findings are consistent with theoretical literature and *A priori* codebook discussed in this research. Importantly, SQB (supported by CM, PYC, and PC) is a novel theme discovered through thematic analysis within this section. The factor was proven to negatively influence AI-powered HRM execution. The emerging finding was subsequently reviewed and adjoined in LR Chapter in this research.

In sum, the results and thematic analysis showcased in this Chapter have illuminated the answers for RQ1 and RQ2 from this study. In addition, the research at this stage achieved the overall objectives of exploring opportunities and challenges brought by AI technologies in the transitions from manual HR practices to AI-powered HR practices. This indicates an adequate possibility and feasibility degree of AI technologies in HRM based on the contemporary context. From this QUAL study, the relationship of the individual adoption factors could be observed from **Table 4.12**.

Table 4.12: Finalised constructs based on Qualitative Research's results

Finalised Constructs	Proposed evaluating factors	Interview sources	Frequency	Percentage Coverage	Importance Level Evaluation
Effort Expectancy	Ease of use Job Compatibility	P1, P2, P3, P4, P5, P6, P7, P9, P10, P11, P12, P13, P14, P15, P16, P17	16	88.89%	Importance
Performance Expectancy	Cost-effectiveness Task Versatility	P1, P2, P4, P5, P6, P8, P9, P10, P12, P13, P14, P15, P16	13	72.22%	Moderately Importance
Social Influence	Employer Branding Subjective Norms	P1, P2, P3, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13, P14, P15, P16, P17, P18	18	100%	Highly Importance
Facilitating Condition	Leadership Support Innovation Driven	P1, P2, P3, P4, P5, P6, P8, P7, P10, P11, P12, P13, P15, P16, P17, P18	16	88.89%	Importance
Perceived Risk	Bias Concerns Fear of the Unknown Perceived Unemployment Privacy Concern	P1, P2, P3, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13, P14, P17, P18	16	88.89%	Importance
Status Quo Bias	Cognitive misperception Perceived Cost Psychology Commitment	P1, P2, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13, P15, P14, P16, P17, P18	17	94.45%	Highly Importance

Table 4.12 illustrates the six empirically identified factors that impact the adoption of AI technologies in the HR field. The frequency analysis reveals that the parent constructs of EE,

PE, SI, PE, PR and SQB are key reasons which influence AI adoption intention in HRM (Illustration of factors' weights can be viewed at **Appendix 4.2 and Appendix 4.3**). Most noticeably, SI and SQB are considered highly important factors to impact on users' decision making (evident with highest coverage percentage in thematic analysis with 100% and 94.45% theme coverage respectively). Hence, the empirical findings in this qualitative research (QUAL) contribute to establish a foundation to examine RQ3 which is regarding measuring the impact of the influential factors on AI-HRM collaboration. In addition, the research outcomes synthesise the insights of RQ1 and RQ2 which are about exploring opportunities and threats and the current perceptions and attitudes of HR professionals toward AI in the HR realm. Reflecting on these findings, this qualitative research has attained the expected results for RQ1 and RQ2. The findings of this research confirm the significance of predetermined factors of EE, PE, SI, PE, PR in terms of impacting HR professionals' adoption intention. It further discovered the emerging factor of SQB to significantly influence AI adoption predisposition in HRM. The Phase 1 of this research critically contributes to establish a concrete foundation for the Phase 2 of the quantitative research to examine the correlations coefficient of dependent and independent variables. At this junction, the constructs extracted from this stage were further examined to investigate the research phenomenon.

4.5 Chapter Summary

Chapter 4 of this study has empirically examined the preliminary constructs proposed in Chapter 2 to discover and identify the adoption variables in the context of AI and HRM. This chapter deployed an exploratory approach stemming from an inductive strategy to conduct data analysis on 18 semi-structured interviews with the recruited participants in AI-HR principles. Therein, the empirical findings in this QUAL study are instructive for the refined research model. In the initial stance, the empirical results depicted a high awareness of the AI adoption trend in the HRM field among the participants. Further, the research validated all UTAUT factors (EE, FC, PE, and SI) and Perceived Risk (PR) as critically impacting adoption intentional behaviours of HR professionals. Based on the disruptive nature of AI development in the business market, HRM demonstrates that it is also not immune to the embracing the continuous innovation of AI as evident on the impact of SI (100% theme coverage) and the acknowledgement of other UTAUT factors. Concurrently, the research marked a milestone when discovering a substantial impact of the emerging adoption influencing factor of Status Quo Bias (SQB) with 94.45% theme coverage. In this vein, the empirical findings therein elicit another subtext beside PR, triggering the context of low AI adoption in HRM contemporarily. As a result, the findings culminated in the achievement of RQ1 and RQ2 of this research and generated the mechanism for the process of research model refinement. Thus, the next chapter will further discuss the refinement process based on the empirical results of the research's Phase 1 (QUAL) to prepare for the launch of Phase 2 (quant): the quantitative research.

CHAPTER 5: REFINED CONCEPTUAL FRAMEWORK AND HYPOTHESES ESTABLISHMENT

5.1 Introduction

Mirroring Chapter 2 of this study, the associated constructs used to formulate the preliminary conceptual framework were too generic to address the research issues. In fact, the finite empirical evidence to support the thesis's arguments at that stage generated the foundation for Phase 1 (QUAL) of the research in order to concretely scaffold the thesis's assumptions to a profound hypothesis. Hence, within this Chapter, the correlations between main constructs and the variables were established. After the empirical findings from Phase 1, this Chapter provided the extended contains for LR discussed in Chapter 2 in order to form the interlinkage of the tested constructs and presented variables. In this vein, the key purpose of Chapter 5 is to refine the initial conceptual framework and establish testable hypotheses among the variables in the research model. In particular, the discovered constructs in Chapter 4 were adopted to contribute to form the official conceptual framework for the thesis. At this stage, measurement items for each identified construct were clarified and the survey questionnaire for the quantitative research was adapted based on previous studies affiliated to technology-adoption research. Hence, the preliminary conceptual framework proposed in Chapter 2 was refined utilising the empirical qualitative findings of Chapter 4 and the extended concepts introduced in this chapter. Specifically, each main construct was represented with associated variables, which are identified as key measurement items for the main constructs.

5.2 The Refinement of Research Conceptual Framework

As initially proposed in Chapter 2 of the research, the UTAUT technology adoption model underpins the preliminary conceptual framework of this study. All the technology adoption determinants including Effort Expectancy (EE), Facilitating Condition (FC), Performance Expectancy (PE), Social Influence (SI) were assumed to be the critical drivers for AI adoption intention from the HR professionals. The interaction of the individual factors with AI adoption intention in HRM are expected to result in enhancing traditional HRM in terms of augmenting HR practices' performance and sharpening business strategy. Tailored to UTAUT theories, the expectations on the ease in using novel technology, augmentation of the current performance, appropriate support for the technology establishment and the pressures from the society are considered as a lubricant for AI adoption intention in the field of manpower management. Furtherance, a psychological factor of Perceived Risk (PR) was also initially proposed to impact the adoption intention of HR professionals. It was categorised as a detrimental factor for the adoption of AI in HRM. The factor, as exposed by HR professionals, could be rooted from various reasons, which was acknowledged and further explained in this chapter to establish corresponding subset factors to measure the main constructs. Hence, the initial proposed model designed PR as the psychological antecedent against the adoption intention. The position agrees with related prior studies conceptualising PR as counter-driving forces behind the HR professionals' adoption intention. Nonetheless, it is worth acknowledging that the dearth of knowledge in this area of AI and HR research necessitates a profound justification of the initial conceptual framework to ensure the applicability of the model to this research context.

In fact, the research proceeds further revealing a total six factors in the qualitative analysis in Chapter 4 including (EE, FC, PE, SI, PR and Status Quo Bias - SQB) which significantly impact the intention of HR professionals to embed AI technologies in the contemporary HR practices. In fact, from the theoretical point of view, UTAUT factors (EE, FC, PE, and SI) were conceptualised as key drivers for AI adoption in this scope of HRM. Echoing the QUAL study from this research, within the constructs of EE, the acknowledgement of the demand for easiness and compatibility in working with AI assists in highlighting the existence of EE in the research model as presented in the qualitative analysis. Following the similar vein, the declaration of management role and innovation-driven businesses were demonstrated to constitute the FC for AI to be built upon the current HR practices. Further, as stated in the discussion of opportunities and challenges of AI adoption HRM in Chapter 4, the belief in AI adoption in HRM as a long-term investment (cost-effectiveness) and its capacity to augment the existing traditional HR practices are scrutinised to the formulation of PE factor in the adoption model. Ultimately, the factor of SI was confirmed by the HR professionals when acknowledging the gravitation in adopting AI in businesses. The participants emphasised the pressures from society in AI adoption while also highlighting the benefits from brand reputation. The above discussion was in line with Xue et al. (2024) who portend that all UTAUT factors have distinct degrees of impacts on users' technology adoption intention. Thus, all the adoption factors extracted from UTAUT theory are the most critical to pressure the HRM field to incline towards AI adoption. Hence, the research conceptualised the four UTAUT factors (EE, FC, PE, and SI) in the research's refined conceptual framework

Further to the above, Perceived Risk (PR) was also acknowledged in the preliminary conceptual framework in Chapter 2 to critically impact HR professionals' adoption intention. In fact, this psychological factor aligns with the position of the literature derived from related technological adoption research regarding its degree of impact on the users' perceptions (Wu and Wang, 2005; Hong and Cha, 2013; Tan and Ooi, 2018). Hence, the factor was initially conceptualised and embedded in the research model. In light of the research's findings in Chapter 4, this thesis therein validated the impact of this psychological factor in terms of negatively influencing the intention of HR professionals in the adoption tendency. Despite the tremendous impact of AI across business sectors, certain exposures and concerns inherent in confidentiality and the employment-related nature of HR and the unclear mindset about AI could be considered to hamper the adoption gravitation of the advanced technologies. Hence, this research agrees with the recent sources indicating the existence of PR (Chatterjee and Bhattacharjee, 2020; Zarifis and Cheng, 2022) as an influencing factor on AI adoption intention in HRM. Anchored to this, the generic specification of PR in the refined conceptual framework is compatible with AI adoption intention variable.

Importantly, the empirical findings in Chapter 4 discovered an emerging factor of Status Quo Bias (SQB), which formulates a new linkage explaining the current context and nexus of AI adoption in HRM. According to the existing theoretical proposition, the initial AI influencing adoption factors did not include and recognise the extant appearance of SQB due to the finite evidence of the literature regarding AI adoption in HR practices studies. In contrast, there was a rich body of evidence extracted from the QUAL study indicating the tremendous impact of the factor on HR's professionals' decision-making process regarding adoption intention. In fact, the issue was posed by the existence of an inertia tendency which facilitated the maintenance of the status quo despite the pressure to change the status. The key reasons for the SQB root from various sources which were later discussed in **Section 5.3** regarding the model constructs. Therein, the refined conceptual model in this research acknowledged and conceptualised the factor of SQB in impacting the adoption intention of AI in HRM. This has been empirically verified and discussed in Chapter 4 and further defined in this chapter.

In brief, the four UTAUT factors (EE, FC, PE, and SI) and the psychological factor of Perceived Risk (PR) are retained in the refined conceptual framework due to the alignment of these constructs with the impact on AI adoption intention reflecting the literature and empirical evidence. Noticeably, Status Quo Bias (SQB), which is justified by the notion that HRM is generally committed to the existing status quo, was acknowledged to have a critical impact on the intentional behaviours of HR professionals. This was well-informed in QUAL research regarding its negative influence in generating the inertia in decision-making process (Samuelson and Zeckhauser, 1988) for AI to be adopted in the field. Thus, at this point, the retention of EE, FC, PR, SI, PR and SQB are adequately justified in this study. The model constructs of this research are subsequently discussed in the next section.

5.3 The Model Constructs

The above discussion indicates the six finalised constructs from the refined conceptual framework in this study including Effort Expectancy (EE), Performance Expectancy (PE), Facilitating condition (FC), Social Influence (SI), Perceived Risk (PR) and Status Quo Bias (SQB). Although the key literature regarding the constructs (except the discussion about Status Quo Bias) has been reviewed in Chapter 2 of the study, it is critically necessary to provide further discussions about the correlations of each main construct and its relations to the sub-constructs. An additional detail about SQB was adequately discussed as an evolvement of the current study at this stage. Within this section, the relationships of each main construct and its individual constituent elements were illuminated and clarified, which generated a substantial foundation for the research survey questionnaires and analysis.

5.3.1 Effort Expectancy (EE)

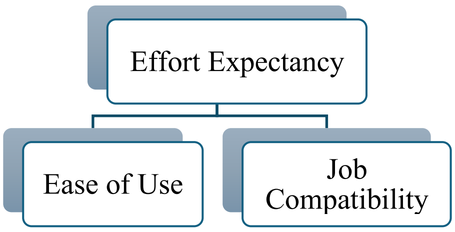

Figure 5.1: Construct of Effort Expectancy

As mentioned previously, EE is one of the key features deployed in the UTAUT Model which illustrates the individual perceptions about the significance and essential level to endorse novel technologies (Venkatesh et al., 2003). The effect of EE on users' attitudes has been manifested in various research anchored to discursive circumstances. The construct is regarded as a vigorous factor in innovation adoption behaviour. Former studies revealed an analogous relation between EE and Ease of Use (EOU) (Palau-Saumell et al., 2019; Lee et al., 2017; Kuberkar and Singhal, 2020), and Job Compatibility (JC) (Lee et al., 2017; Venkatesh and Davis, 2000; Rogiers et al., 2020; Cao et al., 2021) in terms of providing a positive impact on adoption attitude. In the next section, the correlation among the mentioned factors will be elaborated to confirm the reciprocation among the considered elements.

5.3.1.1 Ease of Use (EOU)

It is argued that the EE construct critically incorporates the concepts of EOU features in the TAM model. It is argued that the factor pursues a similar vein to EOU which provides a mechanism to measure how the users perceive the easiness to use the novel technology. Former empirical studies have emphasised the interdependent relationship of EE and EOU in both conceptual frameworks of technology adoption studies (Davis et al., 1992; Boateng et al., 2016; Ying et al., 2021). On closer inspection of EOU, it is postulated that the users' perception is portrayed on how incentives could be produced, which is measured by the enhancement of the targeted function (Im et al., 2008). From this sort of orientation, EOU provides a potential mechanism for an individual to enrich the perceptions of the adopted technologies by endowing a sense of easiness in how contemporary performance is positively altered with the intervention of novel technologies. From this standpoint, EOU is deployed as a substantial subset of EE to discover the behavioural intention of technology adoption.

5.3.1.2 Job Compatibility (JC)

Central to the research in the affiliated field of technology adoption, Job Compatibility (JC) is a cohesive influential factor facilitating an individual willing to adopt new technologies. In relation to this concept, Perceived Usefulness (PU) derived from the TAM model is scrutinised to have some nexus with JC which refers to one's perception of how the use of the technology fitness will enhance his/her job performance (Davis, 1989). According to Venkatesh and Davis (Venkatesh et al., 2003; Davis et al., 1992), the level of JC is defined as the extent to which an individual trusts that the technology is applicable to the job. Furthermore, the relative advantage construct derived from DOI possesses the cognate implication which refers to users' perception of how the adopted innovation's performance is better than its predecessor (Rogers, 1962). Within this thesis, JC is defined as the belief that AI applications will be congruent to the existing HRM performance. In practice, Cooper and Zmud (1990) elaborated on the synergy of the two factors in research measuring JC construct from MRP systems. The study successfully proved JC is a critical competence in explaining human adoption behaviour. In accordance with studies about human motivation, JC contributes as an antecedent to leading consumers' goals toward the technology acceptance (Muñoz-Leiva et al., 2017). It is entrenched that the concept of goal directs individual attention and expedites responses which are considered plausible with the initial objectives (Hmoud and Várallyai, 2020). Due to the co-dependent relationship, JC compactly incorporates to shape the foundation of EE in examining the adoption behaviour. This has been further reinforced in the recent study exploring how AI could be adopted in the recruitment system in the era of Covid-19 (Kim, 2022). In light of the above, the constitution of the EE construct has not been immune to the influence of EOU and JC competencies. By virtue of this, the researcher reinforced the factor of EE by including the inclusive components of EOU and JC elements to strengthen the integration of how the presentation of EE could be demonstrated.

5.3.2 Facilitating Condition (FC)

A common factor of early studies on technology adoption constructs is FC which is defined as the external factors that trigger the simpleness in performing a task. It should be noted that Venkatesh has earlier emphasised the importance of FC in exposing users' perceptions on the availability of required resources and avocation dedicated by organisational capacity, equipment, and essential supports for an individual to perform a task (Venkatesh et al., 2003, 2012). Therefore, FC has been deployed as a crucial element contributing to the positiveness of individual behaviour toward future intentions and decisions. It is further posited that FC authorises researchers to investigate underlying reasons for technology adoption behaviours by apprehending the impact of environmental and organisational finiteness (Hmoud and Várallyai, 2020). In other words, unsuspected circumstances and potential restraints from the organisation's internal contexts could be explored. In the context of this thesis, FC required for AI technologies in HRM includes mandatory resources and knowledge for HR professionals to deploy the technologies (Alwahaishi and Snášel, 2013). Importantly, early empirical studies revealed a transparent and coherent picture of Leadership Support (LS) and Innovation Driven (ID) in the conjunction of forming and clarifying the establishment of the FC construct (Pan and Gao, 2021; Lee et al., 2019; Cao et al., 2021). In the subsequent discussion, the correlation among the mentioned factors will be elaborated to confirm the reciprocation among the considered elements.

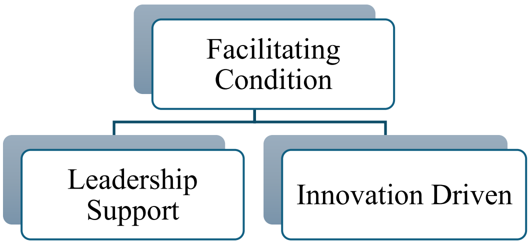

Figure 5.2: Construct of Facilitating Condition

5.3.2.1 Leadership Support (LS)

The role of LS emerges broadly in DOI theory which emphasises the key feature of Leadership to be the initial influence and motivation that precede individuals toward a particular action (Rogers, 1962). Earlier empirical studies postulated the role of LS as an essential node to associate individual interests with organisational collective goals (Carreiro and Oliveira, 2019). In the context of this research, LS refers to the level of support and guidance provided by the management board of an organisation in the procedure of introduction and implementation of novel technologies (Currie and Spyridonidis, 2019). In the organisational context, LS contributes as a cornerstone that exerts significant impact, assisting employees toward innovation and activating diffusion networks (Rogers et al., 2003; Tolba and Mourad, 2011).

To a considerable extent, LS generates a convergent node of information. The lack of centralised information partitions novel knowledge of diffusion. The situation therein generates an impediment to innovation ramification and acceptance. Concentrating upon leadership configuration, centralised networks stem from LS will inherently facilitate the absorption of information among individuals and herein increase the level of acceptance due to the preponderance of knowledge diffused (Valente and Davis, 1999). In fact, it is highlighted that LS significantly affects the implementation of novel technologies when changes occur within an organisation (Robertson et al., 1996; Tolba and Mourad, 2011). Based on the notion of DOI theory, LS plays a substantial role in flexibly customising and designing the demand of technology users, which accelerates changes and innovation adaptation (Robertson et al., 1996). On account of the discussion, LS contributes as an important factor in shaping the FC construct.

5.3.2.2 Innovation Driven (ID)

With the plethora of critical innovations, contemporary organisations continue to witness the seismic digital transformations in the work environment. The dynamic event has increasingly characterised competitiveness attributes among businesses, which significantly influences the individual perception and motivation to be driven towards novel technologies. The concept of ID, in this context, is defined as the adoption influence triggered by the individual motivation and expectation toward using novel technologies (Kim, 2022). It is stated that the concept has remained controversial in measuring the influential level of technology acceptance (Koestner et al., 1987; Miller, 1990). Nevertheless, later empirical findings did not provide sufficient scientific evidence to authenticate the assumption. ID was presented in different studies to demonstrate a supportive influence in terms of innovation adoption "in certain types of achievement context" (Richard, 2012, p.353). The variable, in parts, inherently co-functions with the mechanism of hedonic motivation which refers to the happiness feeling obtained by acquiring innovations (Chen et al., 2016). The factor was further indicated to be substantial in presupposition for the decision of innovation adoption (Venkatesh et al., 2012). The consequences of innovation adoption were therein articulating with motivational theories, which significantly impacts and directs human adoption behaviours. Some previous studies illustrated certain reservations upon the antecedent variable, however, a recent study indicated that ID contributed greatly to behavioural control in the context of acceptance generated by personal innovativeness (Deb et al., 2017). Therefore, within this research, ID extracted from FC obtains an explanatory indicator for adoption intention.

5.3.3 Performance Expectancy (PE)

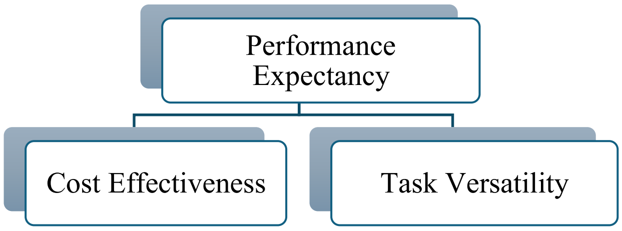

Figure 5.3: Construct of Performance Expectancy

One of the significant constructs stems from UTAUT, which determines intentional behaviours towards adoption, is PE. As discussed priorly from LR Chapter, PE is construed as the degree that consumers believe the use of innovations will enhance their job performance (Venkatesh and Davis, 2000). PE is deemed to be the major predictor for people's adoption behaviours where the relationship has been proved to be congruent with previous studies in technology adoption fields such as chatbot (Kuberkar and Singhal, 2020), cloud service (Rastogi et al., 2018) or app applications (Palau-Saumell et al., 2019). It is denoted as a salient factor to control customers' behaviours due to the ability of reflecting a variety of users' expectation on the innovations including transactional, convenient and ubiquitous aspects of adoption (Thusi and Maduku, 2020). In addition, the factor is argued to involve more general appraisal of technological usefulness without necessarily connecting to the actual use of individuals (Nordhoff et al., 2021). In this study, PE refers to the extent that users believe the application of AI technologies in HRM would be valuable and beneficial for HR functions. Since AI is a novel concept, there are certain performances on HR tasks delivering that users perceive beneficial for the current performances. The factor is considered as relevant to individual perceptions on innovations' values articulating to extrinsic rewards (Xie et al., 2021). To a considerable extent, external motivation regulated by PE could be reflected directly on individual perception of Cost Effectiveness (CV) and Task Versatility (TV). Subsequently, the relationship among the mentioned variables will be enlightened to confirm the reciprocation among the considered elements.

5.3.3.1 Cost Effectiveness (CE)

Studies centring on the adoption of innovation inevitably evaluates the intervention of costs in individual decision-making processes. CE illustrates a positive relationship between the monetary investments and the favourable expectations (Rahimli, 2013). The variable exhibits a direct economic impact of the invested innovation that could generate cost reduction in long-term and optimising the current performances. The connotation roots from expected sustainable process of technology implementation, which is characterised as benefits gained overtime compared to the initial investments (Wang et al., 2020). In essence, the factor is related to perceived value from users which is defined as the weight between perceived benefits and perceived sacrifices (Xiong, 2013). Scholars have also used the factor as an essential determinant for innovation adoption and acceptance due to its direct influence on human intentional behaviours. CE involves in the general assessment of users on the innovation's usefulness based on the monetary investments. In this vein, the consideration of monetary costs, time and efforts are the mediators for decision making (Higueras-castillo et al., 2019). Within the context of this thesis, CE is defined as the belief that AI application in HRM will be financially beneficial for organisational performance. Simply put, CE of AI technologies in HRM based on the perceived overarching usefulness and opportunity costs to acquire the innovations to serve HR functions. In practice, the costs for AI applications are yet considered inexpensive and require organisational contemplations of investment (Higueras-castillo et al., 2019; Jain et al., 2022a; Lee et al., 2021). Although recent studies illustrate a positive trend in AI technologies investments in different stances, the perception of CE of AI in the HR field remains finite (Schwendicke et al., 2021). On the strength of the above, CE is a crucial element describing the investment aspect of users' PE towards the adoption intention of AI technologies in HRM.

5.3.3.2 Task Versatility (TV)

Within the domain of technology acceptance, prior research has illustrated a similar pattern in terms of users' perception on TV of the new technologies. The variable could be reflected within technology acceptance studies which represents how novel technologies enhance the capacity of the current functions (Kim, 2022). In this thesis, TV refers to the belief that AI applications will enhance HRM capacity in delivering tasks. Reviewing the conventional HR functions, the majority of tasks are conducted manually and there is still a high level of sporadicity and lack of interconnection among tasks (Alhgig and Mehta, 2018; Nasir, 2017; Survey, 2021). The introduction of AI technologies is argued to generate the augmentations and transform the capacity of HR functions in terms of flexibility and diversity in multiple functions such as hiring, selection, on-boarding or training and development as discussed earlier in the Chapter 2. TV contributes to influence on users' adoption intention based on the justification of how tasks could be reinforced. Ostensibly, the notion of *task* possesses multidisciplinary meanings which are characterised on the aspects of "complexity, analysability, and equivocality" (Roth et al., 2022, p.231). According to Hackman (1969), tasks could be classified into four types: (1) task qua task, (2) task as ability requirement, (3) task as behaviour requirement and (4) task as behavioural description. **Table 5.1** illustrates the four types of tasks.

Table 5.1: The four types of tasks (Hackman, 1969)

Task types	Meaning
(1) Task qua task	Accounts for certain characteristics and the stimuli associated with tasks
(2) Task as ability requirement	Accounts for grouped skills and attributes to deliver the tasks
(3) Task as behaviour requirement	Accounts for required actions and approaches to perform the tasks
(4) Task as behaviour description	Accounts for grouped behaviours of people to perform the tasks

To further clarify, the word qua, in task qua task is a Latin word which means in the capacity of (Hackman, 1969). In the context of this study, AI technologies will serve types (1) and (3) which are associated with the attributes of the technological entities to enhance the tasks' capacity. Types (2) and (4) portray the requirements from external influences of skill and behavioural factors which do not pursue the similar vein entailed to measure AI technologies' adoption intention within the context. TV integrates to the UTAUT constructs of PE illustrating the expectation from AI technologies to meliorate HR functions in multiple aspects. In this setting, the variable is considered as paramount to coin users' expectancy toward the effectiveness of AI technologies in HRM.

5.3.4 Social Influence (SI)

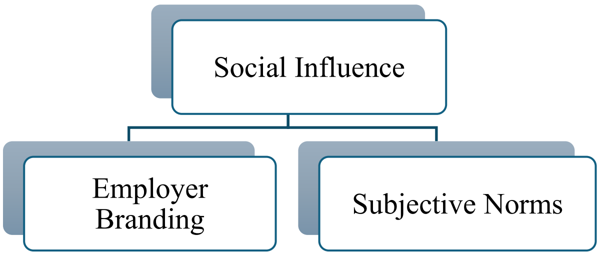

Figure 5.4: Construct of Social Influence

Most theories addressing the issue of technology adoption could not exclude the factor of SI which is a direct antecedent in determining human behaviours reflecting the UTAUT Model discussed in LR Chapter (Venkatesh and Davis, 2000). The construct affirms the level of individual perception on the importance of how others desire to use new technologies or how it complies with their expectations (Jo and Lee, 2019). The factor is further confirmed to determine users' decisions to continue using the technology (Alwahaishi and Snášel, 2013). A study conducted to examine the adoption of AI-powered chatbot also proved the significant level of SI in controlling the human intentions toward this advanced technology (Kutnjak, 2021). The results appear consistent with other research pertaining to technology adoption including the mobile banking adoption (Oliveira et al., 2014) and BI system (Kutnjak, 2021).

The influence from SI also roots from the *norms* which, according to TPB and TRA models, determine human behaviours (Fishbein and Ajzen, 1975). To further explain, the perception of norms is regulated by two features: informational and normative (Deutsch, 1980). The former is generated if the person perceives usefulness in the knowledge while the latter occurs when a person perceives the significance of the knowledge through others' expectation. Within the context of the current digital transformation, SI contributes to depict the generalisation of the use of advanced technology in the business market. This generates a potential mechanism for shaping normative pressure from first-mover cohorts, which psychologically impacts human intentions (Thompson et al., 1991; Deb et al., 2017). SI has herein emerged as a critical adoption parameter in measuring the diffusion level of innovation which are incorporated closely with DOI theory (Rogers, 1962) and TRA model (Fishbein and Ajzen, 1975). The factor possesses similar correlation with certain social and psychological variables inducing Employer Branding (EB) and Subjective Norms (SN). In the subsequent section, the relationships among the mentioned factors will be elaborated to confirm the reciprocation among the considered elements.

5.3.4.1 Employer Branding (EB)

Within the context of this research, EB is a paramount terminology in the HR Field due to the close connection in Talent Acquisition. In essence, EB refers to legions of employer's qualities and attributes enabling an organisation to become distinctive in delivering unique and compelling working experiences for employees (CIPD, 2021). Goodin (1977) coined the early formation of EB in the state of symbolic benefits which is defined as "the extent to which an individual perceives to gain a symbolic reward such as making a favourable impression on others" (p.385). The notion of EB also resonates with a study of the concept of organisational image by Moore and Benbasat (Gary and Izak, 1991) which refers to an individual's perception that the use of an innovation will enrich one's status in society. In fact, further research centred on technology adoption behaviours confirmed the concrete relations between the use of novel technology with social status enhancement. The results from early empirical studies positively reinforced the factor of EB in the context of innovation adoption in organisation. To exemplify, an incumbent study affirmed the high socially rewarding feelings perceived by employees who possessed smart-glass innovation (Rauschnabel et al., 2018). In tandem with the previous study, Mclean lately found a strong correlation in the enhancement of an individual's social image incorporating the use of AI as virtual assistants in organisations (McLean and Osei-Frimpong, 2019). It is argued that EB is a socially related factor which generates a significant momentum for innovation adoption (Black and van Esch, 2021). Due to the shifting landscape of employees' perceptions toward innovations in the digitalisation era, EB herein becomes an integral element in SI in determining technology adoption and acceptance.

5.3.4.2 Subjective Norms (SN)

Dovetailing in LR Chapter, SN is initially considered a fundamental feature in the TRA model which refers to "the degree to which an individual perceives that most people who are important to him think he should or should not use the system." (Fishbein and Ajzen, 1975, p.302). It is also defined as a composite of normative interaction and belief and the mingling of perceived behavioural control that constitute the likelihood of performing an action (Kumar, 2017). This motive is scrutinised to be significantly extracted from exogenous situations rooted from social influence which accordingly impact behavioural intention (Shin, 2010). In the similar vein, studies about technology adoption from Püschel et al. (2010) and Sripalawat et al. (2011) confirmed the prominent impact of the factor in generating human alacrity to adopt innovation. In simple evaluation of the factor, Taylor and Todd (1995) postulated a requisite correlation impacting the level of SN regulated by peer and superior pressures. Simply put, the factor in accordance with human intention is implied to be closely affected by the "expectation of his/her significant referents" (Hung et al., 2012, p.54). The expansion of technology diffusion level in the society inherently triggered the pressure for individual acceptance and adoption. The variable is exhibited to obtain the direct impact to human behavioural reflected in TPB Model (Ajzen, 1991). In other words, the flourishment of innovations emerged in the society elicits individual motivations of adoptions stem from the credence of opportunities and efficaciousness begotten. In light of the discussion, SN is considered as an important element generated from SI.

5.3.5 Perceived Risk (PR)

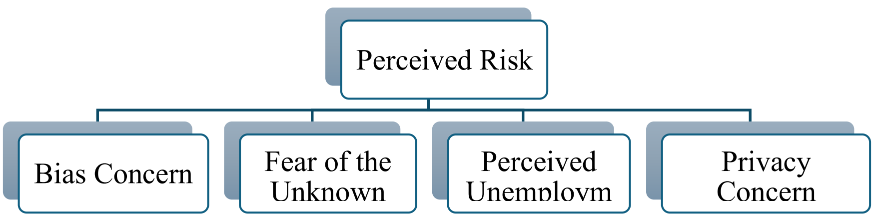

Figure 5.5: Construct of Perceived Risk

According to Vimalkumar et al. (2021), PR refers to the probability of losing something which consequently induces insecurity in people's decision making. Motivational theorists also consider PR as a central construct in determining the level of individual engagement in performing a behaviour. While the vast majority of motivation notions centralise on the facilitating factors, PR is considered as an explicit construct regulated by multidimensional psychological effect rooted in individual anxiety, fear, uncertainty and concerns (Thusi and Maduku, 2020; Al-Saedi et al., 2019a; Hasan et al., 2021). Prior research has linked this subjective notion with the individual decision-making process in technology adoption. In fact, an empirical study about mobile banking adoption demonstrated seven types of risk pertaining to technology adoption namely performance risk, financial risk, time risk, psychological risk, social risk, privacy risk, and security risk (Akturan and Tezcan, 2012). Alongside with related research of technology acceptance, the construct PR in this thesis per se possesses a negative impact on the intention to apply AI technologies. Users usually encounter high levels of psychological risks when confronting novel technologies such as fear and avoiding feelings (Morosan, 2012). The psychology factor awakens discouraging emotions against behavioural intentions (Udo et al., 2010). In practice, through the empirical results from this research, certain features related to the PR construct were detected including users' concerns and fear toward biases, privacy, fear of the unknown and perceived employment. In the next section, the relationship among the discussed factors will be illuminated to confirm the reciprocation among the considered variables.

5.3.5.1 Bias Concerns (BC)

Scholars have been emphasised of the significant hindrance of human adoption behaviours due to the factor of potential biases existing in the system or a process. In the context of AI technologies, conscious or unconscious biases generated from data input could produce insecurity for users. Despite the fact that AI technologies' biases syndicate pre-existing organisational issues with gender and class inequities, which could be detected and resolved by training the data input, BC remains a significant factor in relation to users' perceived trust in novel technologies (Clifton et al., 2020). A recent study by Tuffaha (2022) has further pinpointed potential biases obtained by AI technologies compound biassed human decisions and historic concerns which escalate users' concern on inadequate conclusions. In addition, BC also corresponds to potential risks of AI algorithmic tools to contain automation bias which decreases the reliance of AI technologies in HR adoption (Alon-Barkat and Busuioc, 2022). The algorithm bias embedded in AI technologies rooted from data set fuelled by the users which could be controlled within HR by algorithm management (Park et al., 2021). The potential bias generated from AI algorithmic tools is a pivotal issue of AI adoption in HRM. Although human errors are also scrutinised inexorably in HR practice, trust matter in AI algorithms appears exacerbating compared to the former (Guha et al., 2021). The phenomenon is described as "algorithm aversion" which refers to the users' concerns on treacherous data utilised by AI algorithms (Dietvorst et al., 2018, p.1155). It is argued that the bias sources from AI are primarily rooted in three steps (1) data input, (2) data training and (3) AI programming

(Coval, 2018). Further concerns also centre on possible institutionalised or systematic nepotism which substantially influences HR decision-making practices (Bonchi et al., 2017). In light of the above, it provides a plausible explanation of how BC is construed as a critical variable negatively impacting on human adoption behaviours due to the potential risks of bias emerging.

5.3.5.2 Fear of the Unknown (FU)

The concept of Fear of the Unknown (FU) was profoundly formed by Carleton et al. (2007) which refers to "an individual's propensity to experience fear caused by the perceived absence of information at any level of consciousness or point of processing" (p.107). Prior research relevant to the field of technology also suggests a high level of avoidance devised anxiety rooted from information ambiguity (Venkatesh and Davis, 2000). The feelings regulated by FU illustrate various emotional forms such as frustration and uneasiness. The variable, therefore, could be used to address and explain users' cognitions and behaviours (Bilgihan, 2017). The fear stemming from unknown factors toward the objects, in conjunction with environmental impacts, significantly influences human's intentional behaviour (Arslan et al., 2022). In the context of the research, this is a psychological factor pertaining to the prevalence of unknown anxiety stemming from novel technologies, which is scrutinised as the underlying pretext for technology avoidance. To be specific, the relentless pace of digital transformations accelerates the condition of FU, which eventually expedites the users' level of confidence in experiencing the latest technologies. The sophistication of AI-powered technologies and algorithms has contributed to amplify the users' anxiety upon the actual AI usages (Kaplan and Haenlein, 2019). The concept of AI is emerging and therefore, the diffusion of this innovation has not reached its full capacity. In addition, there is a phenomenon speculated as black box existing in AI algorithms describing the ambiguity in AI's decision-making outcomes (Cheng and Hackett, 2021). The unknown factor identified in this thesis appears congruent with the prior study by Graham (2021) on medical IoT devices where the absence of information increases the level of people's anxiety. The concept of anxiety was also discussed in the UTAUT model as a critical element ushering an individual's hesitation or even fear when "she/he is faced with the possibility of using technology" (Venkatesh and Davis, 2000). In response to the significant influence of the variable, FU is scrutinised as an integral factor to be measured within the construct of PR.

5.3.5.3 Perceived Unemployment (PU)

PU in this thesis is defined as the users' perception about the threat of losing jobs due to the prevalence of AI technologies in HRM. This concept closely links to the factor of job security level discussed across technology adoption research (Bui and Nguyen, 2021; Greenhalgh and Rosenblatt, 1984; Nam, 2019). The concept of job security was first introduced in motivational theories to describe the anxiety generated from employees' perceptions about threat towards their jobs or job-relevance (McGuinness et al., 2021). From the empirical perspective, the incessant evolving of technologies has contributed to the business proliferations and performance enhancement. This was evinced in the previous discussions in LR Chapter regarding AI applications in business management. Nevertheless, the scenario was further emphasised in recent studies to generate mass unemployment and employees' deskilling (Rodriguez-Lluesma et al., 2021). In this sort of orientation, there is a concern of human replacement by advanced technologies, which negatively influence the users' perceptions about novel technology adoption. Regarding the mentioned issue, PU is a seminal factor in determining human behaviours due to the potential risks of unemployment. Given the increase of AI technologies, PU factors are not limited in the context of "job discontinuance" in a short term but a prognostication on "job inexistence in the longer term" (Nam, 2019, p.137). It is also argued that AI technologies deliver the risks of devaluing HR skills, responsibilities and controls, which inevitably hampered the adoption behaviours (Zerfass et al., 2020). Anchoring to the above, this research conveys the variable of PU as a negative factor impacting the behavioural intention owing to the job-loss risk.

5.3.5.4 Privacy Concern (PRC)

The early study about perceived risk has indicated a crucial factor of personal concern characterised by an individual fear toward the unconsciousness of how provided personal information will be used (Akturan and Tezcan, 2012). PRC refers to privacy issues which are inherent to users' awareness over the personal data control. Biucky et al. (2017) construed PRC as the potential risk perceived by users over the personal information when they are used without authorisation (Rauschnabel et al., 2018). Previous empirical studies proved that the factor is an important barrier to the acceptance of innovation (Ratten, 2015; Rahmani et al., 2021; Park et al., 2021; Rastogi et al., 2018; Akturan and Tezcan, 2012; Irum and Yadav, 2019). Psychologically, this is due to the lack of full control over the information stemming from the individual desire of mastering his/her own act and the potential consequences. The result proposed by Xie et al., (2021) also supports this conclusion where the findings proved the factor negatively impacted the users toward the FinTech platform. In fact, given the advanced attributes of AI functions and the lack of comprehensive understanding, PRC contributed as a detrimental element impacting individual trust and perceptions. Likewise, concerns regarding privacy appear as a consistent factor influencing users' decision making towards innovation (Ratten, 2015; Rahmani et al., 2021; Park et al., 2021; Rastogi et al., 2018). Existing studies emphasised the PRC in technology adoption as users' desires to apprehend how data collection's purposes are processed before providing sanction (Pikkarainen et al., 2004). In this sort of orientation, the research also examines the role of PRC and its impact toward the novel subject of AI in HRM. The use of AI would require the availability of collective data as fuel for further learning, analysis and making decisions performed by AI technologies and therefore, this PRC is a critical variable to examine in this given context.

5.3.6 Status Quo Bias (SQB)

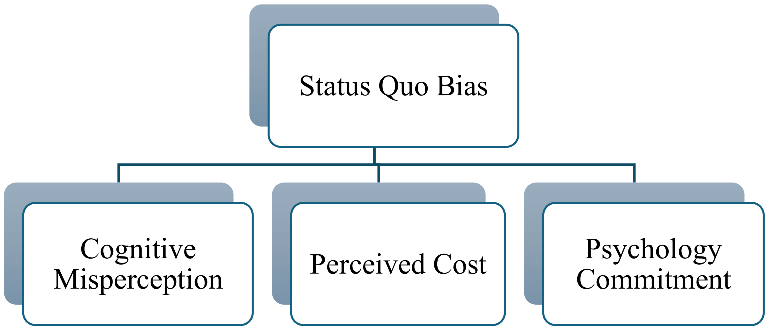

Figure 5.6: Construct of Status Quo Bias

Samuelson and Zeckhauser (1988) first coined the concept of SQB which refers to the bias triggered in individual decision making by maintaining the current status quo despite the urging mechanism towards changes. It is also defined as a predisposition to adhere to the incumbent circumstances or decision potentially initiated from people’s uncertainty and conceivable switching benefits (Hsieh and Lin, 2020). In another theoretical perspective, the prominent “prospect theory” postulated two key features of human behaviour toward decision making processes which are non-rational and reference-dependent (Tversky and Kahneman, 1979, p.89). This contributes to clarify the paradox in human decision making by psychologically addressing this construct as a typical hindrance of technology adoption. The issue is posed by the existence of an inertia tendency which facilitates the maintenance of status quo despite the pressure to alter the status (Greta and Karahanna, 2012). Recent study by Balakrishnan et al. (2021) further proved the direct relationship between status quo and human attitudes in the study of AI-power voice assistant adoption. The study was consistent with the previous research on cloud system adoption when the new system was introduced (Fan et al., 2015). Early theoretical work reveals a relatively clear and consistent picture of users’ resistance which is rooted from social context. In truth, reflecting in the original study of SQB, features of SQB were manifested in influences of rational decision making, psychology commitment, and cognitive misperceptions (Samuelson and Zeckhauser, 1988). The mentioned variables were proved to significantly influence the users’ perceptions towards change (Fan et al., 2015; Som and Gamroth, 2019; Fernandez and Rodrik, 1991; Balakrishnan et al., 2021). Therefore, in this incumbent context, the adoption of AI in HRM can be regarded as an issue in technology adoption or replacement.

5.3.6.1 Cognitive Misperception (CM)

CM is a paramount factor which influences an individual rationality to justify the advantages and disadvantages of the new technology. The variable is argued to engender a foundation for people orientations towards acceptance or resistance of new technology (Balakrishnan et al., 2021). This factor is described as the understanding distortion formulated by the prevailing value and belief (Hsieh and Lin, 2018). Within this research, CM refers to incorrect interpretations and understandings of AI applications in HRM leading to adoption stagnancy. It is posited that CM relies on users' perceived value and cognitive inertia toward changes (Eds and Goos, 2022). Due to the ambiguity of AI concept, CM is yielded to amplify the effects of SQB due to risk-averse concerns (Shankar and Kumari, 2019). In other words, the decision makers based on heuristics perceive a higher value on the current status rather than uncertain alterations (Guenduez et al., 2020). In addition, it is entrenched that individuals have the tendency to remain the status quo if they perceive the chance is 50/50 positive and negative (Weiler et al., 2019). The inference is perceived to be congruent with Prospect Theory (Tversky and Kahneman, 1979) where people weigh more on losses over gains when approaching decision making. At this turning point, it could be observed that AI possesses features of both beneficial and potential risks due to uncertainties. Furthermore, the concept of AI is novel and emerging in the business market, which indicates a potential immaturity of the comprehensive understanding in the AI field. The mentioned points explain the critical role of CM in users' decision-making process in AI adoption within the context of this research. Value perceptions of AI derived from the users could be distorted because of CM which portrays a greater resistance to technology adoption. In the light of the above, CM is considered as an important variable formulating SQB construct in human intentional behaviours.

5.3.6.2 Perceived Cost (PC)

PC is one of the dominant elements in SQB and technology adoption studies which directly influence the acceptance of new IS. The variable integrates with the element of rational decision-making factors constituting SQB. In this research, the notion pertains to the concern on high costs related to AI applications in HRM. The costs discussed within the context are sunk costs and transition costs which negatively influence the adoption intention of users. In specific terms, sunk cost refers to past investments accumulating the operations of the present status. The presence of sunk costs exhibits prior investments and commitments, which accelerates SQB (Hsieh and Lin, 2020). This phenomenon is criticised to generate inertia to the status quo where users exert the enjoyment and safety to maintain the existing state (Balakrishnan et al., 2021). The change to new technologies implicates the risks to the current status of functioning which triggers users "regret avoidance and control" (Lee and Joshi, 2017, p.92). On the other hand, transition costs refer to the switching costs to deploy new technology which is related to the future costs such as costs of purchasing, training, and building required infrastructure. These costs are required when adapting to new circumstances. It is stated that users might perceive pressure pertaining to the requirement of skill and knowledge enhancement to adapt to the new status (Guenduez et al., 2020). The incident eventually increases users' resistance owing to the perceived of spendings associated with the transition procedure. Therefore, it is argued to be the primary factor prohibiting organisations from technological transitions (Mueller et al., 2019). Both discussed types of costs are the main element in SQB's rational decision-making factors hampering the adoption of new technologies. PC is confirmed as critical in elements in intentional behaviours and the result appears consistent through related studies (Mueller et al., 2019; Hsieh and Lin, 2018; Aliman, 2020). From this standpoint, the variable is contributed as a crucial variable in generating SQB.

5.3.6.3 Psychology Commitment (PYC)

This is an important variable extracted from SQB theory which is defined as an interior self-commitment of an individual toward the current status (Samuelson and Zeckhauser, 1988). Under the category of PYC, prior research identifies several integrative factors leading to the resistance to change such as workplace culture, fear of the change and the development of attachment feelings overtime due to reiteration of habits (Nebel, 2015). Within the context of this thesis, PYC is defined as the close-knit attachment with the current HRM outweighing the considerations of AI applications in HRM. In fact, the variable is viewed as a critical factor triggering inertia in technology adoption (Barrane et al., 2018). This is due to the fact that the notion integrates with the psychological desire of longevity of existence which refers to the individual tendency to "regard existing things as good and to regard things that have existed longer as better" (Eidelman and Crandall, 2012, p.3). According to Li et al. (2016), the concept also closely integrates with the "social norms" element due to its relations to "values, customs and traditions" of an individual in the decision-making process (p.193). In essence, PYC is in line with Social Influence Theory (Kelman, 1958) which describes the tendency of an individual to be highly affected by the value rate of the society. The factor is further emphasised to be strengthened due to the investments of resources and time in the existing subject that exacerbate PYC and establish a change-resistance mechanism (Balakrishnan et al., 2021). In this sort of orientation, the status quo emerging is grounded by the individual favours which outweigh the potentially positive features of outcomes of the novel subject. In respect to the above, PYC is an integrative factor generating SQB. The factor, therefore, contributes to measuring the influences of adoption intention of AI technologies in HRM.

In sum, the foregoing discussion acknowledges the interlink between the main constructs to AI adoption intention as well as how prior studies identified interdependence of the main constructs to its representative factors. Additionally, the research therein profoundly illustrates the six key constructs applying to testify the correlations to the adoption intention of HR professionals at Phase 2 (quant). This is also in line with preconceptions proposed in the LR Chapter about the UTAUT factors: Effort Expectancy (EE), Facilitating Condition (FC), Performance Expectancy (PE), Social In fluence (SI); and the psychological factor: Perceived Risk (PR) while also adopting the emerging construct of Status Quo Bias (SQB) in the qualitative research. Anchored to this, the conceptualised definitions of this study's main constructs are showcased in **Table 5.2**.

Table 5.2: The summary of the research main constructs

Main Constructs	Representatives of main constructs	Definitions	References
Effort Expectancy	Ease of use	The belief that AI applications will bring convenience and easiness in HRM	(Fishbein and Ajzen, 1975), Gary C. Moore; Izak Benbasat, 1991), (Muñoz-Leiva et al., 2017)
	Job Compatibility	The belief that AI applications will be congruent to the existing HRM performance	
Facilitating condition	Leadership Support	Active leadership support toward AI adoption in HRM	(Fishbein and Ajzen, 1975), (Kim, 2022), (Rogers, 1962), Muñoz-Leiva et al., 2017), (Thompson et al., 1991), (Palau-Saumell et al., 2019)
	Innovation Driven	The optimistic motivation that AI applications would bring opportunities to HRM	
Performance Expectancy	Cost-effectiveness	The belief that AI application in HRM will be financially beneficial for organisational performance	(Taylor and Todd, 1995), (Venkatesh et al., 2003), (Thompson et al., 1991), (Palau-Saumell et al., 2019), (Alam et al., 2020)
	Task Versatility	The belief that AI applications will enhance HRM functions	
Social Influence	Employer Branding	The belief that AI applications in HRM will bring reputation and attract potential candidate	(Kim, 2022), (Gary C. Moore; Izak Benbasat, 1991), (Rogers, 1962), (Hung et al., 2012), (Fishbein and Ajzen, 1975)
	Subjective norms	The belief that vast AI application in HRM will lead to the acceptance of AI applications	
Perceived risk	Bias Concerns	The inclination that AI applications will deliver bias factors in HRM	(Bankins et al., 2022), (Guha et al., 2021), (Carleton et al., 2007), (Graham, 2021), (Jaradat et al., 2020), (Nam, 2019), (Alt et al., 2021a), (Muñoz-Leiva et al., 2017), (Pitardi and Marriott, 2021)
	Fear of the Unknown	The fear caused by uncertainty and lack of information about AI applications in HRM	
	Perceived Unemployment	The inclination that AI application will remove HR professions	

	Privacy Concern	The fear caused by the uncertainty of how personal information will be used when applying AI	
Status Quo Bias	Cognitive misperception	The incorrect interpretations and understandings of AI applications in HRM leading to adoption stagnancy	(Kim, 2009a), (Samuelson and Zeckhauser, 1988), (Hofman, 2022), (Luarn and Lin, 2005), (Sripalawat et al., 2011), (Yu, 2012), (Kim, 2009a; Hong and Kim, 2002; (Fan et al., 2015), (Davis, 1989)
	Perceived Cost	The concern on high cost of implementation outweighing the considerations of AI applications in HRM	
	Psychology Commitment	The close-knit attachment with the current HRM outweighing the considerations of AI applications in HRM	

5.4 Finalised Conceptual Framework and Hypothesis establishment

In this section, the hypotheses of this research were established to depict the expected relationships among the selected constructs embedded in the refined conceptual framework. The following parts stipulated the hypotheses of the six constructs influencing the adoption intention of HR professionals regarding AI technologies.

5.4.1 Effort Expectancy and AI adoption intention

Effort Expectancy (EE) is defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p450). In other words, EE measures the perceived user-friendliness of a system in operations or processes (Islam et al., 2024). This concept was predominantly derived from the constructs of perceived ease of use in Technology Acceptance Model (Davis, 1989) and ease of use in Diffusion of Innovation (Rogers and Williams, 1983). EE was previously demonstrated to be an influencer of behavioural intention in several studies. For instance, Islam et al. (2022) conducted a study to identify main antecedents of AI adoption in recruitment in Bangladesh using the UTAUT model; and their findings show that EE positively influences HR professionals' behavioural intention to use such technology in recruitment. Similarly, EE is posited to be a determinant of behavioural intention to use AI technology in HR practices (Alam et al., 2020). Therefore, the researcher of the present study hypothesised that

H1: EE is positively related to AI adoption intention in HRM

5.4.2 Facilitating Condition and AI adoption intention

As defined by Venkatesh et al. (2003), Facilitating Conditions (FC) is "the degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system" (p.451). The research argues that the lack of technical and infrastructural facilitation, accompanied with knowledge sharing and other resources will generate ambiguity at the technology acquisition and implementation stage (Dey and Saha, 2020; Islam et al., 2022). In the investigation of users' intention to adopt AI in human resource recruitment in Thailand using UTAUT, Tanantong and Wongras (2024) found that FC significantly influences HR specialists' tendency to use AI in recruitment. Additionally, another study in Bangladesh also highlighted that FC predicts the behavioural intention of users to use AI and assists the adoption of AI-based technologies (Alam et al., 2020). Therefore, the researcher of the present study hypothesised that

H2: FC is positively related to AI adoption intention in HRM.

5.4.3 Performance Expectancy and AI adoption intention

Performance Expectancy (PE) is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). In other words, PE refers to individuals' expectation of improving their functional capabilities by adopting new technologies in a given circumstance (Islam et al., 2022). This concept was predominantly derived from the constructs of perceived usefulness in Technology Acceptance Model (Davis, 1989) and outcome expectations in Social Cognitive Theory (Compeau et al., 1999). Several studies have demonstrated its positive impacts on the AI adoption in HRM. For example, Horodyski, 2023) found in their study that PE of AI-based tools in recruitment has a positive influence on the behavioural intention to use them. Likewise, in an investigation of using AI for talent acquisition, Islam et al. (2024) revealed that PE significantly and positively influences behavioural intention to use AI in the recruitment process. Therefore, the researcher of the present study hypothesised that.

H3: PE is positively related to AI adoption intention in HRM.

5.4.4 Social Influence and AI adoption intention

Venkatesh et al. (2003) defined Social Influence (SI) as "the degree to which an individual perceives that important others believe he or she should use the new system" (p.425). This concept was primarily drawn upon the subjective norm in Theory of Planned Behaviour (Ajzen, 1991). In other words, SI refers to the pressure on technology users which originates from different social entities, such as friends, colleagues, relatives or neighbours (Islam et al., 2022). The literature has underscored the pivotal role of SI in technology use across different areas, including mobile technology in healthcare, talent acquisitions in recruitment process or ERP employment in corporations (Tanantong and Wongras, 2024). In an examination on Ethiopian electronic medical recording system, Shiferaw and Mehari (2019) revealed that SI established a positive association with behavioural intention to use AI technology among doctors and nurses. The same pattern was found in the investigation of AI adoption in HRM practices, which indicates the significant role of SI in the tendency to employ AI for recruitment processes (Islam et al., 2024). Therefore, the researcher of the present study hypothesised that:

H4: SI is positively related to AI adoption intention in HRM.

5.4.5 Status Quo Bias and AI adoption intention

Status Quo Bias (SQB) is defined as "a non-rational or biassed preference for the current way of doing things", including three different categories, such as cognitive misperception, rational decision making, and psychological commitment (Samuelson and Zeckhauser, 1988, p.7–59). This concept validates how and why organisational factors prefer to stay away from changes due to technological innovation (Almatrodi et al., 2023). As AI has been rapidly implemented across industries, its adoption can simultaneously lead to biases originating from the interaction between humans and AI (Malin et al., 2024). The literature reveals that people intend to stay with existing technology and are reluctant to use new technology due to the status quo, which indicates the suitability of SQB in the research domain about user resistance to new technology (Shankar and Nigam, 2022). In the previous studies, authors have drawn upon the SQB theory to examine individuals' resistance behaviour in different contexts, such as resistance towards online health services (Zhang et al., 2017), healthcare professionals' resistance toward the use of health clouds (Hsieh, 2015) or consumers' resistance to use online travel agencies (Talwar et al., 2021). Therefore, the researcher of the present study hypothesised that:

H5: SQB is negatively related to AI adoption intention in HRM.

5.4.6 Perceived Risk and AI adoption intention

There are several definitions of Perceived Risk (PR) from intellectuals. For instance, Bauer (1967) defined Perceived Risk as "a combination of uncertainty plus seriousness of outcome involved" (p.23), while Dowling and Staelin (1994) characterised PR as "consumers' perception of the uncertainty and adverse consequences of buying a product or service" (p.119). Collectively, PR refers to a feeling of uncertainty toward the possible negatives of using a product or service. It is indicated in recent literature about information systems that perceived risk contributes to the explanation for behavioural intention of users in terms of adopting new technologies (Hwang et al., 2024). Featherman and Pavlou (2003) conducted a study to measure the negative utility attributable to e-service adoption and suggested that e-services adoption is adversely influenced by performance-based risk perceptions. Similarly, a study to explain the resistance intention towards mobile HRM application examined by Shankar and Nigam (2022) reveals that PR is negatively associated with HRM mobile app adoption. Therefore, the researcher of the present study hypothesised that:

H6: PR is negatively related to AI adoption intention in HRM.

Based on the above discussion, the finalised research hypotheses in this chapter are presented in **Table 5.3**.

Table 5.3: The research's hypotheses statements

	Hypotheses Statements
H1	EE is positively related to AI adoption intention in HRM.
H2	FC is positively related to AI adoption intention in HRM.
H3	PE is positively related to AI adoption intention in HRM.
H4	SI is positively related to AI adoption intention in HRM.
H5	SQB is negatively related to AI adoption intention in HRM.
H6	PR is negatively related to AI adoption intention in HRM.

5.5 Research Framework and Measurement Items Establishment

AI adoption factors identified in QUAL study in Chapter 4 indicates the radicalisation of AI and how continuous innovation is relentlessly intervening in HR practices and in this digitalisation era. Due to that reason, the available measure scales directly operationalising the constructs toward the adoption intention of AI are not available. According to Tight (2017), the operationalisation of latent variables is attained by either creating the measurement scales for the constructs or adapting existing scales from relevant research (Patten, 2017). In this vein, the researcher is authorised to develop primitive measurement items and obtain the essential measures to ensure the validity of the generated scales where associated research has not been conducted (McCall, 2018). As illustrated in **Figure 5.7**, the conceptual framework of this research comprises six main constructs measured by 15 sub-categories.

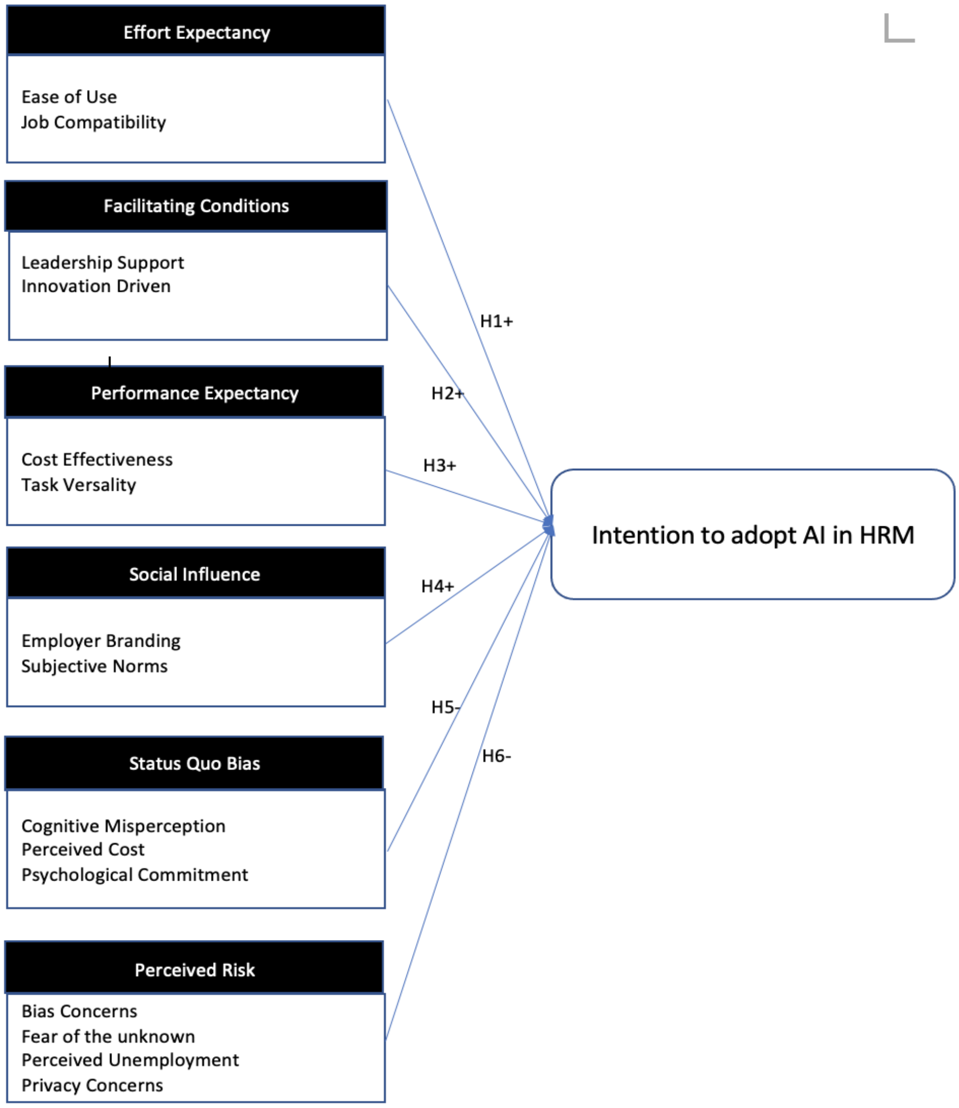

Figure 5.7: Finalised Conceptual Framework

At this stage, a peruse of the existing literature proposed sufficient and compatible measurement scales available to be adapted to this research's constructs. Dovetailing to that, it is not necessary for this research to generate novel measurement scales. Nevertheless, it is worth acknowledging that there is a possibility of measurement errors embedded in the scales during the adaption process to the new research tested subjects, which could lead to the reduction of impact due to measurement errors in the study findings (Creswell, 2017). Given the consideration on the mentioned concern, the process of pre-testing the adapted measurement scales was conducted with knowledgeable academicians and several HR professionals regarding the adoption of AI in HRM. During the process, definitions of the constructs, the chosen measurement items were engendered to support the apprehension of the pilot-testing participants. As a result, the constructive feedback was applied to adjust the adapted measurement items to appropriately accommodate this research's context. Anchored to the discussion above, the measurement items of this study are demonstrated following:

5.5.1 Measurement scale of Performance Expectancy

The measurement of this concept was represented by two sub-concepts: Cost Effective and Task Versatility. Cost Effectiveness was operationalised with four items adapted from (Thompson et al., 1991; Taylor and Todd, 1995; Venkatesh et al., 2003; Palau-Saumell et al., 2019). Meanwhile, Task Versatility was measured by four items adapted from (Taylor and Todd, 1995; Venkatesh et al., 2003; Alam et al., 2020). These items are considered appropriate for the study because they were captured from origin theories and recently studies which investigated the same domain. The item scales are presented in **Table 5.4**.

Table 5.4: Measurement of Performance Expectancy

Performance expectancy			
Cost-effectiveness	CE1	The use of AI technologies in HRM will increase the quality of output of my job	(Thompson et al., 1991), (Taylor and Todd, 1995), (Palau-Saumell et al., 2019), (Venkatesh et al., 2003)
	CE2	The use of AI technologies in HRM will increase the opportunities for me to deliver more meaningful jobs	
	CE3	The use of AI technologies in HRM will offer better value for the organisational investment money	
	CE4	The use of AI technologies in HRM will increase the flexibility in delivering my job	
Task Versatility	TV1	I believe the use of AI technologies in HRM will improves my productivity	(Taylor and Todd, 1995), (Venkatesh et al., 2003), (Alam et al., 2020)
	TV2	I believe the use of AI technologies in HRM will be useful in my job	
	TV3	I believe the use of AI technologies in HRM saves my time	
	TV4	I believe the use of AI technologies in HRM will increase my chances of getting a raise	

5.5.2 Measurement scale of Effort Expectancy

The measurement of this concept was represented by two sub-concepts: Ease of Use and Job Compatibility. Ease of Use was operationalised with four items adapted from (Fishbein and Ajzen, 1975; Muñoz-Leiva et al., 2017). Job Compatibility was also measured by four items adapted from (Gary and Izak, 1991; Muñoz-Leiva et al., 2017). These items are considered appropriate for the study because they were captured either from origin theories or recently studies which investigated the same domain. The item scales are presented in **Table 5.5**.

Table 5.5: Measurement of Effort Expectancy

Effort expectancy			
Ease of use	EOU1	Learning to work with AI technologies in HRM will be easy for me	(Muñoz-Leiva et al., 2017),

	EOU2	I believe the use and interaction with AI technologies in HRM require less mental effort.	(Fishbein and Ajzen, 1975)
	EOU3	I believe I would find AI technologies easy to use for whatever HR task I want to do	
	EOU4	Overall, I believe the use of AI technologies is easy in HRM	
Job Compatibility	JC1	I believe the use of AI technologies will significantly assist me with different HR practices	(Muñoz-Leiva et al., 2017), Gary and Izak, 1991)
	JC2	I believe the use of AI technologies will increase the effectiveness in performing different HR practices	
	JC3	Overall, I believe the use of AI technologies can be useful in assisting me to perform different HR practices	
	JC4	My job-related activities with AI technologies will be clearer and more understandable	

5.5.3 Measurement scale of Social Influence

The measurement of this concept was represented by two sub-concepts: Employer Branding and Subjective Norms. Employer Branding was operationalised with three items adapted from (Rogers, 1962; Goffman, 1967; Muñoz-Leiva et al., 2017). Meanwhile, Subjective Norms were measured by four items adapted from (Fishbein and Ajzen, 1975; Hung et al., 2012). These measured items are appropriate to use for this study because they were in line with origin theories and timely updated with recent studies. The item scales are presented in **Table 5.6**.

Table 5.6: Measurement of Social Influence

Social influence			
Employer Branding	EB1	Organisations which are currently applying AI technologies in HRM have more prestige than those who do not use them	(Muñoz-Leiva et al., 2017), (Goffman, 1967), (Rogers, 1962)
	EB2	Organisations which are currently applying AI technologies in HRM have a higher status	
	EB3	Using AI technologies in HRM will enhance the status symbol in my organisation	
Subjective norms	SN1	People who are important to me think that I should use AI technologies	(Hung et al., 2012), (Fishbein and Ajzen, 1975)
	SN2	People who affect/influence my behaviour think that I should use AI technologies	
	SN3	People whose opinions that I value prefer that I must use AI technologies	
	SN4	In general, the organization has supported the use of AI technologies	

5.5.4 Measurement scale of Facilitating Conditions

The measurement of this concept was represented by two sub-concepts: Leadership Support and Innovation Driven. Leadership Support was operationalised with four items adapted from Rogers (1962) and Thompson et al. (1991). These items are considered valid because they are both from the original Personal Computer Utilisation Model and Diffusion of Innovations. Innovation Driven was measured by four items adapted from Rogers (1962) and Hung et al. (2012). These measured items are appropriate to use because they were in line with origin theory and timely updated with recent studies. The item scales are presented in **Table 5.7**

Table 5.7: Measurement of Facilitating Conditions

Facilitating conditions			
Leadership Support	LS1	My organisation will be supportive of AI technologies to be used in HRM	(Thompson et al., 1991), (Rogers, 1962)
	LS2	The management board of my company will be helpful in introducing AI technologies in HRM	
	LS3	My departmental co-workers will be assisted by the management board to broadly use AI technologies in HRM	
	LS4	Overall, my organisation will be investing in AI technologies in HRM	
Innovation Driven	ID1	I have heard about AI technologies in HRM, and I would like to look for a way to experiment with it	(Hung et al., 2012), (Rogers, 1962)
	ID2	I would like to experiment with AI technologies in HR practices	
	ID3	In general, I am enthusiastic about AI technologies applied in HRM	
	ID4	Among my colleagues, I usually the first to try out new technologies	

5.5.5 Measurement scale of Perceived Risk

The measurement of this concept was represented by four sub-concepts (presented in **Table 5.8**): bias concerns, fear of the unknown, perceived unemployment, and privacy concern. To begin with, the bias concerns variable was measured by four items adapted from the investigation of AI adoption in retailing (Guha et al., 2021), and AI decision making in HRM (Bankins et al., 2022). Measured items are considered appropriate because they are used to test people's intention within HRM and business-related contexts. Next, the Fear of the Unknown variable was measured by four items adapted from Carleton et al. (2007) whose research comprehensively developed a scale for intolerance of uncertainty; and Graham (2021) whose study explored the fear of the unknown while interacting with IoT devices in the healthcare industry. The Perceived Unemployment variable was measured by four items adapted from Nam (2019) who investigate the association between new technology usage and perceived job insecurity in US; and Jaradat et al. (2020) who conducted research within the same domain in the Gulf. Finally, the Privacy Concern variable was measured by four items adapted from previous studies about relationship between potential risks and intention to use mobile banking (Muñoz-Leiva et al., 2017), Chatbot adoption in banking system (Alt et al., 2021), and the role of privacy concerns in interaction between human and voice-based AI (Pitardi and Marriott, 2021).

Table 5.8: Measurement of Perceived Risk

Perceived Risk			
Bias Concerns	BC1	The results generated by AI technologies in HRM is not trustworthy to me	(Bankins et al., 2022), (Guha et al., 2021)
	BC2	The results generated by AI technologies in HRM contain bias factors	
	BC3	I do not believe in results generated by AI technologies in HRM	
	BC4	The results generated by AI technologies in HRM bring unfair outcomes	
Fear of the Unknown	FU1	The ambiguities brought by AI technologies in HRM stress me	(Carleton et al., 2007), (Graham, 2021)
	FU2	Applying AI technologies in HRM makes me uneasy, anxious, or stressed	
	FU3	The ambiguities brought by AI technologies in HRM upset me greatly	
	FU4	I lack confidence due to the ambiguities brought by AI technologies in HRM	
Perceived Unemployment	PU1	My organisation will use AI technologies to replace my position in HRM.	(Jaradat et al., 2020), (Nam, 2019)
	PU2	My organisation will find someone who is skillful in AI technologies to replace my position in HRM.	
	PU3	My position in HRM will be threatened by AI technologies	
	PU4	Overall, the use of AI technologies in HRM will eliminate many HR jobs.	
Privacy Concern	PRC1	Privacy information could be misused, inappropriately shared, or sold when using AI technologies	(Alt et al., 2021), (Muñoz-Leiva et al., 2017), (Pitardi and Marriott, 2021)
	PRC2	Personal information could be intercepted or accessed when using AI technologies	
	PRC3	Personal information could be collected, tracked, and analysed when using AI technologies	
	PRC4	Privacy could be exposed or accessed when using AI technologies	

5.5.6 Measurement scale of Status Quo Bias

The measurement of this concept was represented by four sub-concepts (presented in **Table 5.9**): cognitive misperception, perceived cost, psychology commitment. Specifically, the Cognitive Misperception variable was measured by four items adapted from origin theory

(Samuelson and Zeckhauser, 1988), and study investigated the resistance to adopt new IT (Kim, 2009). In a similar vein, the Perceived Cost variable was measured by four items adapted from origin theory (Samuelson and Zeckhauser, 1988), study investigated the role of perceived financial cost toward behavioural intention to use mobile banking app (Luarn and Lin, 2005), research about the same phenomenon in Thailand conducted by Sripalawat et al. (2011), and (Yu, 2012). Eventually, the Psychology Commitment variable was measured by four items adapted from origin theory (Samuelson and Zeckhauser, 1988), study investigated ERP adoption in organisations (Hong and Kim, 2002), study investigated the resistance to adopt new IT (Kim, 2009), and research about cloud system adoption (Fan et al., 2015).

Table 5.9: Measurement of Status Quo Bias

Status Quo Bias			
Cognitive misperception	CM1	Adopting AI in HRM would not enhance the effectiveness on the job than working in the current way	(Kim, 2009), (Samuelson and Zeckhauser, 1988)
	CM2	Adopting AI in HRM would not enable me to accomplish relevant tasks more quickly than working in the current way	
	CM3	Adopting AI in HRM would not increase my productivity than working in the current way	
	CM4	Adopting AI in HRM would not improve the quality of work I do than working in the current way	
Perceived Cost	PC1	The cost of using AI technologies in HRM is higher than applying manual HRM in a long term	(Luarn and Lin, 2005), (Sripalawat et al., 2011), (Yu, 2012), (Samuelson and Zeckhauser, 1988)
	PC2	AI technologies applied in HRM charges me a lot of money	
	PC3	Applying AI technologies in HRM is a burden to me	
	PC4	The AI application fee is expensive in HRM	
Psychology Commitment	PYC1	Our organisation will not comply to the new way of working with AI technologies in HRM	(Kim, 2009; Hong and Kim, 2002; Fan et al., 2015), (Samuelson and Zeckhauser, 1988)
	PYC2	Our organisation will not operate with the new way of working with AI technologies in HRM	
	PYC3	Most members will oppose the change to the new way of working with AI technologies in HRM	
	PYC4	Our organisation will not agree with the new way of working with AI technologies in HRM	

5.5.7 Measurement scale of Intention to Use

The measurement of Intention to Use was adopted from Davis (1989) and Sripalawat et al. (2011). These items are considered appropriate for the study because they were captured from origin theories and recently studies which investigated the same domain. The item scales are presented in **Table 5.10**.

Table 5.10: Measurement of Intention to Use

Intention to use	IU1	I plan to use AI technologies in the future	(Davis, 1989), (Sripalawat et al., 2011),
	IU2	I intend to use AI technologies in the future	
	IU3	I predict I would use the AI technologies frequently in the future	

5.5.8 The Research Measurement Scale's Selection

It is asserted that the selection of the appropriate measure scale for research is significant in assisting the researcher to effectively obtain, gather and further analyse the data for a study (Saunders et al., 2009). As indicated in Chapter 3 of this research, 5-Point Likert measurement scale was selected for this study due to its capacity to measure diverse and nuanced precision. Specifically, the chosen scale enabled the researcher to seize the intensity of the research's participants in terms of perceptions and feelings toward AI adoption in HRM by providing a 5-range of responses from "Strongly disagree" to "Strongly agree" (Likert, 1932). Hence, multifaceted essence of AI adoption factors can be captured, which was not restricted to binary or too many options. This aligns with opinions that the granularity of 5-point Likert scale enriches the degree of accuracy and insights of the gathered data, which facilitates further interpretations in data analysis process (DeCastellarnau, 2018). Further, the selected scale can encapsulate the participants' expressions and opinions in a simple way due to its ease of use and straightforward manner. In truth, due to its prevalence in social science research, the benchmarks from the scale are indicated to obtain transparent format resulting in the reduction in cognitive loads on the respondents and increase the validity and reliability aspects of the collected responses (Boone et al., 2012; Joshi et al., 2015). Echoing the above sentiments, this study adopted the 5-point Likert scale to effectively approach the research context of AI adoption intention in HRM. The **Table 5.11** illustrates a snapshot of this research measurement scale and items.

Constructs	Variables	Item	Measurement	Sources
Performance expectancy	Cost-effectiveness	4	5-Point Likert Scale	(Thompson et al., 1991), (Taylor and Todd, 1995), (Palau-Saumell et al., 2019), (Venkatesh et al., 2003)
	Task Versatility	4	5-Point Likert Scale	(Taylor and Todd, 1995), (Venkatesh et al., 2003), (Alam et al., 2020)
Effort expectancy	Ease of use	4	5-Point Likert Scale	(Muñoz-Leiva et al., 2017), (Fishbein and Ajzen, 1975)

	Job Compatibility	4	5-Point Likert Scale	(Muñoz-Leiva et al., 2017), Gary C. Moore; Izak Benbasat, 1991)
Social influence	Employer Branding	3	5-Point Likert Scale	(Muñoz-Leiva et al., 2017), (Goffman, 1967), (Rogers, 1962)
	Subjective norms	4	5-Point Likert Scale	(Hung et al., 2012), (Fishbein and Ajzen, 1975)
Facilitating conditions	Leadership Support	4	5-Point Likert Scale	(Thompson et al., 1991), (Rogers, 1962)
	Innovation Driven	4	5-Point Likert Scale	(Hung et al., 2012), (Rogers, 1962)
Perceived Risk	Bias Concerns	4	5-Point Likert Scale	(Bankins et al., 2022), (Guha et al., 2021)
	Fear of the Unknown	4	5-Point Likert Scale	(Carleton et al., 2007), (Graham, 2021)
	Perceived Unemployment	4	5-Point Likert Scale	(Jaradat et al., 2020), (Nam, 2019)
	Privacy Concern	4	5-Point Likert Scale	(Alt et al., 2021a), (Muñoz-Leiva et al., 2017), (Pitardi and Marriott, 2021)
Status Quo Bias	Cognitive misperception	4	5-Point Likert Scale	(Kim, 2009a), (Samuelson and Zeckhauser, 1988)
	Perceived Cost	4	5-Point Likert Scale	(Luarn and Lin, 2005), (Sripalawat et al., 2011), (Yu, 2012), (Samuelson and Zeckhauser, 1988)
	Psychology Commitment	4	5-Point Likert Scale	(Kim, 2009a; Hong and Kim, 2002; Fan et al., 2015), (Samuelson and Zeckhauser, 1988)

5.6 Chapter Summary

In conclusion, this chapter sharpened and refined the proposed conceptual framework in Chapter 2 based on the findings of the qualitative studies discussed in Chapter 4. In practice, the general constructs of AI adoption factors assumed in Chapter 2 were respectively proven with the context-specific constructs derived from the discussions with HR professionals regarding the incumbent HRM landscape and AI diffusion in the realm. Furtherance to the above, the proposal of the preliminary constructs, which lacks the support of empirical evidence was enhanced and well-pronounced which strengthens the initial hypotheses. Especially, the discovery of the emerging factor of Status Quo Bias (SQB) was a significant milestone to enrich the current conceptual framework regarding AI adoption in HRM. Therein, this chapter continued to discuss and present the six final constructs and their casual relationships to establish the research’ s hypotheses. In addition, the connection between the main constructs and sub-constructs based on the causation relationship absorbed from prior studies, were discussed to create the foundation for measurement scale establishment. To elaborate, the research constructs were operationalised via the development of the measurement scale adapted and justified from the existing literature. At this junction, whether the hypothesised causal relationships of EE, FC, PE, SI, PR and SQB to the adoption intention are correctly predicted is subject to the verification of the statistical examination discussed in the subsequent chapter.

CHAPTER 6: QUANTITATIVE RESEARCH (Quant)

6.1 Introduction

Through the distilling model proposed in Chapter 5, the research further proceeded to Phase 2 of quantitative study. The research was conducted to provide a statistical perspective pertaining to the hypotheses. This chapter illuminates the third research question (RQ3) *"To what extent do the explored determinants relate to the intention to adopt AI in HRM?"* by concentrating on examining the correlation between the critical adoption factors of AI technologies in the HR realm. In addition, the statistical findings from the chapter provided a distinct angle via the acceptance and elimination processes of preceding selected elements. This explains the fast-paced nature of research related to technology and innovations conducted in the 4th Industrial Revolution era (Schwab, 2024). Specifically, this Chapter examined the selected six factors to examine the impact degree on the HRM adoption intention. The analysis and findings acquired from this quantitative research are derived from Statistical Package for the Social Science (SPSS) analysis to synthesise sophisticated and robust data. The empirical data was collected from 146 respondents who are HR Professionals based in England. Anchoring to the analysed data, it provides an evaluation standard to estimate the continuous innovation effect in HRM with the influence of AI-powered technologies. The author further synthesised and evaluated simultaneously the contemporary occurrences in the business market and AI diffusion rate to conclude the results. Eventually, the Chapter provides a critical approach to authenticate the potential impact of the adoption factors, which contributes to evaluating the conceivable collaborations of AI technologies and HRM.

6.2 Demographic Information

Dovetailing to the previous chapter, AI terminology was illustrated and perceived as an incipient and diversified concept in the HR realm with various functions applied in HR practices. The motives to resort to AI from HR stances were reasonably explained with thematic analysis. In order to further investigate the phenomenon, the research strategy at this stage is to confirm the impact degree of adoption intention factors towards actual adoption through quantitative analysis using the data extracted from HR professionals through different HR levels. Ultimately, the survey questionnaire was distributed through different HR communities' channels including personal connections to individuals working in the HR sector, the Chartered Institute of Personnel Development (CIPD) members and HR Professional groups across occupational networks (**Appendix 6.1**). The survey questionnaire was designed and conducted through Qualtrics, a recommended platform for this research, and the pilot testing was conducted with experienced research experts regarding its validity and relevance.

In all, 225 candidates participated in the quantitative research. Among those, there were 67 candidates who did not comprehensively complete the survey, 11 candidates who did not meet the inclusion criteria and one candidate decided to withdraw at the end of the survey. Eventually, the total number of validated collected surveys for this research was one 146. The demographic information of the research respondents is illustrated in **Table 6.1**. The proportion of demographic information collected will be discussed in the following sections.

Table 6.1: Research Participants' Profile (generated by the researcher)

Criteria	Frequency	Remark
Working Sector (SIC Code extracted)		
Education	36	25%
Manufacturing	23	16%
Accommodation and food service activities	16	11%
Financial and insurance activities	13	9%
Human health and social work activities	11	8%
Arts, entertainment, and recreation	10	7%
Public administration and defence; compulsory social security	9	6%
Transport and storage information and communication	6	4%
Others (designated across nine remaining sectors)	22	14%
Job Designation		
HR Executives	46	32%
HR Practitioners	88	60%
HR related professionals	12	8%
Working experiences		
1-5 years	83	57%
11-15 years	17	12%
16-20 years	1	1%
6-10 years	29	20%
Over 20 years	16	11%
Familiarisation with AI		
Advanced	6	4%
Developed	29	20%
Limited	46	32%
Moderate	61	42%
None	4	3%
Total Participants	146	100%

6.2.1 Sampling Technique and working sectors of the participants

According to the illustrated background data from **Table 6.1**, there was a significant degree of diversity reflecting the industries, working experiences and AI familiarisation among the HR professionals. Although the concept of AI is argued to capture a larger recognition in some industries such as manufacturing or IT sectors, the applications are dominantly covered alternative business operations including marketing, supply chain or logistics management. As previously discussed in Chapter 4, the germination of AI-powered HRM has recently emerged and has not reached the critical mass point of prevalence application. Hence, it could be reasonably assumed the apprehensive level of HR professionals across industry are at an equal margin line.

Specifically, the industries listed in the research were extracted from the England Standard Industrial Classification (SIC) Codes from Office of National Statistics (Office for National Statistics, 2012) with a total of 17 components (**Appendix 6.2**) to fully reflect different sectors and ensure the options availability for the participants. Within the presented table, the author displayed main categories which were highly manifested through the survey questionnaires. Initially, the survey questionnaire was not designed to fixate particular sectors in response to the primary strategy of this research, which prioritises and invites multidiscipline sectors. It is noteworthy that the demographic section is considered as a non-parameter in measuring the adoption impact in the research. In fact, the awareness of AI technologies has been contemporarily increasing across industries and there are multiple sectors that have recognised the advanced-technology pattern. The diverse proportion of participants working in different industries crucially contributes to demonstrate the diversity and the diffusion rate of AI in the current HR market. In addition, due to the essence of exploratory research, the setting establishment for inclusion criteria was mollified with the purpose of increasing multiplicity aspects. Hence, the background information provided retrofits readers with a more transparent view regarding the diffusion of AI in HR across distinct sectors.

As discussed in Chapter 3, for Phase 2 of the quantitative study, probability sampling technique was applied to suitably proceed further the research phenomenon. The mechanism of selecting this sampling method rooting from exploratory research nature and the large population size of HR professionals. As mentioned previously, the research embraced the diversity of HR professionals from different sectors. This is because AI was a novel and emergent concept when conducting this research. Hence, the limitation of the sample size to a specific and characterised cohorts might not provide sufficient data to interpret the phenomenon of AI in HR market. To further clarify the sampling technique, among the four different sub-techniques under probability sampling including simple random sampling, systematic sampling, stratified sampling and cluster sampling (Saunders et al., 2009), the researcher employed the simple random sampling strategy. The simple random strategy refers to a sampling technique involving a random selection of individuals from the population without characterised criteria or grouping (Saunders et al., 2009). Hence, this approach provides an ease and a better accessibility to large sample size and allows equal opportunity for each individual to be included in the sample. However, one of the disadvantages of this sampling technique is the collection unstratified data which reduces the adequate stratum to be presented in the research sample (Leavy, 2023). This can decrease the fair analysis of subgroups embedded in the selected sample. Hence, the acknowledgement of the limitation from this sampling technique was presented in Chapter 8 in **section 8.7** of research limitation of this research.

Reflected in the data, the proportions regarding industries of HR professionals involved in the research regarding AI-powered HRM were depicted as follow (from the highest to the lowest): education (25%), manufacturing (16%), accommodation and food services (11%), financial and insurance activities (9%), Human health and social work activities (8%), arts, entertainment, and recreation (7%). Hence, the ratio of HR professionals participating in the research arguably provides diverse nuances among sectors when exhibiting an overarching view of AI diffusion in HR across industries, dominantly in education and manufacturing sectors. However, in recent years, AI applications are gradually becoming prevalent across industries and therefore the coverage of the advanced technologies in HR realms across industries is unexceptionable. It is argued that HR function possesses similar performance traits and is portrayed as an integral part of businesses in most industries (Ahmad and Schroeder, 2003). In this vein, the industry information therein contributes to enhance diversity of innovation awareness and demonstrate the ubiquity of AI in HRM among different sectors.

6.2.2 Job Designation

Table 6.1 also reveals the job designations of HR professionals participating in the second phase of the research. In particular, the respondents recruited in this thesis were employed in HR related roles from executives to administrators and HR-related professions such as HR advisors and consultants. As explained in the Methodology Chapter, unlike the majority of research regarding technology adoption intention, the managerial roles were not the only source that the author seeks to investigate the adoption intention although leadership is entrenched as a significant feature in technology adoption. In contrast, the dynamic of the business market has induced critical transformation in contemporary business models and organisational structures, which challenges the authority of innovation transference in decision-making process (Teece, 2018). Prior studies suggest the transition is rooted from various economic and social factors, which challenge the hierarchy system of the old economy (Sprinkle and Urick, 2018). By the virtue of it, the research provided a more extensive inclusiveness in HR professionals from different levels.

The sample of HR professionals was as follows: HR practitioners (60%), HR executives (32%), and HR related professionals (8%). To elaborate, executive level in HR professionals would acquire the job function delineates in *decisional spectrum* (discussed in Chapter 4). In contrast, practitioners' levels would possess job roles which are mainly captured in *administration* *spectrum*. In this research, the respondents could specify their positions in the survey questionnaire if they are unsure about the position. Importantly, the primary concentration at this stage is on the stances of HR professionals since the HR functions are considered as mostly applied within their onuses. Based on the positions of the participants, their HR main functions are embedded in either administration or decision-making scope. This ensures the knowledge sufficiency and insightful stances about the research subjects to be acquired from the selected respondents.

6.2.3 Working Experience

It is illustrated in Table 6.1 that nearly 60% of the participants were involved in the HR field with 1-5 years of work experience. The subsequent group of 20% belongs to the more senior employees with the industry years ranging from 6-10 years. Further, the most senior groups, which ranged from 11 to above 20 years, also represented about 20% of the sample size. Hence, it could be seen from the sample group, the dominance of HR professionals (around 60%) participated in this research belongs to the entrance level in the HR profession. The majority of the HR professionals with early working experience participated in this research could be reasonably explained due to the growth of young generations (e.g. Generation Z) in the employment market. In fact, the research subject and prospect regarding AI have the proclivity to capture the attention of the younger generations due to the larger usage of technology embedded in their experience (Vitezić and Perić, 2021). Nevertheless, there has not been much research to explore the dynamic of this emerging generation regarding the research subject because the focal point has mostly been senior employees. Hence, the research is considered to provide a practical perspective from both entry-level and senior HR professionals in the contemporary HR market.

6.2.4 Familiarisation of AI

Within this research, the researcher facilitates the self-awareness feature from the participants by providing a measurement scale of AI familiarisation with five modes to rank the "concept apprehension". According to **Table 6.1**, most of the respondents stated to acquire limited to developed understandings regarding AI. Only 4% of the respondents claimed to have advanced knowledge about AI and three respondents chose the option of not familiar with the concept. As mentioned earlier, the demographic section does not contribute to measuring the adoption intention but to explore the proliferation of the concept. The question, therefore, was designed to examine the diversity and the degree of diffusion in AI acceptance within the HR market. As reflected on the collected data, the familiarisation of AI in HR is considerably increasing with the dominant responses (42%) of moderate understanding and (20%) at developed stage.

This is in line with the report from (Mckinsey, 2024) of the increase in AI awareness across business sectors. Although 32% of the respondents stated they had limited understanding regarding AI, this also indicates that the concept was initially raised into their concerns. On grounds of it, the identified understanding levels from the participants is considered adequately supported for the further testing on AI adoption intention in this research.

6.3 Process of Data Management

To ensure the quality of data, the processes of preparing and managing the research's data was stringently maintained. This is in line with the recommendation that data preparation and management while conducting research is critically substantial at further stages of data analysis (Lucko and Mitchell, 2010). Initially, the project questions for the questionnaire were developed based on the variables identified in the qualitative research. The questions were shaped by adapting the pre-existing questions in prior associated research (discussed in Chapter 3). After the establishment of the questionnaire items, Qualtrics (the preferred online platform) was applied to structure and monitor the survey results as well as retain the empirical data collected from the participants. The use of Qualtrics online survey contributes to maintaining the quality of entry data in terms of accuracy and instant notifications on research progression. The collected data was further exported for SPSS analysis. During the data collection phase, answers which did satisfy the inclusive criteria were excluded to maintain the consistency and accuracy for the research. The cleansed data was subsequently transferred to the SPSS version 25 for regression analysis. To execute this, the coding process was applied on the selected variables. This is to generate an abbreviation system supporting the illustration of data on this statistical software.

Furthermore, the process of evaluating the data corpus is entrenched as critical in terms of controlling missing data and managing the normal data distribution in statistical analysis (Dannels, 2018). In this thesis, the process was conducted to investigate any anomalies or missing data that potentially impacts the data analysis. Specifically, at the outset, the mitigation approach on the missing data was applied in the design stage of the survey questionnaires on Qualtrics. "Force response" function was applied across the questions to circumvent the participants from skipping questions or submitting the survey questionnaire without completing all sections. At the second layer, the data collected from Qualtrics was exported to an excel file for further inspection before being imported to SPSS software. Within the Excel platform, the filter function was applied to identify any missing data which, if it occurs, would be presented blank on the cell of that variable. Nevertheless, the strict application of "force response" function on Qualtrics at the first stage successfully ensured the comprehensiveness of the data. Data cleansing was subsequently conducted for further stages of data analysis.

6.4 Summary of main constructs and measuring variables

AI Adoption Intention in HR (IU) was measured based on the six main constructs identified in the qualitative research. Within each construct, the represented variables were applied to directly illustrate the correlation between the independent variables and dependent variables (IU). In fact, the attachment of each variable to the main constructs were examined and illustrated in prior research in related fields regarding technology adoption (discussed in the extended literature review). **Table 6.2** illustrates how the variables were coded on SPSS software.

Table 6.2: Coding process for selected constructs on SPSS (generated by the researcher)

Independent Variables	Coding	Measurement codes
Construct 1: Effort Expectancy (EE)		
Ease of Use Job Compatibility	EOU JC	EOU1 - EOU4 JC1 - JC4
Construct 2: Facilitating condition (FC)		
Leadership Support Innovation Driven	LS ID	LS1 – LS4 ID1 – ID4
Construct 3: Performance Expectancy (PE)		
Cost Effectiveness Task Versatility	CE TV	CE1 - CE4 TV1 – TV4
Construct 4: Social Influence (SI)		
Employer Branding Subjective Norms	EB SN	EB1 - EB4 SN1 – SN4
Construct 5: Status Quo Bias (SQB)		
Cognitive Misperception Perceived Cost Psychology Commitment	CM PC PYC	CM1 – CM4 PC1 – PC4 PYC1 – PYC4
Construct 6: Perceived Risk (PR)		
Bias Concern Fear of the Unknown Perceived Unemployment Privacy Concerns	BC FU PU PRC	BC1 - BC4 FU1 – FU4 PU1 – PU4 PRC1 – PRC4
Dependent Variable	Coding	Measurement codes
Intention to adopt AI	**ITA**	**ITA1 – ITA4**

Dependent variable: To measure ITA, the research applied three-item measurement which was utilised in the prior research regarding technology adoption by Venkatesh et al. (2003). The three items are: (1) "I plan to use AI technologies in the future", (2) "I intend to use AI technologies in the future" and (3) "I predict I would use AI technologies in the future". A 5 Point-Likert scale, ranging from level 1 "Strongly Disagree" to level 5 "Strongly Agree", was subsequently used to evaluate the items. Statistical test for data distribution was subsequently applied in SPSS. The results were next used in the Cronbach's Alpha Coefficient test to examine the reliability and validity of the measured items.

Independent variables: In a similar line, the six constructs representing the adoption of influential drivers of AI in HRM were measured by applying four-item measurement on each distinct variable (except for EB variable with three-item measurement) inspired by earlier research. Specifically, according to **Table 6.2**, Construct 1 (EE) includes two variables (EOU and JC), Construct 2 (FC) includes two variables (LS and ID), Construct 3 (PE) includes two variables (CE and TV), Construct 4 (SI) includes two variables (EB and SN), Construct 5 (SQB) includes three variables (CM, PC and PYC) and finally Construct 6 (PR) includes 4 variables (BC, FU, PU and PRC). The total fifteen (15) adoption variables were derived from the nature of the constructs whose relationships were strengthened from prior research. The meticulous measurement and analysis of each construct contributed to illuminate the final research question regarding the degree of use and acceptance of AI by HR professionals. The answers therein were evaluated accordingly with the dependent variables by using the 5 Point-Likert scale that ranges from "Strongly Disagree" to "Strongly Agree". They were subsequently examined for consistency and validity through Cronbach's Alpha Coefficient test.

To further explain, in this stage of the research, the researcher enhanced the possibility of each variable into the inclusion and exclusion process to accomplish the irrevocable constructs. This included the portrayal of the dominant variables of each construct through conducting a certain number of regression analyses in order to (*1) statistically eliminate the irrelevant variables*; and *(2) obtain finalised groups of variables forming the measured domains*. The analysis process will be further discussed in the latter part of this chapter.

6.5 Statistical Examination for Data Distribution

Data normal distribution is one of the necessities to be considered in order to validate data in reliability tests. Normality refers to the shape of the distribution points based on the dataset and its association to the benchmark of normal distribution for statistical approaches. Hence, the initial step to examine whether the empirical data is normally distributed was conducted on SPSS. Specifically, the data from Qualtrics platform was imported into SPSS and the variables were coded with the purpose of ease for analysis. Next, the value of each construct was initially calculated on SPSS applying the function "compute variable" positioned at the "transform" tool. The final value of each construct was defined applying the mean of each construct' measurement items.

Subsequently, to visualise the distribution of data, the calculated constructs were chosen for descriptive analysis. It is posited that it is necessary to consider the Skewness and Kurtosis function to compute the normality coefficients in data distribution (Hair et al., 2019; Kline, 1986; Tabachnick and Fidell, 2019). The two mentioned coefficients are legitimate indications to explore the extent of normality in data distribution. The **Table 6.3** illustrates the data descriptive statistics of both Skewness and Kurtosis coefficients) of the normality of the dataset.

Table 6.3: Skewness and Kurtosis coefficients of the research constructs (extracted from SPSS)

Descriptive Statistics							
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Effort Expectancy	146	2.25	5.00	3.6738	.48343	-.115	.931
Facilitating Condition	146	1.75	5.00	3.7894	.51209	-.830	2.794
Performance Expectancy	146	1.13	5.00	3.8844	.52504	-1.206	4.920
Social Influence	146	2.00	5.00	3.6419	.56030	-.333	.543
Status Quo Bias	146	2.50	5.00	3.5879	.38863	.377	1.927
Perceived Risk	146	1.00	5.00	2.9932	.70402	.463	.701
Intention to Adopt	146	1.00	5.00	4.0434	.63277	-1.183	3.762
Valid N (listwise)	146						

As suggested by Blanca et al., (2013), Skewness and Kurtosis coefficients required for normal data distribution are between -2 and +2. Nevertheless, it is also recommended a threshold of -3 and +3 for Skewness and -10 and +10 for Kurtosis (Kline, 1986). It is worth mentioning that the deviation from normality of Skewness and Kurtosis does not generate a significant difference in the overall analysis when the sample size is sufficiently large (Aminu and Shariff, 2014). As indicated by Sainani (2012), a sufficient large sample size will vary depending on the research's problems, however, researchers have provided an estimation in which, despite extreme deviations from normality, an appropriate sample size (n>80) is considered enough to run required statistical tests. Reflecting on the data from this thesis, the sample size at this stage could be justified as sufficient. This is due to the Skewness values in **Table 6.3** fall within the required range of -2 to +2. Despite there being some Kurtosis values above this threshold based on Blanca et al., (2013)'s suggestions; the values were envisaged to maintain the validity in Kline (1986)'s recommended threshold. Hence, it is appropriate to consider that the thesis data is normally distributed.

6.6 Data Quality Examination

In quantitative research, examining the quality of data is necessary before conducting additional statistical analysis (Black, 2005). It is essential to have data quality verified in social science quantitative research in order to strengthen the credibility of results (Smith, 2005). In addition, data quality examination enhances the capacity of research finding communication in terms of the transparency in delivering key messages. In essence, validity and reliability tests are complementary notions which are typically applied to evaluate the quality of research data (Mohajan, 2017). Validity tests contribute to determining the degree of accuracy of the research by measuring the practicability of research ideas in reflection to research context. The test prioritises the investigation of research applicability and the reliability of its conclusion. In principle, examining research's reliability serves to enrich the apprehension of the study and distinguishes research's conclusions from prior suppositions (Khalid et al., 2012). As a result, it is envisaged that validity testing is a paramount element in assessing the study findings' generalisability. In this research, there are four primary facets of validity tests applied within the thesis which are presented in **Table 6.4**.

Table 6.4: Validity examination's criteria (Greener, 2018)

Criteria of validity test	Means	Application
Face Validity	The concentration of this assessment is to objectively decide whether the measurement items are intendedly measuring the identified variables that they are supposed to measure.	This was guaranteed by pre-testing the survey questionnaire's items during the pilot tests
Content Validity	The focal point of this assessment is to examine the extent to which a measure comprehensively captures the notion of a variable.	Content validity was maintained due to the compilation of the measuring items verified in preceding research. Additionally, pilot tests further enhanced this aspect of validity.
Construct Convergent Validity	This assessment is to examine the degree to which, within the same concept, results from one measurement instrument are positively related to other measures.	This was further confirmed through Exploratory Factor Analysis (EFA) in SPSS software (convergent validity test)
Construct Divergent Validity	This assessment is applied to examine the extent to which results from one measurement instrument are not (or weakly) correlated to results obtained through measures of other constructs.	This was further confirmed through Exploratory Factor Analysis (EFA) in SPSS software (discriminant validity test)

In practice, matters associated with validity significantly compromise the legitimacy of the research and its inferences. According to Saunders et al. (2009), the validity factor in research assesses whether a study correctly measures what it promised to capture. Within this study, the researcher concretely established the validity criteria as illustrated in **Table 6.4** with the applications of both subjective and empirical approaches. To elaborate, the subjective approach is demonstrated through the collected opinions obtained from HR professionals and research experts during the pilot test in the stage of pre-adoption and distribution of the thesis's survey questionnaire. This approach is thus a contribution to content validity tests. Simultaneously, this study further applied statistical methods of EFA to examine construct validity (the degree of divergence and convergence of the measurement items). In the latter part of this thesis, the outcomes of the discussed tests are thoroughly addressed.

6.7 Research Reliability Examination

The reliability coefficient is critically significant in determining the degree of research reliability and it is widely applied in quantitative research (Sürücü and Maslakci, 2020). Specifically, Cronbach's **α** (alpha) is a measurement to evaluate the internal consistency of the measured constructs (Saunders et al., 2009). The Cronbach's **α** coefficient plays an important role in calculating the collective relations of a set of measurement items to each other. Fundamentally, an ideal Cronbach's **α** coefficient should fall into a range of 0.6 to 0.9 to be accepted in terms of appropriate reliability (Kane et al., 2016). **Table 6.5** illustrates the level of variable acceptance in Cronbach's **α** coefficient test.

Table 6.5: Ranges Cronbach's α value (Kane et al., 2016)

Cronbach's α coefficient	Internal Consistency
$\alpha \geq 0.9$	Excellent
$0.8 \leq \alpha \leq 0.9$	Good
$0.7 \leq \alpha \leq 0.8$	Acceptable
$0.6 \leq \alpha \leq 0.7$	Questionable
$0.5 \leq \alpha \leq 0.6$	Poor
$\alpha \leq 0.5$	Unacceptable

Researchers subsequently must peruse the coefficients to decide whether to abolish insufficient variables (if occurs) and refine the measurement items to enhance the reliability of the scale. In this quantitative research, Cronbach's **α** coefficient test was executed on SPSS software across 15 independent variables and the six overall constructs. Each measurement item underwent a reliability test in grouped variables [Cronbach's **α** for EOU (EOU1, EOU2, EOU3, EOU4)] and distinct constructs [Cronbach's **α** for EE (EOU1…EOU4; JC1…JC4)]. The Cronbach's **α** coefficient results from this study are demonstrated in **Table 6.6**.

Table 6.6: Cronbach's α coefficient test' results

Constructs	Variables	Items	Corrected Item-total Correlation
Effort Expectancy - EE (Cronbach's Alpha = 0.820)	Ease of Use – EOU (**Cronbach's Alpha = 0.791)**	EOU1	0.542
		EOU2	0.588
		EOU3	0.667
		EOU4	0.619
	Job Compatibility – JC (**Cronbach's Alpha = 0.781**)	JC1	0.570
		JC2	0.591
		JC3	0.652
		JC4	0.547
Facilitating condition - FC (Cronbach's Alpha = 0.829)	Leadership Support – LS (**Cronbach's Alpha = 0.847**)	LS1	0.738
		LS2	0.725
		LS3	0.521
		LS4	0.769
	Innovation Driven – ID (**Cronbach's Alpha = 0.792**)	ID1	0.652
		ID2	0.665
		ID3	0.717
		ID4	0.420
Performance Expectancy – PE (Cronbach's Alpha = 0.86)	Cost Effectiveness – CE (**Cronbach's Alpha = 0.757**)	CE1	0.551
		CE2	0.574
		CE3	0.641
		CE4	0.466
	Task Versatility – TV (**Cronbach's Alpha = 0.752**)	TV1	0.621
		TV2	0.542
		TV3	0.589
		TV4	0.465
Social Influence - SI (Cronbach's Alpha = 0.821)	Employer Branding – EB (**Cronbach's Alpha = 0.827**)	EB1	0.694
		EB2	0.734
		EB3	0.630
	Subjective Norms – SN (**Cronbach's Alpha = 0.829**)	SN1	0.730
		SN2	0.700
		SN3	0.719
		SN4	0.492
Status Quo Bias – SQB (Cronbach's Alpha = 0.717)	Cognitive Misperception – CM (**Cronbach's Alpha = 0.844**)	CM1	0.671
		CM2	0.682
		CM3	0.700
		CM4	0.668
	Perceived Cost – PC (**Cronbach's Alpha = 0.697**)	PC1	0.556
		PC2	0.559
		PC3	0.409
		PC4	0.418
	Psycho Commitment – PCM (**Cronbach's Alpha = 0.792**)	PCM1	0.686
		PCM2	0.483
		PCM3	0.560
		PCM4	0.697
Perceived Risk - PR (Cronbach's Alpha = 0.942)	Bias Concerns – BC (**Cronbach's Alpha = 0.871**)	BC1	0.780
		BC2	0.697
		BC3	0.727
		BC4	0.700
	Fear of Unknown – FOU (**Cronbach's Alpha = 0.918**)	FOU1	0.782
		FOU2	0.825
		FOU3	0.812
		FOU4	0.826
	Perceived Unemployment – PU (**Cronbach's Alpha = 0.88**)	PU1	0.790
		PU2	0.736
		PU3	0.796
		PU4	0.643
	Privacy Concern – PCC	PCC1	0.749

	(**Cronbach's Alpha = 0.92**)	PCC2	0.822
		PCC3	0.814
		PCC4	0.880
	Intention to Adopt – ITA (**Cronbach's Alpha = 0.87**)	ITA1	0.790
		ITA2	0.769
		ITA3	0.696

The summarised results presented in **Table 6.6**, in comparison with the standard Cronbach's **α** coefficient ranges in **Table 6.5**, indicate the sufficient reliability of all constructs and variables of this research. Particularly, with an average of 0.8315 and all Cronbach's **α** coefficient results of the constructs lying in acceptable to excellent range, the overarching reliability of this thesis is categorised as satisfactory. The statistical figure implies a sufficient reliability of research's measurement items in terms of internal consistency of latent variables.

6.8 Exploratory Factor Analysis (EFA)

Fundamentally, factor analysis (FA) is a crucial element in quantitative research in terms of providing information regarding reliability, the quality of items and validity of constructs (Paatero et al., 2002). It functions based on the mechanism that observable variables could be subsided to fewer variables sharing familiar variance. The concept of FA encompasses a variety of distinct and related techniques. In principle, the FA procedure aims to project correlation frameworks among observed variables rooted on a smaller group of latent variables. It establishes a theoretical approach which is immune to error variability (Mindrila et al., 2017). In social science research, this method is widely applied with the purpose of identifying causal dimensions referred to as a common factor and estimate the degree of variance in observed variables (Fidel, 2008). This multiple approach contributes to accommodate researchers to interpret the complexity of patterns of relationships in multiple variables. FA is accommodating with two primary approaches of Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). The former approach is used to investigate the foundational correlations among the variable sets while the latter is primarily used to confirm theories which potentially possess subterranean structure of variable sets (Pallant, 2010). Within the study, the techniques of confirming the factors were disregarded with the purpose of maintaining the core insistence of the research outcomes. There are two primary reasons for this direction of the research:

Firstly, echoing the nature of sequential exploratory mixed-method research, identifying the face factors of intentional behaviours of AI adoption in HRM are the targeted orientation. The nature of exploratory research roots from the imperative of obtaining in-depth import of an emerging research subject. An overarching acknowledgement of AI adoption behaviours are yet to be stipulated and, therefore, further confirmation examination of ulterior relations of factors would not further contribute to refine the conceptual framework. In fact, CFA could fundamentally enrich the research analysis if there is a rigorous theory reinforcing the structure (Edlund and Nichols, 2019). Nonetheless, due to the precarious nature of innovation and adoption factors, there are potentially associated concepts which influence conceptual structure, which would be overlooked if this thesis interprets the results from confirming the factors. Thereby, CFA examination in this stage would trigger limited implications of the research subject.

Secondly, the main aim of this research at the current stage is to explore the defined framework of AI applications and acceptance in HRM, which requires a predominant and meticulous peruse on related adoption factors. This is to serve the long-term research purpose of the targeted research subjects of AI in HRM, where in future research, a concentration on certain HR practices and functions would distil irrelevant adoption constructs. To elaborate, the two different spectrums of decisional and administrative clarified in Chapter 4, would alter the perception on the use and acceptance of AI in a particular HR function. However, due to the establishment of an overarching AI adoption framework of this thesis, all identified factors must be considered regardless of its distinct compatibility in comparison to different HR functions. Therefore, the EFA test was applied to measure the foundation relations among the variable sets. The application of CFA would be saved for future research regarding AI applications in a specific HR function such as recruitment, selection, or learning and development.

6.8.1 Assessing criteria of the compatibility of data for EFA

6.8.1.1 Sample size

In principle, there is no universal agreement on a particular range of numbers if the data set is large. However, there is a concern on the correction coefficients among the variables if the data set is considered not generalised enough (Pallant, 2010). In fact, there are congruities on the acknowledgement of sufficient sample size for the factor analysis. **Table 6.7** illustrates different suggestions from research scholars regarding EFA's sample size.

Table 6.7: Recommended Ratio of sample size for EFA

Authors	Remarks
(Hundleby and Nunnally, 1968) and (Everitt, 1996)	10:1 Ratio (10 cases for 1 item)
(Cattell, 1966)	3:1 or 6:1 Ratio (3 cases for 1 item or 6 cases for 1 item)
(Gorsuch, 1983) and (Kline, 1986)	General sampling at least 100 cases
(Comrey and Lee, 2013)	Scale suggested: 50 – very poor, 100 – poor, 200 – fair, 300 – good, 500 – very good, and 1,000 or more – excellent.

(Pituch and Stevens, 2015)	Not given a particular ratio, above 150 is good, suggested if less then 150 cases, apply Barret's sphericity's test
(Tabachnick and Fidell, 2019)	5:1 Ratio (5 cases for 1 item), if less than 150 cases, loading markers must be > 0.7

Across 225 cases involved in this research, there were 146 valid cases for quantitative analysis after data refinement. Delving to this result, further tests and loading markers must be concretely applied to ensure the validity and credibility of the statistical analysis. In brief, the loading markers for the tested items in this thesis were above 0.7 and Barret's sphericity's tests of the variables were less than 0.05, which indicates the sufficiency of statistical values generated from the empirical data. The detailed explanations will be illustrated and discussed in the next following result-interpretation sections.

6.8.1.2 Strength of intercorrelation

The second criterion to be evaluated before applying EFA is to assess the strength of intercorrelation among items. Therefore, to appropriately determine the sufficiency of FA, there are statistical measures which are significant in authorising the suitability of data factorability. In particular, there are indexes which must be considered in accessing data adequacy. **Table 6.8** illustrates the fundamental criteria in EFA data assessment.

Table 6.8: EFA's intercorrelation indexes

Kaiser-Meyer-Olkin (KMO)	Bartlett's test of sphericity	Eigenvalue rule is Kaiser-Meyer-Olkin	Factor loadings
Kaiser-Meyer-Olkin measure generates the value to determine the compatibility of factor analysis. KMO index should be in a range (0.5 ≤ KMO ≤ 1) to implement EFA. In case the value is less than 0.5, EFA feasibility is not available.	*Bartlett's test of sphericity* measure is applied to determine correlation ability of the observable variables. The significance of Bartlett's test (Sig.) must be less than 0.05 to demonstrate correlation ability in the correlation matrix.	*Eigenvalue rule* is *Kaiser-Meyer-Olkin criterion* which represents the overall amount of variance accounted for a factor. According to this rule, any eigenvalue that is less than one (<1) will be eliminated.	*Factor loadings technique* examines *the* correlation affiliation between the original variables and the latent factors. Squared factor loadings indicate what percentage of the variance in original variables is explained by a factor. Factors loading must be above (≥ 0.3) to be accepted.

Sixteen (16) measurement variables (as presented in **Table 6.6)** in this research were adopted in EFA processed through SPSS software. Results of the appropriateness of dependent and independent variables were benchmarked correspondingly to the required intercorrelation indexes. The next section released the outcomes of data adequacy tests though communicating the results of KMO and Bartlett's Tests of the variables. For further data interpretation, Varimax Rotation technique was recruited to regulate the loading patterns of the research's measurement items. Principal Component Analysis (PCA) was applied to interpret the result through the accepted eigenvalue as indicated in **Table 6.8.** In common parlance, the factors with an eigenvalue that is greater than 1 will be eliminated.

6.8.2 Results of the compatibility of data for EFA test

Table 6.9: KMO and Bartlett's Test of dependent variable (extracted from SPSS)

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.724
Bartlett's Test of Sphericity	Approx. Chi-Square	220.587
	Df	3
	Sig.	.000

In response to Kaiser, the KMO index for ITA is 0.724 (> 0.5) which indicates the adequacy of data for EFA. In addition, the significance of Bartlett's test is lower than 0.05 which indicates that EFA is compatible for this set of data. To further evaluate the data set, PCA was conducted as presented:

Table 6.10: Total Variance Explained of dependent variable (extracted from SPSS)

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.382	79.401	79.401	2.382	79.401	79.401
2	.383	12.781	92.182			
3	.235	7.818	100.000			

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component
	1
Intention to adopt 1	.912
Intention to adopt 2	.902
Intention to adopt 3	.858

Extraction Method: Principal Component Analysis.
a. 1 components extracted.

There is only one (1) component that was extracted when conducting EFA for the dependent variable. This is considered reasonable since it is expected to have only one factor represented for the dependent variable. It is suggested that if the original dependent variable is separated into multiple factors, the research framework and dataset may need to be revised. Based on that, it is reasonable for the research framework and dataset to be used in this study.

Data Compatibility test for EFA test for independent variables

To ensure the convergence and divergence of the EFA test, the dataset underwent five different trials and retained the final result as follows. According to **Table 6.11**, it is indicated that the result is valid since all the indices are within the acceptable range. Particularly, the KMO index is greater than 0.5 (KMO = 0.836) and the significance of Bartlett's test is also less than 0.05 (sig. < 0.05).

Table 6.11: KMO and Bartlett's Test of independent variables (5th trial)

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.836
Bartlett's Test of Sphericity	Approx. Chi-Square	3161.412
	df	561
	Sig.	.000

Table 6.12: Total Variance Explained of independent variable from 5th EFA test

Total Variance Explained

Component	Initial Eigenvalues Total	Initial Eigenvalues % of Variance	Initial Eigenvalues Cumulative %	Extraction Sums of Squared Loadings Total	Extraction Sums of Squared Loadings % of Variance	Extraction Sums of Squared Loadings Cumulative %	Rotation Sums of Squared Loadings Total	Rotation Sums of Squared Loadings % of Variance	Rotation Sums of Squared Loadings Cumulative %
1	8.041	23.649	23.649	8.041	23.649	23.649	6.123	18.009	18.009
2	6.437	18.932	42.580	6.437	18.932	42.580	3.296	9.695	27.703
3	2.460	7.234	49.814	2.460	7.234	49.814	2.808	8.260	35.963
4	2.031	5.974	55.788	2.031	5.974	55.788	2.592	7.625	43.588
5	1.889	5.556	61.345	1.889	5.556	61.345	2.579	7.586	51.174
6	1.368	4.023	65.368	1.368	4.023	65.368	2.429	7.144	58.318
7	1.198	3.523	68.890	1.198	3.523	68.890	2.355	6.925	65.244
8	1.015	2.986	71.876	1.015	2.986	71.876	2.255	6.633	71.876
9	.848	2.493	74.369						
10	.820	2.412	76.781						
11	.696	2.046	78.827						
12	.607	1.787	80.614						
13	.580	1.706	82.320						
14	.538	1.582	83.903						
15	.518	1.525	85.427						
16	.449	1.320	86.747						
17	.421	1.238	87.985						
18	.409	1.204	89.189						
19	.400	1.176	90.366						
20	.372	1.094	91.460						
21	.327	.961	92.421						
22	.305	.897	93.318						
23	.293	.861	94.179						
24	.263	.775	94.953						
25	.238	.700	95.653						
26	.228	.670	96.323						
27	.223	.655	96.977						
28	.200	.589	97.566						
29	.194	.570	98.137						
30	.163	.479	98.616						
31	.153	.450	99.066						
32	.122	.360	99.426						
33	.105	.310	99.736						
34	.090	.264	100.000						

Extraction Method: Principal Component Analysis.

Table 6.12 of *Total Variance Explained* (TVE) summarises the total variance explained by the factor analysis and provides an indication about the number of valid factors. The *Initial Eigenvalues* domain consists of three columns. The first column provides the eigenvalues of all the factors in a descending order. It is then followed by the percentage of each variance and eventually the cumulative percentage of all variances. In this research, EFA was reassessed until the elimination process of measurement items reached the sufficient level reflected in the observed components. In relation to this, the selection and elimination procedure were conducted in five trials of EFA within this research (**Appendix 6.3**). Hence, to summarise the process, there were eight (8) factors identified by TVE in the final trial, which accounted for 71.876% of the total variance (illustrated in **Table 6.12**). To further progress, Pattern Matrix was analysed to determine the appropriate measurement items as portrayed in **Table 6.13**.

Table 6.13: Pattern Matrix of measurement items from 5th EFA test

	Component							
	1	2	3	4	5	6	7	8
FU4	.866							
FU3	.834							
FU2	.832							
FU1	.804							
BC1	.775							
BC3	.758							
BC2	.748							
BC4	.741							
PU4	.512							
PRC4		.887						
PRC3		.874						
PRC2		.825						
PRC1		.705						
CM1			.813					
CM3			.763					
CM4			.691					
CM2			.673					
TV3				.794				
TV2				.686				
TV1				.680				
CE3				.626				
EOU3					.796			
EOU4					.780			
EOU1					.742			
EOU2					.699			
LS1						.827		
LS2						.823		
LS4						.812		
EB2							.801	
EB1							.784	
EB3							.782	
PYC3								.823
PYC4								.816
PYC1								.701

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 8 iterations.

Fundamentally, a particular variable should load higher on one factor and lower on other factors (Holmes, 2020). The decision to select or retain a particular factor (if cross loading occurs for the majority of items) was executed throughout different EFA tests where the overarching items were well illustrated on the rotated matrix. In fact, it is argued that the decision on selecting or eliminating items cannot rely on a "simple structure" since FA involves complexity and sophisticated interpretation from researchers' understanding of the research subjects (Pallant, 2010, p.127). In practice, a facile result extracted from FA is not inevitable since there are scenarios where *(1) numbers of components are loaded by variables* and *(2) solely one or two variables load on a component*. In such cases, it is suggested to repeat the rotation to recruit "optimal solution" (Pallant, 2010, p.258). Adhering to the same principle, the researcher applied a similar process for the EFA tests.

Given six main constructs covering fifteen represented variables in this research, it is complex for the selection process since there is a tendency where certain measurement components of a variable are loaded in other variables which belong to the same construct. In this case, to augment the selection-and-elimination decision, it is important to envisage the research topic to deliver the causation decision (Pett et al., 2003). From this theoretical standpoint, to maintain Construct Convergent Validity, the researcher would initially not eliminate components of distinct variables grouped in one parent construct. The rooted cause is due to the fact that they inherently represent the large theme of the research's observed variables. In contrast, measurement components of variables loaded in other variables which belong to a distinct construct would be envisaged to retain or eliminate. The adjustment was adopted based on theoretical justifications and the significance level of that variable reflected on the given construct.

In the previous EFA trials, the loading regression values of items possessing a smaller value than the recommended standard will be eliminated. As claimed by Lộc (2017), if the difference between these factor loadings is smaller than 0.3, the items must be disregarded. In addition, conforming to Tavakol and Wetzel (2020), sufficient loading value for EFA must load a minimum of 0.5 in value since the indicated value depicts an appropriate convergence of measurement items reflected on the respective variable. Hence, the loading regression values of the measurement items at this final trial were satisfied (greater than 0.5) in accordance with the suggested minimum level. It can be observed in **Table 6.13** that the measurement items were grouped in distinct categories reflecting the parent constructs. Since the overall measurement items satisfied the required validity aspects of EFA, the researcher finalised the variables as presented in **Figure 6.1**

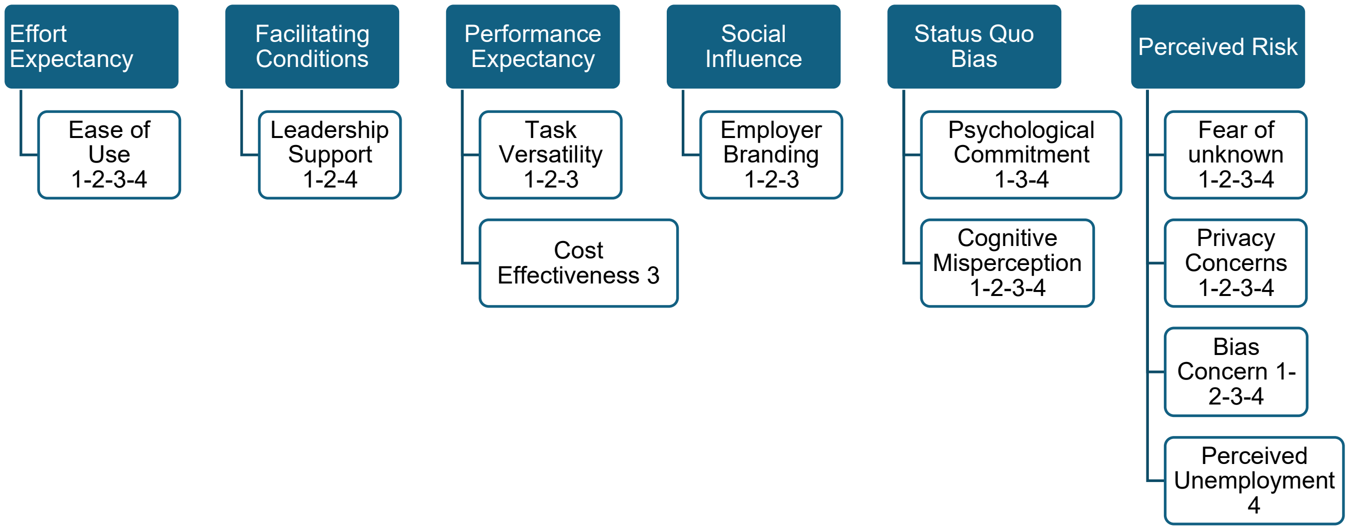

Figure 6.1: Distilled measurement items after 5th EFA test

In order to enhance the conformity of the factor extraction, Cattell's Scree Test was subsequently conducted to verify the smallest number of factors demonstrating the variables' interrelationship. According to Cattell (1966)**,** the eigenvalues of the factors plotted above the elbow-shaped curve must be retained as they provide the explanation of the total variance in the dataset. Following the mentioned rule, it can be observed from **Figure 6.2** that there were 11 factors with the sufficient eigenvalues (≥ 1) as suggested by Hair et al. (2019). The number equals with the total in dependent variables of the six main constructs retained after EFA test.

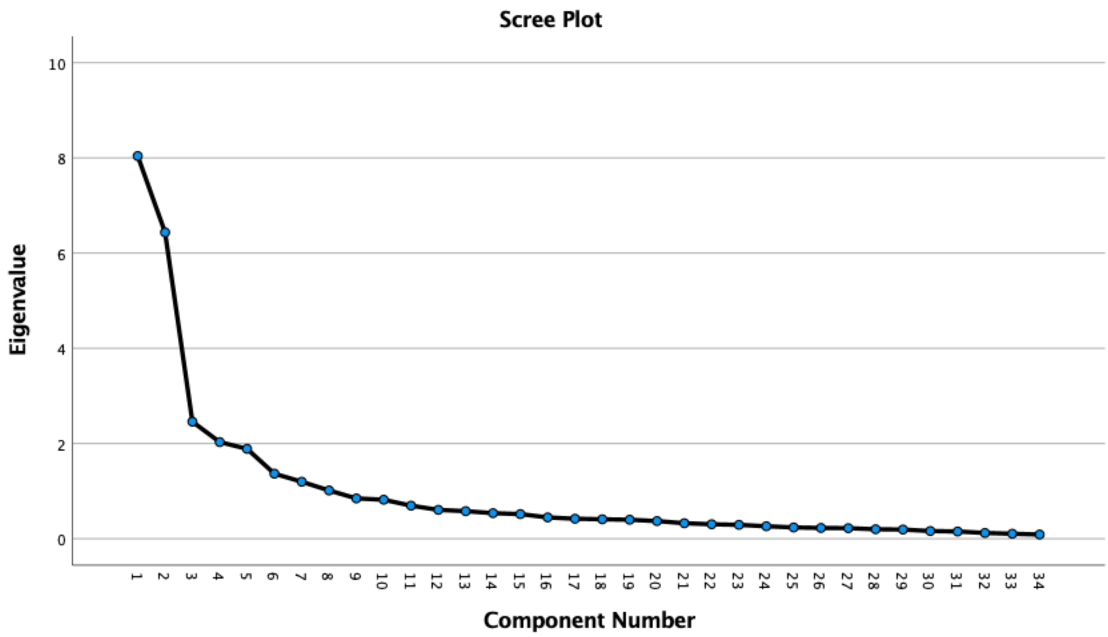

Figure 6.2: Distribution of eigenvalues in Scree Test Result

In sum, the final constructs for the research model after the EFA examinations were finalised and grouped as illustrated in **Table 6.14**

Table 6.14: Finalised constructs distilled through EFA

Parent Constructs	Variables	Observed items	Variable type
Effort Expectancy (EE)	Ease of use	EOU1, EOU2, EOU3, EOU4	Independent
Facilitating Condition (FC)	Leadership Support	LS1, LS2, LS4	Independent
Performance Expectancy (PE)	Task Versatility	TV1, TV2, TV3	Independent
	Cost Effectiveness	CE3	Independent
Status Quo Bias (SQB)	Cognitive Misperception	CM1, CM2, CM3, CM4	Independent
	Psychological Commitment	PYC1, PYC3, PYC4	Independent
Perceived Risks (PR)	Fear of Unknown	FU1, FU2, FU3, FU4	Independent
	Privacy Concern	PRC1, PRC2, PRC3, PRC4	Independent
	Bias Concern	BC1, BC2, BC3, BC4	Independent
	Perceived Unemployment	PU4	Independent
Social Influence (SI)	Employer Branding	EB1, EB2, EB3	Independent
	Intention to use AI	IU1, IU2, IU3	Dependent

6.9 Pearson Correlation Analysis

After finalising the constructs through EFA, the research further progressed with Pearson Correlation Analysis. The analysis is entrenched to display the direction and intensity of the variables' linear relationship. Hence, correlation coefficients are conducted in statistics to measure how significantly two variables relate to each other. The Pearson correlation coefficient (*r*) is designed for interval level variables, and it could obtain only the values ranging from -1 to +1 which indicates the positive (+) or negative (-) relationship between two variables. The intensity of the variables' relationship is determined based on the (*r*)'s absolute number. In correlation analysis, the correlation of 1 or -1 is considered as perfect since it suggests that the value of a variable can be confirmed by obtaining the value of the other variable. On the contrary, the value of 0 in a correlation depicts no relationship between variables. Based on the previous explanation, the researcher assessed the direction and strength of the relationship. The row Sig. (2-tailed) indicates the index used to test the meaningful correlation between variables:

- Sig. <0.05 demonstrates a meaningful correlation.
- Sig. >0.05 demonstrates no meaningful correlation.

Table 6.15: Correlations among variables

Correlations								
		EE	FC	PE	SI	SQB	PR	IU
EE	Pearson Correlation	1						
	Sig. (2-tailed)							
	N	146						
FC	Pearson Correlation	.240**	1					
	Sig. (2-tailed)	.003						
	N	146	146					
PE	Pearson Correlation	.195*	.219**	1				
	Sig. (2-tailed)	.019	.008					
	N	146	146	146				
SI	Pearson Correlation	.308**	.364**	.419**	1			
	Sig. (2-tailed)	<.001	<.001	<.001				
	N	146	146	146	146			
SQB	Pearson Correlation	.356**	.451**	.531**	.445**	1		
	Sig. (2-tailed)	<.001	<.001	<.001	<.001			
	N	146	146	146	146	146		
PR	Pearson Correlation	.132	.179*	-.293**	-.042	-.066	1	
	Sig. (2-tailed)	.111	.031	<.001	.613	.425		
	N	146	146	146	146	146	146	
IU	Pearson Correlation	.169*	.376**	.605**	.574**	-.633**	-.230**	1
	Sig. (2-tailed)	.042	<.001	<.001	<.001	<.001	.005	
	N	146	146	146	146	146	146	146

According to the above table, the significance value (2-tailed) between independent variables and dependent variables is smaller than 0.05 which demonstrates that there is a meaningful correlation between them. The Pearson correlation coefficient (r) between dependent variable (*Intention to Use AI*) and five independent variables of *Effort Expectancy, Facilitating Condition, Performance Expectancy and Social Influence* have positive Pearson Correlation values which are 0.169; 0.376; 0.605; 0.574 respectively, which portrayed that there was a positive correlation between dependent variable and these five variables. On the contrary, correlation coefficient (r) between *Intention to Use* and *Perceived Risk and Status Quo Bias* were -0.633 and -0.230 respectively which illustrated a negative relationship between dependent variable and the two observed variables.

6.10 Multiple Regression Analysis

To project the relationship among variables, multiple linear regression was applied at this stage. In principle, multiple linear regression is formulated to analyse and explain the causation effect between one continuous dependent variable (Y) and two or more independent variables (X)

(Uyanık and Güler, 2013). According to Hair et al. (2019), the equation of multiple regression analysis is coined as follow.

$$\boldsymbol{Y = \beta 0 + \beta 1 x 1 + \cdots + \beta n x n + \varepsilon}$$

Y = dependent variable

X_i = independent variable

β_1 = parameter

ε = error

In multiple regression analysis, there are certain indexes to be envisaged to assess correlation coefficients of individual pairs of variables, level of significance and the number of cases. To be specific, the criteria are adopted in accordance with the following rules.

R squared or Adjusted R square: applied to visualise the degree of variance of two variables. The coefficient of determination was computed through square R value. The Adjusted R square reflects the explanation level of dependent variables by independent variables in the regression model. This index ranges from 0 to 1 indicating the meaning of the statistical model.

Significance of F: applied to examine the suitability degree of the model to conduct the regression. If significance is less than 0.05 (<0.05), multiple regression is concluded to be appropriate for the data set. This index could be traced in ANOVA Table from SPSS.

Significance of t: used to test the statistical meaning of coefficient. If significance is <0.05, independent variable is concluded to influence dependent variable. This index can be found in the Coefficient table.

Table 6.16: Model Summary (extracted from SPSS)

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.772[a]	.596	.579	.41074	1.817
a. Predictors: (Constant), PR, SI, EE, FC, PE, SQB					
b. Dependent Variable: IU					

In social sciences, it is entrenched that if the Adjusted R Square is larger than 35%, it indicates a respectable amount of variance explained (Pallant, 2010). In this case, according to **Table 6.16**, the Adjusted R square was 0.579 (57.9%) which depicted that 57.9% variance of the Intention to Adopt AI could be explained by independent variables.

Table 6.17: ANOVA Table (extracted from SPSS)

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	34.609	6	5.768	34.190	<.001[b]
	Residual	23.450	139	.169		
	Total	58.059	145			
a. Dependent Variable: IU						
b. Predictors: (Constant), PR, SI, EE, FC, PE, SQB						

The research progressed with accessing ANOVA table to examine model appropriateness to conduct regression analysis. As shown in **Table 6.17**, the significance value of F was smaller than 0.05 (sig. = 0.000) which indicated that multiple regression models are suitable for this research in accordance with the data set. In this regard, Standardised Coefficients Beta values were subsequently scrutinized. **Table 6.18** demonstrates the Correlation Coefficients between groups of variables.

Table 6.18: Coefficients Table (extracted from SPSS)

Coefficients[a]								
		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	.518	.364		1.424	.157		
	EE	.103	.058	.106	1.772	.079	.820	1.220
	FC	.096	.060	.102	1.601	.112	.718	1.393
	PE	.289	.078	.256	3.717	<.001	.611	1.638
	SI	.275	.059	.303	4.695	<.001	.700	1.430
	SQB	-.445	.094	-.345	4.755	<.001	.551	1.814
	PR	-.111	.053	-.124	-2.091	.038	.830	1.205
a. Dependent Variable: IU								

According to the result from the Coefficient Table, the coefficient of **Effort Expectancy** was smaller than zero (β = 0.106) which means that this variable has a positive impact on the dependent variable. However, the significant value was greater than 0.05 (sig. = 0.079) demonstrating that Effort Expectancy is statistically insignificant to explain the Intention. Therefore, hypothesis 1 was not supported by the data.

Rejected H1: Effort Expectancy has positive impact on the intention of AI adoption in HRM.

The coefficient of **Facilitating Condition** was greater than zero (*β* = 0.102) which indicated that this variable has a positive motivation effect on the dependent variable. However, its significant value was greater than 0.05 (sig. = 0.112), this variable is also statistically insignificant to explain the Intention. Therefore, hypothesis 2 was not supported by the data.

Rejected H2: Facilitating Condition has positive impact on the intention of AI adoption in HRM.

The coefficient of **Performance Expectancy** was greater than zero (β = 0.256) which addressed that this variable has a positive motivation effect on the dependent variable. As its significant value was also smaller than 0.05 (sig. < 0.001), this variable has statistical meaning in explaining the intention. **Therefore, hypothesis 3 was supported by the data.**
Accepted H3: Performance Expectancy has positive impact on the intention of AI adoption in HRM.

The coefficient of **Social Influence** was greater than zero (β = 0.303) which stated that this variable has a positive motivation effect on the dependent variable. As its significant value was also smaller than 0.05 (sig. < 0.001), this variable has statistical meaning in explaining the intention. **Therefore, hypothesis 4 was supported by the data.**
Accepted H4: Social Influence has positive impact on the intention of AI adoption in HRM.

The coefficient of **Status Quo Bias** was smaller than zero (β = -0.345) which signified that this variable has a negative effect on the dependent variable. As its significant value was smaller than 0.05 (sig. < 0.001), this variable has statistical meaning in explaining the intention. **Therefore, hypothesis 5 was supported by the data.**
Accepted H5: Status Quo Bias has negative impact on the intention of AI adoption in HRM

The coefficient of **Perceived Risk** was smaller than zero (β = -0.124) which stated that this variable has a negative effect on the dependent variable. As its significant value was also smaller than 0.05 (sig. = 0.038), this variable has statistical meaning in explaining the intention. **Therefore, hypothesis 6 was supported by the data.**
Accepted H6: Perceived Risk has negative impact on the intention of AI adoption in HRM

The results of the correlation analysis (**Table 6.15**) indicate that several independent variables such as effort expectancy, facilitating conditions, performance expectancy, social influence, perceived risk, and status quo bias—are significantly associated with intention to use AI. However, the multiple regression analysis (**Table 6.18**) shows that only performance expectancy, social influence, status quo bias, and perceived risk retain statistically significant effects when all predictors are entered simultaneously. Effort expectancy and facilitating conditions, although positively correlated with intention to use AI, do not exhibit significant unique effects in the regression model. This apparent inconsistency can be explained by both statistical and contextual factors related to the research design and participant group.

First, correlation analysis examines pairwise relationships in isolation, while regression analysis estimates the unique contribution of each independent variable after controlling for others. As shown in **Table 6.15**, several predictors—particularly performance expectancy, social influence, and facilitating conditions—are moderately intercorrelated. When entered together into the regression model, this shared variance reduces the unique explanatory power of effort expectancy and facilitating conditions. This interpretation is supported by **Table 6.18**, where the standardised coefficients for effort expectancy ($\beta = .106$, $p = .079$) and facilitating conditions ($\beta = .102$, $p = .112$) fall below conventional significance thresholds once stronger predictors are accounted for.

Second, the relatively modest sample size ($n = 146$) may also have contributed to the non-significant regression effects for some predictors. While the sample size is adequate for correlation analysis and regression modelling, smaller samples reduce statistical power in multivariate models, making it more difficult to detect small or moderate unique effects when several predictors are included simultaneously. As a result, variables such as effort expectancy and facilitating conditions—whose effects appear weaker relative to other predictors—may not reach statistical significance despite showing meaningful bivariate relationships with intention to use AI.

Third, characteristics of the research participants provide further contextual explanation. The sample also comprises HR professionals working in organisational environments where AI adoption remains at an early or exploratory stage. In such contexts, respondents may have limited direct experience with AI systems, which can reduce the salience of operational factors such as ease of use and infrastructural support. Instead, intention formation is more strongly influenced by anticipated performance benefits and social or organisational signals regarding the strategic importance of AI. This is reflected in the strong regression effects of performance expectancy ($\beta = .256$, $p < .001$) and social influence ($\beta = .303$, $p < .001$).

6.11 Summary Quantitative Research Findings

The results and statistical analysis showcased in this chapter has elaborated the answers for RQ3 from this thesis. In addition, the thesis therein achieved the overarching objective of confirming the impact of exploratory factors from qualitative research on AI adoption intention in HRM. The relationship of each adoption factor could be observed from **Table 6.19.** This section will provide more discussions about the findings of this quantitative study regarding the supported and rejected factors from the adoption model in HRM.

Table 6.19: Summarised hypotheses testing

Tested Hypothesis	Research Decision
H1: Effort Expectancy has positive impact on the intention of AI adoption in HRM	Not Supported
H2: Facilitating Condition has positive impact on the intention of AI adoption in HRM	Not Supported
H3: Performance Expectancy has positive impact on the intention of AI adoption in HRM	Supported
H4: Social Influence has positive impact on the intention of AI adoption in HRM	Supported
H5: Status Quo Bias has negative impact on the intention of AI adoption in HRM	Supported
H6: Perceived Risk has negative impact on the intention of AI adoption in HRM	Supported

Effort Expectancy (EE) was hypothesised to positively influence the intention of adopting AI in HRM; however, its impact was rejected from the result of this quantitative study which is in line with the study of Horodyski (2023). In their investigation about the intention to adopt AI in the recruitment process, authors proved that EE is statistically not associated with the behavioural intention to use AI in HRM practices (specifically recruitment). Likewise, Islam et al. (2024) examined the employment of AI in hiring talents, where they hypothesised that EE positively influences behavioural intention to use AI in such processes. Nevertheless, the role of EE was later found to have insignificant impact on behavioural intention. These findings suggest that user's perception of how easy or difficult it is to use AI in HRM may not considerably influence HR professionals' intention to employ this advanced technology. Additionally, it is essential to recognise the role of other factors in shaping users' intention toward the use of AI in HRM.

Facilitating Condition (FC) was hypothesised to positively impact the intention of adopting AI in HRM; however, its significant role was rejected from the result of this quantitative examination which is in line with the study of Hmoud and Várallyai (2020). The authors investigated the determinants of AI adoption in HR Information Systems (HRIS) in which FC is one of the influencing factors. Nevertheless, the significant impact of FC on HR professionals' intention toward AI-based HRIS was rejected during the statistical analysis. Although this result contradicts with the original theory and other articles (Tanantong and Wongras, 2024; Islam et al., 2024) in which FC were considered as a significant determinant, the denial of this factor in this paper is supported by El-Masri and Tarhini (2017) and Teo (2012), which examine the propensity to use advanced technology.

Both Performance Expectancy (PE) and Social Influence (SI) were demonstrated to have a positive impact on the intention of adopting AI in HRM. These findings, with no surprises, are in line with the original theory and supported by a number of studies (Horodyski, 2023; Islam et al., 2022). This suggests that individual expectations about the usefulness of advanced technology and other behaviours or opinions will drive the adoption rate of that advanced technology.

Perceived Risk (PR) was indicated to have a negative relationship with the intention to adopt AI in HRM and it was proved valid in this section. It is known from the literature review that PR is individual perception of potential negatives associated with new tools or techniques, thus it is deductively comprehensible that the more risks involved with AI technologies, the less likely HR professionals will adopt them into the daily operations. The result in this study is supported by the study of Rukadikar and Khandelwal (2024) who highlighted that risks related to security and privacy negatively influence the adoption of AI in HRM practices. This also raises concerns for HRM managers, AI developers and designers when building and adopting AI technologies.

Lastly, this study supports the hypothesis that Status Quo Bias (SQB) has a negative impact on the intention of AI adoption in HRM. SQB theory indicates personal preferences to remain their current status and resist switching to new technology (Shankar and Nigam, 2022). In the previous studies, authors have drawn upon the SQB theory to examine individuals' resistance behaviour in different contexts, such as resistance towards online health services (Zhang et al., 2017), healthcare professionals' resistance toward the use of health clouds (Hsieh, 2015) or consumers' resistance to use online travel agencies (Talwar et al., 2021). Although there is no explicit empirical evidence to support this hypothesis, it is reinforced by literature which reveals that people gravitate toward and attach to the existing technology and become suspicious about using new technology due to the status quo (Shankar and Nigam, 2022). Therefore, the more biases of status quo users possess, the less likely they will switch to a new state.

6.12 Chapter Summary

This chapter systematically tested the hypotheses presented. With respect to the research method presented from Chapter 3, multiple regression analysis was employed to access 146 validated research survey questionnaires gathered from HR professionals across West Midlands, England. To assess multidisciplinary validity aspects, data preparation and cleaning was conducted on SPSS software to ensure the values suit within required parameters and acceptable range. Loading factor was analysed in each EFA test to ensure the freeloading of measurement items and variables reflected in the six parent constructs. The profound process of hypothesis testing was achieved after evaluating the value of beta and significance level in correlation coefficients analysis. The results revealed the acceptance or discard of certain predetermined hypotheses. From this point, the next chapter will accommodate the discussion tailored to illuminating the three mainstay research questions of this thesis.

CHAPTER 7: RESEARCH DISCUSSION

7.1 Introduction

Emanating from the aspiration of ascertaining the emerging impacts of AI in the realm of HRM, this research centred on exploring and investigating AI adoption factors through conducting mixed-method research. Underpinned by the theory of UTAUT, and psychological elements, the thesis further proposed a potential AI-powered HR framework stemming from the AI-HR influential adoption factors.

At Phase 1, exploratory research (QUAL) was employed where the qualitative results (Chapter 4) postulated the adoption factors through thematic analysis. This initial research validated the supposition of UTAUT's factors and Perceived Risk element anticipated in Chapter 2. Furthermore, the research discovered another emerging psychological component impacting adoption decisions of Status Quo Bias. The findings reshaped the original conceptual framework by including the uncharted psychological component. The research adopted the refined conceptual framework illustrating the interlink of the discovered constructs with their representing variables as proposed in Chapter 5.

At Phase 2, the quantitative research (quant) (Chapter 6) subsequently provided statistically confirmative findings of the adoption elements. Particularly, the diminution of constructs through exploratory factor analysis (EFA) authenticated the relationship between the charted factors with adoption intention. The refined model was evaluated through multiple regression analysis to examine the significant level and the congruence of the model. Hypothesis testing was sequentially deployed when the research reached the satisfactory model.

In brief, the empirical data analysis emerged from this research provided a relatively clear and consistent picture of how AI technologies are transforming and impacting adoption decisions in the HR field. On the ground of the findings, the results delineated a prospective mechanism for AI diffusion in HRM. Hence, this Chapter significantly communicates and elucidates the primary outputs of the thesis delved on the extant milieu and literature within the digitalisation era.

7.2 Empirical Findings

The predetermined theoretical research model established in this research could be reasonably confirmed according to the results distilled though empirical data analysis. Although not all hypotheses were supported, the majorities were verified to solidly correlated with adoption intention of HR professionals as reflected in research's literature review. In fact, whilst Chapter 4 revealed the potential impulsion of AI-HR inclusive adoption criteria, Chapter 6 denoted the actual influential elements onto AI adoption mechanism in the extant HRM context. This showcased concrete evidence of (1) the high proportion of identifying related themes in compared to the A priori codebook; (2) the suitability of EFA and coefficient correlation analysis; and (3) the equivalently positive support for the majority of hypotheses. From this sort of orientation, the thesis retains the theoretical model of UTAUT with the four accepted constructs and two psychological factors as finalised in the Chapter 5. The retained model in this research identifies correlations among the variables which will be elucidated in causation impacts rooted from chronological explanations. Amalgamating the results from the theoretical and empirical data analysis from this thesis, the primary clusters of discussion are reflected through the impact of Social Influence (SI), Performance Expectancy (PE), Perceived Risk (PR) and Status Quo Bias (SQB) onto AI-adoption decision of HR professionals.

In fact, **Phase 1 (February 2022 to June 2022):** Qualitative Research (QUAL) was officially launched where empirical data were collected through interviews with selected AI-HR professionals and meticulously analysed to ensure thematic analysis reached its saturation point. Within this timeframe, AI was prospectively introduced into the market and considered as a bedrock for significant development and business adoption for the coming years. The milestone indicated an emerging AI concept and was potentially categorised in the *Innovator stage* in the Diffusion of Innovation Model.

Phase 2 (September 2022 to January 2023): Quantitative Research (quant) was conducted where the surveys were disseminated online to HR professionals in the West Midlands areas and the raw data were gathered via Qualtrics platforms. Notably, there was a significant transition of the degree of AI diffusion during this period of time. According to the Annual Report on AI Index of Stanford University, 2022 to the beginning of 2023 was denoted as the era of deployment of AI due to its enlargement in monthly releasing models (Maslej et al., 2023). Tailored to this, AI had been potentially progressing to the Early Adopter stage where its applications were on the tremendous growth in the market.

The **Figure 7.1** illustrates the progression of AI diffusion within the timeframe conducting the thesis. Notoriously, the two distinct phases of this research had incidentally occurred in different evolvement stages of AI developments, which provides a significant triaxiality lens for data interpretation. Echoing the growing evidence of agile AI progression, the findings of this research illustrate the precarious and proceeding attributes of technology advancements as long as their impacts on the nature of research in related fields of technology adoption. The research will progress with data interpretation and discussion in each innovation phase, specifically the *Innovators*: Qualitative Research and the *Early Adopter*: Quantitative Research.

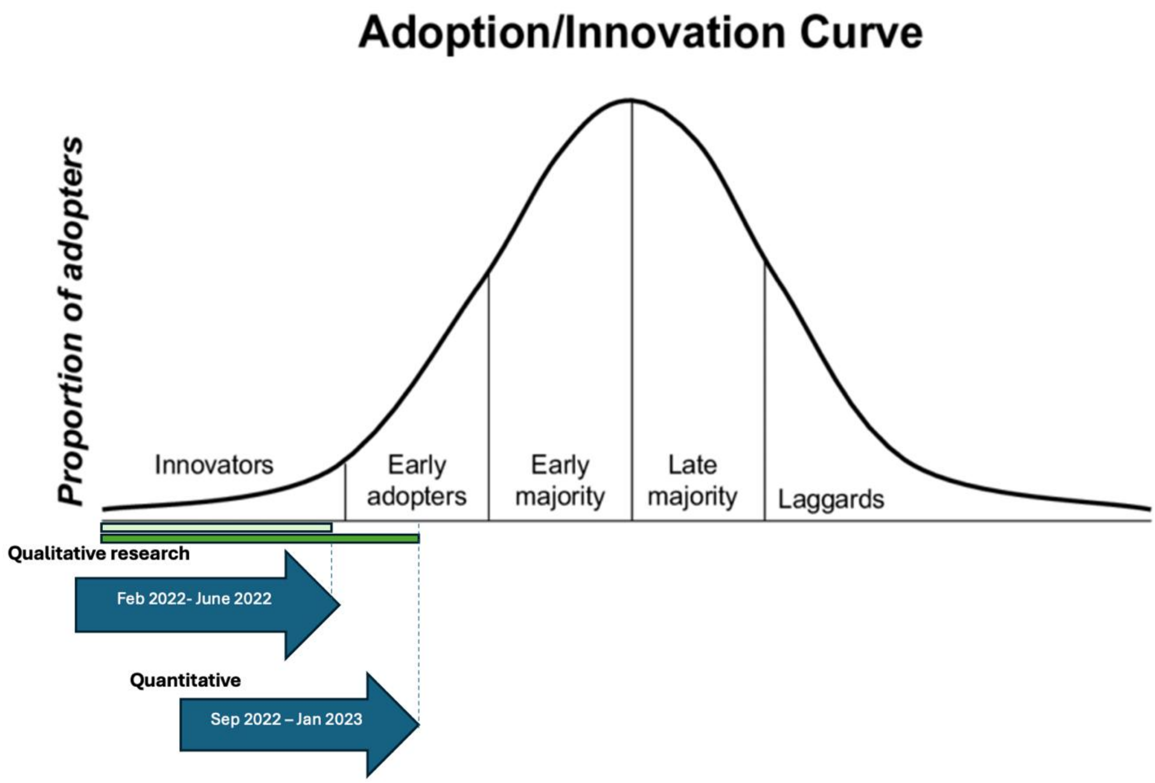

Figure 7.1: Relations of research milestones in accordance with AI development trend based on DOI Model (2022-2023)

7.2.1 Innovator Stage of AI Adoption – QUAL Research

Anchoring to the data outputs extracted from thematic analysis in Chapter 4, it is apparent the predetermined themes aligned with the theoretical model of this thesis. Evidently, the final themes extracted from the interviews appeared consistent with the five factors specified in the *A priori* codebook (coverage percentages of FC=88.89%, SI=100%, PE=72.22%, EE= 88.89%, and PR= 88.89%). In addition, the qualitative research successfully recognised the emerging theme of Status Quo Bias (SQB) with 94.45% of coverage percentage. Conceding to the empirical results, the qualitative phase of the thesis portrays an ideal relationship among the predetermined and spotted constructs within this study. Hence, the results confirm the clusters of UTAUT's factors, PR and SQB factors as pressures for AI adoption in HRM. The **Figure 7.2** shows the outcome of data analysis from qualitative research.

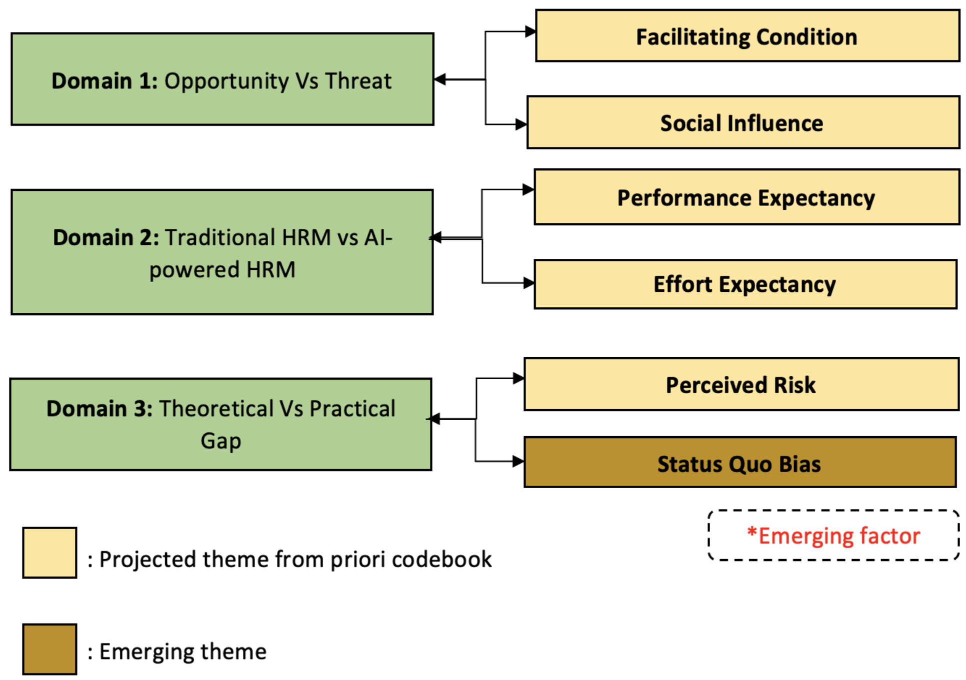

Figure 7.2: Finalised model from qualitative research

As illustrated in **Figure 7.2**, there are six factors impacting the AI adoption intention of HR professionals. Significantly, based on the coverage percentages of theme segments discussed in Chapter 4, the factors of SI (100%) and SQB (94.45%) are identified as core influential factors in AI adoption intention in HRM. Intriguingly, the two dominant factors belong to the two opposing adoption groups. To elaborate, Domains 1 and 2 illustrate the positive factors (FC, SI, PE and EE) impacting adoption intention while Domain 3 contains the two adverse factors (PR and SQB) of AI adoption. At this junction, the research successfully indicated the six adoption constructs with the main emphasis on the SI and SQB.

Specifically, based on the coverage percentages of theme segmentations, SI (100%) and SQB (94.45%) are core influential factors in AI adoption. Intriguingly, the two dominant factors belong to the two opposing adoption groups with SI (positive factor) and SQB (adverse factor). The findings mould a concrete elicitation of the positive and negatives risks of AI adoption in HRM and highlight the affiliation in RQ1and RQ2: "To what extent does the use and acceptance of AI in HRM generate opportunities and challenges for businesses?" and "How do HR Professionals perceive and relate to the use and acceptance of AI in HRM?".

Contextually speaking, the Covid-19 pandemic has enlarged the scale of remote working for most businesses in all fields due to the requirement of social distancing and even brought existence crisis threats to all organisations failing to adapt. It is stated that the pandemic has been escalated and challenging the resilience of many business models struggling to compete against "centric companies that can leverage data and machine learning" to generate essential insights and improve capacity (Napier et al., 2020, p43). The present incident has become the accelerator for the working pattern transformation, which provides a hindsight for businesses to re-examine procedures of management. The situation appoints and explains the seminal impact of **Social Influence (SI)** in shaping novel approaches in HRM. This poses a necessary radicalisation in HRM by cautiously scrutinising the management approach to prepare for novel working patterns (Akinjiyan, 2020).

In practice, digital transformation and the emergence of novel concepts such as contextual data or Big Data analytics has significantly disrupted business functions. In this vein, HRM is not immune to the disruption of AI technologies. This could be portrayed regarding how data make sense and turn into valuable sources for HRM analysis and strategy formulation (Budhwar et al., 2022). This reflects on the empirical data collected from the qualitative research of this study. In fact, **Effort Expectancy (EE), Performance Expectancy (PE)** and **Facilitating Condition (FC)** were, therefore, reflected as significant elements in AI-HR adoption by HR professionals in this duration. By the dint of the global issues, the potentials related to digital adoption were envisaged to upgrade business performance. This is in line with Dennis 's (2021) work emphasising on the gap that some organisations are exploring how technology can perform at work and while the others are concentrating on building approaches to work with it. Hence, the study elicits the triggering mechanism of HR professionals in reevaluating the HR functions and context in the measurement of AI-HR potentials. Subsequently, HRM practices are more likely to make a decision and establish critical approaches on using and accepting AI in HRM. In essence, multiple functions in management could be streamlined and digitalised through various sectors applying AI (Martin and Leurent, 2017).

By the cause of dramatic influence on the potential applications of AI, employees may perceive the new technology advancement as a detrimental impact in HR field. The mentioned perceptions could be perceived as a hindrance for businesses to adopt AI into their organisations. In fact, the empirical work from this study revealed a relatively clear and consistent picture of how **Perceived Risk (PR)** and **Status Quo Bias (SQB)** are the major concerns of HR professionals. Thus, the notions of PR and SQB negatively impact AI-HR strategic collaboration. The finding highlights the critical influence of the psychological determinants in HR professionals' perception. This proposition is also in line with the position that certain perception regarding risks is triggered when the users are introduced with novel technological subjective (Pitardi and Marriott, 2021). The participants acknowledged the possible threats delivered by AI in terms of unemployment, privacy data exposure, potential bias from machine and human, and general fear in terms of the unknown matter due to the uncertainty nature. This visualises a practical gap between the proposed benefits of AI technologies and the hindrance of application owing to the factor of PR. Significantly, an emerging factor of SQB was explored within this study as a converse adoption mechanism toward AI advancements. Samuelson and Zeckhauser (1988) first coined the concept of SQB which refers to the bias triggered in individual decision making by remaining the current status quo as a mechanism towards changes. Paramount to this definition is the assertion that this is a psychological construct illustrated the typical hindrance of technology adoption (Eidelman and Crandall, 2012). This explains why the issue posed the existence of an inertia tendency which facilitates the maintenance of status quo despite the pressure to alter the status (Greta and Karahanna, 2012). This concept was supplementarily adjoined in LR as it is validated within this section. In effect, thematic analysis results in this thesis established a new realm of AI influential adoption factor, which is not envisaged within the preceding framework. Reflecting upon Diffusion of Innovation (DOI) theory (Rogers, 1962), the AI-HR adoption determinants possess a symmetry to **Innovator Stage** as described in the Research Timeframe section. Conceding to this, the findings from qualitative research are consistent with the predetermined AI adoption factors embedded in the UTAUT Model. It also acknowledged the existence of PR and discovering SQB as a significant factor impacting AI adoption intention in HRM. Thus, the study at this stage indicates that HRM encapsulates a crucial capability in augmenting conventional HR functions. This position requires innovations to be accelerated in HR professionals' perceptions.

7.2.2 Early Adopter Stage of AI Adoption – Quant Research

Proceeding to the data outputs extracted from the statistical analysis in Chapter 6, the empirical data derived from the quantitative research intriguingly revealed another angle of the influential adoption factors in HRM. At this second phase, the statistical evinces that AI-HR adoption intentions are significantly affiliated with Social Influence (SI) (β = 0.328 sig. at the 0.001), Performance Expectancy (PE) (β = 0.248 sig. at the 0.001), Perceived Risk (PR) (β = -0.121 sig. at the 0.001) and Status Quo Bias (SQB) (β = -0.326 sig. at the 0.001) while Effort Expectancy (EE) and Facilitating Condition (FC) (both sig. less than 0.001) illustrated no statistical meaning in the AI adoption decision of HR professionals. **Figure 7.3** exhibits the outcome of data analysis from quantitative research.

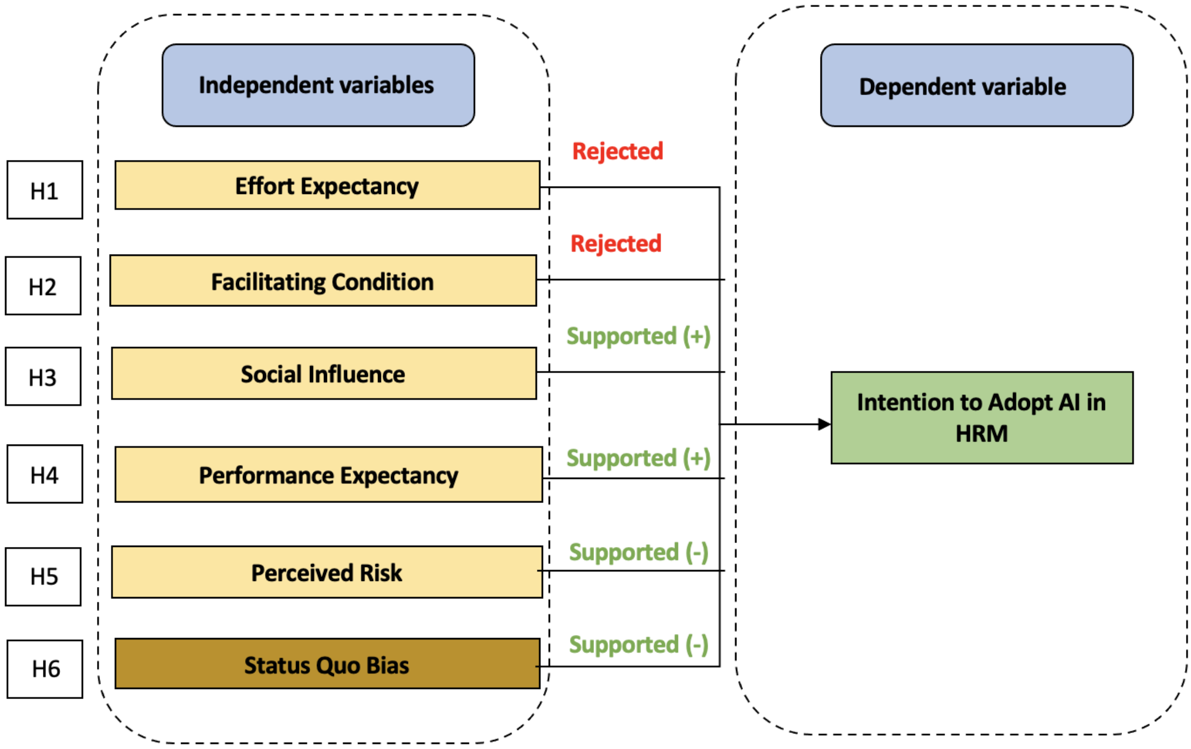

Figure 7.3: Finalised model from quantitative research

As can be seen from **Figure 7.3**, there were two UTAUT factors (EE and FC) eliminated from the AI adoption intention model in HRM. From this standpoint, the overall research findings are threefold:

(1) This research extends the Unified Theory of Acceptance and Use of Technology (UTAUT) conceptual framework, generating a novel research model include six independent constructs namely EE, FC, PE, SI from the UTAUT model, and additional components of PR and SQB.

(2) This research shadows the two adoption factors which dominantly influence HR professionals' intentional behaviours: SI and SQB. This is significantly highlighted and well-announced in both qualitative research (QUAL: 100% and 95.45% theme coverage respectively) and quantitative research (quant: β = 0.328 and *β* = -0.326 coefficient respectively).

(3) This research narrows the adoption of influencing factors with the diminishing of FC and EE (both sig. less than 0.001) in the AI-HR adoption model.

In fact, as explained in the Research Timeframe in **Figure 7.1**, the two phases of conducting the mixed method (QUAL-quant) research aligned with conspicuous milestones of AI advancements in the market. If Phase 1 was launched at the beginning 2022, Phase 2 was occurring at the end of 2022 to early 2023. In fact, ChatGPT was introduced by the end of November 2022, which marked another foundation for AI perceptual evolvements (Ray, 2023). Hence, it could be arguably considered this second phase when launching the quantitative research to match with the **Early Adoption** stage of AI, echoing to DOI theory (Rogers, 1962). Specifically, it marked a radicalisation of AI usage in the business market and therefore, this was not immune to the HR realm. At this junction, the refined conceptual framework demonstrated a marginalisation of FC and EE as adoption factors at this innovation diffusion stage. In fact, Venkatesh et al. (2003) has early emphasised the importance of FC in exposing users' perceptions on the availability of required resources and avocation dedicated by organisational capacity, equipment, and essential supports for an individual to perform a task. Therefore, FC has initially been deployed as a crucial element contributing to the positiveness of individual behaviour toward future intentions and decisions in the research model. Nevertheless, the plethora of prevalent AI applications and services in the market, therein, potentially explains for the atrophy of FC in HR professionals' adoption perception.

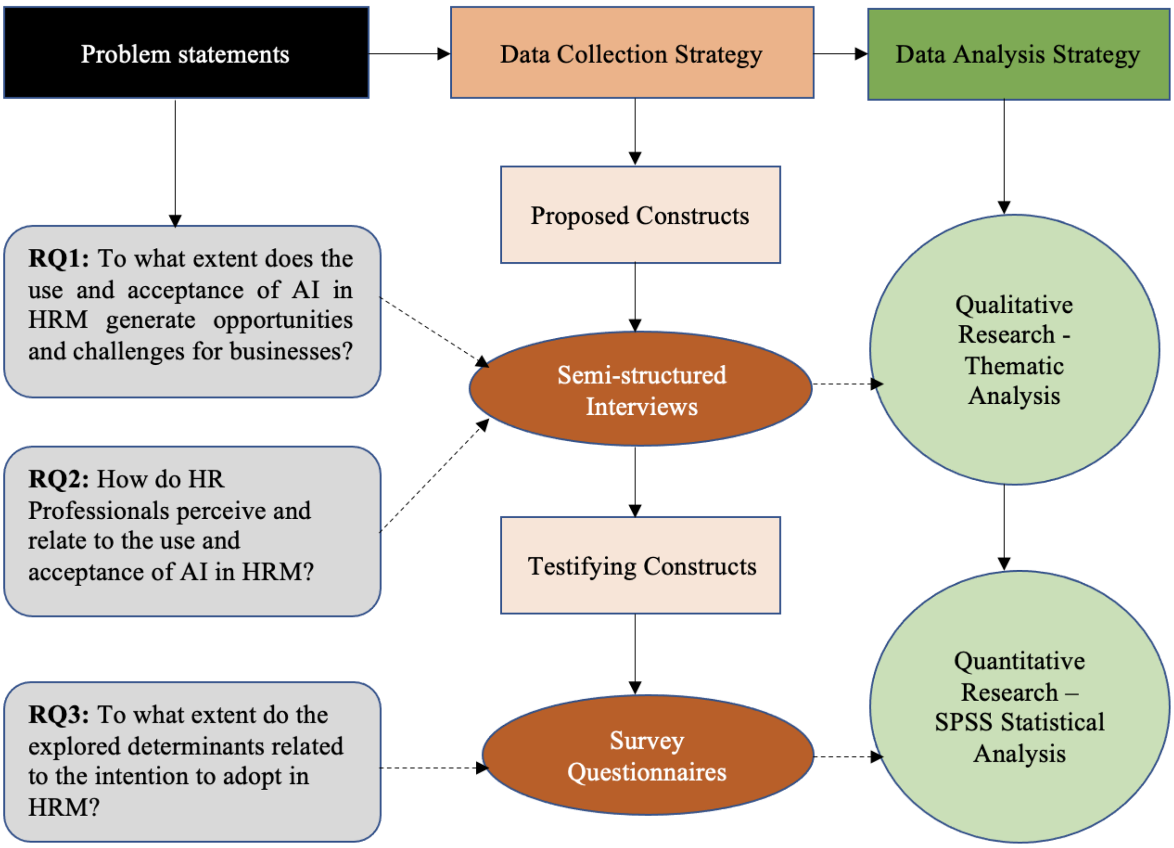

Figure 7.4: Comprehensive Research Framework Establishment (designed by researcher)

In sum, recapitulating from the empirical findings, this research has successfully illuminated the ulterior influence of AI-powered technologies in the HR realm. Particularly, the degree of AI acceptance and adoption in HRM as well as the key factors on AI-HR adoption were demystified within the two phases of the research. In tandem with the exploration of adoption factors, the research provides a practical bridge portraying a potential collaboration mechanism between HR functions and AI technologies. The discussion, therein, is comprehensively synthesising the three research questions proposed in Chapter 1 by explicitly structuring the research design and outset. As can be seen above, **Figure 7.4** exhibits the exhaustive anatomy dedicated to examining the problem statements shaped in the three primary research questions (RQs). Subsequently, the following discussion will represent the answers for the RQ3 in terms of enlightening the correlations of each individual explored determinants to the AI adoption intention in HRM.

7.3 Key Determinants impacting AI adoption intention in HRM

The previous section has provided a snapshot summarising the research findings from both Phase 1 (QUAL) and Phase 2 (quant) of this study regarding the exploration of the AI adoption in HRM. Hence, this section is dedicated to clarifying and discussing the critical nexus of each adoption determinant of AI in HRM including EE, FC, PE, SI, PR and SQB reflecting the current context of AI-HR upon the extant literature and practical situations.

7.3.1 Effort Expectancy (EE) and AI adoption intention

The first hypothesis examined in this research (H1) envisaged a no statistical impact of Effort Expectancy (EE) on the intentional behaviours of HR professionals towards AI adoption. As a form of technology adoption facilitators, there has been accumulating evidence in the literature suggesting the substantial role of EE in technology adoption studies (Berkowsky et al., 2017; Koo et al., 2021; Al-Saedi et al., 2019b). In fact, Venkatesh et al. (2003) emphasised the impact of this factor by concentrating on the easiness perceived in using the technology, which facilitates the adoption intention whereas certain cumbersome and difficulties related to that technology may hinder the adoption behaviours. The manifestation of the EE factor could be reflected upon how the technology interface and designs, learning process feature the efficiency and the ease while using. Due to that reason, this research was expected to follow the similar vein indicating the crucial impact of EE in the context of AI adoption in HRM.

Nevertheless, contrary to the expectation, the empirical outcome from this study highlighted no statistically significant relationship between EE (sig. less than 0.001) and AI adoption intention of HR professionals. In other words, this research stresses on the insignificant impact of EE in the AI adoption intention in HRM context, which contradicts with studies adopted in the EE factor in technology adoption model. However, the research results from this study appeared to be consistent with the studies regarding the adoption of digital reference service (DRS) in Pakistan organisations (Khan et al., 2017) and AI adoption in the Korean librarian system

(Andrews et al., 2021). The mentioned research also discarded the factor of EE from the conceptual framework. Specifically, their arguments are rooted from the outweigh of the usefulness factor over the ease-of-use feature when considering adopting novel technologies. This is also in line with Williams et al. (2015) and Park and Kim (2014) asserting on the lesser influence of EE on technology adoption behaviours if users solely value the technology's benefits and expected outcomes. In addition, Andrews et al. (2021) further argued that AI technologies may possess a particular degree of vagueness since the adoption and implementation of AI in practice are yet to saturate. To elaborate, the factor of EE inherits the sense of self-supported feeling. In fact, such efforts could not be widely experienced due to the under- or mis- use of AI technologies in the current business market. Hence, this research shared the common belief based on the empirical findings, which showcased in the absence of significance of the EE factor in AI-HR adoption model in this stage of AI innovation diffusion.

Further to the above, the elimination of EE from the AI adoption intention in HRM could also be arguably acknowledged due to the increase of digital literacy in the society owing to the abrupt evolution and prevalence of AI applications. Mirroring the earlier discussion regarding the Research Timeframe while conducting the two phases of this research, it could be transparently observed the agile essence of AI diffusion into the HR market. In effect, the introduction of Chat GPT, AI Gemini and other associated AI have been relentlessly launched into the society, which marked a significant milestone influencing the user's attitudes and perception toward AI technologies (Gond et al., 2024). Hence, the growth of users who are accustomed to interacting and using AI technologies could possibly lead to the dismissing of the importance level of the EE factor in the adoption model. In fact, the argument possesses the same symmetry with Baptista and Oliveira's (2015) study regarding the adoption of mobile banking applications. The study pointed out the minimal role of EE when the technology becomes prevalent and the familiarity of using the technology increases. From this standpoint, EE factors may not necessarily contribute to the adoption intention of HR professionals as critically discussed above. Hence, H1 of this study was rejected from this research in terms of not significantly influencing the intentional behaviours of HR professionals.

7.3.2 Facilitating Condition (FC) and AI adoption intention

Facilitating Condition (FC) was the second adoption element to be measured in the context of AI adoption intention in HRM. The factor is related to any existing support from organisational perspectives regarding management or infrastructure to adopt the new technology (Venkatesh et al., 2003). In HR setting, the conditions embedded in FC could be exemplified such as the organisational resources and supports, task compatibility and adequate knowledge equipped for the HR professionals to deploy the technology effectively. It is posited that FC is a necessary facilitator to influence users toward positive adoption intention (Dwivedi et al., 2019) and acceptance behaviours (Guo, 2014). Indeed, prior studies regarding technology adoption have found a positive relationship between FC and intentional behaviours (Dwivedi et al., 2019; Islam et al., 2022). Furthermore, it is evident from recent studies regarding the role of FC on AI- specific adoption intention (Böhmer and Schinnenburg, 2023; Eftimov and Kitanavikj, 2023). Hence, the above discussion highlights the critical role FC to reinforce adoption intention of new technologies. Anchored to the mechanism, the factor was deemed to critically impact on the adoption intention of HR professionals as presented in this research preliminary conceptual framework. Nonetheless, the factor of FC was eliminated from this study model in Phase 2 of quantitative research. In fact, the statistical outcomes indicate the absence of significant essence in FC in AI-HR adoption model with sig. less than 0.001. At this junction, this research disagrees with a body of literature in AI adoption found a positive nexus between FC and AI adoption intentional behaviours (Islam et al., 2022; Andrews et al., 2021; Islam et al., 2024; Ronaghi and Forouharfar, 2020).

It could be reasonably argued that to a certain extent in HR contexts, other adoption-influencing factors are more likely to overshadow the significance of FC. In truth, echoing the existing literature, several studies acknowledged the similar sentiment in highlighting the impacts of other UTAUT factors such as Performance Expectancy (PE) or Social Influence (SI) over FC in the adoption model. This is in line with latter study from Venkatesh et al. (2016) emphasising the crucial impact of the analysed context. In particular, it is highlighted that in the setting where the advantages of the technologies are transparent and attractive to users, the willingness to adopt the technology would increase regardless of the current FC availability (Venkatesh et al., 2016). In the setting of HR, this means that if HR professionals perceived the usefulness of AI in augmenting their current performance, the attitudes towards the adoption would possibly outweigh the concerns about the available support. This acknowledgement is perceived to align with the next section in this chapter regarding the constructs of PE on AI adoption intention of HR professionals.

Further to the above, the increase in technology literacy and digital competence could be acknowledged as a driver of the diminution of FC from the research model. In fact, this argument was previously discussed to clarify the current status of EE in the AI adoption model. To further elaborate, the situation highlights the reduction of reliance from technology users on organisational supports once the familiarisation to the technology increases. Hence, following the similar vein of the discussion of EE in AI-HR adoption context, the prevalence and agile disruption of AI in the market in the recent years have generated a robust foundation for AI users to establish their confidence and digital-savvy ability to work with AI innovations. The situation marks a seismic shift in the AI adoption landscape where the employees are accustomed to various AI applications and become more comfortable to navigate AI technologies independently. In practice, this assumption is in line with studies from Gupta et al. (2008) examining the adoption of ICT in government organisation and Hmoud and Várallyai (2020) investigating the adoption of AI-HRIS in HRM. The mentioned studies both discarded the factor of FC from their technology adoption intention model. Hmoud and Várallyai (2020) further claimed that the hastening advancement in digitalisation supports from external sources such as data storage from clouds or 4G, 5G networks have also contributed to lessening the importance of FC in adopting AI. Thus, this study shared the common stance in acknowledging the absence of importance from the FC factor from the AI-HR adoption intention model. In this vein, the discussed dynamic results and the empirical findings from this study accentuate the elimination of FC as a crucial factor in the AI-HR adoption model.

7.3.3 Performance Expectancy (PE) and AI adoption intention

Venkatesh et al. (2003) indicated that Performance Expectancy (PE) is the most significant factor in predicting the users' intention in adopting the new technology. The features of PE factor could be manifested either through task-related and personal expectations toward the performance. This could be exemplified through the augmentation of the work such as timesaving on routinised tasks, the increase in outputs' quality or quantity or the reductions of efforts and costs in achieving the tasks. Hence, this research proposed a similar symmetry in which PE (represented by the factors of Task Versatility and Cost Effectiveness factors as indicated in Chapter 5 and Chapter 6) would positively impact the AI adoption intention in HRM. In particular, this indicates that the HR professionals believe that AI will support their performance in HR functions. Echoing the extant literature, there is a rich body of evidence demonstrating the impact of PE in technology adoption and acceptance such as blockchain acceptance in organisations studied by Handoko and Lantu (2021) and AI adoption in libraries by Andrews et al. (2021). Indeed, the empirical results of this study reveal a similar direction in which PE is statistically significant and has positive influence on AI adoption intention in HRM, with the standardised coefficients $\beta = 0.248$ and sig. at the 0.001. Thus, this research outcome emphasises the crucial impact of PE in the adoption model of AI in the HR realm within this research scope.

In the first instance, AI-HR collaboration for innovation is not an original tacit resource to replace human factors in the business sustainable circle. Instead, technological adoption research postulates that innovation adoption by upgrading internal structure is an essential strategic advancement that drives business performance capabilities (Zhu et al., 2006; Hannah, 2019; Jöhnk et al., 2021). Therefore, HR scrutinises more on the contemporary core functions such as recruitment (Pan et al., 2022b) and performance evaluation (Fenwick et al., 2023). In practice, the significant growth of digital-supported networks has brought more considerations to business operational models in terms of how to deploy effectively and efficiently the availability of those assistant networks to maximise business performance. Echoing the growing evidence supporting AI-augmented performance, this provides a concrete mechanism explaining the acknowledgement of the PE factor in HR professionals' mindset in evaluating AI adoption elements. In regard to the context of West Midlands regions, the area is well-known to engender the critical industry base for the development of local economy, which generates a continuous momentum to maintain the competitive and innovation edges. Chatterjee et al. (2021) demonstrates a similar sentiment by acknowledging the role of PE as strategic responses to regional innovation acceleration. In this vein, HR professionals are specifically attuned to the expected AI augmentation in the traditional HR practices which could help to enrich decision-making process, streamlines HRM practices and leverage the overall business performance in this 4th Industrial Revolution era (Basnet, 2024). Hence, PE is highly acknowledged in this study to positively impact the AI adoption intention of HR professionals. Furthermore, the positive impact of PE in the AI adoption model is also aligned with the recent UK governments' policies on the importance of digital transformation, including the recognition of AI impact in business performance and productivity (UK Government, 2022). This is also in line with Ikegwu's (2022) statements highlighting the industry trends of pursuing data-driven insights and compatible automation in various business functions in order to optimise business performance. As noted in the above discussion, the role of PE is highly relevant to HR adoption context. The empirical findings from this research underscore the crucial impact of PE on AI adoption intention model in HRM. Hence, H3 was supported in this study. The acknowledgement of PE from this research was consistent with associated research (Chao, 2019; Patil et al., 2020; Chowdhury et al., 2023) regarding technology adoption within business.

7.3.4 Social Influence (SI) and AI adoption intention

Social Influence (SI) is the fourth adoption determinant examined in this research. Echoing the tenets of technology adoption model (Venkatesh et al., 2003), the factor is shown to strongly influence the behavioural intention to use new technology. The factor is entrenched to encompass and explain how people's interaction and social settings could foster or impede technology adoption. Reflecting on the literature, it was hypothesised that SI would positively impact AI adoption intention of HR professionals. Indeed, the research results from this study confirmed the significantly positive impact of this factor in both QUAL (100% theme coverage) and quant research (β = 0.328). In this context, SI demonstrates its substantial role in showcasing the positive social environment and collective endorsement features of AI adoption in HRM. This was in line with Chatterjee et al. (2021) study to acknowledge that social pressure and responses to innovations engenders greater degree of acceptance attitudes in HRM due to the alignment of employees' behaviour in tandem with the expected concept of new norms in organisation. The impact of SI in the AI adoption model could be reasonably explained anchored to the immense impact of AI from the local businesses and institutions due to the pressing effects on transforming economic landscapes. In effect, the prompt extension of AI algorithms and solutions in recent years has showcased a large number of functions which could be adopted within HRM. Thus, Böhmer and Schinnenburg (2023) has recently posited that AI technologies are demonstrating a tremendous penetration into the HR market with the ability to upgrade current HR processes applying a variety of technical solutions. In addition, the thriving of studies regarding AI in HRM and the high awareness and diffusion of its terminology in HR market has also been confirmed in the previous arguments within this study (Hmoud and Várallyai, 2020; Basu et al., 2022; Arslan et al., 2022). Hence, this research critically emphasises the existence of SI in the context of AI adoption and HRM. To further explain, the adoption of AI technologies in HRM is not simply considered as a follow-suit technical upgrade: it necessitates strategy formulation to align with the economic goals and enrich brand reputation.

Indeed, reflecting on the essence of organisations in the West Midlands regions, the continuous transitions towards an industry and knowledge-based areas have significantly revealed the high possibility for AI adoption in HRM. In light of this, the SI factor in this study represents a stark innovation impetus formed by collective and shared knowledge embedded in the rich industrial heritage of the region. Brown and Mawson (2019) echo a similar sentiment by recognising the role of SI in innovation adoption manifesting through the perceived endorsement and usage of advanced technologies in local, professional and industrial networks in generating entrepreneurial ecosystems. This would potentially create a social pressure for organisations to reshape the businesses' strategy to attract talent in the dynamic contexts. Hence, the situation partly explains why employer branding was retained in the final EFA test of quantitative research. Further to the above, it is worth indicating the SI in AI adoption in HRM could potentially be coined by the pivotal role of the educational and academic system in terms of distributing AI knowledge and forming learner's attitudes. Indeed, Zhang et al., (2024) highlight the collaborations and partnerships between educational institutions and regional businesses, such as Knowledge Transfer Partnership projects (KTPs), accentuates the cultivation of innovation diffusions, which strengthens and enlarges the scale of SI impacts on AI adoption into HRM. Thus, the organisational initiatives coupled with the above-mentioned public endorsement are generating the society-business synergy in adopting AI into HRM. The research, therein, underscores the significant role of SI in AI adoption intention in HRM.

Building on the prior discussion, this research also presents the contradiction to several associated studies that discard the impact of SI in the adoption model. In fact, recent studies of Tanantong and Wongras (2023) and Islam et al. (2024) regarding AI adoption in recruitment and hiring talents in the context of Thailand and Bangladesh respectively declared the insignificant impact of SI in HR professionals' intentional behaviours. The arguments lie in the high cultural contexts conceived in the social structures of Asian countries which value long-term tradition and family-oriented approaches (collectivism and high uncertainty avoidance nature) on HRM functions (Tanantong and Wongras, 2023; Islam et al., 2024). The mentioned contexts demonstrate the opposite directions with the nature of high individualism and lower uncertainty avoidance in England setting as collated with Hofstede's Cultural Dimension (Hofstede and Bond, 1984). Individualism is a cultural dimension in Hofstede's model referring to the individualistic degree of a society in which the emphasis lies on personal achievements and prioritise the needs of oneself rather than securing long-term values of groups or society. Uncertainty avoidance refers to the degree of tolerance for risk and ambiguity in a society.

Hence, the above explains the reasons why SI factor is discarded from certain AI-HR adoption models and the justification of adopting the factors in other research models will depend on the contexts of the research subject. Within the scope of this research, SI is acknowledged to positively influence the adoption of intentional behaviours of HR professionals. The empirical findings are consistent with relevant studies (Xue et al., 2024; Dwivedi et al., 2019; Jain et al., 2022b) which recognised a similar positive link with SI in adoption intentional behaviours.

7.3.5 Perceived Risk (PR) and AI adoption intention

The factor of Perceived Risk (PR) has been adopted in various technology adoption models due to certain psychological impact associated with the exposure data and information from users (Gaber et al., 2020; Alt et al., 2021b; Hong and Cha, 2013). As previously discussed in Chapter 1 and Chapter 5, this factor is scrutinised to significantly impact the adoption intention of technology users. Hence, PR was the fifth factor proposed in the preliminary research conceptual framework. This factor was hypothesised to negatively influence on intentional behaviours of HR professionals toward AI applications. Indeed, the empirical results from both QUAL (88.89% theme coverage) and quant (β = -0.121 sig. at the 0.001) studies of this research have confirmed its critical impact in influencing AI-driven decisions from HR professionals. In practice, a rich body of recent research has emphasised the power of PR factor to certain extents such as the concern regarding privacy (Chatterjee et al., 2022), bias (Du, 2024), unknown: limited understanding about the subject (Devineni, 2024) and unemployment (Chiarini et al., 2023) under the theme of AI adoption across business functions and sectors. This is significantly in line with the retention of all four sub-factors (fear of the unknown, privacy concern, bias concern, and perceived unemployment) under the parent construct of PR. In this vein, the impact of PR in AI-HR adoption context can be possibly argued to pursue a similar gravitation.

Echoing the nature of HRM functions, HR practices are well-known for a relation to handling sensitive employee and organisational data such as employment contracts, performance evaluations, salary and reward management ranges (Armstrong and Taylor, 2023). Hence, there would be a high proportion of concerns on the perceived risk levels regarding data breach and information misinterpretation caused by AI technologies. In fact, Chatterjee et al. (2022) asserted that PR rooted from data security could significantly trigger AI-adoption barriers in the HR field since stakeholders may not afford the loss of organisational data as well as handle potential legal and ethical issues related to that risk. In addition to privacy risk, this study also acknowledges the risk related to certain bias concerned in the HR field. In fact, Devineni (2024) highlighted a certain degree of bias and ethical related issues applying AI in decision-making processes. In the context of HR, this risk would lead to potential unfair and unethical treatments to particular groups of stakeholders, which accounts for the encumbering of organisational cultures and morales. Hence, the adoption perception of AI in HR is detrimentally impacted by the PR factor. In effect, the risk perceived in AI regarding bias is partly due to the existence of unknown or unclear AI patterns in the market. Nevertheless, as strongly exhibited in the previous section regarding the factors of SI in positively impacting the adoption of AI in HRM, the PR factor could be potentially hampered in proportionate with the prevalence and rapid advancement of AI in the business market.

It is also worth mentioning the risk rooted from the perceived unemployment when adopting AI technologies. Indeed, this attribute of risk has been addressed in certain studies regarding

AI adoption in certain business functions (Nam, 2019; Chiarini et al., 2023). Reflecting upon this research, this perception towards risk was acknowledged by HR professionals as discussed in Chapter 4 of this study. To be specific, the factor of PR outlines the job insecurity scenarios for HR professionals to lose their jobs over the AI tools or diminish their role value in the organisations. The assertion regarding the factor of PR is also acknowledged in recent research investigating the job and career behaviours with AI integration in the workplace (CBER, 2022; Presbitero and Teng-Calleja, 2023). Hence, the empirical findings from this research underscore the crucial impact of PR on negatively impacting AI adoption intention model in HRM, resulting in the support of H5 in the AI-HR adoption intention model.

7.3.6 Status Quo Bias (SQB) and AI adoption intention

Status Quo Bias (SQB) is the final factor to be examined in this research in relation to measuring the adoption intention of AI in the realm of HRM. The factor of SQB plays an important role in this research in explaining the contemporary nexus of AI adoption intention of HR professionals. Initially, this factor was not included in the preliminary conceptual model due to the limited studies deployed in the research model regarding technology adoption in organisations. Nevertheless, the factor emerged in the QUAL research in Phase 1 of this study and subsequently adopted in the refine research model as discussed in Chapter 5. This factor was first coined by Samuelson and Zeckhauser (1988) which represents the bias triggered in individual decision making by remaining the current status quo as a mechanism towards changes. SQB factor could be demonstrated through inertia tendency embedded in the uncertainty, the perceived loss in making wrong decisions and sunk-cost fallacy (Tykocinski and Ortmann, 2011; Tait and Miller, 2019). Echoing that mechanism, SQB was hypothesised to negatively impact the AI adoption intention in the HR field. Indeed, the empirical findings from this research emphasised the critical impact of SQB in the current AI adoption intentional behaviours of HR professionals as evident in both QUAL (94.45% of theme coverage) and quant (β = -0.326 sig. at the 0.001) research. Thus, this study highlighted the impact of SQB in negatively affecting HR professionals' adoption intention towards AI innovations.

In fact, this psychological phenomenon has been recently acknowledged in several studies regarding the adoption in AI technologies in organisations examining the new normal after the Covid-19 event and the occurrence of the 4th Industrial Revolution in the world (Schwaeke et al., 2024; Almatrodi et al., 2023; Godefroid et al., 2023). Despite the critical mechanism for AI-adoption germination in businesses, the factor of SQB is envisaged to significantly impact the adoption intention of potential users. Wu (2016) argued that the attachment to the old system could possibly stem from the individual inclination toward a familiarising system despite certain inconveniences embedded in usage. In HR settings, the factor of SBQ may possess a certain degree of uncertainty introducing concerns regarding ethics, job or privacy security and AI-generated bias as discussed in the previous section explaining the nexus of PR to AI adoption intention. Hence, the factor of PE could be arguably blamed to enlarge a preference for SQB. The above discussion regarding the dynamic of the context contributes to reinforce the research outcomes from the quantitative research of this study where the two sub-factors of psychological commitment and cognitive misperception were retained and represented for the construct of SQB after the EFA test. The discussion stressed the substantial impact of this SQB factor in the AI-HR adoption model, generating a concrete foundation for the acknowledgement of H5 to be accepted in this study. Hence, this research therein shares a similar stance with relevant studies (Godefroid et al., 2023; Almatrodi et al., 2023; Schwaeke et al., 2024) highlighting the impact of SQB in negatively impacting adoption intention of AI technologies in HRM. In sum, the study has profoundly communicated the key findings and possible implications for the research questions regarding AI adoption intention in the realm of HRM. The next section is dedicated for further recommendations based on the empirical results of this study to facilitate the adoption and collaboration of AI in the manpower management field.

7.4 Summary of key findings of the research and a suggested Adoption Framework in HRM

The empirical findings presented in Chapter 4 (qualitative phase) and Chapter 6 (quantitative phase), together with the integrative discussion in **Section 7.3**, provide a comprehensive understanding of the current landscape of AI adoption within HRM. This section explicitly positions the findings in dialogue with the LR and critically reflects on dominant academic and practitioner discourses surrounding AI, HR analytics, and technology adoption in HR. In doing so, it articulates how this study contributes to ongoing debates on AI-enabled HRM and extends existing technology adoption frameworks.

7.4.1 Clarifying the Conceptual Misunderstanding between HR Analytics and AI-Powered HRM

A key finding of this study lies in its empirical clarification of the persistent conceptual ambiguity between HR analytics, automation, and AI-powered HRM that has been widely observed in both academic and practitioner-oriented literature. Prior research frequently conflates these concepts, often treating AI as an extension of data analytics or rule-based automation. The qualitative findings (Chapter 4) reveal that many HR professionals interpret AI adoption primarily through the lens of advanced analytics and reporting tools, rather than as systems involving machine learning, predictive modelling, or adaptive decision-making capabilities. This misunderstanding is not merely semantic but has substantive implications for adoption intention. The quantitative results (Chapter 6) demonstrate that such conceptual confusion may amplify perceived risk (PR) and reinforces status quo bias (SQB), as HR professionals remain uncertain about what AI adoption actually entails and how it differs from existing HR information systems. By empirically evidencing this distinction, the study responds to recent critical calls in the literature for greater conceptual precision in AI-in-HR research and challenges techno-deterministic assumptions that portray AI adoption as a linear or inevitable progression.

7.4.2 Extending Technology Adoption Theory in the Context of HRM

Building on the UTAUT framework, this study contributes to the technology adoption literature by empirically demonstrating the limitations of traditional adoption models when applied to AI in HRM contexts. While UTAUT has been widely used to explain technology acceptance, the findings show that not all core constructs retain explanatory power in the context of AI adoption by HR professionals. Specifically, Effort Expectancy (EE) and Facilitating Conditions (FC) were not retained in the final quantitative model, suggesting that AI adoption concerns in HR are less about usability or infrastructural support and more deeply rooted in psychological and socio-organisational factors. The retained constructs — Social Influence (SI) and Performance Expectancy (PE), alongside Perceived Risk (PR) and Status Quo Bias (SQB) — offer a more nuanced explanation of adoption intention. The negative and significant effects of PR and SQB highlight that AI adoption in HR is fundamentally shaped by uncertainty, perceived threats to professional identity, and concerns regarding accountability, ethics, and job security. This finding extends prior adoption studies by empirically validating the relevance of behavioural and cognitive resistance mechanisms, which remain under-theorised in mainstream AI adoption research.

7.4.3 Challenging Instrumental and Techno-Optimistic Narratives of AI in HR

A further critical finding of this study is its critical engagement with the dominant instrumental framing of AI in HR literature, which often emphasises efficiency gains and predictive accuracy. While Performance Expectancy (PE) was found to significantly influence adoption intention, the qualitative findings reveal that HR professionals' expectations of performance improvement are conditional, cautious, and frequently tempered by ethical and professional concerns. This challenge prevailing narratives that frame AI as a value-neutral tool and supports emerging critical scholarship that problematises AI as a socially embedded technology. The findings demonstrate that HR professionals do not simply evaluate AI on technical merit but assess it in relation to professional judgement, organisational culture, power dynamics, and responsibility for people-related decisions. In doing so, this study repositions AI adoption in HR as a socio-technical and sensemaking process rather than a purely rational or efficiency-driven choice.

7.4.4 Implications for AI Adoption and Organisational Practice in HRM

At this stage, the research identifies concrete mechanisms underlying the problem statements outlined in the introductory chapter and shifts towards articulating how organisations can mitigate the barriers to AI adoption in HRM. The findings suggest that organisations play a critical role in shaping adoption intention by actively addressing the psychological and institutional factors embedded in AI implementation.

First, providing targeted training and equivalent education is essential to demystify AI technologies and reduce technology-related anxiety. Consistent with prior studies (Hoque and Sorwar, 2017; Hassija et al., 2024), the findings indicate that clearer understanding of AI capabilities and limitations can mitigate perceived risk and enhance HR professionals' confidence in engaging with AI-powered tools.

Second, reinforcing security and privacy protocols is central to addressing trust-related concerns. The heightened awareness of cybercrime risks, particularly in the post-COVID context (Buil-Gil et al., 2021), exacerbates resistance to AI adoption in HR due to the sensitivity of employee data. Strengthening information systems governance and transparency can therefore reduce perceived risk and weaken status quo bias by fostering institutional trust.

Finally, addressing transparency in AI deployment and employment security concerns is critical. The qualitative findings highlight fears related to algorithmic bias, black-box decision-making, and role displacement. Proactively engaging with these concerns, clarifying the human-in-the-loop role of HR professionals, and reaffirming the centrality of human judgement can mitigate resistance and promote a sustainable human–AI ecosystem within HRM. This reframing positions AI not as a replacement for HR expertise but as an augmentative tool that supports, rather than undermines, professional practice

In conclusion, the proposed recommendations were based on the implications regarding the AI adoption determinants in the HR context. It is reasonable to argue its applicability depending on the various HR settings, culture and related factors regarding novel technologies emerging in the context. Therein, the research proposed an overall framework for AI-HR adoption, reflecting on the AI adoption factors in HRM within this research scope. **Figure 7.5** presents the 3R process to revise HR functions incorporating and adopting AI into the workplace's system.

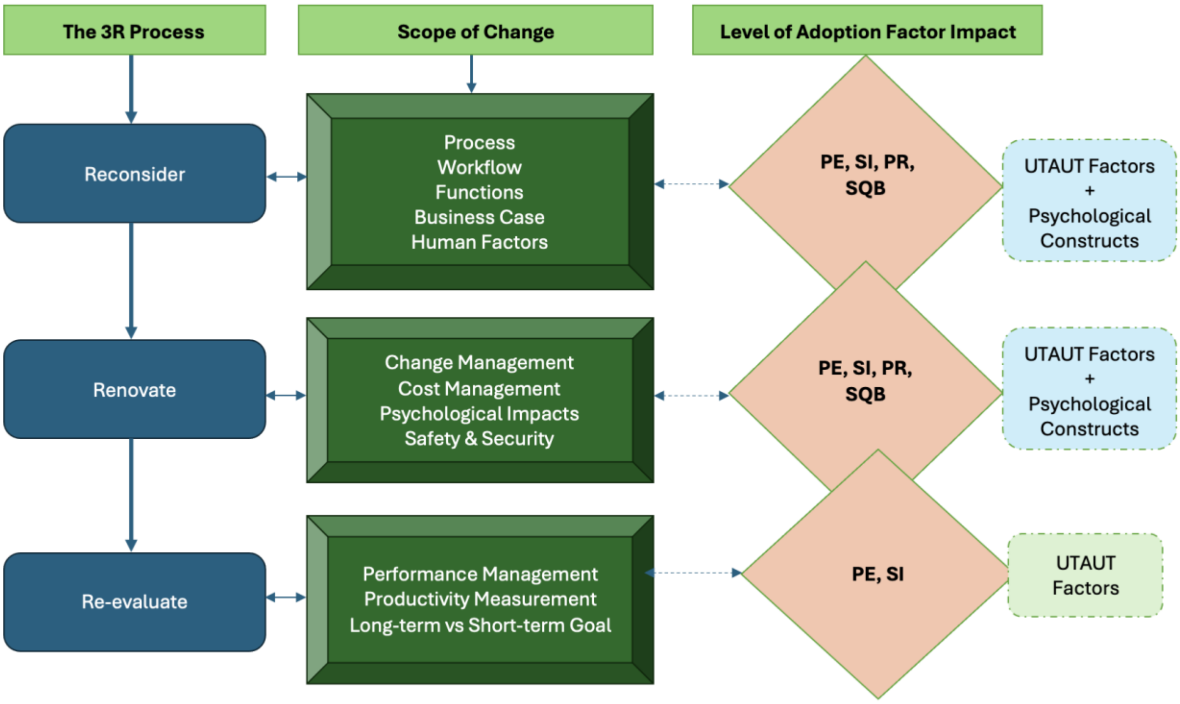

Figure 7.5: The suggested 3R process for AI-HR adoption (designed by researcher)

As can be seen from the **Figure 7.5**, there are three core steps in revising the HR process in order to adopt AI in HRM. The description for each stage is presented as follow.

Stage 1: Reconsider

At this initial stage of AI adoption, it is crucial for organisations to peruse the current HR functions and processes. As illustrated in the above figure, this involved the examinations of the current needs for AI applications by analysing the workflow, process, HR cases and relevant manpower requirements. This Reconsider process would assist to estimate the predicted required resources for AI-powered HRM integration in later phases.

Stage 2: Renovate

After considering the current HR capacity, change management is suggested to be facilitated to well control issues related to the factors of PR (privacy, bias, employment, and unknown factors) and SQB (misconception and psychological commitment). Hence, change and cost management, psychological controls as well as safety and security elements are introduced to the second phase of the adoption process. Reflecting upon the framework, the appearance of both facilitators (UTAUT factors) and hinders (psychological factors) are still available in the adoption process.

Stage 3: Re-evaluate

This is deemed to be the final step in the adoption of AI in the HRM framework. At this phase, the HR professionals are supposed to have certain familiarisation in utilising AI technologies. Thus, at this junction, the issues related to PR and SQB should be eliminated from the adoption process as illustrated in **Figure 7.5** at Phase 3. Tailored to that, the organisation could concentrate the adoption effort in maintaining the assurance and measurement of HR performance and productivity when integrating with AI. In addition, Return on Investment (ROI) could be deployed to efficiently evaluate the success rate of adopting AI in HR practices.

7.5 Chapter Summary

The main aim of this chapter was to deliver the discussions of the empirical outcomes of the data analysis regarding the stated hypotheses of the research. Chapter 7 began with a discussion regarding the overall findings of this thesis which results in the final research conceptual framework. The hypotheses were subsequently addressed in the context of contemporary literature as well as providing the possible mechanism for the research results. On the contrary to the expectation, Effort Expectancy (EE) and Facilitating Condition (FC) were statistically proven to have no statistically significant influence on the AI adoption intention of HR professionals, which led to the rejection of **H1**: Effort Expectancy has positive impact on the intention of AI adoption in HRM and **H2**: Facilitating Condition has positive impact on the intention of AI adoption in HRM. Hence, this study did not find EE and FC as significant determinants to accentuate the AI-adoption intentional behaviours from HR professionals. The potential root of the research outcomes could be due to the agile evolvements of AI technologies' capacity and their intervention in business markets. These issues are argued to relentlessly challenge the business structure, leadership role and the perception on AI usage. On the other hand, AI adoption intention is found to be significantly impacted by PE, SI, PR, and SQB, thereby validating the research's associated hypotheses **H3**: Performance Expectancy has positive impact on the intention of AI adoption in HRM; **H4**: Social Influence has positive impact on the intention of AI adoption in HRM; **H5**: Status Quo Bias has negative impact on the intention of AI adoption in HRM and **H6**: Perceived Risk has negative impact on the intention of AI adoption in HRM. Notoriously, the finding of this research emphasises on the crucial impact of SI and SQB as validated in both QUAL and quant research to have the greatest impact on HR professionals' intentional behaviours on AI adoption. Overall, the findings of this research confirm the existence of certain UTAUT factors and two psychological factors in impacting AI adoption intention in HRM. Moreover, the empirical outcomes demonstrate consensus with several emerging studies while acknowledging the area of discrepancy among some others. Penultimately, several recommendations for an AI Facilitation Framework were correspondingly proposed. The research continues with the next chapter to outline the study's implications while locating the research's limitations, future orientation, and opportunities for associated studies.

CHAPTER 8: RESEARCH CONCLUSION AND FUTURE ORIENTATION

8.1 Introduction

This chapter summarises the thesis by revisiting research's chapters and providing a synthesis in research objectives to the core research questions as well as indicating the research's contributions in theoretical, political and practical lens. Alongside with the key remarks, research limitations are discussed to ensure the objective perspectives while also recommending the orientations for associated future research in the disciplines. Finally, the research conclusion summarises key findings of this study, highlighting its core contributions to the empirical knowledge of AI adoption in HRM.

8.2 Summary of the attainments of Researcher's objectives through Chapters

Inspired by the concept of AI-HR collaboration in the digital era, the thesis was initiated with the primary purpose of bridging the disjunction between theory-practice in the proposition of AI-powered HRM. The research anchored to prominent models of technology acceptance, especially the UTAUT model, while exploring and providing evidence-based literatures of the contemporary HRM contexts derived from HR professionals regarding AI demands. Due to the radicalisation of AI technologies and fierce competition within the business market, the expectations of HR practices are not immune to the request of upgrading its functions to perform more agilely and effectively in this 4^{th} Industrial Revolution era (Schwab, 2024). Hence, the study attempts to synthesise UTAUT theory in accordance with HRM demands in practice to explore the possibility of acceptance and collaboration of AI technologies in the human field. It further examines the level of impacts of individual acceptance factors of AI capabilities under the HR professionals' perspectives regarding adoption and innovation. The research is configured into eight chapters as following.

Chapter 1 provides the research background and rationales for further research investigations. The onus of the chapter lied on scarcity of empirical literatures of AI adoption in HRM realm, the nascent establishment of AI and HR concepts, the recent emergence and disruption events of AI advanced technologies as well as accelerating factors from exogenous and endogenous business environments fostering the AI-HR collaboration. It emphasised the potential proposition of AI-powered HRM with practical business examples and the appearance of novel AI-HR terminologies. A strategic dilemma was displayed in associated AI-integrated HRM to augment HR conventional practice, enhance the concept of Strategic HRM (SHRM) and business' success and competitiveness.

In general, the fitness of the AI-HR collaboration model is considered as under-researched due to the prompt advent of AI technologies introduced into the market. A few researchers attempted to test the adoptive suitability of AI technologies in discrete HR functions such as recruitment, performance evaluation or retention management. Alternatively, other research centred on Systematic Literature Review (SLR approach) to explore the exhaustive AI-HR adoption potentials. Either approach generally absents itself from the considerations of integrative HR functions or empirical perspectives from HR professionals regarding adoption intention. In addition, revising the models of technology adoption, the prior research in the HR discipline might obtain a gap in identifying adoption factors, such as psychological elements (as later discovered within this study as significant components in decision making). Given the context of the novel AI phenomenon and the demand to testify theory-based research in HRM, the thesis poses a lacuna that is worth a prompt exploration to keep pace with the perpetual disruptions of AI technologies in the market.

Moreover, in considering recent research models and theoretical frameworks, this thesis engenders an opportunity to testify the technology adoption variables through scientific investigation (QUAL-quant research). This allows the generation of compatible research frameworks to address key research aims and objectives. Despite the fact that there are proposed applications of certain technology-adoption frameworks, there has been no consensus on ideal models to verify AI adoption intention in the HR discipline. It is also argued that the selection of integrative models in each research will vary due to the considerations of individual models. In other words, the chosen model has to serve the requirement of accommodating researchers in achieving research's objectives and clarifying the research gap. By virtue of the aforementioned premises, the research allows the perusal, development and refinement of the overall technology adoption frameworks and related psychological concepts to exhaustively evaluate how the advent of AI generates pressures or drives AI-HR implementation to enhance business-strategy and success. Related to this, the initial aim of this thesis as proposed in chapter 1 as: *"To explore and accumulate scientific evidence of the critical context based on the current stage of AI applications in HRM with the purpose of formulating a congruent conceptual framework for empirical analysis."*

Chapter 2 continues accommodating the research's aim and objectives, this chapter was showcased in two LR lenses: empirical and theoretical. It is claimed that HR is integral for business success in a VUCA world. Hence, this research attempts to initially provide a ground-standing apprehension of conventional HR concepts with its core functions and the evolvement of the concept through the integration of AI advancements. The empirical LR reveals a considerable awareness of the AI-HR augmentation in the business market, which reasonably presents fundamental driven factors for AI-HR collaboration potentials. Concurrently, the primordial AI-powered HRM concept generates a nexus between organisational strategic resources (data), augmented HR functions (automation and decision-making spectrums) and overall business competitiveness. Furthermore, the theoretical LR centred on key theories of technologies adoptions and associated psychological factors impacting the adoption intentions to explore the potential elements to be notified before conducting the empirical research. The two LR lenses assisted the researcher in acknowledging the relevant crevasses in the recent literature, thereby establishing the orientations for the study. In a nutshell, this chapter depicted critical unnoticed spots to excavate including four key points.

- The lack of empirical research to align the concept of AI-HR collaboration leading to obscuring practical integration of AI in HR discipline.
- The lack of long-term consideration in utilisation AI advancements to drive HR performances, which interlinks overall business success and competitiveness.
- Inconsistent results on the adoption drivers of AI-powered HRM and the lack of empirical studies centring on influencing factors to adoption intention from HR professionals.
- The lack of empirically validated model which bridges theorical and practical nodes on AI applications in HRM.

Chapter 3 posed a critical question of the AI adoption willingness from HR professionals and the impact level of each adoption factors to HRM in driving businesses' competitive advantages acquired from AI technologies. At this stage, the researcher outlined the research directions and proposed an overarching research method (a mixed QUAL-quant approach) to satisfy the nature of exploratory research. The thesis applied an abductive approach as a core to certify research's processes and protocols for conceptual framework refinement. Main emphasis of this chapter was on the discussions of methodologies and justification for research decision making. Two phases of data collection were indicated in this mixed-method (QUAL-quant) research. Indeed, although there were noticeable variables identified in LR, it was too generic and lacked scientific validation to address as key variables. Hence, the research adopted the QUAL method at the first phase with the purpose of refining the preliminary conceptual framework. This provided the content of the subsequent chapter.

Particularly, data from the first phase was gathered through semi-structured interviews conducted with 18 AI-HR professionals in West Midland, England. Since the primary nature of this study is based on exploratory research, this first phase was the foundations for research's conceptual framework refinement. Specifically, the results from Phase 1 contributed to illuminating RQ1: "To what extent does the use and acceptance of AI in HRM generate opportunities and challenges for businesses?" and RQ2: "How do HR Professionals perceive and relate to the use and acceptance of AI in HRM?". Moreover, this chapters illustrated the survey questionnaire design and distribution approach to HR professionals (after pilot study conducted) to access the refined model in Phase 2 (quant method) of the research. SPSS was used to access and analyse the empirical data with the considerations on validity, reliability and correlation of the variables.

Chapter 4 showcased the empirical results from the QUAL study (Phase 1). *A priori* codebook was initially developed, which was anchored to the framework adapted from the LR. It was considered that the researcher's theoretical bias from pre-existing knowledge could be excluded with this orientation. Thematic analysis was applied with the assistance of NVivo software to conduct the initial coding and extract the key themes. The analysis revealed key explorations of AI adoption perceptions from HR professionals through three contradictory pairs of Opportunity Vs Threat; Traditional HRM vs AI-powered HRM; and Theoretical Vs Practical Gap. Specifically, each lens communicated significant messages regarding the degree of AI concept diffusion in HRM, the recognised AI-powered HR functions in businesses and the challenges towards adoptions. The three crucial angles distilled from this qualitative research emphasised on the evidence found in the LR regarding how continuous innovation, AI advancement contributes to the adoption intention based on the main model of UTAUT. Importantly, among the findings, psychological elements were discovered to contribute to adoption tendency from HR professionals. The key results from this chapter depict a positive tendency of AI in establishing a critical strategy, resources and continuous innovation (in combining AI concept in SHRM) in businesses. The empirical findings demonstrate a strong alignment among UTAUT factors (PP, EP, SI and FC), emerging psychological factors (PR and SQB) in considering AI in augmenting the conventional HR process. Based on this chapter, RO1, RO2, RO3 and RO4 were achieved.

Chapter 5 provided the extended context of LR and refined the conceptual framework of the study. The findings of Chapter 4 visualised potential interlink of the main UTAUT and psychological components with some sub-factors constituted the concepts. The main focus of this chapter was significantly based on dissecting and analysing individual associated variables (discovered key codes in Chapter 4) and analysing its relations to the main UTAUT and psychological constructs. Hence, the literature-based hypotheses were generated to build the nexus among the constructs. Measurement items were selected by adapting to the extant literature to operationalise the refined framework. At this stage, measurement items for each identified construct were clarified and the survey questionnaire for the quantitative research was adapted based on previous studies affiliated to technology-adoption research. The conceptual framework proposed in Chapter 2 was refined utilising the empirical findings of the previous chapter and the extended concepts introduced in this chapter. Specifically, each main construct was represented with associated variables, which included key measurement items for the main constructs. The emerging psychological factors of PR and SQB were also discussed and quantified in this chapter to constitute the overall conceptual framework for Phase 2 (quant research).

Chapter 6 delivered the quantitative phase of this mixed-method research. Adopting Statistical Package for Social Science (SPSS) software to analyse quantitative data collected from 146 HR professionals across West Midlands, England, the refined conceptual model was analytically assessed in this Chapter 6. Exploratory Factor Analysis was mainly adopted to predict the correlations framework among the observed variables. The results discovered in this chapter empirically validated most of the constructs' relationships. In fact, the thesis reveals that Effort Expectancy (EE) and Facilitating Condition (FC) have no statistically significant influence on AI adoption intention in HRM, contradictory to the proposed hypotheses. Thereby, hypothesis H1 and H2 were rejected. On the contrary, Performance Expectancy (PE) and Social Influence (SI) were investigated to exert statistically positive impact; and Perceived Risk (PR) and Status Quo Bias (SQB) exposed statistically negative impact on AI adoption intention in HRM as stipulated. This resulted in acceptance of the proposed hypotheses of H3, H4, H5 and H6. Based on this chapter, RO1 and RO2 were enriched with more extant literature and background regarding technological evolvement, which was communicated in the subsequent chapter.

Chapter 7 highlighted the key findings and provided a comprehensive picture of AI evolvements in the market occurring while this study was being conducted. It summarises the prompt-pace nature of the AI phenomenon penetrating in the market and explains how it potentially impacted the adoption intention's factors in HRM principle. It bridged and reasonably explained why some adoption factors in the quantitative research had no statistically significant effect on AI-HR adoption, as indicated in the qualitative research. The chapter generated a matrix of communicating and marshalling the key findings through the research questions (RQ1, RQ2 and RQ3).

Chapter 8 recapitulates the core content of research and main discussions. The current study's chapter presents the thesis' conclusion by initially introducing the research overview, essential implications, potential limitations and suggestions for research's future direction.

8.3 Aligning the Research Aim and Objectives

This thesis's main aim of exploring the AI adoption intention in HRM was sectioned into five research objectives as indicated in Chapter 1. The **Table 8.1** illustrates the research's objectives and their connections and attainments in regard to each chapter.

Table 8.1: Synopsis of the attainments of Researcher's objectives – A Navigating Table

Research Questions Relatedness	Objectives	Chapters
RQ1, RQ2 and RQ3	*Objective 1:* To explore and provide scientific evidence of the critical context based on the current stage of AI applications in HRM with the purpose of formulating a congruent conceptual framework for empirical analysis.	Chapter 1, 2,4,5,6,7
RQ2 and RQ3	*Objective 2:* To synthesise the possibility and feasibility of AI technologies in HRM by measuring the impact degree of each AI adoption construct determined from the first phase of exploratory research.	Chapter 2,4,5,7
RQ1	*Objective 3:* To discover the underlying opportunities and challenges brought by AI technologies in the transitions from manual HR practices to AI-powered HR practices.	Chapter 2,4,7
RQ2 and RQ3	*Objective 4:* To critically evaluate the future of AI implications in HRM and make the inference on how AI technologies could be conflated to augment HR functions.	Chapter 4,5,6,7
RQ1, RQ2 and RQ3	*Objective 5:* To potentially establish a theoretical foundation and adoption framework for AI applications to be feasibly transferred into HRM practices.	Chapter 7, 8

This thesis applied a (QUAL-quant) mixed-research method to achieve its objectives. The literature review investigated in Chapter 2 demonstrates a concrete foundation for imparting answers to RQ1, RQ2 and RQ3 of this research. Indeed, the review of anterior studies conceived the critical areas of potential chasm and alignment of the proposition of AI and HRM. This is associated with RO1 of the thesis, which is "*To explore and provide scientific evidence of the critical context based on the current stage of AI applications in HRM with the purpose of formulating a congruent conceptual framework for empirical analysis*." The literature reveals different perspectives from theorists who assert the verification and suitability of the existing relationship between AI and the HRM field. Nevertheless, the scarcity of empirical confirmation of this under-researched topic makes the premise confront arguments and controversies. The indicated reasons polish an increase in demand to examine the theoretical proposition. Hence, Chapter 2 achieved its role in establishing the bedrock for attaining the thesis's RO1. Particularly, Chapter 4 described meticulously the stages of data collection and the process of analysing the data to verify the proposed proposition of Chapter 2. It is considered as fully attaining its goal in Chapter 5 with collected empirically results indicating core AI adoptions factors in HRM which associate with UTAUT and psychological factors.

Subsequently, RO2 and RO3 of this thesis were achieved similarly as the procedure assisting the researcher in RO1. In fact, deliberating RO2, **section 2.2.12** reviewed the role of Strategic Human Resource Management (SHRM) with the assistance of AI applications across HR functions to augment its performance. It was emphasised that the traditional HRM's performance could be productively outshined in HR functions with the adoption of AI algorithms in operational (quantifiable) and decisional (quantifiable and situational) spectrums (as discussed in **section 4.3.3** Chapter 4). In addition, Chapter 4 also elaborated the core HR functions to collaborate with AI which were selected by HR professionals. In fact, the empirical data revealed that Recruitment and Administrations were two favourable realms of AI deployment. The findings continued to edify that various HR professionals inclined towards the adoption of AI in certain HR bundles, which is a crucial driver for AI-powered HRM. Specifically, **section 4.3.2** enlightened the internal milieu triggering the potent mechanism in the initiation of AI adoption with some dominant categories discovered and consequently being recruited as testing variables for quantitative research. Applying the research methodology in Chapter 3, RO2 and RO3 were also achieved in Chapter 6. Based on the explained research sequence, the expected outcomes for RO1, RO2 and RO3 provided in Chapter 2 was eventually attained.

For the RO4 of this thesis, which is "*To critically evaluate the future of AI implications in HRM and make the inference on how AI technologies could be conflated to augment HR functions*". The empirical and theoretical reviews in Chapter 2 highlighted the possible relationships among the AI solutions in various HR practices such as performance management, recruitment, on-boarding and engagement. This provided the fundamental perspective from the AI consumer behaviours in HRM reflecting upon the demand in the extant market, hence, emphasised this research's objective. The previous discussion induced the extension of a generic preliminary research direction for the exploratory Qualitative research at Phase 1. In addition, the rarity of the context-based research about AI in the HR field notified the demand to investigate the potential AI application deployment in the HRM process. Anchoring to that, the empirical findings of RO1, RO2 and RO3 simultaneously produced the necessary information to access the potential areas in HR where AI could functionally assist and redefine the tasks. Conforming to that, in Chapter 7, the discussion also summarised the germinability and the expansion of HR functionalities conditioned AI embedded in HR procedure. This emphasises the future superintendence of human factors onto AI technologies at initial stage of adoption and later stage of adaptation in response to the growth of innovation diffusion in the HR field.

Lastly, the RO5 "*To potentially establish a theoretical foundation and adoption framework for AI applications to be feasibly transferred into HRM practices*." was accomplished in Chapter 6 and discussed in detail in Chapter 7. Based on the distilled constructs in Chapter 6, the AI-HR Adoption Model specified the adoption constructs potentially involved in each stage of the adoption process. In fact, the results obtained in the quantitative research in Chapter 6 and the further discussions based on the research timeframe in Chapter 7 exemplified the agile nature of technology evolvements in terms of rejection and acceptance behaviours of users. Dovetailing to that, it would be reasonable to state that the canonical constructs for adoption intention will evolve proportionately to the level of diffusion of technology and the degree of familiarisation of users towards its usages. Hence, this research explicated and presented the adoption constructs applicable for the time beings where the research was being conducted. Following the above, the thesis comprehensively achieved its final aims and objectives.

8.4 Research Result

To this point, this research overarchingly appraises the connections of the research findings with the research objectives and research questions. Specifically, the RQ1 targeted the answers to the question: "*To what extent does the use and acceptance of AI in HRM generate opportunities and challenges for businesses?*". From the empirical data collected from interviewing the recruited AI-HR professionals in Chapter 4, the core answers were discovered. In fact, although the apprehension of the AI concept to HRM are at infancy stage (reflecting upon the definition provided by the HR professionals), above 76% of the HR professionals categorised the advent of AI as "opportunity" to transform the existing HR performance. The study continued to acknowledge the two factors of Effort Expectancy (EE) and Facilitating

Condition (FC) as proposed in the Literature Review to be impactful in accentuating AI adoption decision process. This fosters the opportunity for AI-powered HRM to improve business's performance as presented in terms of job fits and versatility, ease of use and long-term cost effectiveness.

In addition, the empirical findings underscored the expected AI-powered HR functions which are favoured by HR professionals such as recruitment (dominantly) and administration (handling employment enquiries and managing leaves) which were emphasised to augment business management's performance. The challenges of adoption were also encapsulated with the confirmation of HR professionals in conceding the ineluctable risks brought by AI including bias, privacy, unknown matters (FOTU) and unemployment factors. Hence, the confirmation of the elements advocated the existence of Perceived Risk (PR) constructs in the adoption model.

Importantly, the extension of the UTAUT's adoption factors was illuminated by discovering the emerging factor of Status Quo Bias (SQB), which rooted from psychological commitment, conceptual misperception and perceived cost. This was cited to be one of the significant factors (proven both in qualitative and quantitative research) embedded in the adoption decision-making process of the HR professionals. Based on that, the other adoption hindrances were asserted by HR professionals reflecting in the emerging theme of Status Quo Bias (SQB) where the misunderstanding of AI concept, sunk cost and the commitment with the conventional HR procedures were insisted as key determinants detaching the professionals from the intention to adopt AI. The subsequent RQ2 addressed in this thesis is "*How do HR Professionals perceive and relate to the use and acceptance of AI in HRM?"*. The analysis from the qualitative research (Phase 1) was illuminated in Chapter 4. The exploratory qualitative research findings explicit some key research findings.

To begin with, at the Innovator Stage of Diffusion of Innovation (DOI), HR professionals demonstrated a high degree of awareness of the imminent approaching of AI intervention in HR functions, however, the concept of AI was not fully apprehended by the majority of HR professionals. Hence, the acceptance is not reaching its full potential. The research participants also acknowledged the extant impediments existing within traditional HRM practices (such as mundane, repetitive tasks and human bias). The claims set a robust premise for HRM in AI transformation. The findings also revealed the inclination of HR functions powered by AI, which were toward the operational spectrums more than the decisional one at the early stage of adoption.

Furthermore, the research significantly highlighted the impact of Social Influence (SI) in the UTAUT model in influencing the adoption intention, with 100% of theme coverage from the empirical data. This accentuates the impact of society in amplifying the new trends of HRM procedure with AI power. Following a similar vein, Performance Expectancy (PE) was emphasised to be the significant theme influencing the adoption intention of HR professionals. Specifically, the expected performance from AI-powered HRM was demonstrated in the aspects of speediness, consistency, large data storage and boosting transparency. Finally, the emerging factor of Status Quo Bias (SQB) addressed an opposing view regarding AI's relatedness in HRM due to certain commitments acclaimed by HR professionals with the conventional HR procedures.

Following the qualitative results from the exploratory stage of the research, it can be affirmed that the HRM realm is experiencing and embracing the continuous innovation of AI intervention. This conceptualised a critical dynamic of AI adoption and implementation in the HR principle. Therein, the research progressed to enlighten the final research question: *"To what extent do the explored determinants relate to the intention to adopt AI in HRM?".* Therefore, the quantitative research was conducted to verify the refined research model. The model firstly hypothesised a positive correlation of UTAUT constructs (PE, EE, SI and FC) towards the adoption intention of AI technologies in HR functions to enhance SHRM and business performance. Moreover, the model postulated a negative correlation of the two psychological elements (PR and SQB) in AI adoption intention of HR professionals.

Theoretically, the adoption factors at this stage would shadow all the discovered adoption constructs from qualitative research. Notably, Phase 2 of this research statistically deducted two factors from the AI adoption intention's equation. At this quantitative research phase, the thesis anchored to the dynamics of AI development pace in the market to synthesise the driving forces behind the fluctuations of adoption factors of AI in HRM. In brief, the quantitative research findings reveal the important findings. Specifically, Effort Expectancy (EE) is an accentuating factor pressures positive impact on the adoption intention of AI in HRM. However, the construct has no statistically significant impact on the dependent variable, which is contrary to H1 of this thesis. Hence, H1 was rejected. Similarly, Facilitating Condition (FC) demonstrated no statistically significant influence on adoption intention of AI in HRM, contradict to H2 of this thesis. Therefore, H2 was rejected. In contrast, Performance Expectancy (PE) and Social Influence (SI) were proven to be facilitating factors, which positively impact AI adoption intention in HRM. This is in line with H3 and H4 of this thesis. Based on the results, these hypotheses were accepted. Simultaneously, this research found that Perceived Risk (PR) and Status Quo Bias (SQB) negatively impact the adoption intention of AI in HRM. The constructs also showed statistically negative impact on the dependent variable as proposed, thereby it validated H5 and H6 of this research.

In conclusion, the empirical findings extracted from this thesis provides an insightful understanding of how AI advancements could penetrate the adoption intention of HR professionals to enhance its existing performances, businesses' competitiveness and long-term strategies as a whole. It shadows the current adoption situation of AI in HRM with the stress on SI (positive adoption factor) and SQB (negative adoption factor) as the main drivers that generated the stagnancy or an impetus for AI-powered HRM. This research successfully highlights the key influencing elements of AI adoption in the HRM realm progressing through anchoring to satisfy each research objective as summarised in **Table 8.1.**

8.5 Research Originality Evaluation on Research Contributions

As articulated in the research questions and gaps, this study makes a substantive contribution to the literature on AI adoption in HRM by advancing both theoretical understanding and empirical evidence on how HR professionals engage with AI innovations. Thus, the contribution of this thesis is positioned explicitly with HRM scholarship, rather than solely within general technology adoption research, by foregrounding HR-specific contexts, decision-making dynamics and professional concerns. This study adopts an exploratory mixed-method design as its core approach, enabling a rigorous examination of the diffusion and adoption intention of AI within HRM. This approach allows the study to move beyond static adoption models and capture the dynamic and context-sensitive nature of AI adoption in HR functions. In doing so, the study also establishes how AI adoption contributes to organisational innovation and strategic development within the HR domain. In line with Guetzkow et al. (2004) framework for assessing research originality, this thesis demonstrates originality across multiple dimensions, including research approach, research context, data, method and findings as illustrated through **Figure 8.1**.

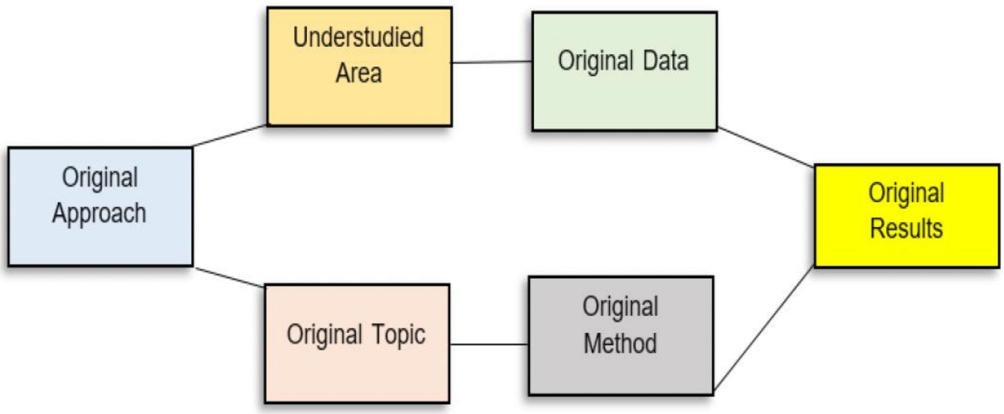

Figure 8.1: Researcher Originality Categories (Guetzkow et al. 2004)

Additionally, rooting from the empirical findings of the study, it is also critical to examine the degree of research originality to the existing literature on AI adoption intention in HRM, as summarised in the **Table 8.2** below.

Table 8.2: Research Originality Assessment

Contribution Areas	Description	Original Categories	Originality Contribution
Provide an empirical validation of how AI advancements linked with the HR functions and practices in augmenting organisational performance	The research provided evidence to bridge the theoretical proposition of AI adoption intention in accordance with certain HR functions favoured by HR professionals such as recruitment, learning and development, and other associated HRM practices.	*Understudied Area & Original Topic*	✓
	The research addressed certain impediments stemming from the traditional HR practices revealed by HR professionals such as repetitiveness, mundane and time-consuming tasks and human errors.	*Original Result & Data*	✓
Provide assessment and validation of the research model regarding AI adoption intention factors in HRM	The research applied a mixed-method (QUAL-quant) approach to investigate the phenomenon of AI in HRM contexts.	*Original Method*	✓
	The research identified the determinants of AI adoption intention factors in HRM as proposed in UTAUT models (EE, PE, FC and SI)	*Original Approach*	

	The research acknowledged the existing appearance of additional two psychological factors (PR and SQB) embedded in the adoption decision-making process of AI in HRM.	*Original Approach*	✓
Provide an empirical examination of the extant impact of AI in the realm of HR.	The research affirmed the intersection between traditional HRM and the AI adoption intention factors anchoring to the diffusion level of AI in the market (an elimination of EE and FC from adoption intention model)	*Original Result & Data*	✓
	The research assessed and illuminated opportunities and threats concerned by HR professionals regarding AI adoption in the realm.	*Original Result & Data*	✓
	The research presented the predominantly AI-favoured areas of operational spectrum compared to decisional spectrum in HRM at the early stage of adoption.	*Original Result & Data*	✓
Provide innovative and groundbreaking insights to navigate and facilitate the use and acceptance of AI in HRM	The research acknowledged the core adoption factors to suggest an AI-HR collaboration framework in the early stage of adoption	*Understudied Area*	✓
	The research proposed core issues regarding adoption stressing on PR and SQB, which allows informed decision-making process and policies to well control the negative impacts.	*Original Result & Data*	✓

	The research presented the profound impacts of AI in multiple HR functions, which addresses the incremental demands of strategy establishments in businesses.	*Original Result & Data*	✓

As summarised in **Table 8.2**, the study makes six distinct and novel contributions to the understanding of AI adoption factors in HRM. Specifically, the thesis addresses a clear theoretical and empirical gap in the literature, where prior research has either treated AI adoption superficially or examined isolated HR functions — such as recruitment (Albassam, 2023), employee engagements (Azadeh et al., 2018), or training and development (Bhatt and Muduli, 2023) — without offering an integrated HRM perspective. While scholarly interest in AI and HRM has increased, existing studies remain fragmented and limited in scope (Budhwar et al., 2022). This thesis directly responds to this limitation by systematically examining AI adoption intention across HRM as a functional domain, grounded in the perspectives of HR professionals. The empirical findings demonstrate that AI adoption demand in HRM is shaped not only by technological capability but also by perceived insufficiencies in existing HR processes and the need for functional augmentation across HR activities. In this way, the study offers a practical evidence of how HR professionals interpret the value and applicability of AI technologies within their work.

In addition, it is worth pointing out that this research is arguably considered as one of the earliest attempts to explore the adoption intention of the two dimensions of AI and HRM (as precedingly explained in the research conduction timeline). Conducted during a period when AI had not yet become ubiquitous in HR practice, the study offers a timely and foundational insights into how HR professionals conceptualise, evaluate, and respond to AI innovations. Methodologically, the study makes a significant contribution by applying a mixed-method design to validate and extend the UTAUT framework within an HRM context. The qualitative phase enabled the inductive identification of salient adoption factors, while the quantitative phase empirically tested their explanatory power. Through this process, the study validates the relevance of UTAUT constructs—Effort Expectancy (EE), Performance Expectancy (PE), Facilitating Conditions (FC), and Social Influence (SI)—and extends the model by incorporating two psychological constructs: Perceived Risk (PR) and Status Quo Bias (SQB). The inclusion and empirical validation of PR and SQB represent a novel theoretical contribution to HR adoption research, highlighting the importance of psychological and behavioural constraints in shaping AI adoption intention among HR professionals.

The findings further reveal important temporal and diffusion-stage effects in AI adoption. While effort expectancy (EE) and facilitating condition (FC) emerged as salient factors during the qualitative phase, bot constructs were eliminated during the quantitative phase due to lack of statistical significance. In line with this, the research made its contribution to the business and HR strategic management centring on different diffusion stages of AI innovations in the realm of HR. This shift demonstrates that adoption intention in HRM is not static, but evolves alongside technological familiarity, organisational exposure, and changing expectations. By empirically capturing this evolution, the study contributes to HR and business strategy literature by illustrating how adoption drivers vary across different stages of AI diffusion in HRM. Moreover, the research highlights a stronger emphasis on operational augmentation rather than full decision automation in the early stages of AI adoption within HR. This insight challenges narratives of AI replacing human judgement and instead positions AI as a complementary tool that supports HR professionals' work. As such, the study introduces an alternative perspective on AI–HR collaboration, offering a more realistic and HR-centred understanding of AI integration.

Finally, this thesis makes original contribution by identifying and empirically validating the role of Perceived Risk (PR) and Status-Quo Bias (SQB) as central mechanisms underlying resistance, hesitation, and avoidance in AI adoption in HRM. These findings provide explanatory depth to ongoing debates about why AI adoption in HR remains uneven despite increasing technological capability. The study further proposes an AI–HR Collaboration Framework, offering a structured lens through which organisations can address ethical, legal, and organisational challenges associated with AI adoption. Collectively, the findings enrich HRM and technology adoption theory, advance empirical understanding of AI innovation in HRM, and provide a robust foundation for future research into AI–HR integration. Conceding to this, the next section outlines the core implications from this research.

8.6 Research Implications

This section sets out the theoretical, policy and practical implications arising from the empirical findings. By examining AI adoption intention in HRM at an early diffusion stage, this research provides actionable insights into how HR professionals evaluate and engage with AI technologies. The implications extend beyond technology adoption to inform HRM theory development, governance and policy design, and HR strategic practice.

8.6.1 Theoretical Implication

Since this study is anchored from established academic theories and models, it has demonstrated the crucial and unique contributions to AI innovation, technology adoption in HRM literature. In effect, throughout this research, the role of UTAUT factors as a lubricant for enhancing AI adoption intention in HRM is well-proven and validated. Therefore, the argument derived in this study puts forward the significant opportunity to exploit and integrate AI technologies in the field of manpower management.

Specifically, the thesis demonstrates its unique contribution to the UTAUT theory and successfully acknowledged the additional impacts of Perceived Risk (PR) and Status Quo Bias (SQB) to the AI adoption intention in HRM. Especially, the research's findings in both qualitative and quantitative affirmed the high coefficient of SQB and Social Influence (SI) toward adopting the intention of HR professionals. This indicates the strong correlations of the two mentioned constructs to adoption intention at the time being of AI diffusion. As a result, the research enriches the applicability of the theoretical model and extends the adoption constructs by integrating the associated elements of psychological impacts while highlighting the most influential adoption factor of UTAUT, which is SI, at this early adoption phase in HRM. Hence, this research is one of the earliest attempts in the HRM domain to authenticate and declare the conceptual insights for AI adoption intention empirically.

Further, it could be observed from the quantitative research that the elimination of EE and FC from the adoption model significantly reveals the agile pace of the evolvement of adoption intention in the market (review the in-depth discussion in Chapter 7). Tailoring to this, this study has reassessed and evaluated the contemporary impacts of UTAUT adoption intention factors through different innovation diffusion phases. In this case, the study refutes the previous research on the UTAUT model which adopted an etic position to assume all adoption factors were sufficient across contexts. The findings also advocate the critical value and necessity of the DOI model as a reflection and median point to scrutinise the extant and perpetual transformation of AI adoption phenomenon in the HR realm. To this end, the thesis proposes opportunities for empiricism of the core adoption factors in the AI-HR collaboration framework.

8.6.2 Policy Implication

Further along the theoretical implications, the study has attempted to provide certain policy implications since it is important to locate the AI adoption intention factors within the political contexts. In fact, the significance of UTAUT factors (SI and PE) and psychological factors (PR and SQB) within HRM adoption at this current diffusion settings are illustrated with regard to the counteraction of the two mentioned dimensions. While one appraises the critical demand for transformation of traditional HRM to AI-powered HRM, PR and SQB were highlighted in this research to be the impediments toward adoption intention, which restricts the access to augment current HR performance. In this vein, the research suggests directions and guidance for policy makers in order to facilitate AI adoption in HRM. Specifically, with regard to the role of policy makers, it is critical to marshal and regulate standardised practices to supervise the compliance and effectiveness at the inceptive adoption stage. From this research, it could be seen that while organisations attempt to adopt AI, it is essential to acknowledge and tackle issues regarding ethical, privacy or misconception (PR and SQB related elements) about AI. Hence, this research makes its contribution to knowledge by highlighting and providing empirical evidence regarding benefits and challenges of AI adoption in HRM. Therein, it underlines the foundation understanding for governments or industry parties to support AI innovations in its diffusion's levels while mitigating and managing the risks.

At the same time, the research has successfully secured its attempt to balance both theories of technology adoption's logic and integration in a way that they explain the extant context of AI innovations adoption in HRM and provides meanings for the uneven-distributed values of adoption factors in this realm. Specifically, this follows from the previous discussion in Chapter 7 which lightens a rich picture of the occurrence of the adoption factors' discrepancy in the two phases of the research. Particularly, while Effort Expectancy (EE) and Facilitating Condition (FC) factors were deemed to be critical in establishing the gravitation of AI in HRM at Phase 1, the mentioned elements were discarded at the second phase, indicating its insignificance in AI adoption intention model. With this regard, this study suggests strategic approaches to be established through different diffusion stages of AI in HRM in order to target the appropriate adoption factors. Hence, AI adoption facilitations and success are contingent upon contiguous research, fundings and training programmes to be invested and supported by governments to aid in the enactment of informed policies in AI and HR principles. The investigation would entail a deeper level of considerations on demographics and industry-based factors to precisely navigate adoption intention of AI in the HR realm. This is to enrich future decision-making processes and AI formulation policy.

8.6.3 Practical Implication

With respect to the practical contribution, this study significantly demonstrates the core AI adoption factors currently influencing the HR field, which confirms the willingness of HR to embrace the advent of AI to be integrated in certain HR functions. In light of this research, certain HR functions which were favoured by HR practitioners were indicated, which highlights their expectation to adopt AI in the routine HR tasks in order to augment performances and increase efficiency. Indeed, the viable relationship of AI and HRM was supported with the acknowledgement of Performance Expectancy (PE) in both phases of the research. Based on this, AI vendors and business leaders would need to consider the appropriate integrations of AI technologies in specific functions which plausibly enriches HRM values in enhancing business performance. Thus, this would entail a collaboration and reliance between businesses and AI vendors in order to suitably integrate AI-powered HR functions in the businesses' operations.

In the similar vein, by recognising the key hindrance elements in adopting AI technologies in HR practices, the research discovered the factor of Status Quo Bias (SQB), which was emphasised in both phases of the study to be significantly influencing adoption intention of HR professionals. The role of SQB is found in this study to possess a great impact in generating the stagnancy of HR in approaching the novel technology advancements rooted from cognitive misperception and psychology commitments embedded in the constructs of SQB. In attempts to establish the acceptance and adoption attitudes, organisations would have to indicate the cost of being laggards in the diffusion level in the field. In practice, while this research was being conducted, certain businesses have started to invest and embed AI into the HR system in order to eradicate inefficiency, enrich performance and captivate significant values such as enhancing brand reputation and talent acquisition. Hence, educational and training programmes to bridge the extant KSAs (skills, knowledge and attitudes) of the employees are required to decimate the impact of SQB in AI adoption intention. In furtherance to this, this research also stressed on the importance of change management and business value evaluation while assessing the contemporary HR practices. This would further propose the considerations on calculating Return on Investment (ROI) to actually measure the monetary values in adopting AI in HRM.

8.7 Research Limitation

Due to the nature of empirical research, it is essential to acknowledge certain limitations constraining the study from reaching its full potentials. The declaration of the research limitations is to ensure the elimination of potential bias embedded in the research execution and further marshal novel avenues which are opportunities for future research. The limitations of this thesis are indicated as following.

This study is England-based, and the data were gathered solely from West Midlands regions in England (a specific geographical area). Due to that condition, it may impact the generalisation degree of the research outcomes to the broader contexts. However, the conceptual framework of this study is generalisable considering the prestige of the UTAUT model in technology adoption research. It is argued that sourcing data from one geographical environment to illustrate a larger and global perspective could be controversial (Reddy and Dávalos, 2003). In fact, it is worth mentioning that the scattering of AI advancement and development in HRM is potentially distinct across domestic regions and the discrepancy could be enormous when comparing the evolving pace of AI in developed, developing and undeveloped countries. Hence, examining the adoption intention of AI in HRM will not be sufficient if data was collected at regions or countries where the AI concept was yet coined or business models were greatly inclined towards transactional approaches, which potentially outsource HR functions. The selection of West Midlands, England organisations due to its ability to satisfy the requirements of the mentioned criteria and the researcher's high accessibility to HRM networks. Dovetailing to that, this study embraces a higher proportion of particularisation and does not necessarily imply the generalisability to other AI adoption intentions in HRM in different areas. Therefore, analysis of other geographical territories (in either local or global scales) would exhibit a higher proportion of generalisations of the research's findings.

In addition, the research not only examines the adoption intention of AI in HR within one sector. In fact, this study gathered data across sectors to satisfy the exploratory nature of it through uncovering emerging trends and insights of AI potentials in the HR realm. Notwithstanding that, multidiscipline sectors could possess different HR standards, policies and technological infrastructure readiness for AI adoption. Hence, the degree of familiarisation and expertise of AI advancements can proportionately vary across sectors which potentially leads to uneven perceptions among HR professionals about AI adoption intention. Reflecting upon this study, around 25% HR professionals participated originated from the Education sector which might influence the generalisation level of adoption intention of AI in HRM to other realms. However, it is important to mention that UTAUT and psychological factors examined in this study still express significant values due to the early advent of AI development in the market. In other words, not only the HR function but other core business functions such as supply chains, marketing and accounting are not immune to the approaching trend of AI intervention in the discipline. This creates a starting point for HR across sectors to review and monitor the growth of the innovation in order to generate appropriate business strategies coping with the dynamics.

Another limitation emerging from this study is the persistent risk of conceptual conflation between AI technologies for HRM and existing HR analytics and digital HR systems. Across the qualitative phase, participants frequently referred to AI using broad or ambiguous terminology, often describing predictive analytics, automation, or self-service systems as forms of AI. This tendency mirrors wider patterns observed in practitioner discourse, software vendor marketing, and consultancy narratives, where advanced analytics-driven tools are routinely labelled as AI, despite lacking adaptive or autonomous capabilities. This conflation has important implications for the interpretation of the findings. While participants expressed relatively high awareness of AI and strong intentions to adopt AI-enabled HR solutions, their responses often reflected expectations associated with predictive HR analytics rather than with more advanced forms of AI. As a result, the measured adoption intentions may partially capture attitudes towards data-driven HR decision support more broadly, rather than towards AI in its stricter technical sense. This does not invalidate the findings, but it does suggest that adoption intentions are shaped by how AI is socially constructed and understood within HR practice, rather than by precise technical definitions. It is important to acknowledge that this ambiguity may have constrained the ability to fully disentangle perceptions of AI from perceptions of HR analytics within the dataset. In particular, survey responses may reflect overlapping interpretations of constructs such as performance expectancy and facilitating conditions, given participants' limited direct experience with AI-specific systems.

A variety of mathematical and statistical models were initially attempted to utilise in this research to examine and analyse the relationship of AI adoption factors in HRM such as Structural Equation Model (SEM), Generalised Linear Model (GLM), Multinomial Regression and Confirmatory Factor Analysis (CFA). Nevertheless, the research finds that the considered models were not applicable to the data at this early phase. In fact, an attempt to recruit a larger sample size (>150 participants) were made but only 146 valid survey questionnaires were secured after 3 months launching the surveys to the HR-professional network. Importantly, the closure of the survey questionnaire at that time was also due to the uncertainty of prolonging the licence of Qualtrics from BCU (**Appendix 8.1**). Due to the abrupt and uncertain nature of the incident, the researcher had to end the survey questionnaire process to secure the database, which reduced the expected robustness of the dataset. In addition, as discussed in the previous chapters, the nature of research testing technology adoption was precarious due to its abrupt evolvement characteristics. Consequently, CFA and SEM were not utilised to explain the adoption intention model of AI in HRM owing to the mentioned reason. Hence, although the other statistical models and tests possess greater power to explore and increase sense-making ability of data, the thesis applied Multiple Regression Model (MRM) and Exploratory Factor Analysis (EFA) to simply synthesise the correlation between adoption factors to AI adoption intention. It is worth reiterating that QUAL-quant research was selected to execute in this thesis which asserts a more substantial proportion of qualitative research's outcome in explaining the research's problem statements. Based on this, future research could enrich the data analysis by enhancing the robustness of the dataset and using alternative sophisticated statistical models to enrich idea establishment and authenticate the relationships between factors impacting adoptions and the adoption intention.

Finally, the initial recruitment scheme for the qualitative research's participants was above 20 HR professionals to enable the encapsulation of sufficient implications of AI-HR adoption research. Nevertheless, the research was conducted during the dynamics of Covid-19 where there were certain impediments on participant recruitment due to the restrictions of lockdown and interruptions of businesses' operations. This resulted in a tremendous obstacle for the researcher to reach out to the HR-professional network. In addition to this, the process to recruit HR participants to involve in empirical research presents significant challenges. This is owing to the fact that the HR participants with high expertise, responsibilities and priorities may obtain certain boundaries to be engaged or explicitly declare their positions, which generates a complication to secure the participation. As a result, the qualitative study could secure 18 candidates since it was challenging to recruit a larger number of participants. Despite the recruitment hurdles, the qualitative analysis was successfully captured as it reached the saturation points of theme establishment. Nonetheless, future studies could complement the research's implications with a greater number of participants in order to communicate more functional perspectives from HR professionals regarding adoption intention.

8.8 Research Future Orientation

Following the discussion of this research's limitations, the study poses certain areas for future investigations and research directions. Therefore, the thesis provides potential areas for further developments as follow.

To begin with, this thesis successfully acknowledges the perception and acceptance of AI in HRM while measuring the adoption intention, future studies can continue investigate the actual use and acceptance of AI technologies in HRM when AI diffusion reaches higher adoption level such as Early Majority or Late Majority based on Diffusion of Innovation (DOI) model (Rogers, 1962). In reality, the practical applications of AI in HR are still in the primordial stage, longitudinal studies to examine the adoption of AI in HRM is critically essential in terms of navigating and scrutinising the impact of AI adoption factors in the field. This enables deeper apprehension of AI development and strategy establishment for businesses in the junction of the continuous evolvement of organisational and HR performance.

As acknowledged in the limitation of the study, a second research outcome would embed higher explanation levels of the adoption intention factors of AI in HRM in the West Midlands, England area due to the participant recruitment process. Hence, comparative research approaches on alternative cultures or geographies could provide the insights as well as elucidate the variance in terms of adoption intention or actual AI usages in HRM practices in different areas. With this in mind, the suggested research could also inculcate this study's findings as reflections or comparison tools while measuring the impact level of AI adoption in the selected research contexts.

Additionally, sector-based research can provide promising directions in order to deepen the understanding of AI-HR collaboration and adoption in distinct industries. In fact, the tailored insights extracted from the proposed studies can enrich the diffusion level of AI in HRM with appropriate industry-specific strategies. This will assist businesses to evaluate the AI novel synergies, applications and implementation. Hence, research following this direction can enhance HR strategic capability on the competitiveness of organisations operating in the studied industry.

The conceptual conflation issue could be addressed in several ways. Particularly, greater conceptual precision could be introduced at the design stage through clearer definitional framing and the use of scenario-based or vignette methodologies that explicitly distinguish AI-powered HR applications from analytics-driven or automated systems. In addition, future quantitative studies could employ refined measurement instruments that differentiate between levels of algorithmic autonomy, learning capability, and decision-making support. The longitudinal and comparative research designs could also examine how conceptual clarity evolves as AI becomes more embedded in HR practice, allowing researchers to observe shifts in understanding, usage, and adoption drivers over time.

Penultimately, further research could develop in the directions of uncovering barriers and addressing impediments of actual deployment of AI in HRM. As this stage potentially reaches its peak of AI diffusion, confirming the use and acceptance factors utilising sophisticated statistical software and models would reveal rich insights of AI readiness in the HRM realm. This helps to generate a concrete facilitating and adoption framework for AI-powered HRM to be formed and sharpened. The suggested directions will tremendously enhance research's generalisation capacity in the field and advance more equitable and contextual adoption strategy in HR practices.

Finally, this study utilised UTAUT1 to examine the adoption intention but not UTAUT 2 (which includes additional three more adoption factors of Hedonic Motivation, Price Value and Habit) due to the paucity of AI applications and usages in HRM. To further explain, the mentioned factors would make sense when the employees have opportunities to experience and work with AI in their routine tasks, which was not applicable in this early diffusion stage. Indeed, the qualitative research at Phase 1 did not evacuate the mentioned themes or collected enough nodes to generate the themes. Thus, future studies can consider modifying the research model examined in this study to explore the driving factors of AI adoption in HRM. This will enlarge the scope of AI adoption factors and provide novel angles to navigate the growth of the advanced technologies in this principle.

8.9 Chapter Summary

Chapter 8 brings closure to the study regarding exploring the adoption intention of AI in the realm of HRM. Within this chapter, the comprehensive summary of the thesis' s overview and main purpose was precedingly reiterated. Further, the chapter also exhibited the research's outcomes when simultaneously articulating the research objectives to demonstrate how that procedure formed the foundation to illuminate the research's questions. The navigation of research's outputs to enlighten the research questions were also accessed in accordance with the originality and novelty contribution in AI adoption and HRM fields. Ultimately, underlying limitations, research opportunities and directions in the associated themes of AI and HRM anchoring to this research's findings were accordingly proposed. Thus, at this stage, the study is considered as fully achieved and attained its expected results as well as assert its predominant values. More implications and interpretations regarding the nexus of AI deployment in the field of HR are suggested to be continuously explored and investigated to discover the disruptions of AI in existing management theories and capacities of the advanced technologies in augmenting HRM and business performance.

8.10 Research Conclusion

To conclude, this research shows that AI adoption in HR is shaped less by technology itself and more by how HR professionals understand, interpret, and socially negotiate AI within their organisations. While AI is often discussed as a powerful and transformative technology, this study demonstrates that HR professionals frequently struggle to distinguish AI from HR analytics, automation, and other digital HR tools. As a result, adoption intentions are not driven by technical usability or organisational infrastructure, but by social influence and resistance to change. This is in line with the result of both qualitative and quantitative of this research where social influence emerged as the strongest positive driver of adoption, while status quo bias was the strongest barrier. Performance expectancy also mattered, indicating that HR professionals are willing to engage with AI when they believe it will deliver clear value, but only once social legitimacy and cultural acceptance are established. In contrast, ease of use and facilitating conditions had no significant effect, challenging common assumptions in technology adoption research.

This matters because it reframes the AI adoption problem in HR. The findings suggest that slow and uneven adoption is not primarily a failure of system design or technical readiness, but a consequence of conceptual ambiguity, professional identity concerns, and entrenched ways of working. When AI is treated as an umbrella term for all advanced HR technologies, expectations become blurred and adoption decisions are shaped by social cues rather than informed understanding. This research therefore shows that successful AI adoption in HR requires more than investment in tools or training. It requires clear differentiation between AI and analytics, strong leadership signalling, and deliberate efforts to challenge the status quo. By revealing that social and behavioural forces outweigh technical ones, this study provides new and important insight into why AI adoption in HR remains difficult—and what organisations and researchers must address to move forward responsibly and effectively.

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APPENDIX

CHAPTER 3: RESEARCH METHOD

Appendix 3.1: Interview questions

Research Interview Questions

1. **Interviewer Introduction:**

Hello, my name is Anh Phan, a PhD research student at Birmingham City University (BCU). I am currently conducting research on the topic of Artificial intelligence (AI) in Human Resource Management (HRM). I would like to express my gratitude for your participation and the precious time dedicating to my research. I would like to notify you that my research has been approved by the BCU Research Panel and the Ethics Committees. I have sent in prior the authorisation letter to my participants. Your participation in this research is completely voluntary and you are free to withdraw at any time. Please note that there are no incentives rewarded for this research participation. Your confidentiality and personal information are ensured to be protected. There is no yardstick for correct or incorrect answers. I would like to record the interview with your permission for practical and ethical purposes. Ultimately, you are free to include your experiences or feelings when answering my research interview questions so the meanings of your responses can be captured entirely.

2. **Interview Questions:**

General questions:

- Could you please introduce yourself?
- How long have you been working in (HR/AI industry)?

Questions pertaining to traditional HRM

- What is the nature of your business? (Your mission, vision and main product or service)
- What is the size and structure of your HR department and the company?
- What is your opinion about manual HRM processes?
- What is the HRM technological tool/system that your company currently adopting?
- What do you think are the benefits of the current manual HRM?
- What are the challenges of the current manual HRM?

Questions pertaining to AI in HRM

- What appears in your mind when you hear the term AI?
- What do you think are the advantages when applying AI in HRM?
- What do you think are the challenges when applying AI in HRM?
- What functions in HRM do you think AI adoption will be best beneficial?

Questions pertaining to Attitude towards AI in HRM

- To what extent do you agree or disagree with the statement "AI will replace human jobs"? Could you please justify your response?
- What do you think more about AI (a threat or an opportunity)?
- What manner do you think your colleagues would have when applying AI in HRM (chatbot, co-bot, automatic HRM functions (recruiting, selection, training and development, succession planning)? (positive/negative/neutral)? Could you please justify your response?
- If your organisation decided to adopt AI, what do you think would be the main reasons?
- If your organisation decided not to adopt AI, what do you think would be the main reasons?

Questions pertaining to Adoption Intention/ prospects of AI in HRM

- Do you think it easy to apply AI into HRM? Do you think your organisation will consider applying AI in HRM?
- What is your anticipation for the future of AI in HRM?
- According to your opinion, is it important to bring innovation into HRM? Why?

3. **Interview Ending**

This is the end of the research interview. Thank you very much for your time participating in the research. If you have any further concerns or comments, please do not hesitate to be in touch with me via my email at **nhat.phan@mail.bcu.ac.uk.**

Appendix 3.2 : Follow-up Questions

Follow-up Questions

1. **Organization scope**
   - What do you think about the potential market of AI for SMEs at this stage, especially in HR Department?
   - At the current moment, the majority of AI applications are employed mainly by large organisations, have you aimed to target or already targeted AI application packets for SMEs, especially in HR Field?
   - With potentially small amount of data generated from SMEs, do you think it is an obstacle for SMEs to apply AI at work since data is claimed to be "fuel" for AI?
   - What do you think about the cost for SMEs to adopt AI application? What will be the main factors for SMEs not to consider AI application at this stage?
2. **Required Capacity**
   - Are there any primary requirements for the organisation's facility if they would like to adopt AI into their business?
   - Some organizations have not had a proper enterprise system to manage daily operational activities. If so, it is possible to apply AI?
   - As an AI vendor, are you going to provide a full equipped package to establish a foundation for AI, or you require a certain level of enterprise system to build on?
3. **Skills, Training and performance expectancy**
   - How long does it usually take for an employee to get acquainted with the new system?
   - Which skills do you think will be required for an HR practitioner to be able to work with AI? Do the applications of AI will require intensive training for users? If yes, what types of training to be required?
   - What is organisation's most expected factor when deciding to adopt AI (cost efficiency, productivity). Are there any other potential factors that you think will strongly influence on their decision to adopt AI in HRM?
4. **Finance**
   - Since AI is an advancement technology, what is the minimum required investment to adopt AI? Would you mind giving us the cost structure (hardware, software, database, maintenance)?
   - Do you think cost will be the main obstacle for companies to consider applying AI technologies?
5. **Area of application**
   - If businesses start to adopt AI in HRM, which business sectors would you think will be the pioneer and why?
   - Which functions in HR that organisations concentrate most when being in touch with your company?
6. **Awareness**

- What are the popular approaches that customers are introduced about your service (word of mouth, social media, industry fame)? Which channels will be potential to reach your customers?
- Do you have any intention to expand AI products in HRM in the future?

7. **Perceived Risk**
   - What are important factors to possibly build the collaboration and trust between employees and AI applications?
   - Do you think lack of trust would be the main reason for a company not to adopt AI technologies?
   - Do you have any approaches or strategies in place to improve users' trust on the products?

Appendix 3.3: Participant Information Sheet

PARTICIPANT INFORMATION SHEET

This research is being undertaken by Anh Nhat Phan and the project is supervised by Dr. Mohamed Hawela (Mohamed.Hawela@bcu.ac.uk) and Dr. Wahabalbari Ahmed (Wahabalbari.Ahmed@bcu.ac.uk). This research aims to explore the use and acceptance of Artificial Intelligence in Human Resource Management. The research will be written up and submitted for assessment and may be used for external publication.

QUESTIONS AND ANSWERS – ABOUT THIS RESEARCH

Please note that this information sheet provides the basic information about this research project. If you have any further questions, I will be happy to answer then before you decide whether to give your consent to participate in the research.

Question	Answer
1. What is the title of the project?	The Use and Acceptance of Artificial Intelligence in Human Resource Management
2. What research is being conducted?	This research aims to explore the use and acceptance of Artificial Intelligence in Human Resource Management. The research objectives are: ● O1: To identify the current stage of AI implementation in HRM ● O2: To understand the possibility and feasibility of applying AI in HRM ● O3: To understand the impact of AI on HRM practices ● O4: To understand the opportunities and challenges brought by AI in the transitions from traditional HRM to the AI applications in HRM. ● O5: To understand the role of HR Managers and future of AI implication in HRM.
3. Why have I been invited to participate?	You have been invited to participate as a professionally competent and knowledgeable practitioner in the area.
4. What input do you require from me?	The research will require information about views, opinions, and information about AI/HRM.
5. How will I participate?	You will be asked to complete online interviews or online survey questionnaires
6. When will I need to participate and how long will it take?	You will be invited to participate in the interview for maximum 30 minutes/ alternatively, you might be invited to participate in a survey questionnaire which could take up to 20 minutes maximum to complete.

7. Who will have access to the data I provide?	Supervisor, course team, external examiner and I at Birmingham City University.
8. How will the data be used?	The data will be analysed and documented in a research report. It will not contain any personal details of participants or organisations involved in this work. The findings of the study may also be submitted for external publication in an academic journal or conference.
9. How long is the duration of the research project?	Data will be retained until the PhD research is completed to allow the findings to be published (up to 3 years when the PhD completed). Contact with participants will be short and intermittent so as not to disrupt you working arrangements.
10. Will my data be secured?	All information is stored electronically on the University's secure 'One Drive'; it will not be stored on personal devices.
11. How long will data be stored?	All data collected will be destroyed right after the PhD research is completed to allow time for findings to be analysed and published. The findings of the study may also be submitted for external publication in an academic journal or conference. All participants' identities will be anonymised.
12. What will happen to the data at the end of the research?	All data will be securely disposed of, and only anonymised data will be used for publishing results. At no time will data be passed to a third party.
13. Can I have access to the research results?	Yes. The results will be made available to participants on request at the end of the project. A summarised report of the dashboard system will be sent to the company.
14. What if I do not wish to participate in this research?	You are not under any obligation to participate. You can choose not to participate without detriment. Participation is completely voluntary.
15. What if during the research I change my mind about participating in the project?	You may withdraw from the research at any time and in any stage of the research. Please contact me via email nhat.phan@mail.bcu.ac.uk and your data will be removed from the project.
16. Who do I contact if I have any concerns about the research or the study generates any adverse effects?	In the first instance, please contact my supervisors Mohamed Hawela via email at Mohamed.Hawela@bcu.ac.uk, Wahabalbari Ahmed Wahabalbari.Ahmed@bcu.ac.uk and the Faculty Academic Ethics Committee via email BCU_ethics@bcu.ac.uk to review the matter
17. What do I do if I have questions about the project?	Please contact me via email nhat.phan@mail.bcu.ac.uk

Appendix 3.4: Research Consent Form

CONSENT FORM

Title of Study:	The use and acceptance of Artificial Intelligence in Human Resource Management
Researcher Contact Email	Nhat.phan@mail.bcu.ac.uk

This research is being undertaken by Anh Nhat Phan, a doctoral student at Birmingham City University. The research is supervised by Dr Mohamed Hawela (mohamed.hawela@bcu.ac.uk) and Dr Wahabalbari Ahmed (wahabalbari.ahmed@bcu.ac.uk). This research aims to measure the use and acceptance of Artificial Intelligence in Human Resource Management. The research will ideally be written up and submitted for assessment and may be used for external publication.
Please note that you are able to withdraw from this study at any time by completing the Request to Withdraw Form and send it back to me at nhat.phan@mail.bcu.ac.uk, my supervisors Mohamed Hawela via email at Mohamed.Hawela@bcu.ac.uk, Wahabalbari Ahmed

Wahabalbari.Ahmed@bcu.ac.uk and the Faculty Academic Ethics Committee via email BCU_ethics@bcu.ac.uk. All responses will be treated in confidence and will not be shared with any third party. Data be anonymised to protect your identity, and all information collected will be securely destroyed upon successful completion of the award.

Please can you answer the following questions:

Question	**Response**
Have you read and understood the information sheet inviting you to participate in this research?	Yes/No
Have you been given the opportunity to ask any questions you have about the research?	Yes/No
Do you agree to participate in the research, as outlined in the information sheet?	Yes/No
Do you understand that you are free to withdraw from the study without giving reasons?	Yes/No
Do you give permission for the researcher and their supervisor named above to have access to the data provided by you?	Yes/No
Do you understand that the data collected from you will be anonymised, securely stored during the research and securely destroyed at the end of the study?	Yes/No

Please sign below to confirm that you have voluntarily decided to participate in this research project named above and that you have read and fully understood the accompanying information sheet.

Signature of Participant:	Date:
Name of Participant:	
Signature of Researcher:	Date:
Name of Researcher:	
Signature of Supervisor:	Date:
Name of Supervisor:	

Appendix 3.5: Access Request Letter (Phase 1)

ACCESS REQUEST LETTER (Phase 1)
(Individual)

12-07-2021

Dear Sir/Madam,

My name is Anh Nhat Phan, and I am a doctoral student in the School of Business at Birmingham City University. I would like to kindly invite your participation in my doctoral research study that I am conducting titled: The acceptance and use of Artificial Intelligence in Human Resource Management. This study is conducted for research purposes.

This research is under the supervision of Dr Mohamed Hawela (Mohamed.hawela@bcu.ac.uk) and Dr Wahabalbari Ahmed (wahabalbari.ahmed@bcu.ac.uk).

I will be grateful if you may help by participating in this research. The interview will last for about 30 minutes on Microsoft Team or face-to-face meeting.

I confirm that all responses will be treated as confidential and only used for academic research. Data will only be analysed or reported in aggregated form; no one response will be identifiable, and no personal or company names will be included in the research write-up. The research will be written up to be assessed by the University, and it may be used for external research publication.

In the case you opt to withdraw from the research, you can fill out the **Request to Withdraw Form** and send it back to me at nhat.phan@mail.bcu.ac.uk or my supervisor Mohamed Hawela via email at Mohamed.Hawela@bcu.ac.uk, Wahabalbari Ahmed Wahabalbari.Ahmed@bcu.ac.uk and the Faculty Academic Ethics Committee via email. Your data will be removed and destroyed immediately when your request is received.

Thank you for your time. I look forward to your valued response. In the interim, should you have any queries, please do not hesitate to contact me at nhat.phan@mail.bcu.ac.uk or to my research supervisors at Mohamed.hawela@bcu.ac.uk and wahabalbari.ahmed@bcu.ac.uk and the Faculty Academic Ethics Committee via email BCU_ethics@bcu.ac.uk.

Yours faithfully,

Anh Phan

Appendix 3.6: Access Request Letter (Phase 2)

ACCESS REQUEST LETTER (Phase 2)
(Head of department)

12-07-2021

Dear Sir/Madam,

My name is Anh Nhat Phan, and I am a doctoral student in the School of Business at Birmingham City University. I would like to kindly invite your participation in my doctoral research study that I am conducting titled: The acceptance and use of Artificial Intelligence in Human Resource Management. This study is conducted for research purpose.

This research is under the supervision of Dr. Mohamed Hawela (Mohamed.hawela@bcu.ac.uk) and Dr. Wahabalbari Ahmed (wahabalbari.ahmed@bcu.ac.uk).

I will be grateful if you may help by allowing the participation of your employees in this research. Your employees will be invited to participate in the interview for maximum 30 minutes; or alternatively, they might be invited to participate in a survey questionnaire which could take up to 20 minutes maximum to complete.

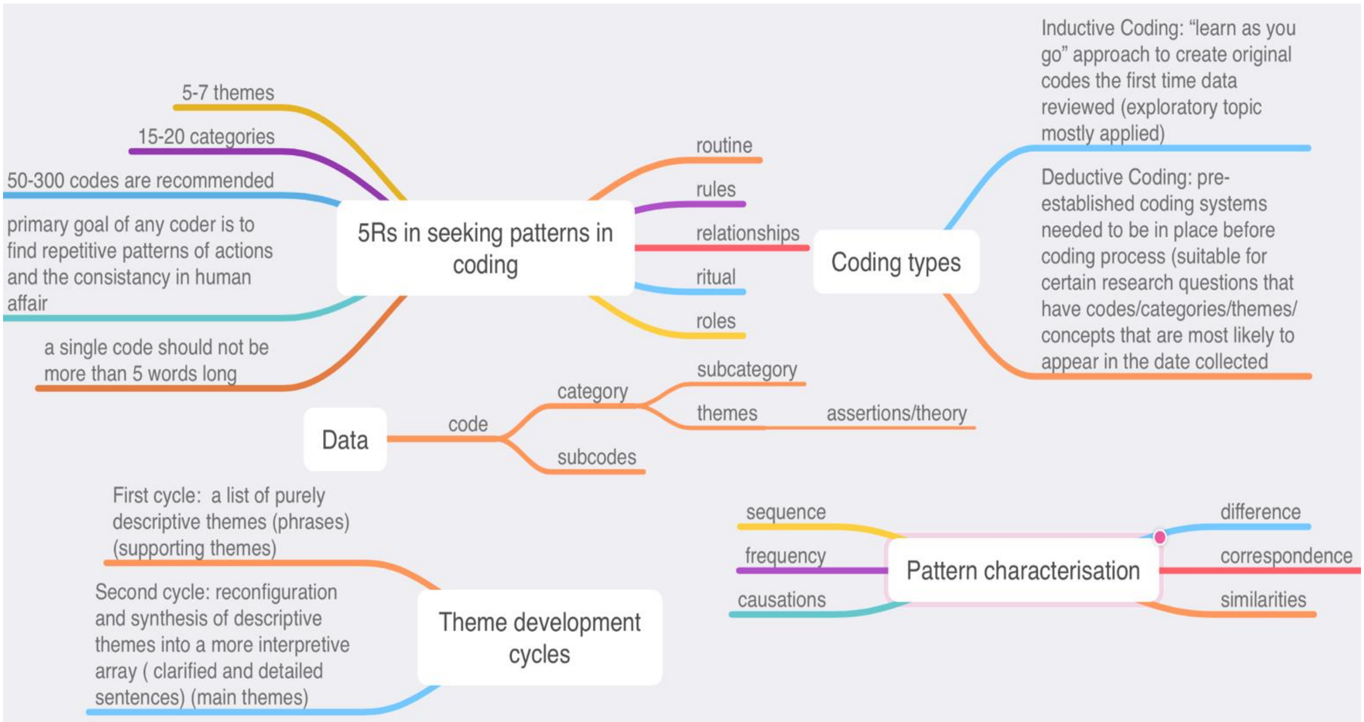
I confirm that all responses will be treated as confidential and only used for academic research. Data will only be analysed or reported in aggregated form; no one response will be identifiable, and no personal or company names will be included in the research write-up. The research will be written up to be assessed by the University, and it may be used for external research publication. The participation in this research is voluntary, and your employees are free to withdraw from the research at any stage. In the case your employees opt to withdraw from the research, you can fill the Request to Withdraw Form and send it back to me at nhat.phan@mail.bcu.ac.uk or my supervisors Mohamed Hawela via email at Mohamed.Hawela@bcu.ac.uk , Wahabalbari Ahmed Wahabalbari.Ahmed@bcu.ac.uk and the Faculty Academic Ethics Committee via email BCU_ethics@bcu.ac.uk . The data will be removed and destroyed immediately when your request is received.

Thank you for your time. I look forward to your valued response. In the interim, should you have any queries, please do not hesitate to contact me at nhat.phan@mail.bcu.ac.uk or to my research supervisors at Mohamed.hawela@bcu.ac.uk and wahabalbari.ahmed@bcu.ac.uk and the Faculty Academic Ethics Committee via email BCU_ethics@bcu.ac.uk.

Yours faithfully,

Anh Phan

Appendix 3.7: Coding Guide



Appendix 3.8: Record of Experience Log in qualitative research (an example of the first interview)

First interview **Date of conduct: 18th February 2022** **Mode of interview: MS Team meeting** **Brief description of the experience:** (What happened? Where was I? What was I doing? How did this come about? How do I feel about this event?) This was the first interview that the researcher conducted with the participant in the Recruitment Department of PwC company. The interview was occurring on MS Teams in

video-recording mode to ensure comprehensive meanings through physical movements, body language and communicative tones to be completely captured. The date and time were chosen by the participant to make sure a sufficient and comfortable timespan was provided for the interview to be conducted. The researcher had certified and received the authorisations from the participant for recording purposes. The interview lasted for around 25 minutes following the semi-structured interview questions where follow-up questions are required to be generated and deployed in clarification-required situations. During the interview time, the researcher strictly followed the proposed questions and created a friendly and pleasant atmosphere where the participant could freely express their ideas regarding the research topic.
Important Observations The participant was excited when mentioning AI technologies in HRM and described how she used those technologies in her current and previous jobs. There are several potential themes had been repeated by the participant such as employer brand (social influence) and speedy work performance (Performance Expectancy). The feeling of being sufficient in adopting the updated technologies was well-described. The participant compared her companies with other SMEs and the challenges she confronted while working in her previous job, mainly manually conducted tasks. The participant indicated the importance and strategic approaches for companies that are the first movers in adopting AI technologies.
Researcher's self-reflection for strategic research method (What do I need to change/develop/work on?) Since this was the first interview, there were certain aspects that must be improved and reinforced. It also had been pinpointed by the researcher's supervisors that the follow-up questions should be available to obtain richer data. In the first interview, the researcher concentrated and invested the majority of effort in the predetermined theme from the preliminary conceptual framework. Reflecting on the interview while it was occurring, more information regarding the incumbent information system and technologies questions should have been taken into consideration. Although the emerging themes were available such as features where cost and ease of use of AI, the researcher recognise that potential bias could emerge if the interviewee was asked to answer questions regarding the aspect of the current company.
<u>**Developmental Plan**</u> **What do I need to do with this learning?** - Follow-up questions will have to improve - The participant will need more information about the particular context to be able to provide richer answers - More questions regarding the challenges of the business while implementing AI need to extend **How has this experience helped me?** - Good chance to understand the context and improve the rapport building skill with the HR professionals. - Time and information constraints for HR professionals were acknowledged, questions will have to be well-prepared in case the participant could not share the IT infrastructure.

Appendix 3.9 : Participant Recruitment Leaflet

THE USE AND ACCEPTANCE OF ARTIFICIAL INTELLIGENCE IN HUMAN RESOURCE MANAGEMENT

PHD RESEARCH

Researcher: Anh Phan (Birmingham City University)

Participant Invitations

I am recruiting potential participants for my research who are working in Human Resource Field or Artificial Intelligence industries to participate in a short interview. The interview should last no longer than 30 minutes and could be arranged via any social platforms (Zoom, MS Team, Skype) or face-to-face meetings which suit the participants. The purpose of the interview is to understand your points of view about the mentioned topic on AI and HRM, which will become the potential foundation to identify the influential adoption factors of AI in HRM.

Your points of view regarding the mentioned research topic will significantly contribute to the exploratory findings of the impact of the emerging advanced technologies in the current labour market, especially in Human Resource Management.

Doctoral Researcher:
Anh Phan

Doctoral Research:
Exploring how AI technologies impact the current business world (HRM)

Keywords: AI, HRM, HR, innovation, business, technology, perception

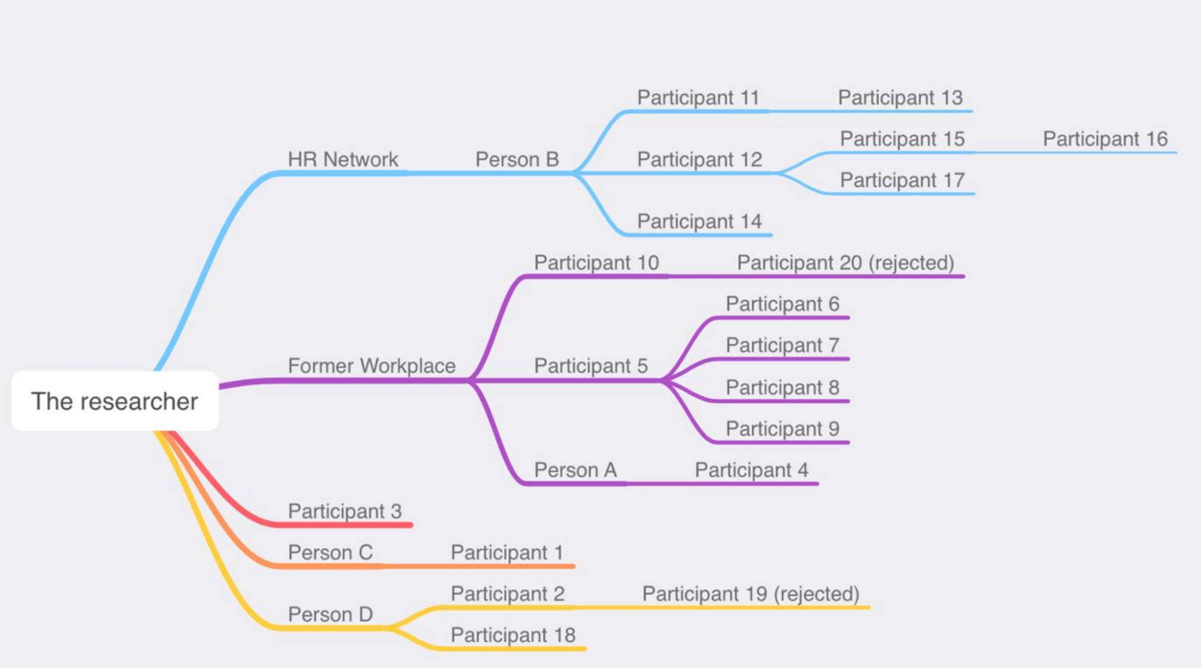
RESEARCHER CONTACT

Email: nhat.phan@mail.bcu.ac.uk

Phone: +44 7562428259

LinkedIn: https://www.linkedin.com/in/anh-phan-aab01785/

Appendix 3.10: Snowballing - Participant Recruitment



Appendix 3.11: Draft version of the Research Survey Questionnaire

RESEARCH QUESTIONNAIRE

Part 1: Demographic information

1. **Gender**

☐ Male ☐ Female ☐ Preferred not to say

2. **Age**

☐ 20-30 ☐ 31-40 ☐ 41-50 ☐ 51-65

3. **What best describes the industry you work in?**

☐ Business ☐ Education ☐ Manufacturing ☐ Others,

Please specify________

4. **Working Position**

☐ HR Executives ☐ HR Practitioners ☐ Others, please name ___________

5. **Working experience**

☐ <5 years ☐ 5-10 years ☐ 11-20 years ☐ >20 years

6. **AI understanding**

6.1 Are you familiarised with the term "Artificial Intelligence"?

☐ **Yes** ☐ **No**

6.2 How do you evaluate your understanding about AI?

☐ None ☐ Limited ☐ Moderate ☐ Developed ☐ Advanced

Part 2: Research questionnaire:
Please provide your responses to the following statements: (Scale of 5 from disagree, slightly disagree, neutral, agree and strongly agree)
Questionnaires establishment based on the key constructs and main variables:

Performance expectancy			
Cost-effectiveness	CE1	The use of AI technologies in HRM will increase the quality of output in my job	(Thompson et al., 1991), (Taylor and Todd, 1995), (Palau-Saumell et al., 2019), (Venkatesh et al., 2003)
	CE2	The use of AI technologies in HRM will increase the opportunities for me to deliver more meaningful jobs	
	CE3	The use of AI technologies in HRM will offer better value for the organisation	
	CE4	The use of AI technologies in HRM will increase my flexibility in delivering my job	
Task Versatility	TV1	I believe the use of AI technologies in HRM will improve my productivity	(Taylor and Todd, 1995), (Venkatesh et al., 2003), (Alam et al., 2020)
	TV2	I believe the use of AI technologies in HRM will be useful in my job	
	TV3	I believe the use of AI technologies in HRM saves me time	
	TV4	I believe the use of AI technologies in HRM will increase my chances of career progression	

Effort expectancy			
Ease of use	EOU1	Learning to work with AI technologies in HRM will be easy for me	(Muñoz-Leiva et al., 2017), (Fishbein & Ajzen, 1975)
	EOU2	I believe the use and interaction with AI technologies in HRM require less thought	
	EOU3	I believe I would find AI technologies easy to use for whatever HR task I want to do	
	EOU4	Overall, I believe the use of AI technologies will be easy to use in HRM	
Job Compatibility (JC)	JC1	I believe the use of AI technologies will significantly assist me across different HR functions	(Muñoz-Leiva et al., 2017), Gary C. Moore; Izak Benbasat, 1991)
	JC2	I believe the use of AI technologies will increase the effectiveness in performing different HR functions	
	JC3	Overall, I believe the use of AI technologies can be useful in assisting me to perform different HR functions	

Social influence			
Employer Branding	EB1	Organisations which are currently applying AI technologies in HRM have more prestige than those who do not use them	(Muñoz-Leiva et al., 2017), (Goffman, 1967), (Rogers, 1962)
	EB2	Organisations which are currently applying AI technologies in HRM have an enhanced reputation	
	EB3	Using AI technologies in HRM will enhance the status symbol of my organisation	
Subjective norms	SN1	People whose judgement I trust think that I should use AI technologies	(Hung et al., 2012), (Fishbein & Ajzen, 1975)
	SN2	People who affect/influence my behaviour think that I should use AI technologies	
	SN3	People whose opinions I value prefer that I must use AI technologies	
	SN4	In general, the organisation has supported the use of AI technologies	
	JC4	My job-related activities with AI technologies will be clearer and more understandable	

Facilitating conditions			
Leadership Support	LS1	My organisation will be supportive of AI technologies in HRM	(Thompson et al., 1991), (Rogers, 1962)
	LS2	The senior management of my company will support me in introducing AI technologies in HRM	
	LS3	My colleagues will be assisted by senior management to use AI technologies in HRM	
	LS4	Overall, my organisation will be investing in AI technologies in HRM	
Innovation Driven	ID1	I have heard about AI technologies in HRM, and I would like to look for a way to experiment with it	(Hung et al., 2012), (Rogers, 1962)
	ID2	I would like to experiment with AI technologies in HR practices	
	ID3	In general, I am enthusiastic about AI technologies applied in HRM	
	ID4	At work, I am usually the first to try out new technologies	

Perceived Risk			
Bias Concerns	BC1	I do not trust the results generated by AI technologies in HRM	(Bankins et al., 2022), (Guha et al., 2021)
	BC2	The results generated by AI technologies in HRM include biases	
	BC3	I do not believe in results generated by AI technologies in HRM	

	BC4	The results generated by AI technologies in HRM may bring unfair outcomes	
Fear of the Unknown	FU1	The ambiguities brought by AI technologies in HRM induce stress in me	(Carleton et al., 2007), (Graham, 2021)
	FU2	Applying AI technologies in HRM makes me uneasy or anxious	
	FU3	The ambiguities brought by AI technologies in HRM upset me	
	FU4	I will lack confidence due to the ambiguities brought in by AI technologies in HRM	
Perceived Unemployment	PU1	My organisation will use AI technologies to replace my position in HRM	(Jaradat et al., 2020), (Nam, 2019)
	PU2	My organisation will find someone who is skilful in AI technologies to replace my position in HRM	
	PU3	My position in HRM will be threatened by AI technologies	
	PU4	Overall, the use of AI technologies in HRM will eliminate many HR jobs	
Privacy Concern	PRC1	Private information could be misused, inappropriately shared, or sold when using AI technologies	(Alt et al., 2021), (Muñoz-Leiva et al., 2017), (Pitardi and Marriott, 2021),
	PRC2	Personal information could be intercepted or accessed when using AI technologies	
	PRC3	Personal information could be collected, tracked, and analysed when using AI technologies	
	PRC4	Private matters could be exposed or accessed when using AI technologies	

Status Quo Bias			
Cognitive misperception	CM1	Adopting AI in HRM would be no more effective than working in the current way	(H. Kim, 2009), (Samuelson and Zeckhauser, 1988)
	CM2	By adopting AI in HRM I would not accomplish relevant tasks more quickly than working in the current way	
	CM3	Adopting AI in HRM would not increase my productivity relative to working in the current way	
	CM4	Adopting AI in HRM would not improve the quality of work I presently do	
Perceived Cost	PC1	In the long-term the cost of using AI technologies in HRM is higher than applying traditional HRM	(Luarn & Lin, 2005), (Sripalawat et al., 2011), (Yu, 2012), (Samuelson and Zeckhauser, 1988)
	PC2	AI technologies applied in HRM costs a lot of money	
	PC3	Applying AI technologies in HRM is a burden to me	
	PC4	The cost of applying AI in HRM is considerable	
Psychology Commitment	PYC1	People in our organisation will not embrace the new way of working with AI technologies in HRM	(Fan et al., 2015; Hong & Kim, 2002; H. Kim, 2009), (Samuelson and Zeckhauser, 1988)
	PYC2	Our organisation will not operate with the new way of working with AI technologies in HRM	
	PYC3	Most colleagues will oppose the change to the new way of working with AI technologies in HRM	
	PYC4	Our organisation will not agree with the new way of working with AI technologies in HRM	

Intention to use	IU1	I plan to use AI technologies in the future	(Davis, 1989), (Sripalawat et al., 2011),
	IU2	I intend to use AI technologies in the future	
	IU3	I predict I would use the AI technologies frequently in the future	

CHAPTER 4: QUALITATIVE RESEARCH

Appendix 4.1: General Demographic Information

Interviewees	Title	Years of experience	Date of interview	Gender	Organisational scope	Interview Channel	Total Time
Participant 1	HR Practitioner	2 years	18/2/2022	Female	Large (>1000 employees)	MS Team	45 minutes
Participant 2	HR Consultant	> 10 years	18/2/2022	Male		Face-to-Face meeting	1 hour 5 minutes
Participant 3	HR Practitioner	1 year	22/2/2022	Male	Small-Medium (< 250 employees)	Face-to-Face meeting	1 hour 7 minutes
Participant 4	**HR Executive**	> 10 years	7/3/2022	Female	Small-Medium (< 250 employees)	MS Team	50 mins
Participant 5	HR Practitioner	6 years	7/3/2022	Female	Large (>1000 employees)	MS Team	1 hour 15 minutes
Participant 6	HR Practitioner	1.5 years	11/3/2022	Female	Large (>1000 employees)	MS Team	1 hour 22 minutes
Participant 7	**HR Manager**	2 years	15/3/2022	Male	Small-Medium (< 250 employees)	MS Team	1 hour 13 minutes
Participant 8	**HR Manager**	> 10 years	16/3/2022	Female	Large (>1000 employees)	MS Team	56 minutes
Participant 9	HR Practitioner	3 years	21/3/2022	Female	Small-Medium (< 250 employees)	MS Team	1 hour 29 minutes
Participant 10	**HR Manager**	7 years	22/3/2022	Female	Large (>1000 employees)	MS Team	1 hour 17 minutes
Participant 11	HR Practitioner	2.5 years	22/3/2022	Male	Small-Medium (< 250 employees)	MS Team	1 hour 9 minutes
Participant 12	HR Practitioner	3 years	1/4/2022	Female	Large (>1000 employees)	MS Team	1 hour 14 minutes
Participant 13	**HR Manager**	> 10 years	20/4/2022	Female	Large (>1000 employees)	MS Team	52 minutes

Participant 14	HR Consultant	> 10 years	4/5/2022	Female		MS Team	1 hour 23 minutes
Participant 15	**HR Manager**	> 10 years	6/5/2022	Female	Large (>1000 employees)	MS Team	1 hour 2 minutes
Participant 16	HR Consultant	> 10 years	11/5/2022	Male		MS Team	1 hour 10 minutes
Participant 17	**HR Manager**	> 10 years	18/6/2022	Female	Small-Medium (< 250 employees)	MS Team	1 hour 13 minutes
Participant 18	**AI Leader**	6 years	18/5/2022	Male		MS Team	1 hour 15 minutes

Appendix 4.2: Coding information
Coding references

Files	**Number of coding references**	**Number of nodes coding**
Interview 1	23	14
Interview 2	18	13
Interview 3	6	5
Interview 4	17	9
Interview 5	21	12
Interview 6	19	10
Interview 7	20	12
Interview 8	9	7
Interview 9	14	7
Interview 10	18	10
Interview 11	18	11
Interview 12	15	11
Interview 13	17	8
Interview 14	14	8
Interview 15	12	8
Interview 16	21	13
Interview 17	18	10
Interview 18	17	9

Parent Nodes	**Number of coding references**	**Aggregate number of coding references**	**Number of items coded**	**Aggregate number of items coded**
Perceived Risk	53	53	18	18
Social Influence	57	57	18	18
Status Quo Bias	44	44	10	10
Effort Expectancy	46	46	16	16

Performance Expectancy	40	40	16	16
Facilitating Condition	37	37	16	14

Child Nodes	**Number of coding references**	**Aggregate number of coding references**	**Number of items coded**	**Aggregate number of items coded**
Effort Expectancy\Job compatibility	33	33	16	16
Effort Expectancy\Ease of use	13	13	7	7
Social Influence\Subjective norms	12	12	9	9
Social Influence\Employer branding	10	10	8	8
Performance Expectancy\Cost effectiveness	12	10	7	7
Performance Expectancy\Task Versatility	28	30	15	15
Facilitating Condition\Innovation Driven	35	35	16	16
Facilitating Condition\Leadership support	14	14	9	9
Status Quo Bias\Psychological Commitment	15	15	12	12
Status Quo Bias\Cognitive misperception	14	14	10	10
Status Quo Bias\Perceived Cost	15	15	10	10
Perceived Risk\Fear of the unknown	20	20	9	9
Perceived Risk\Privacy concern	4	4	3	3
Perceived Risk\Bias concern	20	20	10	10
Perceived Risk\Perceived unemployment	9	9	8	8

Illustrations of factors weights

Table: Responses from HR professionals/ AI leaders expressing their opinions regarding AI's Effort Expectancy (EE) in HRM

Themes	**Sample responses**
Job compatibility	"So, recruitment […] especially within Iceland because we have the MSL system, it cuts down a lot a lot of time instead of doing the right to work checks […] the technology where we pick out highlights or special words from CVs. And then we short list them and then they get interviewed. So, the managers don't see the CV […] we have thousands of CVs, and it will take a lot of time to go through." "[…] instead of someone putting or adding the details of the new joiner into the system. Instead of manually doing this, like taking a photo, straight away from the card." "We create a virtual world like the game SIM (psychometric tests), so candidates come with a character and come to talk to us like this." "Other things like sickness, if we need to keep an eye on someone, sickness patterns or records that would help us to identify trends on someone's sickness pattern. […] because now we do have to do it manually" "Artificial intelligence could help us predict employees' retention, employees' behaviour "What kind of employees stays with us? What is the average payroll" and […] if we start making records of those as well, then we can predict that "what's the next steps that our employees going to take?" "How they navigate their decisions within our company?" and others of their prospects." "[…] HR helpline […] they will just ask us to self-service by going to our EY website, just to check all or it's like a dictionary where we can just check all our HR processes on what we need to do."
Ease of Use	"Adoption of AI will be best beneficial like a lot of the admin tasks like inserting details into the database. Instead of having a human being do that […] an AI can identify all the details from a client or to input all those data in." "It's less time consuming and it's quicker to do things, get tasked done […] we were adopting new AI systems, and it meant that there was a self-service type of system where employees could input information, and it would come straight through to HR rather than just having to fill out forms and then having to wait for them to give it into us." "We want everything to be interlinked and streamlined and we think that it would make the whole process and the whole system easier." "That's an inappropriate amount of time being wasted on repetitive questions […] an AI intelligence could easily address. And would be more useful and intuitive." "It'll be able to take on more difficult tasks that human beings can't physically do […] we can't remember as much information and I feel like AI, because it's computer-based, they'll be able to do certain tasks faster."

Table: Responses from HR professionals/ AI leaders expressing their opinions regarding AI's Social Influence (SI) in HRM

Themes	Sample responses
Employer Branding	"But if your company doesn't adopt that on the AI basis and you don't follow the market trend, you're not going to attract your clients to use your services or evolve with your services because your client wants to also be attracted all the services. So, AI is one thing that people will use it for branding" "[…] it's the call of competitive edge. It is really. And when you've got many businesses and you're all doing the same thing, find details matter." "Because of the competition, once again everything is about competition. They will come up with a lot more advanced systems as well that they can use (to attract employees)"

	“A lot of organizations have adopted hybrid working and I feel like likewise AI and HRM, you know things will change in the future and in order for companies to stay relevant, we need to adapt to those changes.” “The demand to use this is there. It's all about measuring the weighing up the risk and opportunities of the equation to make sure you are moving just fast enough to innovate”
Subjective norms	“[…] eventually they must do it because if they want to stay on the game, we have an agreement on these technologies. Otherwise, they're not going to survive” “They don’t aware, they are not tech-savvy […] we have business acumen and to have this technology and digital scheme that smaller organisations, don't have yet, but they will still need to have.” “I think that's probably been a big driving force that nearly all our competitors are online, either through zoom or tablet or app, and that's where we're moving to as well. So, we offer both now.” “The main one that comes to mind is them being up to date with the technology. So […] big companies are growing constantly, you must adapt too” “I am pretty sure that if one or two started to go down that road, we would all want to follow up pretty quickly because broadly we all like to be in line”

Table: Responses from HR professionals/ AI leaders expressing their opinions regarding AI's Performance Expectancy (PE) in HRM

Themes	Sample responses
Cost Effectiveness	"[…] a lot of admin work can be automated, and it is going to be a lot of advantages of the cost-effective" "Cost-saving, you save a lot of costs […] You don't have to pay salaries to workers every single month. So, you can downsize your organisation, help the business to save more costs and then just use one system to sort of run the business." "You don't have to worry about litigation, injury claims or employment tribunal claims because the machine is never going to take you to an employment tribunal. It'll save you money in that regard." "[…] it as an opportunity to free up their time to do to add more value and other areas. […] we're cost efficiencies in you know like constantly on the table or who knows maybe it would be an opportunity to restructure and do something differently" "[…] it might require a major investment upfront in the technology, but over time over months and years ahead that that cost pays off and the efficiency savings come through. So, manual will almost always be more expensive in the long term" "There would be significant cost saving because it would make us more efficient, and it would free up time to do the more meaningful things that could make a difference to wiser people in the organisation."
Task Versatility	"when you put the salary or even the bank details of someone on the system you need to be very careful what you put because this person might not get paid right and if you put the wrong details […] You can take a photo of the card (using AI) of the person and upload the photos so the machine can pick it up, so you kind of eliminate the human error." "[…] auditing, so keeping colleagues' records and that is definitely amazing, documentation and making sure that you have like the employee handbook […] that resolves in admin, that's the best thing to do for it as well as the case management side of things within my role" "[…] (in hiring) you know that there's not going to be someone who's been left in the dark or they've had their interview that haven't been contacted. It makes sure that we keep that communication" "(decision making) The advantages of it (AI) are allowing you to do things productively […] provides insight, deep learning, intuitive thinking around creating that data diagnostic approach, which then a human can interpret." "There will be enquiries around policies and procedures being in a place where actually you're able to talk to chatbot or technology like that, and they're able to pick up on keywords or filter out your information out definitely." "Rather than going to wait on the call for an hour, at least, an AI chatbot can put you through to different departments straight away or help you to answer the questions that it's in the AI system itself."

Table: Responses from HR professionals/ AI leaders expressing their opinions regarding AI's Facilitating Condition (FC) in HRM

Themes	Sample responses
Leadership support	"They (leaders) are currently in the process of developing a self-service app for employees to use […] to book their annual their own annual leave and things like that. […] they're currently in the process of developing this and I believe this should be completed within eight months." "I did. We've talked about it. It's on the agenda […] we're hybrid working team meetings, meetings like these one-to-one meetings. I've been to executive committee meetings where I've sat at my dining table, and we've used zoom technology and it's kind of the norm now" "[…] with the advent of the pandemic, more organizations have looked to AI and systems to take ownership of that element because onboarding has become a much more remote experience." "They (leaders) are thinking to do soon because the workload is growing for all of us. So, one of their ways to improve that is creating new systems or improving the existing ones." "It's something we've (leaders) talked about so much in team meetings and what difference and value we think that could add if our systems were robust enough to allow us to do it. […] I know that they (employees) would see that as positive because it's something we've talked about."
Innovation Driven	"[…] regard to recruitment, again it is completely changed whenever I interview someone, one of the first questions asked is "how do you work? Are you all in the office? Are you hybrid? Are you remote?" So, I think the pandemic has changed a lot, not only in HR but within businesses alike" "I just see it is impacting broadly […] I see it is impacting recruitment, selection, whether that the machine type or whether it be that the deep dive on Psychometrics, training and development." "we'll see a cautious but steady move to more people using it […] AI then becomes an additional kind of entity, whereas I think in some of the more manufacturing processes leads type organisations, will be adopted quicker" "But now it's people losing jobs, no, it's because we evolve. It's an opportunity for us to civilise and evolve to a better world" "I'm excited to see how it will help us work better and it will make jobs a lot easier for a lot of us or the tedious tasks that we do the repetitive tasks […] it should hopefully make way for us to do things that are more meaningful at work, like taking on projects.

Table: Responses from HR professionals/ AI leaders expressing their opinions regarding AI's Status Quo Bias (SQB) in HRM

Themes	Sample responses
Psychology Commitment	"I also refer that interaction. It's a lot better and sometimes you get the problem resolved a lot quicker and […] when you're speaking to a human, you feel more valued, which is what I prefer." "I must admit, last year we did put together a spreadsheet. That we felt probably better to manage it and we're not having to deal the machine all the time" "Everything is working fine, so I don't necessarily see that needs to be improved. […] I believe everything seems to be working just fine now about that." "[…] it's a change and what people don't like is change. I think certainly in the immediate, I do think there would struggle the adaptation." "It can be time-consuming cause some people don't like change and they're so used to using a certain doing things a certain way that. Then they're closed-minded to try something new." "When you're moving from manual to electric using artificial intelligence, it's a bit difficult for people. They get disengaged because some people just don't like changes, they cannot adapt to change." "The biggest challenge is it's not just about data in HR, it's about the things that you pick up through conversations, it's about the things that you pick up through relationships. It's not always about data and information" "a lot of senior leaders in responsible positions and organizations still want to carry on the way they were, not recognizing that the world has moved on. So that is the biggest barrier."
Cognitive Misperception	"It doesn't think like a human. You can't hear […] you can't look at anything that's outside the box, doesn't take a human element, human perspective to it." "[…] I believe everyone responded in a negative manner because it's taking so long already to get systems that are more up to date and can help with the needs of the business" "It could help in terms of delivering the information, but anything outside of that I don't feel like AI will be able to assist with and I think that's where a human would need to be involved." "I don't think about this as to what benefits would be, I suppose with anything with manual and automated hits it has its pluses and minuses." "I'm thinking of something smarter than us up then as humans. […] that was very scary to me because […] artificial intelligence, I believe it's something that's meant to be smarter than us." "The first thing that comes to my mind is the movie The Matrix. And Tesla Self-service machines and robots. That's the first thing that comes to mind when I think about artificial intelligence […] there are also people that could use AI for bad reasons."
Perceived cost	"[…] I implemented was a career development portal which was quite expensive and obviously, I do have a training budget and I have to weigh up the losing majority of my training budget to implement this […] for the company and cost-wise." "It is expensive, and you need to hire the right people to do that, and especially the small organisation, cannot really do this." "Also because of cost, because to adopt AI, first thing it will cost […] it will be huge cost upfront, although long term it might be better because you're not going to pay salary to […] hundred people using AI." "I don't think it would be cheap, and I don't think many people would want to invest too heavily in it. But for my organization, it would be a big cost because we're not big enough to invest millions into artificial intelligence." "Number 1 would be the cost because we're not a hugely profit-making organization so it would probably be a bit difficult to get such a system or spend so much money on AI" "Costs sometimes are a factor because obviously if you're updating on an annual basis or whenever the new version comes out, you have to pay the provider an annual fee to have the latest version and to get support."

Table: Responses from HR professionals/ AI leaders expressing their opinions regarding AI's Perceived Risk (PR) in HRM

Themes	Sample responses
Bias Concern	"You remove the bias of that, however, who creates the robots? the human. The person who creates that can be biased and can give biased options to robots. I don't know if that makes sense." "But another view of it is that it's not very personal and it doesn't really represent HR, which is humane, and it doesn't really sit right with us to speak to a computer […]." "[…] one application of this where the company was looking for IT people and it was found that a big percentage of the ones getting through the process was male and he was found really that that was down to cognitive bias." "There is debate around things like subconscious bias because the person whose programme these things got subconscious bias that then feeds through into the programmes" "There isn't currently a framework in which I believe it could be used ethically." "They cannot be trusted. And especially with the sort of bureaucratic way that whole world is run will certainly the most part. There's no way the people at the bottom would get know how it's used." "I think there's something about fairness and bias. […] the data used to train these models often has got bias embedded within it, and […] it can amplify and extend and genuinely cause real-world harm and poor outcomes to people, and unfortunately, that's often too vulnerable groups"
Privacy concern	"Losing control of personal data and employees not feeling comfortable talking to a screen or a robot" "People might perceive any risk […] about the level of information and ways in which data and information are held in relation to those solutions. I think people will always have ongoing challenges with that." "I think the bigger challenge is looking at going to be around human rights, I think it's going to be around confidentiality." "I think privacy concern is increasing. There are a lot more cases where I suppose the media have made that fear amplified because there's always new stories that certain details have been leaked, a firewall has been breached and data is in the public domain."
Fear of the unknown	"Although it's saving us a lot of money, saving us a lot of time but it could have longer disadvantages or consequences in the future that we don't know about is yet." "I think without knowing exactly what it means and what it entails […] probably a bit of a threat in my mind because I just don't know that" "I think negative and that would be due to the unknown. When one doesn't understand what the implication that benefits or challenges are […] it can be seen as something that will take over." "I do see artificial intelligence can be a scary concept for some [..] it's more about being scared of the unknown rather than actually having any real basis for the fear." "There might be a degree of fear about what this would mean for their business model, and it might be a lack of insight in knowing where to start."

Perceived Unemployment	"[…] different departments will view this differently. The more admin the role is the more they view it as a threat because AI is replacing the admin roles." "Artificial intelligence, I believe it's something that's meant to be smarter than us. And like I said earlier, something that will replace us slowly." "It can be a threat to current members of staff. It will hit a particular sector that is heavily reliant upon artificial intelligence." "it's a threat in the sense that AI has the potential to replace human jobs, so it will put people's employment status at risk definitely in the future." "The only downside would be fewer jobs and therefore unemployment for less qualified and more administrative employees." "The fear I think is on the part of HR practitioners. […] if you are introducing technology that replaces what you can currently do, then you will have a natural fear that your job is going to be eroded and eventually you'll be redundant."

CHAPTER 6: QUANTITATIVE RESEARCH

Appendix 6.1: Distribution networks

Channels of distribution	Distribution nodes	Means of distribution
Personal Distribution	Professional platforms - LinkedIn	Posts (personal and specialised group posts) And Individual inboxes
Individual Connection	HR Professionals and distribution nodes connected via snowballing techniques. The detailed contacts of the recipients cannot be disclosed due to the requirement of the researcher to the participants and Ethics Committee.	Email
LinkedIn (HR professional groups in England)	HRIS | HR Technologies	Approved
	Human Resources Data | HR Metrics | People Analytics	Approved
	CIPD Students the Midlands	Approved
	HR Professionals and Recruiters - Careers and Jobs Listing - Job Seekers	Approved
	HR Circle	Approved
	MY HR CAREER and the MORNING CLUB - parts of Surrey and N Hampshire CIPD	Approved
	CIPD Main Group	Approved
	CIPD Conferences and Exhibitions	Approved
	Human Resources (HR) Professionals	Approved
	CIPD Kent	Approved

	CIPD Manchester	Approved
	Human Resources (HR) & Talent Management Executive	Approved
	HR Jobs and Ideas - Human Resources, talent management, hiring tech, networking group	Approved
	CIPD Central London Branch	Approved
	HR Professionals | Powered by HRCI and HRPA	Approved
	Human Resources: HR | Recruiting | Startups | Fortune 500 | Blockchain | Web3 | Metaverse	Approved
	HR Jobs	Pending approval
	Linked: HR (#1 Human Resources Group)	Pending approval
	Artificial Intelligence and Business Analytics (AIBA) Group	Approved
Facebook (HR professional groups in England)	HR Discussion Group UK	Approved
	HR Hub	Approved
	UK Employment Laws & HR Advice	Approved
	The Human Resources Group	Approved
	Jobs in Birmingham	Approved
	HR & Recruitment Professionals UK	Approved
	HR Employment Help & Advice	Approved

	HR Professionals	Approved
	Local jobs in Birmingham	Approved
	HR Jobs Opportunities	Approved
	HR - Human Resource: Job AddA / Forum	Approved
	HR & Recruitment Professionals UK	Approved
	CIPD	Approved

Appendix 6.2: Standard Industrial Classification (SIC) Codes (Office for National Statistics, 2012)

Section Code	Industry
Section A	Agriculture, Forestry, Fishing
Section B	Mining and Quarrying
Section C	Manufacturing
Section D	Electricity, gas, steam, and air conditioning supply
Section E	Water supply; sewage, waste management and remediation activities
Section F	Construction
Section G	Wholesale and retail trade; repair of motor vehicles and motorcycles
Section H	Accommodation and food service activities
Section I	Transport and storage information and communication
Section J	Financial and insurance activities
Section K	Real estate activities professional, scientific, and technical activities administrative and support service activities
Section L	Public administration and defence; compulsory social security
Section M	Education
Section N	Human health and social work activities
Section O	Arts, entertainment, and recreation
Section P	Activities of households as employers; undifferentiated goods - and services-producing activities of households for own use
Section Q	Activities of extraterritorial organisations and bodies

Appendix 6.3: EFA test

Trial 1: The First EFA Run Test

KMO and Bartlett's Test of independent variables (1st trial)

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.813
Bartlett's Test of Sphericity	Approx. Chi-Square	6122.568
	Df	1711
	Sig.	.000

A presented in above table, it is indicated that the EFA is suitable for this set of data since all the indices are within the acceptable range. Particularly, the KMO index is greater than 0.5 (KMO = 0.813) and the significance of Bartlett's test is also less than 0.05 (sig. < 0.05). To further analyse the data set, EFA Rotated Matrix of item loadings was delivered. **Table 6.12** of *Total Variance Explained* (TVE) summarises the total variance explained by the factor analysis and provide an indication about the number of valid factors. The *Initial Eigenvalues* domain consists of three columns. The first column provides the eigenvalues of all the factors in a descending order. It is then followed by the percentage of each variance and eventually the accumulative percentage of all variances. In this research, EFA was reassessed continually until the elimination process of measurement items reached the sufficient level reflected in the observed components. The selection and elimination procedure will be showcased in five trials as presented in following sections.

Dovetailing to results extracted from SPSS, it could be seen that at the first EFA test, there are thirteen (13) factors recorded eigenvalue greater than 1 (identified by TVE). In this regard, the 13 components explains and accounts for 71.59% of the variance (as illustrated in **Table 6.12**).

Table 6.12: Total Variance Explained of independent variable from 1st EFA test (extracted from SPSS)

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.007	22.046	22.046	13.007	22.046	22.046	7.912	13.410	13.410
2	10.618	17.997	40.043	10.618	17.997	40.043	5.322	9.021	22.431
3	3.258	5.522	45.565	3.258	5.522	45.565	3.828	6.488	28.920
4	2.517	4.267	49.832	2.517	4.267	49.832	3.767	6.384	35.304
5	2.238	3.793	53.626	2.238	3.793	53.626	3.507	5.944	41.247
6	1.767	2.995	56.621	1.767	2.995	56.621	3.135	5.314	46.561
7	1.625	2.755	59.375	1.625	2.755	59.375	2.863	4.853	51.414
8	1.361	2.307	61.682	1.361	2.307	61.682	2.754	4.668	56.082
9	1.297	2.198	63.880	1.297	2.198	63.880	2.517	4.265	60.348
10	1.255	2.127	66.006	1.255	2.127	66.006	1.962	3.325	63.672
11	1.148	1.946	67.953	1.148	1.946	67.953	1.849	3.133	66.806
12	1.111	1.884	69.836	1.111	1.884	69.836	1.463	2.479	69.285
13	1.038	1.759	71.596	1.038	1.759	71.596	1.363	2.311	71.596
14	.974	1.651	73.246						
15	.904	1.532	74.778						
16	.870	1.475	76.253						
17	.807	1.368	77.621						
18	.778	1.318	78.940						
19	.735	1.245	80.185						
20	.681	1.155	81.340						
21	.661	1.120	82.460						
22	.622	1.053	83.514						
23	.588	.997	84.511						
24	.567	.961	85.472						
25	.515	.873	86.346						
26	.467	.792	87.138						
27	.464	.786	87.924						
28	.439	.744	88.668						
29	.436	.739	89.406						
30	.423	.718	90.124						
31	.393	.666	90.790						
32	.387	.656	91.445						
33	.366	.621	92.066						
34	.340	.577	92.643						
35	.329	.557	93.200						
36	.301	.511	93.711						
37	.294	.498	94.209						
38	.274	.465	94.674						
39	.255	.432	95.106						
40	.251	.425	95.531						
41	.245	.415	95.946						
42	.227	.384	96.330						
43	.213	.361	96.692						
44	.198	.336	97.027						
45	.184	.312	97.339						
46	.179	.303	97.642						
47	.176	.297	97.940						
48	.158	.268	98.208						
49	.140	.237	98.445						
50	.137	.232	98.677						
51	.131	.222	98.899						
52	.119	.201	99.100						
53	.108	.184	99.284						
54	.088	.149	99.433						
55	.086	.145	99.578						
56	.076	.129	99.707						
57	.068	.116	99.823						
58	.062	.105	99.928						
59	.042	.072	100.000						

Extraction Method: Principal Component Analysis.

When the research rotation provided a “clean” result of the represented variables and constructs, Correlation Analysis was adopted to shape the determined framework of the research. Furtherance, **Table 6.13** illustrates the variables which have been rotated with loading factors in the first trial EFA test.

Table 6.13: Pattern Matrix of measurement items from 1st EFA test

Rotated Component Matrix[a]

	Component												
	1	2	3	4	5	6	7	8	9	10	11	12	13
Fear of Unknown 4	.831												
Fear of Unknown 2	.828												
Fear of Unknown 1	.813												
Fear of Unknown 3	.791												
Bias Concerns 1	.777												
Bias Concerns 4	.765												
Bias Concerns 3	.762												
Bias Concerns 2	.755												
Perceived Unemployment 2	.639										.515		
Perceived Unemployment 3	.623										.563		
Perceived Cost 3													
Cognitive Misperception 1		.725											
Cognitive Misperception 3		.709											
Cognitive Misperception 2		.677											
Innovation Driven 1		.647											
Innovation Driven 2		.638											
Cognitive Misperception 4		.634											
Innovation Driven 3		.594											
Cost Effectiveness 2													
Psycho Commitment 2													
Task Versality 3			.668										
Task Versality 1			.649										
Cost Effectiveness 3			.638										
Task Versality 2			.611										
Cost Effectiveness 1			.513										
Job Compatibility 1			.503										
Cost Effectiveness 4													
Privacy Concerns 4				.882									
Privacy Concerns 3				.854									
Privacy Concerns 2				.813									
Privacy Concerns 1				.716									
Leadership Support 4					.784								
Leadership Support 1					.771								
Leadership Support 2					.739								
Leadership Suppot 3					.594								
Subjective Norms 4													
Subjective Norms 2						.731							
Subjective Norms 1						.647							
Subjective Norms 3						.614							
Innovation Driven 4						.605							
Task Versality 4													
Ease of use 1							.778						
Ease of use 3							.742						
Ease of use 4							.721						
Ease of use 2							.676						
Psycho Commitment 3								.783					
Psycho Commitment 4								.755					
Psycho Commitment 1								.710					
Employer Branding 1									.779				
Employer Branding 3									.751				
Employer Branding 2									.739				
Job Compatibility 2										.776			
Job Compatibility 3										.509			
Job Compatibility 4													
Perceived Unemployment 1	.618										.619		
Perceived Unemployment 4											.538		
Perceived Cost 2												.614	
Perceived Cost 1												.520	
Perceived Cost 4													

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 20 iterations.

Conforming to (Tavakol and Wetzel, 2020), sufficient loading value for EFA must load a minimum of 0.5 in value. In principle, the value depicts an appropriate convergence of measurement items reflected on the respective variable. According to **Table 6.13**, the loading regression values of certain measurement items are satisfied in accordance with the suggested minimum level. In contrast, the loading regression values of items possessing a smaller value than the recommended standard will be eliminated.

In this case, based on the suggested rule, there are eight (8) items: *Perceived Cost 3* (PC3), *Perceived Cost 4* (PC4), *Cost Effectiveness 2* (CE2), *Cost Effective 4* (CE4), *Psycho Commitment 2* (PYC2), *Subjective Norms 4* (SN4), *Task Versatility 4* (TV4), *Job Compatibility 4* (JC4) were eliminated due to insufficient factor loadings. Specifically, the factor loadings of the mentioned items were smaller than 0.3 and were not showcased in the rotated component matrix.

In addition, **Table 6.13** also reveals a cross loading among three (3) items of *Perceived Unemployment 1* (PU1), *Perceived Unemployment 2* (PU2), *and Perceived Unemployment 3* (PU3). The items were loaded in two observed components 1 and 11, which indicates an indiscriminate validity. As claimed by (Lộc, 2017), if the difference between these factor loadings is smaller than 0.3, the items should be disregarded. In this vein, PU1, PU2 and PU3 were eliminated to ensure the unique value in rotated matrix.

Eventually, the component of *Job Compatibility 1* (JC1) was loaded in variables of *Task Versality* and *Cost Effectiveness.* The component's factor loading was smaller compared to the others loaded in the same column. In addition, this measurement item did not belong to the parent construct of Performance Expectancy. Therefore, JC1 was eliminated. In addition, based on the discussed rule, the variable of *Innovation Driven* was disregarded from the model due to two reasons: *(1)* its measurement components were loaded in two different variables of *Cognitive Misperception* (3 components) and *Subjective Norms* (1 component), which indicates an inconsistency in loading the meaning of the parent construct (*Facilitating Condition*); *(2)* Factor loadings of its components were smaller in comparison to the mentioned variables' ones (as illustrated in **Table 6.13**), which illustrates a weak correlation with the parent construct. In brief, for the First Trial Test, the remaining components were distilled as presented in **Figure 6.1**:

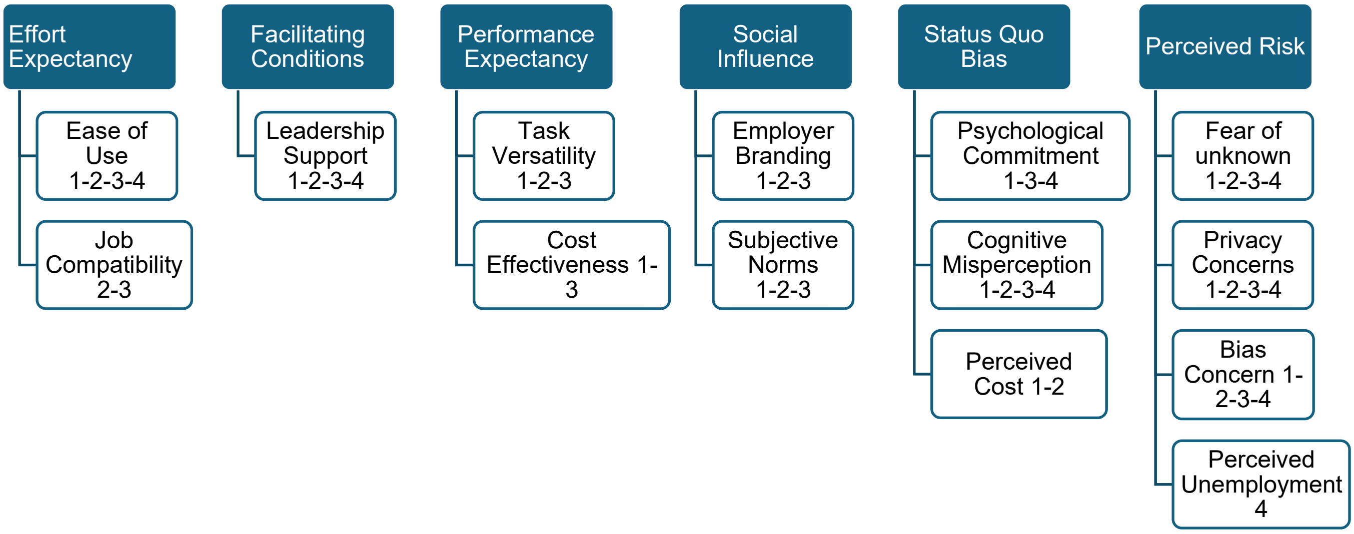


Figure 6.1: Distilled measurement items after 1st EFA Test

Trial 2: The Second EFA Run Test

After eliminating insufficient items at first trial, the EFA was conducted to reassess the remaining factors. As can be observed from **Table 6.14**, the KMO index for the second trial was 0.837 (higher than 0.5) and the significance of Bartlett's test (sig.) is lower than 0.05, which indicates that EFA is suitable for this set of data.

Table 6.14: KMO and Bartlett's Test of independent variables (2nd trial)

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.837
Bartlett's Test of Sphericity	Approx. Chi-Square	4025.951
	df	903
	Sig.	.000

Since the dataset's fitness was verified, TVE and rotated matrix were continuously considered as illustrated in **Table 6.15** and **Table 6.16.**

Table 6.15: Total Variance Explained of independent variable from 2nd EFA test.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.046	21.038	21.038	9.046	21.038	21.038	6.421	14.933	14.933
2	8.365	19.454	40.492	8.365	19.454	40.492	3.827	8.899	23.832
3	2.776	6.456	46.948	2.776	6.456	46.948	3.677	8.552	32.384
4	2.245	5.221	52.169	2.245	5.221	52.169	3.109	7.230	39.614
5	1.938	4.507	56.675	1.938	4.507	56.675	2.728	6.345	45.959
6	1.566	3.641	60.317	1.566	3.641	60.317	2.689	6.253	52.212
7	1.308	3.042	63.359	1.308	3.042	63.359	2.435	5.664	57.876
8	1.165	2.708	66.067	1.165	2.708	66.067	2.370	5.511	63.387
9	1.093	2.542	68.609	1.093	2.542	68.609	2.246	5.223	68.609
10	.971	2.259	70.868						
11	.920	2.139	73.007						
12	.851	1.979	74.986						
13	.800	1.862	76.848						
14	.738	1.717	78.565						
15	.697	1.621	80.187						
16	.633	1.472	81.659						
17	.572	1.331	82.989						
18	.550	1.278	84.267						
19	.537	1.248	85.515						
20	.493	1.147	86.662						
21	.479	1.115	87.777						
22	.426	.990	88.767						
23	.418	.971	89.738						
24	.410	.954	90.693						
25	.375	.872	91.565						
26	.334	.778	92.343						
27	.306	.711	93.054						
28	.291	.676	93.730						
29	.270	.627	94.357						
30	.267	.621	94.978						
31	.261	.606	95.585						
32	.248	.576	96.160						
33	.227	.528	96.688						
34	.204	.475	97.163						
35	.191	.443	97.606						
36	.179	.416	98.022						
37	.164	.382	98.403						
38	.156	.362	98.766						
39	.146	.341	99.106						
40	.122	.283	99.389						
41	.095	.221	99.610						
42	.089	.207	99.816						
43	.079	.184	100.000						

Extraction Method: Principal Component Analysis.

As can be observed from **Table 6.15**, there were nine (9) factors identified by TVE at the 2nd trial. The components for this trial explained for 68.609% of the total variance. The study progressed by envisaging the indices of the Pattern Matrix as illustrated in **Table 6.16**.

Table 6.16: Pattern Matrix of measurement items from 2nd EFA test

Rotated Component Matrix[a]

	Component								
	1	2	3	4	5	6	7	8	9
FU4	.836								
FU3	.820								
FU2	.817								
FU1	.790								
BC1	.790								
BC3	.767								
BC2	.751								
BC4	.745								
PU4	.515								
PC1									
TV3		.759							
TV2		.689							
TV1		.670							
CE3		.601							
CE1		.548							
JC3		.521							
JC2									
PRC4			.875						
PRC3			.865						
PRC2			.829						
PRC1			.691						
PC2			.550						
LS1				.825					
LS4				.804					
LS2				.772					
LS3				.511					
EOU3					.789				
EOU4					.772				
EOU1					.714				
EOU2					.658				
CM1						.695			
CM3						.687			
CM4						.580			
CM2						.537			
EB1							.780		
EB2							.777		
EB3							.756		
SN2								.746	
SN1								.699	
SN3								.658	
PYC3									.845
PYC4									.753
PYC1									.663

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 11 iterations.

As exhibited in **Table 6.16**, loading factors of the measurement items of *Perceived Cost 1* (PC1) and *Job Compatibility 2* (JC2) were not presented in the rotated matrix, which signifies insufficient acceptance level of factor loading (<0.3). Therefore, the two measurement items were eliminated. Subsequently, the research progressed with the analysis of other measurement items which loaded in multigroup. Specifically, *Job Compatible 3* (JC3) (rotated in Performance Expectancy) and *Perceived Cost 2* (PC2*)* (rotated in Perceived Risk) were also expelled from the model since both items were not categorised in the predetermined parent constructs. Additionally, factor loading indices of both measurement items were smaller in comparison to the variables' ones of the same group (JC3 = 0.52; PC2 = 0.55) (as illustrated in **Table 6.16**). This indicates a weak correlation with the parent constructs. At this junction, the two variables of "Perceived Cost" and "Job Compatibility" were comprehensively eliminated from the running model. Dovetailing to the second test, the model was refined as presented in **Figure 6.2**.

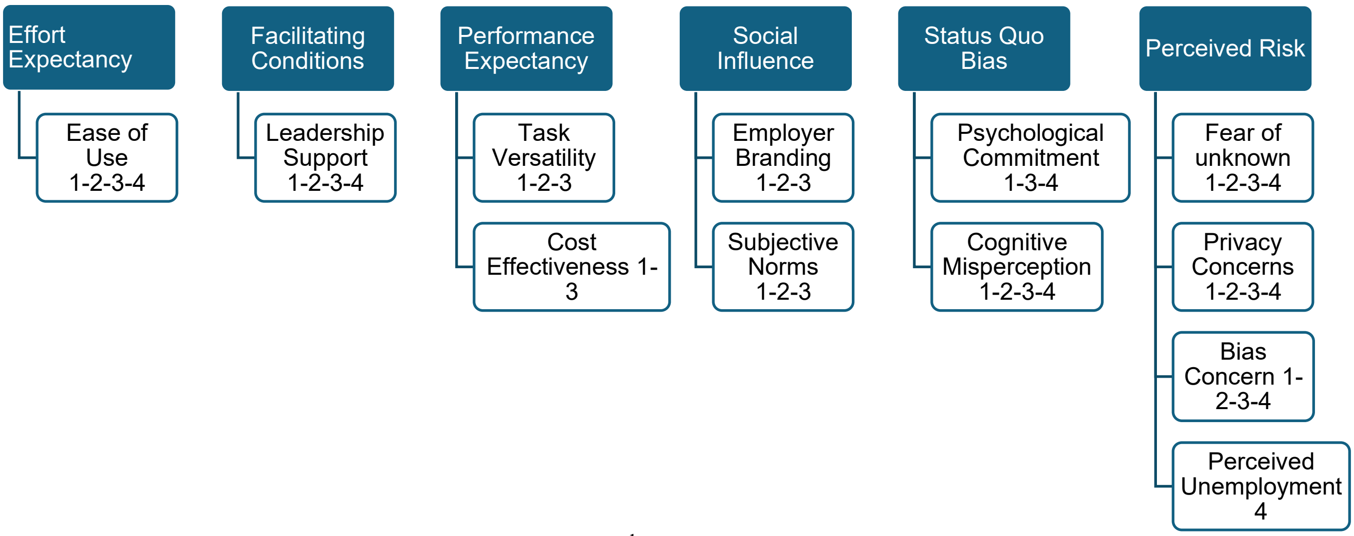


Figure 6.2: Distilled measurement items after 2nd EFA Test

Trial 3: The Third EFA Run Test

The EFA was conducted at the 3rd trial to reassess and reflect the removal of the preceding items. According to **Table 6.17,** The KMO index was 0.838 (higher than 0.5) and the significance of Bartlett's test (sig.) was lower than 0.05 indicated that EFA is appropriate for this set of data.

Table 6.17: KMO and Bartlett's Test of independent variables (3rd trial)

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.838
Bartlett's Test of Sphericity	Approx. Chi-Square	3693.735
	df	741
	Sig.	.000

Table 6.18: Total Variance Explained of independent variable from 3rd EFA test.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.388	21.508	21.508	8.388	21.508	21.508	6.188	15.866	15.866
2	7.934	20.344	41.853	7.934	20.344	41.853	3.242	8.313	24.179
3	2.567	6.582	48.434	2.567	6.582	48.434	3.067	7.865	32.044
4	2.162	5.544	53.979	2.162	5.544	53.979	3.027	7.763	39.807
5	1.919	4.922	58.900	1.919	4.922	58.900	2.921	7.489	47.296
6	1.545	3.962	62.862	1.545	3.962	62.862	2.578	6.611	53.907
7	1.251	3.207	66.069	1.251	3.207	66.069	2.336	5.990	59.897
8	1.134	2.908	68.977	1.134	2.908	68.977	2.284	5.856	65.753
9	1.019	2.613	71.591	1.019	2.613	71.591	2.277	5.838	71.591
10	.863	2.214	73.804						
11	.840	2.155	75.959						
12	.728	1.866	77.825						
13	.705	1.807	79.633						
14	.615	1.577	81.210						
15	.579	1.485	82.695						
16	.544	1.395	84.091						
17	.540	1.385	85.476						
18	.459	1.178	86.654						
19	.446	1.142	87.797						
20	.414	1.061	88.857						
21	.407	1.043	89.900						
22	.376	.964	90.863						
23	.344	.882	91.745						
24	.319	.819	92.564						
25	.302	.775	93.340						
26	.286	.734	94.074						
27	.266	.683	94.756						
28	.255	.654	95.410						
29	.242	.620	96.030						
30	.222	.570	96.600						
31	.207	.530	97.130						
32	.198	.507	97.636						
33	.193	.494	98.130						
34	.160	.411	98.542						
35	.149	.382	98.924						
36	.137	.353	99.276						
37	.105	.270	99.546						
38	.094	.240	99.786						
39	.083	.214	100.000						

Extraction Method: Principal Component Analysis.

According to **Table 6.18,** TVE released nine (9) factors at the third trial test. The components explained for 71.59% of the total variance. The analysis continued with the observations of measurement items on the SPSS's rotated matrix.

Table 6.19: Pattern Matrix of measurement items from 3rd EFA test

Rotated Component Matrix[a]

	Component								
	1	2	3	4	5	6	7	8	9
FU4	.839								
FU3	.821								
FU2	.815								
BC1	.801								
FU1	.790								
BC2	.773								
BC3	.764								
BC4	.748								
PU4	.525								
PRC4		.883							
PRC3		.876							
PRC2		.826							
PRC1		.687							
CM1			.777						
CM3			.732						
CM4			.658						
CM2			.640						
LS1				.824					
LS4				.800					
LS2				.793					
LS3									
TV3					.779				
TV1					.677				
TV2					.673				
CE3					.628				
CE1									
EOU3						.792			
EOU4						.786			
EOU1						.736			
EOU2						.683			
EB3							.788		
EB2							.780		
EB1							.770		
SN2								.793	
SN1								.706	
SN3								.649	
PYC3									.827
PYC4									.789
PYC1									.684

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 8 iterations.

As can be observed from **Table 6.19**, *Leadership Support 3* (LS3) and *Cost Effectiveness 1* (CF1) were deemed to be excluded from the model since Factor Loading indices were insufficient (less than 0.3 and did not present on the rotated matrix). The other measurement items fell into distinct categories (satisfied face and validity criteria) and therefore, the items remained in the model. In summary, the final model for the third trial test is as follows:

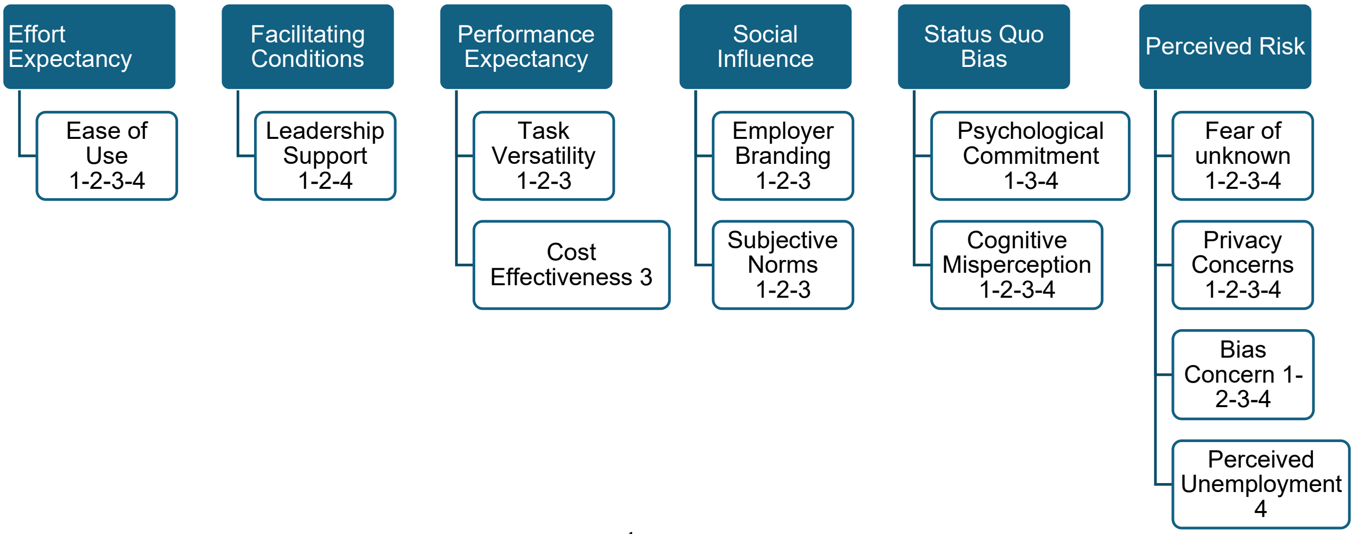


Figure 6.3: Distilled measurement items after 3rd EFA Test

Trial 4: The Fourth EFA Run Test

EFA continued to be conducted to ensure the stability and fitness of the constructs for EFA. The KMO index is 0.842 (higher than 0.5) and the significance of Bartlett's test (sig.) is lower than 0.05, which indicated that EFA is suitable for this set of data (reflected in **Table 6.20**).

Table 6.20: KMO and Bartlett's Test of independent variables (4th trial)

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.842
Bartlett's Test of Sphericity	Approx. Chi-Square	3518.453
	df	666
	Sig.	.000

Table 6.21: Total Variance Explained of independent variable from 4th EFA test.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.054	21.768	21.768	8.054	21.768	21.768	6.242	16.871	16.871
2	7.627	20.613	42.381	7.627	20.613	42.381	3.371	9.111	25.982
3	2.491	6.733	49.114	2.491	6.733	49.114	3.270	8.837	34.820
4	2.096	5.666	54.780	2.096	5.666	54.780	3.267	8.829	43.649
5	1.910	5.163	59.943	1.910	5.163	59.943	2.648	7.155	50.804
6	1.530	4.136	64.079	1.530	4.136	64.079	2.603	7.036	57.840
7	1.204	3.255	67.334	1.204	3.255	67.334	2.436	6.585	64.425
8	1.116	3.015	70.349	1.116	3.015	70.349	2.192	5.924	70.349
9	.991	2.679	73.029						
10	.842	2.274	75.303						
11	.830	2.243	77.546						
12	.696	1.881	79.426						
13	.593	1.602	81.029						
14	.577	1.559	82.588						
15	.543	1.468	84.056						
16	.520	1.405	85.461						
17	.473	1.277	86.738						
18	.433	1.171	87.909						
19	.415	1.121	89.031						
20	.382	1.032	90.063						
21	.349	.942	91.005						
22	.325	.877	91.883						
23	.305	.824	92.707						
24	.300	.810	93.516						
25	.274	.740	94.256						
26	.263	.710	94.966						
27	.243	.658	95.624						
28	.229	.619	96.243						
29	.216	.585	96.828						
30	.204	.551	97.379						
31	.194	.523	97.903						
32	.188	.508	98.410						
33	.150	.407	98.817						
34	.141	.380	99.197						
35	.112	.304	99.501						
36	.096	.258	99.759						
37	.089	.241	100.000						

Extraction Method: Principal Component Analysis.

For the fourth trial, eight (8) factors were identified by TVE which accounted for 70.34% of the total variance. To further progress, Pattern Matrix was analysed to determine the appropriate measurement items as portrayed in **Table 6.22.**

Table 6.22: Pattern Matrix of measurement items from 4th EFA test

Rotated Component Matrix[a]

	Component 1	2	3	4	5	6	7	8
FU4	.868							
FU3	.842							
FU2	.831							
FU1	.803							
BC1	.768							
BC2	.757							
BC3	.751							
BC4	.739							
PU4	.518							
CM1		.735						
CM4		.680						
SN2		.645						
CM3		.637						
CM2		.611						
SN1		.580		.577				
PRC4			.883					
PRC3			.859					
PRC2			.819					
PRC1			.701					
LS1				.788				
LS4				.784				
LS2				.744				
SN3		.500		.660				
TV3					.791			
TV2					.687			
TV1					.678			
CE3					.627			
EOU3						.791		
EOU4						.767		
EOU1						.730		
EOU2						.718		
EB1							.798	
EB3							.765	
EB2							.726	
PYC3								.821
PYC4								.774
PYC1								.686

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 12 iterations.

Regarding the result of the Rotated Component Matrix, *Subjective Norms 1 (SN1)* and *Subjective Norms 3 (SN3)* distributed a cross-loading issue in the rotated matrix, postulating an indiscriminate validity. In accordance with the previous rule, the variance of the factor loading was subsequently considered. The differences between the factor loadings of the two measurement items were both less than 0.3 (SN1 = 0.01; SN3 = 0.16) and therefore, SN1 and SN3 were eliminated in the 4th trial. In addition, *Subjective Norms 2* (SN2) was loaded in a different variable of *Cognitive Misperception* which belongs to another parent construct (*Status Quo Bias*). Factor loading of SN2 was smaller than some of the other measurement items within the group and its correlated items (SN1, SN3) were excluded from the model. This indicates an irresolute relationship of the concept within the test model. Therefore, SN2 was eliminated at the 4th trial. Reflectively, the variable of *Subjective Norms* was completely removed from the model to maintain the consistency of the main construct. The model retains the following items after the 4th EFA assessment:

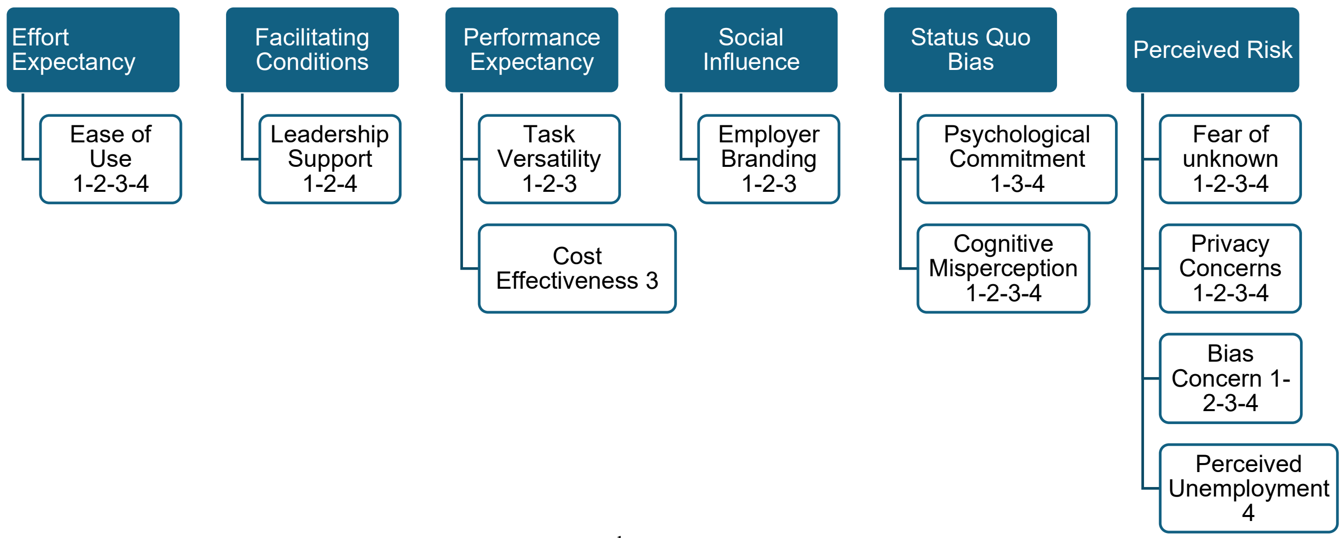
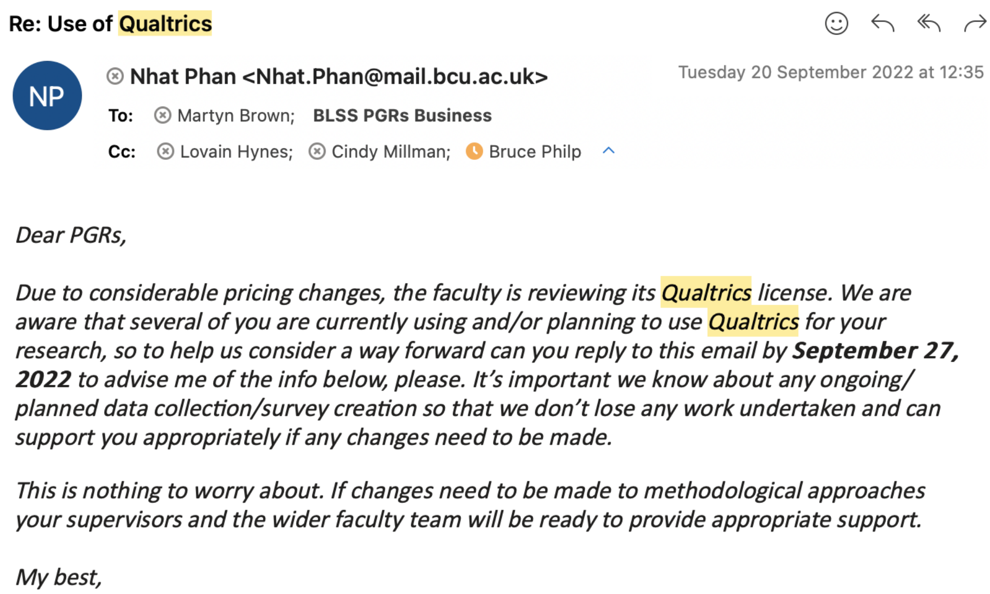


Figure 6.4: Distilled measurement items after 4th EFA Test

CHAPTER 8: RESEARCH DISCUSSION

Appendix 8.1



Re: Use of Qualtrics

NP Nhat Phan <Nhat.Phan@mail.bcu.ac.uk> Tuesday 20 September 2022 at 12:35

To: Martyn Brown; **BLSS PGRs Business**

Cc: Lovain Hynes; Cindy Millman; Bruce Philp

Dear PGRs,

*Due to considerable pricing changes, the faculty is reviewing its Qualtrics license. We are aware that several of you are currently using and/or planning to use Qualtrics for your research, so to help us consider a way forward can you reply to this email by **September 27, 2022** to advise me of the info below, please. It's important we know about any ongoing/ planned data collection/survey creation so that we don't lose any work undertaken and can support you appropriately if any changes need to be made.*

This is nothing to worry about. If changes need to be made to methodological approaches your supervisors and the wider faculty team will be ready to provide appropriate support.

My best,