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AI-Enabled Customised Workflows for Smarter Supply Chain Optimisation: A Feasibility Study

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Abstract

This study investigates the integration of Large Language Models (LLMs) into supply chain workflow automation, with a focus on their technical, operational, financial, and socio-technical implications. Building on Dynamic Capabilities Theory and Socio-Technical Systems Theory, the research explores how LLMs can enhance logistics operations, increase workflow efficiency, and support strategic agility within supply chain systems. Using two developed prototypes, the Q inventory management assistant and the nodeStream© workflow editor, the paper demonstrates the practical potential of GenAI-driven automation in streamlining complex supply chain activities. A detailed analysis of system architecture and data governance highlights critical implementation considerations, including model reliability, data preparation, and infrastructure integration. The financial feasibility of LLM-based solutions is assessed through cost analyses related to training, deployment, and maintenance. Furthermore, the study evaluates the human and organisational impacts of AI integration, identifying key challenges around workforce adaptation and responsible AI use. The paper culminates in a practical roadmap for deploying LLM technologies in logistics settings and offers strategic recommendations for future research and industry adoption.

Keywords: supply chain management; artificial intelligence; large language models; inventory management automation; intelligent process design; logistical systems optimisation; process modelling and analysis

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1. Introduction

Supply chain management (SCM) is a cornerstone of modern business operations, yet inefficiencies in workflows, data integration, and decision-making processes persist. The increasing complexity of global markets demands more adaptable and intelligent solutions that can respond dynamically to evolving needs. While Artificial Intelligence (AI) technologies, particularly Large Language Models (LLMs), offer significant potential for optimising SCM, their application in generating customised workflows remains largely unexplored. In addition, while recent studies have started to explore the role of AI in supply chain contexts (e.g., [1–4]), the practical integration of LLMs for workflow automation and decision support remains significantly underexplored. In particular, there is limited empirical research that investigates their feasibility from technical, operational, financial, and socio-technical perspectives within real-world logistics environments. Current SCM technologies often rely on static models that lack the adaptability required to navigate the dynamic nature of supply chains. This gap highlights the critical need for dynamic, real-time workflow generation tools capable of adapting to specific user requirements within SCM [1,4–8]. This paper addresses this gap by drawing on a collaborative industry-academic project and contributes a structured feasibility study involving two LLM-powered prototypes. The following literature review provides a more detailed examination of current research trends, known limitations, and the specific gap this study seeks to fill. This research introduces the Chain-AI Bot, a novel solution that leverages a multimodal Retrieval-Augmented Generation (RAG) architecture to dynamically generate customised SCM workflows. The Chain-AI Bot combines the power of LLMs with visual and textual data processing, enabling it to understand the nuanced context of user queries and generate tailored workflows in real-time. This multimodal approach, integrating the Qdrant Vector Database and GPT-4 Vision, allows the bot to handle diverse inputs and provide more relevant and accurate workflow outputs. This represents a significant advancement over traditional methods that rely on manual configuration or static templates.

This paper presents a comprehensive analysis of the Chain-AI Bot's development and feasibility, focusing on its technical architecture, performance, and potential impact on SCM. We evaluate the bot's ability to generate customised workflows, highlighting its multimodal RAG architecture and its capacity to handle both textual and visual data. We further investigate the financial implications of implementing such a system and discuss the socio-technical factors that influence its adoption and success within SCM contexts. Finally, a roadmap for implementing LLM-powered workflow editors will be presented, emphasising the role of the Chain-AI bot.

As we navigate the juncture where supply chain intricacies meet the cutting-edge capabilities of LLMs, the research questions that beckon are the following:

- Is it feasible to employ LLMs in generating SCM-related processes, dynamically adapting to the ever-changing demands of the supply chain landscape?
- Is the integration financially feasible, and what are the technical, operational and socio-technical implications for the overall supply chain operations to be considered?

Hence, the overarching aim of this research is to investigate the feasibility and impact of integrating LLMs and chatbot technologies into SCM workflows. The following objectives are addressed in this research:

1. To evaluate the technical feasibility of leveraging LLMs for automating and optimising key SCM processes.
2. To analyse the operational implications of integrating LLMs and chatbot technologies into existing SCM systems, assessing their impact on workflow efficiency, decision-making processes, and overall supply chain agility, through a case study.
3. To conduct a comprehensive financial feasibility analysis of implementing LLM-based SCM solutions.
4. To explore the socio-technical dimensions of adopting LLM-based workflow automation in SCM.
5. To develop a practical and actionable roadmap for organisations seeking to implement LLM-powered workflow editors.

Accordingly, Table 1 illustrates how each research question is addressed throughout the study.

Our investigation contributes to the academic discourse by bridging the gap between advanced artificial intelligence applications and SCM theories. By grounding our study in established theoretical frameworks (e.g., Dynamic Capabilities Theory (DCT) and the

Resource-Based View (RBV)), we provide a nuanced understanding of how LLMs can be strategically integrated into supply chain processes. This approach not only enhances the practical relevance of our findings but also offers theoretical insights into the evolving landscape of SCM in the era of digital transformation.

Table 1. The Research Questions addressed throughout the study.

Research Question (RQ)	Objective(s) Addressed	Method(s)/Data Used	Section(s)
RQ1: Is it feasible to employ LLMs in generating SCM-related processes, dynamically adapting to the ever-changing demands of the supply chain landscape?	1, 2, 5	• Prototype development and evaluation (Q assistant, nodeStream© editor) • Performance metrics (accuracy, latency, adaptability) • Case study simulations in DPC's "Q" system	• Section 4.1 • Section 4.2 • Section 5.2, Section 5.3, Section 5.4, Section 5.5, particularly Framework and Roadmap
RQ2: Is the integration financially feasible, and what are the technical, operational and socio-technical implications for the overall supply chain operations to be considered?	3, 4, 5	• Cost breakdowns (data prep, model training, infra, licensing) • Post-paid token model analysis • Stakeholder interviews and surveys Socio-technical systems analysis	• Section 4.3 • Section 5.4 • Section 5.2, Section 5.3, and Section 5.4

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature, focusing on core SCM challenges, optimisation needs, and the role of AI. Section 3 outlines the methodology employed to address the research objectives. Section 4 presents and discusses the findings, including feasibility analyses and case study results. Finally, Section 6 concludes with a summary of contributions, managerial implications, and future research directions.

2. Literature Review

This chapter synthesises the academic literature that informs and frames this study. It begins with an overview of core supply chain processes (Section 2.1), laying the operational foundation. This is followed by a discussion of challenges in supply chain and the key process-related challenges and the role of AI technologies in addressing them (Sections 2.2.1 and 2.2.2). Section 2.2 presents a structured summary of the literature reviewed, highlighting research trends, gaps, and contributions relevant to the development of AI-enabled supply chain solutions. Finally, Section 2.3 outlines the theoretical underpinnings that support our conceptual and methodological approach. This structured review provides a clear and coherent pathway toward understanding the research problem and shaping the study's objectives.

The concept of supply chains has been integral to commerce for centuries, but in today's globalised and interconnected world, their importance has reached unprecedented levels. A supply chain encompasses the end-to-end journey of products and services, from raw material suppliers to end consumers. Supply chain processes and workflows are the series of steps and activities that coordinate and optimise this journey, ensuring products reach their destination efficiently, on time, and in the right condition [9,10]. Hence, supply chain processes and workflows are the lifeblood of modern businesses, ensuring the efficient movement of goods and services from suppliers to consumers. This section will explore the essential components of supply chains, key processes, and the evolving technologies that drive them, focusing on areas where LLMs like the Chain-AI Bot can be impactful.

2.1. Core Supply Chain Processes

Supply chain processes are multifaceted and can vary across industries, but several core processes are universal [11–13]. These processes can be broadly categorised as follows, highlighting areas where AI-driven solutions like the Chain-AI Bot can enhance efficiency and adaptability:

- **Planning:** This involves creating a strategy for sourcing raw materials, production schedules, inventory levels, and distribution of finished goods. Its key processes include demand forecasting, setting inventory levels, and supplier selection. The Chain-AI Bot can significantly enhance this stage by providing more accurate demand forecasts using real-time data and market trends, allowing for better resource allocation and inventory management.
- **Production:** This involves transforming raw materials into finished products efficiently (Manufacturing) and quality control to ensure products meet quality standards. LLMs can optimise production schedules based on demand fluctuations, reducing bottlenecks and improving overall efficiency.
- **Warehousing:** This process mainly includes storing goods safely and efficiently, and Inventory Tracking to monitor stock levels and movements. The Chain-AI Bot can provide real-time inventory tracking and optimise warehouse space utilisation, reducing storage costs and improving retrieval times.
- **Delivery/Logistics:** Managing the transportation and distribution of finished products to customers. This includes warehouse management, order fulfilment, transportation planning, and ensuring timely delivery. The Chain-AI Bot can refine delivery routes, optimise transportation modes, and provide real-time tracking, enhancing delivery speed and efficiency.
- **Supplier Relationship Management:** Building and maintaining relationships with suppliers to ensure a smooth flow of materials, timely deliveries, quality assurance, and collaboration on improvements. LLMs like the Chain-AI Bot can automate communication, streamline contract management, and enhance collaboration with suppliers, reducing delays and costs.
- **Customer Service:** This includes several business processes, but most importantly, marketing, communicating with customers, order processing, and return management to manage product returns and exchanges. The Chain-AI Bot can handle queries, process orders, and manage returns, providing quicker and more personalised responses, thereby improving customer satisfaction.

2.2. Challenges in Supply Chain Management

Navigating supply chains has always been complex due to various challenges, including logistical bottlenecks, inventory management issues, supplier reliability, demand fluctuations, and operational inefficiencies. Maintaining optimal inventory levels is a delicate balance, ensuring product availability without overstocking. Supplier reliability remains a constant concern, as disruptions can lead to production delays. Fluctuations in consumer demand and market dynamics add to the unpredictability of supply and demand patterns. However, while these traditional challenges persist, a new era has dawned upon supply chain management—the digital revolution. The emergence of digital technologies and the integration of innovative solutions have ushered in a new paradigm in supply chain dynamics. The digital supply chain refers to the utilisation of innovative technologies and the development of information systems. This integration and flexibility enhancement within the supply chain aims to improve both customer service and the sustainable performance of the organisation [14].

2.2.1. Process-Related Supply Chain Challenges

Although the abovementioned challenges can be addressed using optimised business processes and workflows, there are several challenges related to business processes as well that need to be overcome [15]. Some of the key challenges are summarised in Table 2 [4,7,16–19]:

Table 2. Process-related supply chain challenges.

Challenge	Description	Key Solutions
Integration of Technologies	Integrating evolving technologies like IoT, AI, blockchain, and data analytics into existing workflows while ensuring compatibility, secure information sharing, and coordination of physical logistics processes.	Harmonise technology with logistics operations, ensure data standardisation, address skill gaps, and implement robust infrastructure.
Data Management and Analysis	Managing and analysing diverse, high-volume data from multiple sources to generate meaningful insights, ensure data quality, and align skill sets with analytical needs.	Use sophisticated tools for handling diverse data, improving data lifecycle quality, and integrating disparate datasets for unified analysis and decision-making.
Agile and Responsive Operations	Adapting to volatile market conditions and disruptions while maintaining operational efficiency.	Establish agile workflows with real-time data analysis, allowing rapid adjustments and informed decision-making to meet dynamic demands effectively.
Supply Chain Visibility	Achieving real-time, end-to-end visibility across the supply chain despite data silos and fragmented systems, which impede decision-making and forecasting accuracy.	Integrate disparate systems, break down silos, use advanced analytics for real-time insights, and optimise workflows to enhance transparency and responsiveness.
Collaboration and Partnerships	Ensuring transparent communication and coordination among diverse global stakeholders while building trust and accountability.	Standardise processes, integrate systems, advance transparency, and establish robust communication channels to nurture stronger relationships and collaboration.

2.2.2. SCM and AI Technologies

Generative AI, powered by technologies like LLM, is a transformative innovation poised to revolutionise various sectors [4]. LLMs, such as those used in this study, are trained on vast datasets to generate contextually relevant content based on user prompts. While LLMs are widely used in natural language processing, their application in SCM workflow automation remains largely untapped [6].

LLMs are built upon the transformer's architecture, which contains billions of parameters and are trained with an enormous corpus of data. The survey conducted on the LLMs by [20] describes the evolution of the Generative Pre-trained Transformer (GPT) model powered by OpenAI and several other LLMs. The popular LLMs in the Language model are BERT, developed by Google and ChatGPT, developed by OpenAI. However, these models have various functionalities and are used for various kinds of tasks. Bert is used for Text Similarities, Text Classification, and Text Summarisations, although BERT is widely used for Text Similarities and Text Classifications. On the other hand, GPT, powered by OpenAI, is widely used for question answering, translation, and text generation.

GPT is utilised with a decoder stack, whereas BERT is an encoder stack. Due to the nature of the BERT model implemented with the bidirectional encoder, it is suitable for performing text classification and understanding the context making it suitable for performing these tasks, but GPT is implemented with the autoregression model which is suitable for question-answer, text summarisation, and the prompt engineering will enhance the generation of the rich output of abstractive text summarisation.

In the supply chain domain, professionals often face the challenge of extracting key insights from numerous documents efficiently. This task, crucial for supply chain optimisation and inventory control, is time-consuming and labour-intensive [21]. To address this challenge, this study proposes leveraging LLMs to develop an interactive chatbot, streamlining information retrieval and enhancing decision-making capabilities.

The rapid integration of Generative AI (GenAI) and LLMs into SCM has prompted a burgeoning body of literature that aims to reframe traditional supply chain practices through advanced AI capabilities [7,8]. Researchers have proposed various conceptual frameworks and practical applications that promise enhanced decision-making, increased operational efficiency, and improved risk management. However, a critical examination reveals that while these studies provide valuable insights, they also highlight significant gaps and challenges that must be addressed for effective real-world implementation.

Several studies have underscored the transformative potential of AI in supply chain management, noting that the transition into the GenAI era is not merely incremental but revolutionary [7]. Researchers argue that the integration of AI-powered technologies into the supply chain enables unprecedented opportunities for optimisation by enhancing decision-making processes and operational resilience [8]. A key contribution in this domain is the development of a theoretical toolbox for GenAI, which is designed to guide managers through the benefits, applications, and limitations of adopting these advanced systems [7].

Moreover, the inputs-process-outputs framework has been widely adopted to conceptualise the factors critical for building GenAI capabilities. This framework emphasises that technological, organisational, and institutional inputs, when processed through mechanisms such as trust-building and collaborative practices, yield outputs in the form of predictive models and actionable insights [7]. Although these conceptual models provide a structured approach to understanding GenAI in supply chain contexts, they are primarily theoretical. Many studies assume that the adoption of GenAI will automatically translate into improved operational outcomes, an assumption that is challenged by the practical issues of data integration, scalability, and system reliability [2].

The literature documents a wide array of GenAI applications aimed at addressing specific challenges within supply chain operations. For instance, enhanced decision-making through data generation is frequently cited as a major benefit, allowing managers to identify areas for improvement and optimise operations [7]. Predictive analytics has also received considerable attention, with research indicating that AI can significantly improve forecasting accuracy and reduce issues such as overstocking [1].

Furthermore, automation is recognised as a key area where GenAI can contribute, particularly in executing repetitive tasks at both operational and managerial levels [22]. In addition to these operational benefits, studies have explored GenAI's role in risk management, highlighting its ability to process historical and real-time data to pre-empt potential disruptions. Applications extend to sustainability, where GenAI helps streamline logistics, minimise downtime, and analyse supply chain patterns for continuous improvement [22]. Procurement processes have similarly benefited, as AI systems sift through extensive supplier data to develop optimal, inclusive portfolios [2].

Despite these promising applications, the current research is somewhat fragmented. Individual studies tend to focus on isolated aspects of supply chain optimisation without sufficiently addressing how these applications interact within a complex, integrated system.

Consequently, while the benefits of GenAI are well articulated, empirical validations that demonstrate these applications in real-world settings are still limited.

Recent scholarship has broadened the scope of analysis by conceptualising the generative-AI supply chain as a multi-stage process that transforms training data into new content with significant legal and operational implications [23]. Research in this area emphasises that decisions made at one stage of the AI development pipeline can have cascading legal consequences downstream, particularly in terms of copyright compliance and intellectual property rights [23].

This reconceptualisation is valuable as it highlights the interconnectedness of upstream and downstream actors within the AI ecosystem. However, it also introduces new challenges. While the theoretical models offer a comprehensive view of the generative-AI supply chain, practical guidelines for managing these legal risks remain underdeveloped. There is a clear need for future work to translate these conceptual insights into robust compliance strategies that can be operationalized in complex supply chain environments.

LLMs have emerged as a crucial element in the integration of GenAI into supply chain management, primarily due to their ability to bridge the gap between automation and human comprehension. Their applications are diverse, ranging from document generation and coding to complex reasoning about supply chain optimisation. For example, frameworks like OptiGuide allow users to query optimisation outcomes in plain language, thereby demystifying complex combinatorial problems while addressing privacy concerns [6].

A notable advancement in this area is the integration of Retrieve-Augmented Generation (RAG) methodologies. RAG enhances LLM output by incorporating context from expansive knowledge bases, which helps mitigate issues such as hallucinations and the lack of source attribution [3]. Furthermore, iterative and multi-hop retrieval techniques have been shown to enhance inference accuracy by progressively aggregating relevant contextual information.

While these innovations signal significant progress, they also introduce additional layers of complexity. The integration of RAG and similar methodologies requires careful balancing of computational resources, data security, and model robustness. Thus, although LLMs hold considerable promise, the literature suggests that their deployment in supply chain systems must be approached with caution, particularly given the technical challenges associated with large-scale combinatorial optimisation problems.

Despite the promising advances discussed above, several critical challenges remain. Data quality and integration pose significant hurdles, as supply chain data is often generated from diverse sources and may suffer from inconsistencies and security vulnerabilities. Technological reliability is another concern; ensuring that AI models perform robustly in dynamic, real-world environments is a non-trivial task [2,22]. Additionally, ethical issues—ranging from biased training data to potential discrimination, raise questions about the broader societal impacts of GenAI [1,7]. Scalability issues further complicate the integration of AI solutions in large, complex supply chains [22].

The literature indicates that most existing studies are predominantly theory-driven and lack empirical validation. There is a noticeable gap in research that integrates technical, ethical, and managerial perspectives into a cohesive framework. Future research should aim to bridge this gap by conducting empirical studies that validate conceptual models and by adopting interdisciplinary approaches that encompass computer science, organisational behaviour, and even psychology [1,7].

Moreover, the emerging notion of the LLM supply chain, which extends from data curation and model training to deployment and continuous operation, presents a new research agenda. This agenda encompasses challenges related to security, model reproducibility, and the management of technical debt, as well as issues associated with open source licencing and continuous integration practices [24]. Addressing these multifaceted challenges will be crucial for the successful adoption of AI technologies in supply chain management.

To summarise, the extant literature on GenAI and LLMs in supply chain optimisation provides a promising yet preliminary foundation for understanding the potential of these technologies. While theoretical frameworks and conceptual models offer valuable insights into how AI can transform supply chain practices, empirical research validating these models remains scarce. Applications ranging from enhanced decision-making and predictive analytics to automation and risk management are well documented, but their integration into a cohesive operational framework is still an ongoing challenge. Moreover, the evolving legal, ethical, and technical dimensions of the generative-AI and LLM supply chains call for more interdisciplinary and empirically grounded studies (Table 3).

Table 3. Analysis of the key research regarding the use of AI for SCM and the gaps identified in this research.

Research Focus	Key Insights	Limitations/Gaps	References
Conceptual Frameworks	Development of theoretical models, such as the inputs-process-outputs framework and theoretical toolboxes for managers.	Mostly theoretical; limited empirical validation of these models in real-world supply chains.	[7,8]
Optimisation and Decision-Making	AI enhances decision-making by generating insights and improving forecasting accuracy.	Studies often focus on isolated applications rather than an integrated system-wide approach.	[1,7]
Predictive Analytics	AI can improve demand forecasting, reduce overstocking, and optimise inventory management.	Requires high-quality data; model robustness in dynamic environments is a concern.	[1]
Automation	GenAI can automate repetitive operational and managerial tasks.	Potential scalability issues and lack of empirical validation in complex supply chains.	[4]
Risk Management	AI can pre-empt disruptions by analysing real-time and historical data.	Studies lack comprehensive guidelines on operationalising these insights.	[4]
Sustainability and Procurement	AI helps streamline logistics, analyse supply chain patterns, and optimise supplier portfolios.	Ethical concerns and biases in AI-driven decision-making remain underexplored.	[2,25]
Legal and Ethical Considerations	AI development and deployment introduce new legal risks, including intellectual property concerns.	Practical compliance strategies are underdeveloped.	[23]
LLM Applications	LLMs facilitate human-AI interaction, automate documentation, and enhance reasoning in supply chain decisions.	Technical challenges in large-scale implementation, including hallucinations and a lack of source attribution.	[3,6]
Retrieve-Augmented Generation (RAG)	RAG enhances LLM performance by integrating external knowledge to improve accuracy.	Requires balancing computational costs, security, and data privacy.	[3]
Challenges and Future Directions	Data integration, security, scalability, and AI model reliability remain critical issues.	Need for interdisciplinary research integrating technical, ethical, and managerial perspectives.	[1,4,7]

As summarised in Table 3, existing studies on AI applications in SCM have often explored high-level frameworks, predictive modelling, or isolated use cases, but have paid limited attention to the practical workflows, prompting strategies, and human-in-the-loop considerations required for deployment. In particular, there is a gap in studies that investigate how LLMs can be realistically adapted and piloted within real organisational settings, especially in logistics, where legacy systems, cost sensitivities, and staff capabilities present integration challenges. In addition, existing work often overlooks the socio-technical challenges of integrating these tools into legacy systems and workflows, particularly in small or medium-sized logistics firms. This study contributes to addressing that gap by offering a feasibility-focused, process-level analysis of LLM-assisted automation, grounded in a real deployment context. By designing and testing an LLM-based support system in collaboration with a logistics company, we demonstrate the architecture, use cases, and socio-technical considerations involved. Our work complements existing research by bridging technical design with operational constraints and organisational readiness, areas that remain underexplored in the literature.

2.3. Theoretical Underpinnings

This section aims to strengthen the theoretical foundation of the study on LLMs in SCM, ensuring the study's relevance within the broader academic discourse is enhanced.

2.3.1. Dynamic Capabilities Theory

The Dynamic Capabilities Theory (DCT) is critical in understanding how organisations adapt to rapidly changing environments. The dynamic capabilities are the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments [26]. In SCM, DCT elucidates how firms develop and deploy capabilities to respond to market dynamics, ensuring sustainable competitive advantage. For instance, ref. [27] emphasises that sustainable supply chains operate in dynamic environments, necessitating the application of dynamic management theories like DCT. According to this theory, dynamic markets are characterised by unclear boundaries, frequent changes, unpredictable directions, and shifting market players, thus requiring more adaptive strategies. The study aims to apply the DC concept to sustainable supply chain management, where similar dynamic conditions exist. Specifically, this theory explores how organisations can develop and leverage dynamic capabilities in their supply chain to respond to changes in customer behaviour and other external pressures [27].

In the context of this study, DCT provides a useful lens to examine the role of LLMs as an enabler of dynamic capabilities in SCM. As supply chains become more complex due to globalisation, digital transformation, and sustainability requirements, firms must continuously sense, seize, and reconfigure their capabilities to maintain agility and competitiveness. LLMs, with their ability to process vast amounts of unstructured data, generate insights, and facilitate real-time decision-making, align well with these dynamic capabilities.

2.3.2. Resource-Based View

The Resource-Based View (RBV) provides a strategic framework for understanding how firms gain and sustain a competitive advantage by leveraging Valuable, Rare, Inimitable, and Non-substitutable (VRIN) resources [28]. RBV suggests that firms do not compete solely based on external market conditions but rather on the unique resources and capabilities they possess, which can be leveraged for long-term performance and differentiation.

RBV suggests that firms achieve a sustainable competitive advantage when they possess unique resources that competitors cannot easily replicate. In SCM, data-driven insights, AI capabilities, and digital transformation efforts serve as strategic resources that can enhance supply chain agility, efficiency, and risk management [29]. LLMs, as an emerging AI technology, align with this perspective by offering firms advanced predictive analytics, automated decision-making, and improved supply chain intelligence.

This study applies RBV to the adoption of LLMs in SCM, demonstrating that AI-driven capabilities serve as a strategic resource that can enhance supply chain agility, resilience, and innovation. As supply chains face increasing volatility due to global disruptions, sustainability pressures, and digital transformation demands, firms that develop, acquire, and effectively manage AI-powered capabilities will gain a sustained competitive advantage. The integration of LLMs into SCM aligns with the VRIN framework, reinforcing the relevance of RBV in the digital age.

By positioning LLMs as a critical, firm-specific, and inimitable resource, this study extends the RBV perspective to modern AI-enabled supply chain management, contributing to both theoretical and practical advancements in the field.

2.3.3. Socio-Technical Systems Theory and the Use of AI for SCM Optimisation

Socio-technical systems theory posits that organisational effectiveness is contingent upon the interaction between social and technical elements within a system. It emphasises the interconnectedness of technology, organisational structures, and human behaviour, highlighting the need for a holistic approach to system design and implementation [30].

Sociotechnical systems theory provides a holistic framework for understanding the intricate interplay between technical components and social structures within organisational contexts. At its core, sociotechnical systems theory emphasises the notion that the effectiveness of a system depends not only on its technical capabilities but also on the socio-cultural context in which it operates. By considering both technical and social factors in tandem, organisations can design and implement systems that are aligned with the needs, values, and behaviours of their stakeholders. Sociotechnical systems theory advocates for the co-evolution of technology and social systems, recognising that changes in one domain inevitably impact the other. By fostering collaboration, communication, and co-creation among diverse stakeholders, organisations can leverage sociotechnical systems theory to design resilient, adaptable, and human-centred systems that enhance organisational performance and promote collective well-being [31].

Recent studies have applied STS thinking to the integration of AI in SCM. For instance, ref. [32] propose a Supply Chain Socio-Technical AI (SC-STAI) profiling tool designed to map AI-induced transformations within SCM from an STS perspective. This tool aids in diagnosing complexity and uncertainty in large-scale system engineering developments, ensuring that AI advancements in SCM are both effective and sustainable by considering technological, organisational, and social impacts.

Ref. [33] explores the impact of sequential lean implementation within micro-firms from a socio-technical perspective. Their findings highlight the importance of considering both social and technical factors in organisational change processes, providing valuable insights into our study on LLM integration in SCM. Their dual emphasis on technical improvements and social adaptation aligns closely with the challenges and opportunities presented by AI-driven SCM solutions, including LLMs. Their findings reinforce the importance of a socio-technical approach in technology-driven transformations, where success depends not only on the effectiveness of the technology itself but also on the organisation's ability to integrate it into existing structures and practices.

The integration of LLMs in SCM requires firms to navigate both the technical advantages of AI, such as real-time decision-making, automated forecasting, and workflow optimisation and the human factors associated with AI adoption. Hence, there is a need for a balanced socio-technical perspective when deploying AI in SCM, ensuring that both human and technological elements evolve in tandem for long-term success.

3. Research Methodology

This study adopts an exploratory research design to evaluate the integration of LLMs in automating SCM workflows. The primary focus is on understanding how LLMs, particularly as implemented in Chain-AI Bot, can address modern SCM challenges. By combining qualitative insights from the literature as well as our case study (DPC Ltd.), along with quantitative feasibility analyses, this mixed-methods approach ensures a holistic understanding of the potential and practical implications of LLM-based solutions in supply chain contexts.

The design of this study is grounded in the findings of the literature review, which highlighted key gaps in the application of LLMs for automating complex and human-centred supply chain processes. Based on these gaps, the research questions and objectives were formulated to explore the technical viability, operational adaptability, and socio-financial impact of LLM-based SCM solutions. These insights directly informed the structure of the methodology: the technical feasibility study was guided by the lack of empirical prototyping in the existing literature, prompting the development of Chain-AI to assess real-world functionality. The operational feasibility case study was informed by the need to contextualise LLM integration within a real organisational workflow, addressing the literature's identified gap in situated implementations. The financial and socio-technical analysis emerged in response to calls for a more comprehensive evaluation of AI adoption challenges and benefits, ensuring the research provides actionable insights for industry stakeholders.

3.1. Literature Review Methodology

The initial stages of the research involved conducting an extensive literature review to establish a comprehensive understanding of SCM, identify existing patterns and trends, and highlight challenges associated with SCM workflows. This review also serves to identify opportunities for improvement, particularly with the adoption of AI and LLMs.

A systematic search process was carried out across two academic databases: Scopus and ACM Digital Library. These were selected due to their specialised focus on computing and information technology, aligning closely with the subject areas relevant to smart city research, such as computer science, urban planning, and technology integration within urban environments. The search strategy used the following query:

("generative AI" OR "large language model" OR "LLM" OR "AI" OR "Artificial Intelligence") AND ("supply chain management" OR "SCM" OR "Supply Chain") AND ("Business Process Management" OR "Workflows" OR "AI-enabled workflows" OR "customised workflows").

This search yielded 145 papers from Scopus and 119 from the ACM Digital Library. After removing duplicates, 255 unique research papers were identified. These papers underwent a rigorous screening process, where titles, abstracts, and conclusions were examined for relevance. Additional filters, as outlined in Table 4, were also applied.

Table 4. Process-related supply chain challenges.

Criteria	Requirement
Source Type	Journal articles, conference papers, and technical reports
Publication Date	No older than 2015
Subject Areas	Computer science, information technology, smart city topics
Language	English
Accessibility	Papers accessible via institutional contracts

These were further assessed for quality based on methodology, writing calibre, publication venue, and impact factor. Preference was given to highly cited articles, indicating their significance in the field. The screening resulted in 37 papers meeting the eligibility criteria (Figure 1).

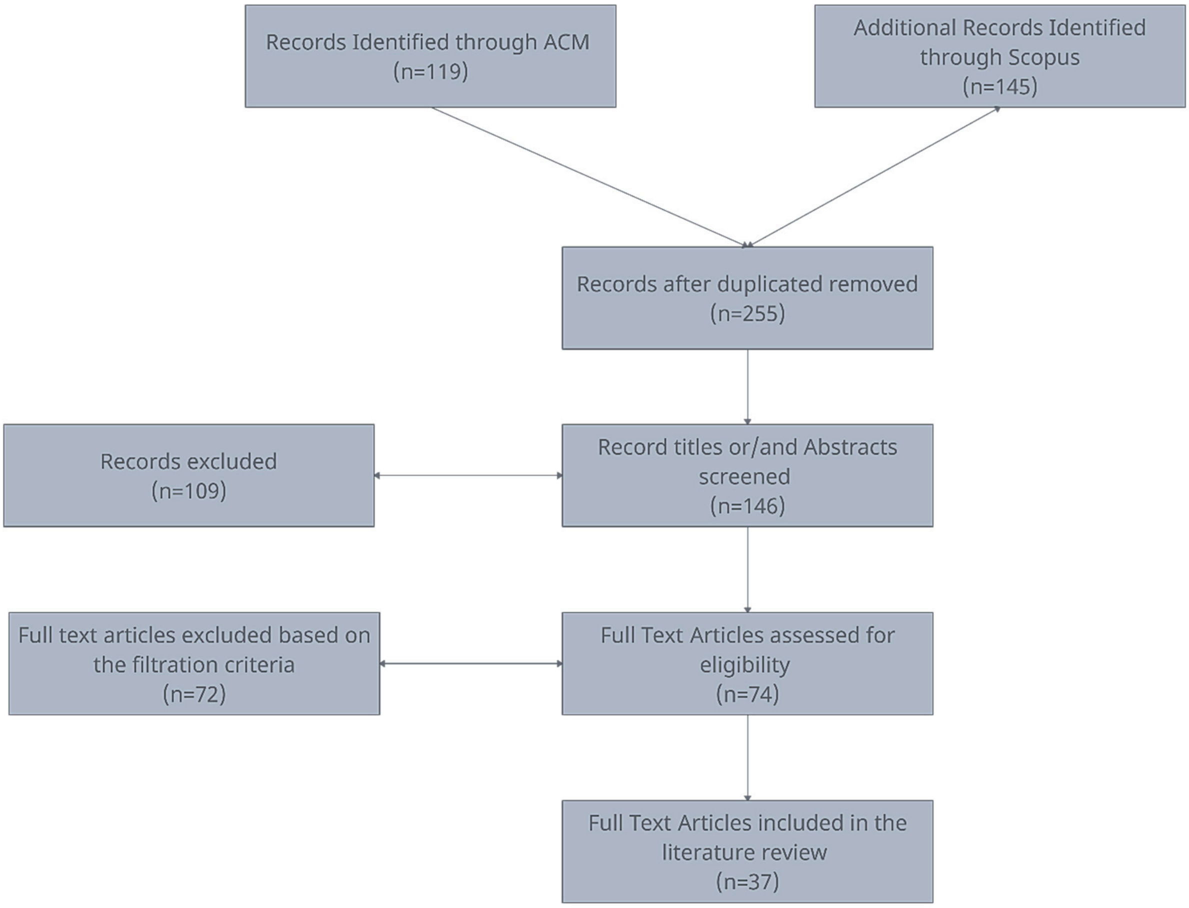

Figure 1. Our state-of-the-art literature review.

3.2. Research Framework and Core Objectives

The research framework is structured around three core objectives:

1. **Technical Feasibility:** To assess the potential capabilities of LLMs for automating workflows in SCM through prototype development.
2. **Operational Feasibility:** To examine operational implications through a detailed case study of DPC's "Q" system.
3. **Financial and Socio-technical Feasibility and Implications:** To evaluate the financial and socio-technical aspects of implementing LLM-based solutions, providing insights for decision-making.

Figure 2 illustrates the research framework, detailing the relationships between the technical, operational, and feasibility studies, as well as the insights gained from the case study and validation methods employed.

3.2.1. Technical Feasibility Analysis

The technical feasibility analysis evaluates the ability of LLMs, specifically OpenAI's GPT-4, to automate key workflows within SCM. This study focuses on the integration of LLMs into SCM processes such as inventory management, demand forecasting, and supplier communication. A prototype system, the Chain-AI Bot, was developed to demonstrate the potential benefits of LLM-based workflow automation. This involved several steps:

- **Performance metrics:** To evaluate the Chain-AI prototypes, metrics such as response accuracy (the LLM's ability to generate contextually accurate responses), latency (the time taken to process data), and scalability (the model's ability to handle varying data volumes) were measured.

- **Data Integration:** The LLM prototypes were tested using structured data from Enterprise Resource Planning (ERP) systems (inventory levels, order statuses, procurement schedules), and unstructured data (supplier communications, product descriptions) to assess the LLM's ability to handle diverse inputs.
- **Validation:** To validate the technical feasibility, the performance of the Chain-AI prototypes was benchmarked against traditional SCM tools. This involved usability testing with SCM stakeholders, as well as gathering qualitative feedback through structured interviews to identify the system's strengths and weaknesses.

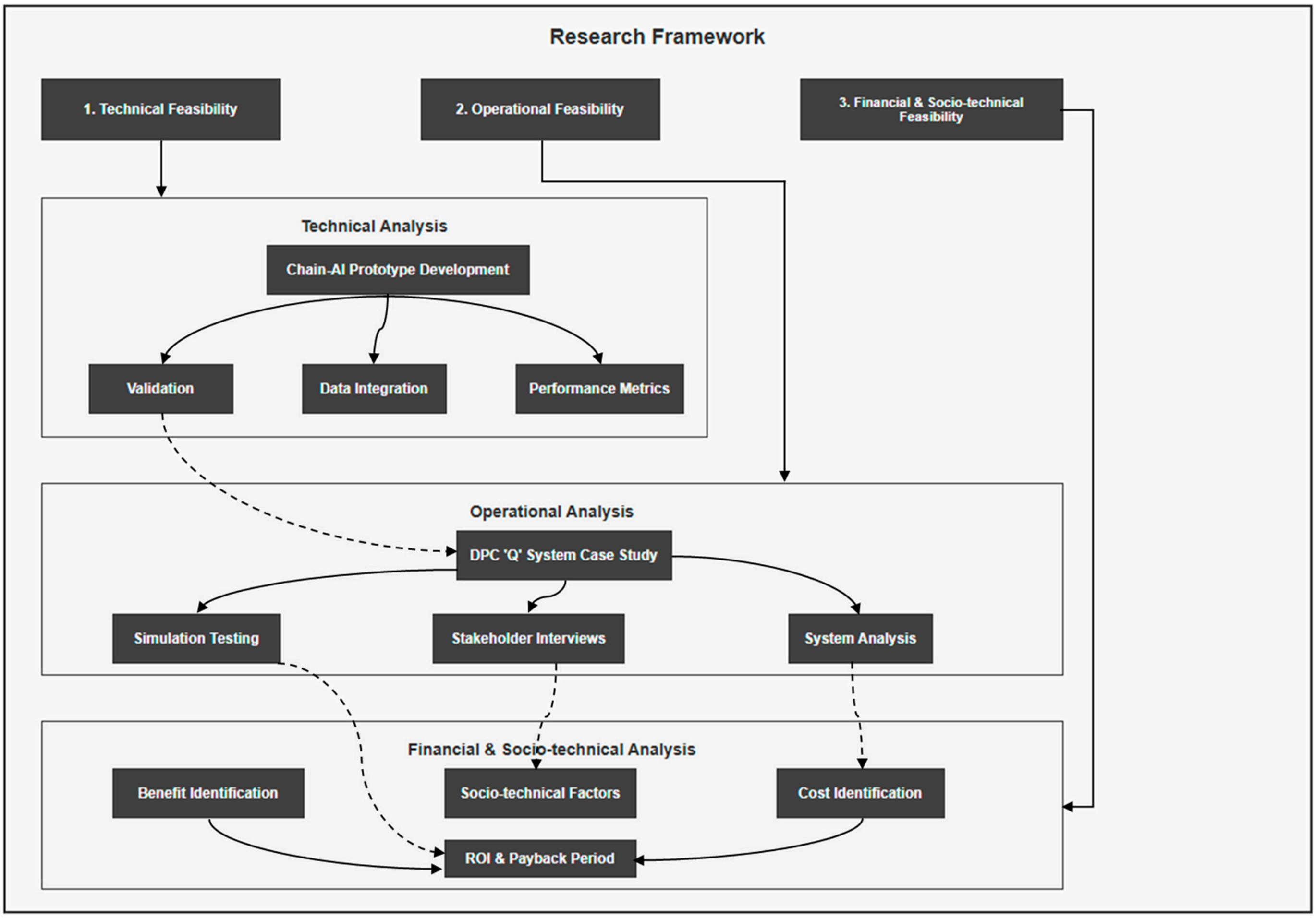

Figure 2. Research framework.

The selection of GPT-4 for this feasibility study was informed by its demonstrated strengths in structured language understanding, complex task decomposition, and consistent generation quality, particularly in domain-specific scenarios such as inventory workflow design. Although we considered open-source alternatives (e.g., LLaMA2, Falcon 3, and Mistral 7b), initial benchmarking showed that their performance in handling multi-step supply chain prompts, workflow formatting, and integration with RAG pipelines was less reliable in early testing phases. Given the study's feasibility focus and its alignment with a real-world SME use case, we prioritised the use of a commercially supported, high-performing model to demonstrate potential impact. Nonetheless, we recognise the importance of ablation-style comparisons across models of different sizes and architectures, which we identify as a priority in our future research.

While the current evaluation focuses on key technical performance indicators, accuracy, latency, and scalability, we acknowledge that assessing the robustness of LLM-generated workflows under adversarial prompts and noisy input data is equally important for production-grade deployment. However, such robustness testing lies beyond the immediate scope of this feasibility study, which is designed to explore foundational capabilities and proof-of-concept performance. The exploration of prompt perturbation, noise injection, and workflow failure tolerance is part of our planned future work, aligned with Phase II of this research programme.

3.2.2. Operational Feasibility Analysis

To assess the operational feasibility of integrating LLMs into existing SCM systems, a case study of DPC's "Q" system was conducted. This system manages workflows related to inventory, orders, and supplier communications. Data was collected through multiple sources to ensure a comprehensive evaluation. A detailed system analysis of the "Q" system logs and workflow configurations was conducted to understand the current state of operations and identify areas for potential improvement. Additionally, interviews with DPC employees, including supply chain managers and IT specialists, provided insights into existing workflow inefficiencies and challenges faced in their operations. To further assess the impact of LLM integration, simulation testing was performed by integrating LLM prototypes into the "Q" system to automate tasks such as order management and stock allocation, enabling an evaluation of their effect on workflow efficiency and decision-making. Validation was conducted through peer review of the case study findings and workshops with key stakeholders at DPC. Furthermore, insights from system logs, stakeholder interviews, and simulation tests were combined to strengthen the validity of the operational findings.

3.2.3. Financial and Socio-Technical Feasibility Analysis

The financial feasibility analysis involved assessing the costs associated with the development, implementation, and maintenance of LLM-based solutions, as well as potential cost savings and return on investment (ROI). This included:

- Cost Identification: Analysis of development costs (AI model training, software integration, hardware infrastructure), implementation costs (system integration, user training, downtime during transition), and maintenance costs (system updates, bug fixes, and data storage).
- Benefit Analysis: Evaluation of potential benefits such as improved operational efficiency, reduced labour costs, decreased inventory costs, and increased sales due to better customer satisfaction.

The socio-technical analysis focused on the human and organisational factors influencing the adoption and success of AI-enabled workflows in SCM. Strategies for managing and optimising these factors were developed to ensure that the technology was implemented in a way that is both effective and human-centred.

4. Research Findings

This section presents the core findings from the comprehensive feasibility analysis of implementing an AI-enabled workflow editor powered by LLMs. The results span technical, operational, financial, and socio-technical dimensions, offering insights into the practicality, efficiency, and challenges of deploying such systems. These findings, derived from both our literature analysis and case study, highlight the potential and limitations of the proposed solutions while addressing key research questions about the technical viability of LLMs in SCM.

4.1. Technical Feasibility

The study reveals that LLMs, particularly ChatGPT, have significant potential in addressing modern SCM challenges, particularly in inventory management challenges. The developed chatbot demonstrates the capability to summarise large volumes of supply chain and inventory data, providing users with actionable insights tailored to specific queries. By integrating prompt engineering, the chatbot ensures content is contextually relevant, enabling supply chain managers and inventory specialists to make informed decisions efficiently [34].

4.1.1. Supply Chain Optimisation Using LLMs

LLMs offer a transformative approach to supply chain operations, enhancing processes like inventory management, shipment tracking, and supplier relationship management. The results of this study indicate that LLMs can incorporate qualitative data such as customer feedback and market sentiment, which traditional models often overlook. This capability allows for a more dynamic and context-aware inventory management system that can anticipate demand based on various factors like viral trends or geopolitical events. This finding aligns with the theories of dynamic capabilities, where organisations must adapt and respond to changes in their environment, and LLMs appear to enable this agility in SCM. The integration of LLMs in SCM moves beyond simple automation to creating adaptable and resilient systems [35,36].

4.1.2. Addressing the Process-Related Challenges of Inventory Management Using LLMs

The findings highlight several practical advantages of LLMs in inventory workflows, addressing key challenges in SCM processes. By analysing historical data and market trends, LLMs enhance demand forecasting accuracy, directly tackling the issue of demand fluctuation. This improved accuracy helps businesses optimise stock levels, reducing costs and waste while aligning with lean management principles, which focus on minimising waste and improving efficiency. Additionally, LLMs provide real-time insights by continuously recommending stock replenishment and identifying bottlenecks, thereby improving workflow efficiency and agility. This capability enables quicker responses to disruptions, supporting resilience theory in SCM, which emphasises the need for organisations to adapt to sudden changes. Furthermore, LLMs facilitate workflow automation by streamlining repetitive tasks such as production scheduling and logistics data analysis. This automation leads to reduced lead times and increased operational efficiency, demonstrating the practical application of LLMs in optimising SCM processes and addressing operational inefficiencies identified in the literature.

4.1.3. The Feasibility of Generating Customised and Dynamic Workflows Using LLMs Based on the Specific Customers' Needs in Real-Time

This section shifts focus to how LLM can generate customised and real-time workflows for supply chains, addressing the need for agile and responsive systems. The core finding here is that LLMs can revolutionise traditional processes by creating agile and responsive workflows that adapt to user needs in real time. The introduction of the Chain-AI Bot exemplifies this capability, demonstrating its ability to collaborate with users and dynamically tailor workflows to meet specific demands. This capability moves beyond static processes, allowing for greater flexibility and adaptability, which is highly valued in modern, dynamic supply chains.

The results of this study demonstrate the feasibility of generating customised and dynamic supply chain workflows using a conversational AI-driven tool, Chain-AI Bot. The bot effectively generates workflows tailored to specific user requirements by interactively processing input and leveraging LLMs to iteratively refine outputs. This capability addresses the need for customised workflows that can manage the complexity and diversity of modern supply chains, aligning with the principles of agile supply chain management, which prioritise flexibility and responsiveness. Automation is central to the system's performance, as the Chain-AI Bot reduces manual intervention in workflow creation through LLM capabilities, significantly enhancing operational efficiency. This supports the goal of optimising decision-making and resource allocation while reducing manual workload and improving overall productivity in SCM. Additionally, Table 5 outlines the tool's key specifications, including input methods, processing sequences, outputs, and functionalities. These specifications highlight the tool's ability to efficiently meet diverse workflow requirements, demonstrating its robustness and versatility in addressing various SCM tasks.

Table 5. LLM tool specifications.

Specifications	Information
Input	• User Queries: Users input specific requirements for a supply chain workflow through conversational prompts. • Training Data: The system is trained on a diverse dataset, encompassing workflows, diagrams, codes, and other relevant information related to supply chain activities.
Process	• Chatbot Interaction: Utilises a chatbot interface to engage users in a conversation. • Questioning Sequence: Based on learned patterns, the system refines queries, adapting its approach to inquire about various supply chain activities and steps. • Learning Mechanism: Learns and adapts its questioning strategy from each user interaction, continuously enhancing future query precision.
Output	• Generated Workflow: Constructs a customised supply chain workflow based on information gathered from user responses. • Adaptive Learning: Gains insights from each interaction to improve future question sequences and enhance workflow generation accuracy.
Functionality	• Customisation: Tailors questions and workflows to meet specific user requirements. • Adaptability: Adjusts questioning strategies based on user feedback to refine workflow generation. • Continuous Learning: Constantly learns from user responses to enhance understanding and accuracy in generating workflows.

Accordingly, Figure 3 illustrates various aspects of the feasible Chain-AI Bot:

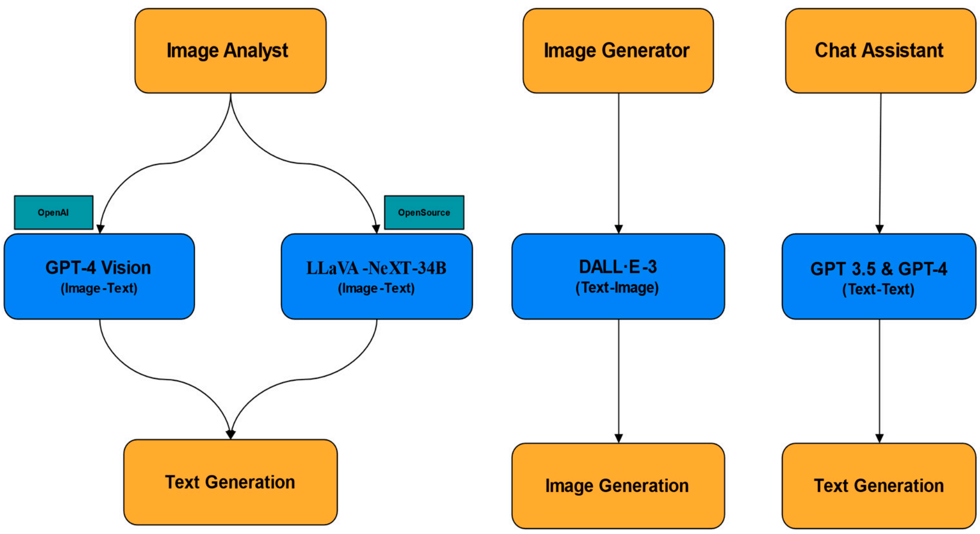

Figure 3. Various aspects of a feasible Chain-AI Bot.

This framework includes the following three main features:

- SCM AI Image Analyst: Image Analyst is an application developed for analysing supply chain-related images and facilitating conversations based on the insights generated. It utilises the following two powerful language and vision models:
    - OpenAI GPT-4 Vision (https://platform.openai.com/docs/guides/vision) (accessed on 21 March 2025).
    - LLaVA-NeXT-34B (https://github.com/haotian-liu/LLaVA) (accessed on 21 March 2025).

Image Analyst employs GPT-4 Vision and LLaVA-NeXT-34B to analyse supply chain-related images. These models process visual data and generate descriptive text, providing insights into the content and context depicted in the images.

Based on the text generated from the image analysis, the Image Analyst initiates interactive conversations with users. It leverages the capabilities of GPT-4 Vision and LLaVA-NeXT-34B to engage users in meaningful discussions about the analysed images, facilitating deeper understanding and creation of customised supply chain workflows.

Hence, Image Analyst combines the strengths of powerful LLMs like GPT-4 Vision and LLaVA-NeXT-34B to offer a solution for supply chain image analysis. The application not only interprets visual data and generates descriptive text but also engages in meaningful conversations, enhancing the user experience and enabling more effective decision-making in the realm of supply chain management (Figure 4).

- SCM AI Chat Assistant: The SCM Chat Assistant is an intelligent conversational tool designed for efficient interaction and information retrieval within the realm of supply chain management. Powered by cutting-edge language models, including OpenAI GPT-3.5 Turbo (https://platform.openai.com/docs/models/gpt-3-5-turbo) (accessed on 21 March 2025) and GPT-4 Turbo (https://platform.openai.com/docs/models/gpt-4-and-gpt-4-turbo) (accessed on 21 March 2025), this chat assistant enables users to ask detailed questions about various aspects of supply chain workflows. By leveraging the advanced capabilities of these models, the SCM Chat Assistant delivers accurate and contextually relevant responses, facilitating streamlined communication and decision-making in the complex landscape of supply chain operations (Figure 5).

The limitations of standalone LLMs, like hallucinating facts or giving outdated information, should be tackled. In this study, this was achieved by implementing RAG architecture with multimodal features [37,38].

The system integrates contextual and visual data using the Qdrant Vector Database and GPT-4 Vision, allowing it to process both textual and visual inputs. This multimodal approach enriches user interactions by leveraging image and text embeddings, resulting in more nuanced and contextually aware workflow outputs. This capability is essential for improving the accuracy and reliability of LLM-generated outputs, addressing a key limitation in applying LLMs to complex SCM tasks. It also highlights the importance of verifiable and contextually grounded outputs in real-world supply chain management scenarios. Additionally, the system enhances information retrieval through the RAG model, which retrieves and conditions domain-specific knowledge from external datasets. This ensures that responses remain accurate and adaptable to rapidly evolving SCM environments, supporting informed decision-making. The developed prototypes further demonstrated the system's functionality by combining visual insights with textual reasoning, confirming the feasibility of seamless user interaction and comprehensive output generation. These prototypes validate the practical application of RAG and multimodal integration in SCM, moving beyond theoretical concepts to demonstrate real-world usability. The findings confirm that RAG can enhance the precision and contextual relevance of LLM-generated workflows.

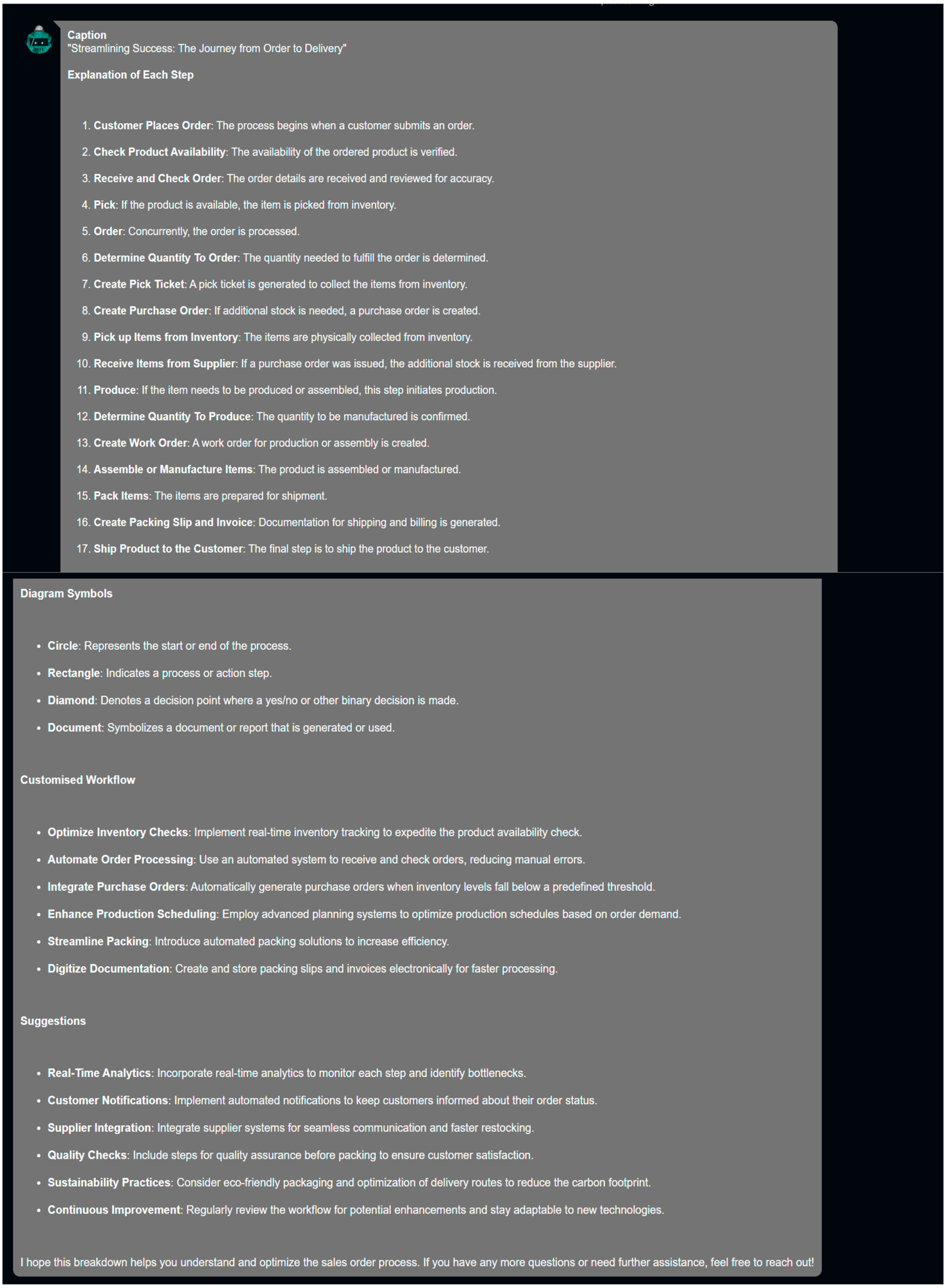

Figure 4. Interactive conversation with the user.

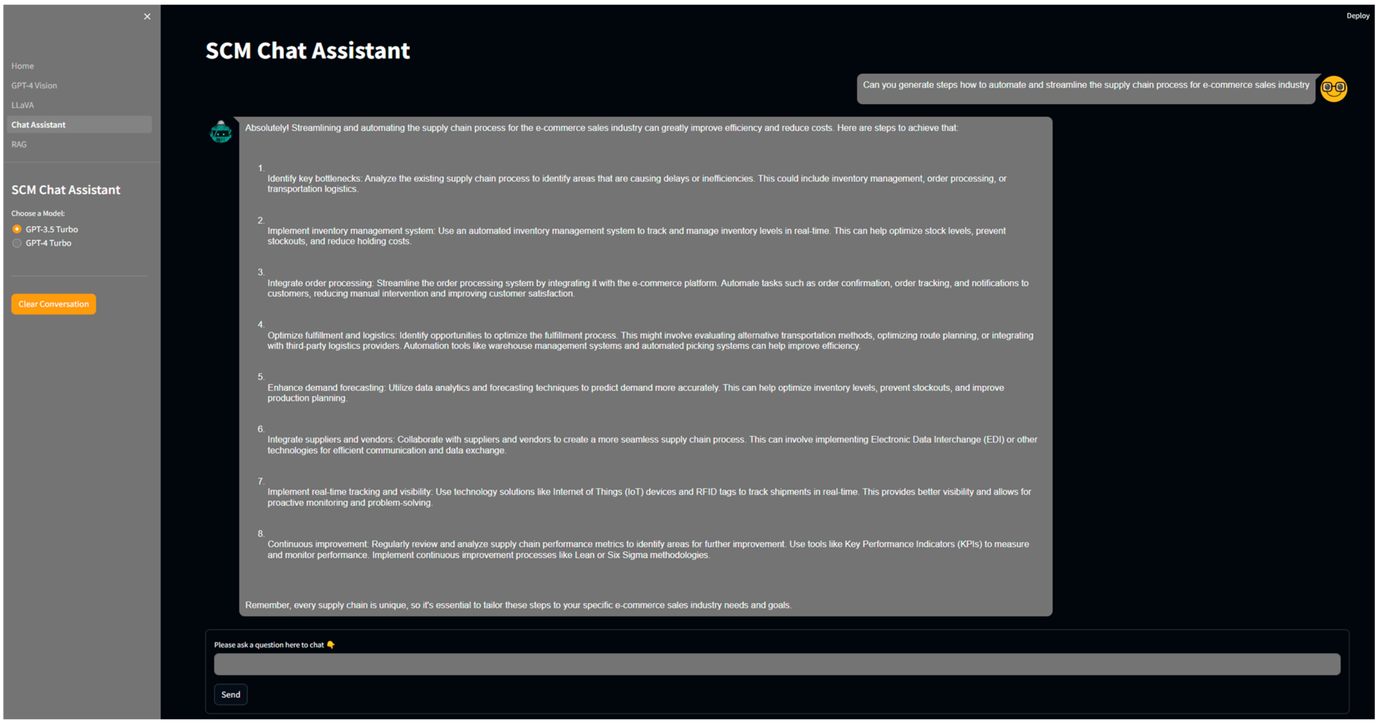

Figure 5. An example of an SCM chat assistant implemented using GPT-4.

Figure 6 illustrates how images and text from various sources can be utilised by RAG and LLMs to produce the output required:

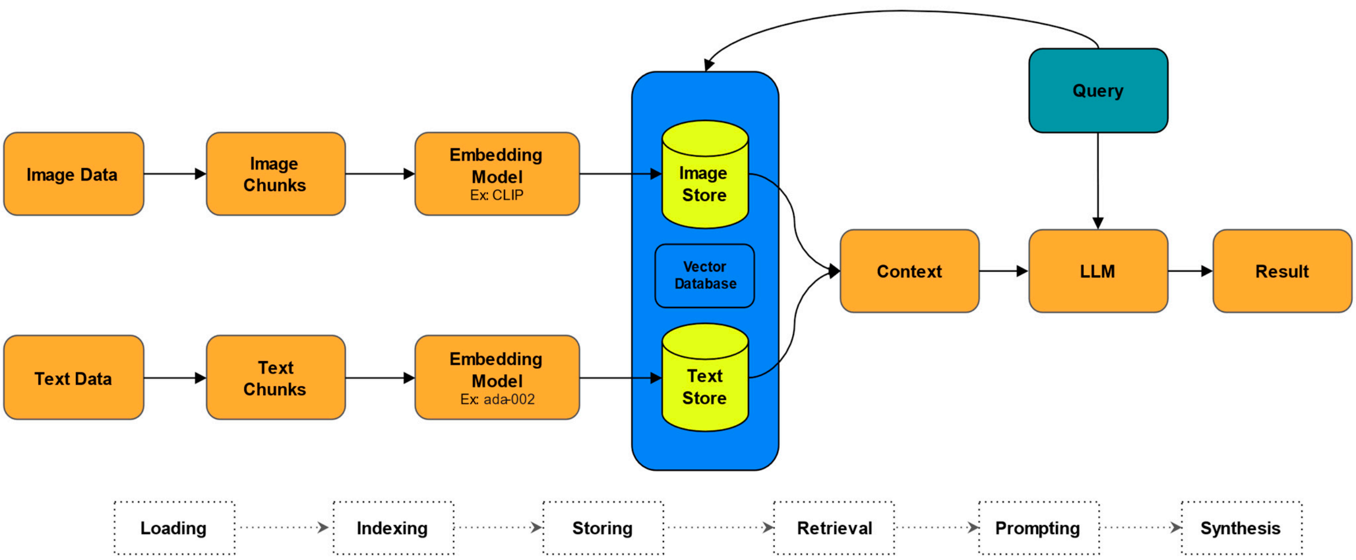

Figure 6. Multimodal RAG architecture for images and text with the vector database in this study.

Our approach integrates advanced technologies, including the Qdrant Vector Database and GPT-4 Vision, to enhance the Multimodal RAG Chat Assistant's capabilities in supply chain workflow generation. Qdrant enables efficient storage and retrieval of vector embeddings for both textual and visual data, facilitating rapid access to supply chain workflow images. GPT-4 Vision, a specialised variant of GPT-4, processes these images to generate textual descriptions, identify patterns, and extract meaningful insights. This multimodal approach improves the system's ability to respond to user queries by combining textual and visual reasoning, ultimately enhancing workflow customisation and decision-making.

The system employs RAG architecture, where the retrieval component accesses Qdrant for relevant embeddings, and GPT-4 Vision analyses the retrieved images before integrating the insights into a cohesive response. By incorporating visual elements into workflow generation, the system improves the Chain-AI Bot's ability to interpret complex supply chain scenarios, offering more nuanced and contextually relevant outputs. This multimodal framework contributes to the evolving role of LLMs in SCM by bridging the gap between textual and visual data processing. The findings underscore the potential of integrating multimodal AI tools in SCM optimisation, aligning with theories of intelligent automation and digital transformation. The study highlights how multimodal LLMs enhance supply chain decision-making through contextual awareness, adaptability, and workflow automation, addressing key challenges such as inefficiencies in inventory management and process optimisation.

Figure 7 illustrates the prototypes created for this research to better understand the feasibility.

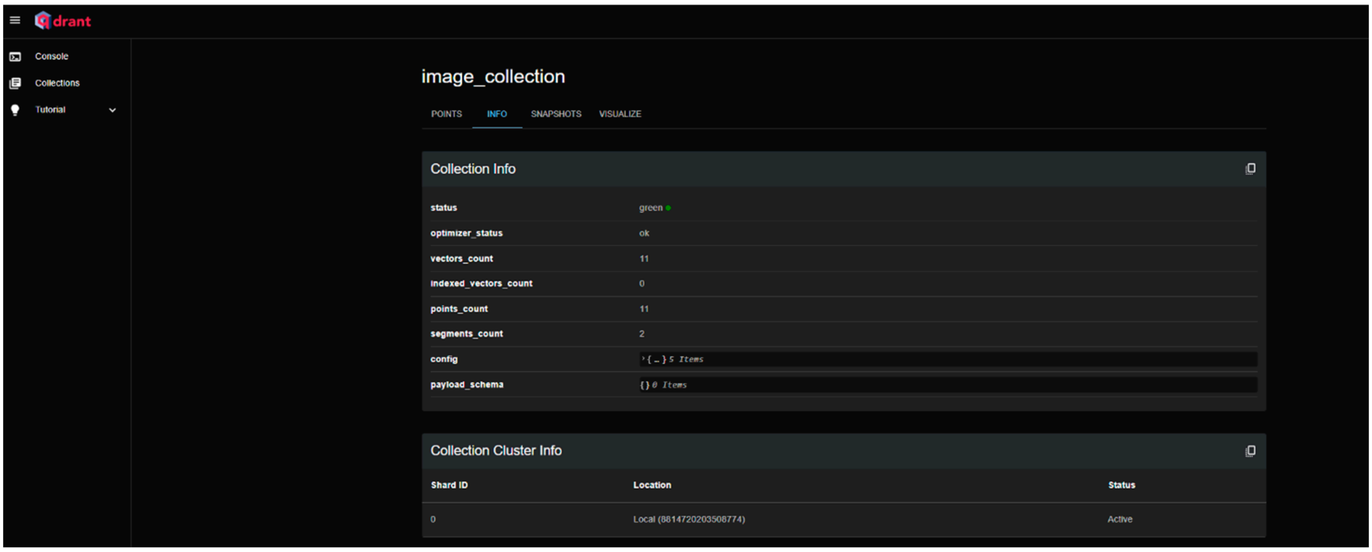

Figure 7. Qdrant cloud vector databases with image embeddings.

Hence, the exploration into the feasibility of employing an LLM-enabled solution for automatic supply chain workflow generation, specifically through the innovative Multimodal RAG SCM Chat Assistant, represents a significant advancement in supply chain optimisation. By integrating RAG architecture with the Qdrant Vector Database and GPT-4 Vision, this approach addresses the complexities of traditional workflow design and management. The assistant not only processes contextual nuances within supply chain operations but also integrates visual data to enhance user interactions. Through a user-friendly chat interface, it dynamically tailors workflows to real-time user demands, ensuring adaptability and continuous improvement. The system's learning mechanism refines its questioning strategy over time, enhancing the precision of workflow generation. These findings substantiate the potential of multimodal LLMs in revolutionising supply chain management by enabling intelligent, adaptive, and automated workflow optimisation. The prototypes developed illustrate a future where supply chain processes are increasingly data-driven, responsive, and efficient, contributing to the broader discourse on AI-driven supply chain innovation.

Furthermore, the use of Microsoft Copilot Studio and Power Virtual Agents for enhancing the interactivity of the Chain AI Chatbot is explored. Data was collected through multiple sources to ensure a comprehensive evaluation of the integration of Microsoft

Copilot Studio and Power Virtual Agents in enhancing the interactivity of the Chain AI Chatbot. This exploration demonstrates how generative AI simplifies chatbot development and improves user experience. Microsoft's tools leverage generative AI to streamline chatbot creation by suggesting actions, responses, and conversational elements, significantly improving usability and accelerating development. Additionally, Power Virtual Agents provides a Power BI analytics dashboard that offers insights into chatbot performance, enabling continuous monitoring and refinement based on usage data. This analytical capability is essential for optimising conversational experiences and ensuring the long-term success of the system. Furthermore, the Chain AI Bot was integrated into the Microsoft Copilot Studio environment to assess its adaptability within different frameworks. This integration highlights the flexibility of the Chain AI Bot and showcases the potential of Microsoft's generative AI tools in enhancing intelligent chatbot interactions (Figure 8).

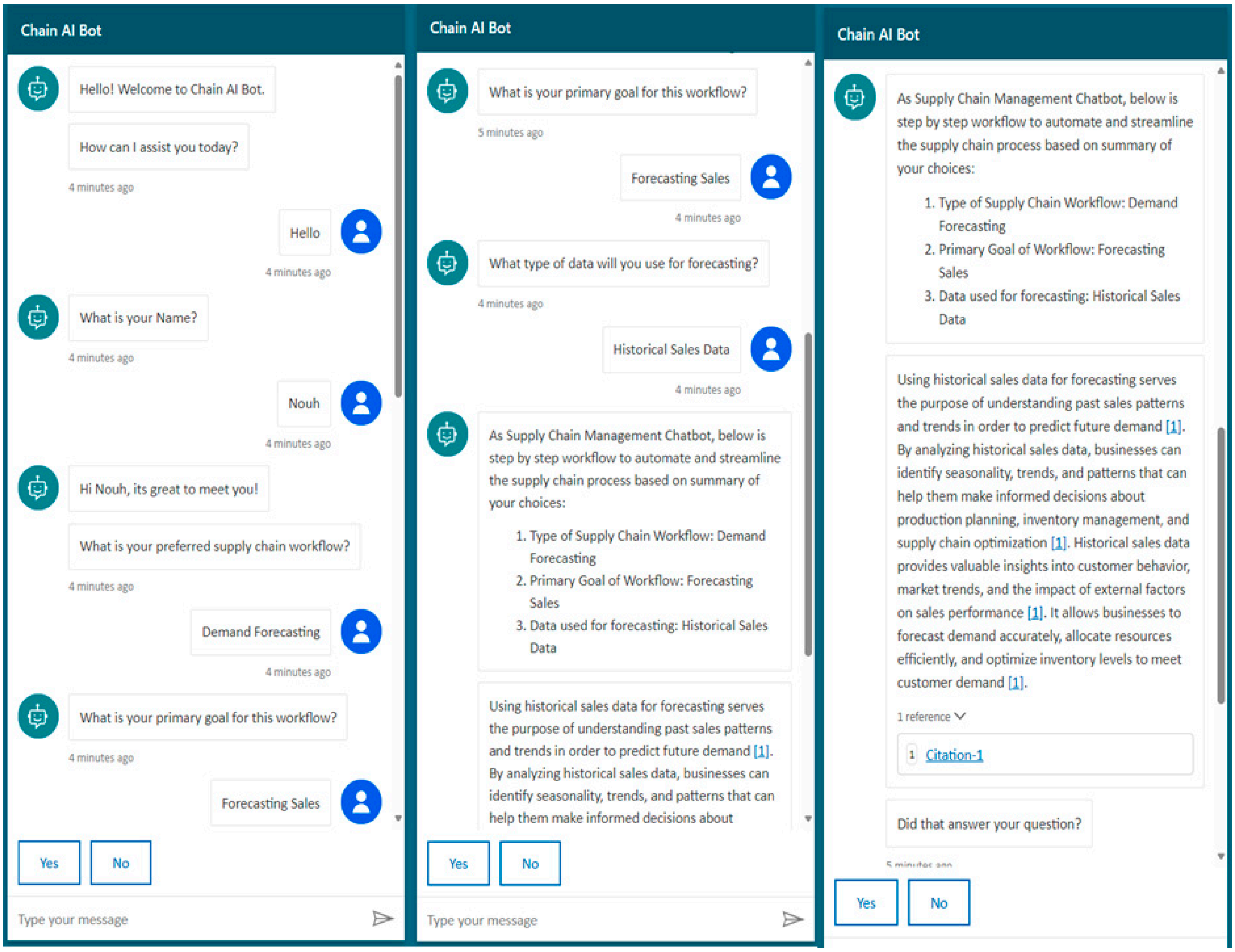

Figure 8. Our Chain-AI Bot outputs in the Microsoft Copilot Studio environment.

4.2. Operational Feasibility (Case Study: DPC Company: The "Q" System)

This section presents the findings from our case study of DPC company and its "Q" system, which manages inventory for the furniture industry. This analysis provides a real-world perspective on how LLM-based solutions can improve operational efficiency in a complex supply chain environment. The focus is on analysing the existing workflows within the "Q" system and identifying the areas where LLMs can provide significant operational improvements, addressing our research questions related to the practical application of LLMs in SCM.

4.2.1. Key Processes of the "Q" System

The key processes of the Q system are explained below. These processes are crucial for understanding the system's operational complexity and for identifying specific areas where LLMs can be integrated to improve efficiency:

- **Order Management:** This is the entry point for fulfilling an order. The system ingests orders from the retailer's website, creating stock groups, allocating items, selecting a logistics company, notifying the logistics company and sending confirmation emails. The system also creates a series of workflows that must be completed to fulfil the order. These include the following:
    - Order Verification: This workflow verifies the order and customer details before moving the order to dispatch.
    - Stock Allocation: This workflow allocates stock items, either from first-party or third-party suppliers, which involves checking availability and confirming delivery dates.
    - Selecting a Delivery Company: This involves selecting a delivery company and calculating the estimated cost.
    - Customer Availability Date: This involves contacting the customer to confirm a delivery date.
    - Contacting Delivery Company: This workflow sends a manifest to the chosen delivery company.
    - Awaiting Delivery Company Response: Staff await confirmation from the delivery company.
    - Delivery Reconciliation: This confirms the order has been delivered and reconciles the estimated delivery cost with actual costs.
- **Stock Management**: The "Q" system includes workflows for managing stock items, including adding, editing, increasing, and decreasing stock levels.
- **Product Management**: The system provides workflows for managing products listed on the retailer's website, including adding, editing, and publishing product details.
- **Range Management**: Similarly to product management, the system manages product ranges using workflows for adding, editing and publishing range details.
- **Customer Service Cases**: The "Q" system manages customer service cases using multiple workflows to simplify and expedite the resolution process. These include creating/editing follow-ups and escalating or de-escalating cases.
- **Container Workflows**: This part of the system manages shipments of stock items owned by the retailer (first-party supplier items). This includes workflows for adding and editing container details and their arrival dates.

This detailed outline is essential for understanding the complexity of the "Q" system and identifying specific points where LLMs can provide valuable enhancements. Figure 9 illustrates these workflows. It is important to note that while the system has several workflows to manage orders, stocks, and products, these workflows are still subject to various challenges, as discussed in the next section.

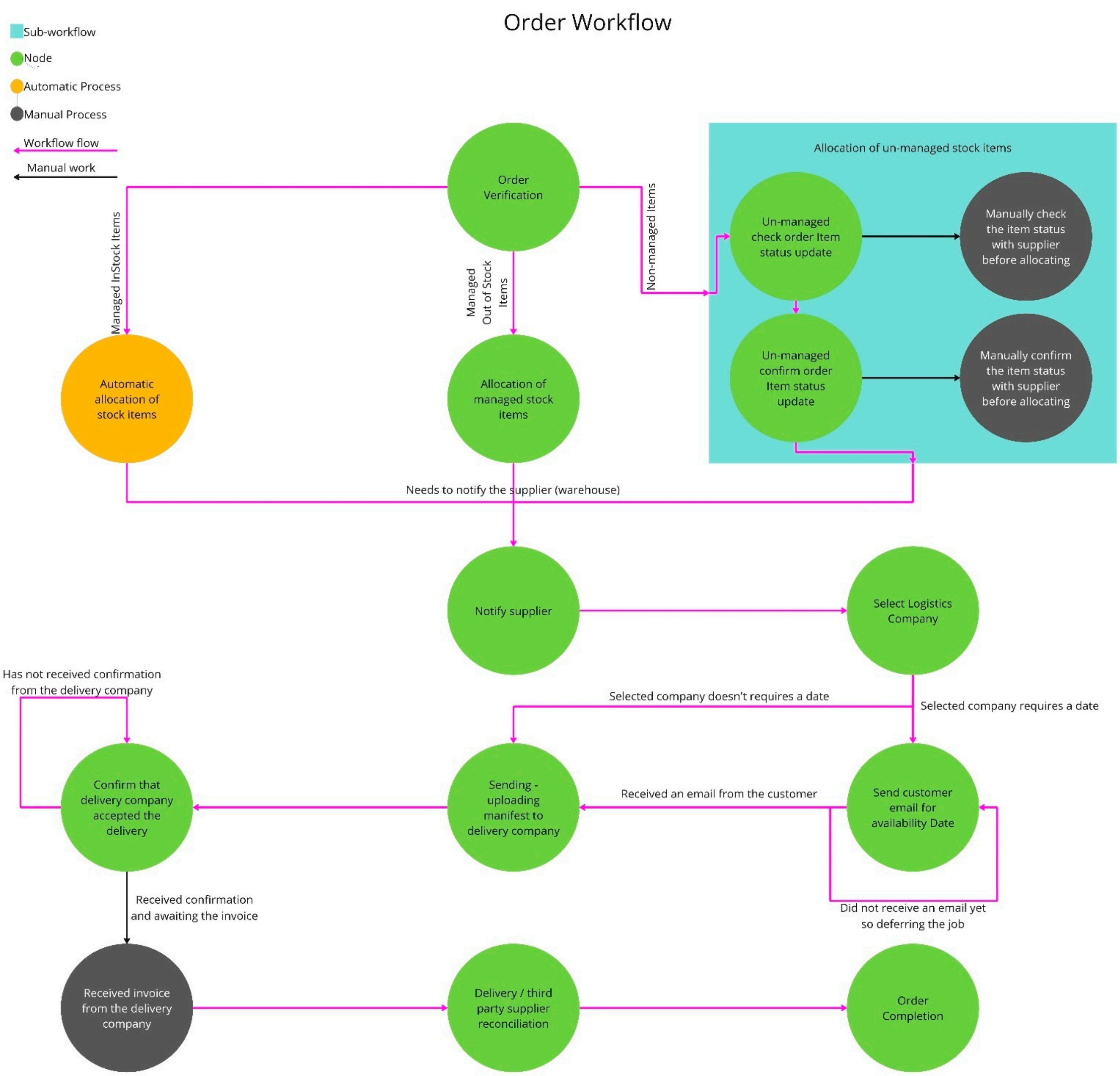

Figure 9. Order workflow in the Q at DPC.

4.2.2. The Key Process-Related Challenge in DPC's "Q" System

This section analyses the key challenges DPC faces with the "Q" system and identifies areas where LLM integration can make the biggest operational impact. This analysis is crucial for addressing the research questions about the practical challenges of using existing SCM systems and how LLMs can overcome these challenges, as follows:

- Supply Chain Connection: A primary challenge is the lack of seamless integration between the retailer, suppliers, and delivery companies. The need to connect these entities to optimise processes and ensure secure data sharing is a major pain point. This challenge aligns with the literature on supply chain visibility and collaboration, highlighting the need for better integration across different stakeholders.
- Delivery Manifest: The delivery manifest workflows are currently complex because each delivery company requires a custom workflow. This results in many workflows to maintain and increases the manual effort involved. Moreover, the manual work

involved in the response-related workflow can be reduced. This finding highlights the inflexibility of the current system and the need for a more adaptable solution, aligning with the research on the importance of agility in SCM.

- Containers Shipment Addition: The process of adding new shipments for first-party supplier items is primarily manual. The "Q" system acts more as a database for this data rather than as a tool that facilitates and streamlines this task. This manual work leads to inefficiencies and increases the risk of errors. This demonstrates a specific pain point where LLM-based automation can significantly reduce manual effort and improve data management.
- Generalised Workflow Framework: Adding a new workflow into the system requires software development, which is time-consuming. The current framework lacks adaptability, highlighting the need for a more flexible, data-driven system. This inflexibility is a critical barrier to rapid process improvement and innovation, showcasing the need for a dynamic workflow management approach that LLMs can enable.

4.2.3. Analysis and Interpretation

Our operational feasibility analysis clearly articulates the operational challenges DPC faces with the "Q" system and prepares the ground for showing how LLMs can help improve these areas. It demonstrates that although the Q system does provide some level of automation, it is not flexible, is difficult to customise, and involves a high degree of manual work. The findings highlight that a significant barrier to operational efficiency stems from the need for manual, bespoke processes. In order to address these limitations, the study indicates that a dynamic workflow generator is required to adapt and automate workflows based on identified needs. This analysis demonstrates that the current system, despite its aim to provide automation, still suffers from inefficiencies, a lack of integration, and inflexibility. The problems uncovered here are consistent with what the literature highlights as common challenges in SCM.

4.3. Financial Feasibility Analysis

The Implementation of an AI-enabled workflow editor using LLMs introduces some unique cost factors. The goal is to address research questions related to the financial viability of LLM-based solutions for SCM. This section moves beyond a simple cost listing and critically evaluates the various cost factors, potential revenue streams, and strategies for ensuring long-term financial sustainability, which is a key aspect of the feasibility study. Table 6 summarises the primary cost contributors and potential strategies for optimisation.

Table 6. Data preparation and annotation cost factors.

Cost Factor	Description	Optimisation Strategy
Data Volume	The quantity of data needed for training and validation	Use smaller, high-quality datasets with augmentation
Data Annotation	Cost of manual annotation processes	Employ semi-automated tools or crowdsourcing methods
Data Licencing Fees	Licencing third-party datasets for commercial use	Negotiate bulk licencing or partnerships
Data Privacy Compliance	Costs related to anonymisation and regulatory adherence	Adopt robust anonymisation tools and practices

The implementation of LLM-based solutions introduces several unique cost considerations, starting with data. LLMs require high-quality, annotated datasets, which present significant expenses. These costs span several areas, each of which is carefully analysed as follows:

- Data Preparation and Annotation: This is a major cost driver. The expenses are influenced by factors such as data acquisition, the volume of data needed for effective training, manual annotation processes, licencing fees for third-party datasets and ensuring data privacy compliance. Strategies to optimise these costs, such as using smaller high-quality datasets with augmentation techniques, employing semi-automated annotation tools, and negotiating bulk licencing, are essential. The significant financial investment in data preparation demonstrates the need for a strategic approach to data management in LLM-based SCM solutions.
- Model Training and Fine-Tuning: Training and fine-tuning LLMs can be computationally intensive and time-consuming. The high computational costs involved in training LLMs demand a scalable infrastructure.
- Infrastructure Costs: Running and maintaining LLMs requires robust infrastructure, including servers with high computational power and storage capabilities. The cost will vary depending on factors such as usage volume, model size, and required response times. The study notes that experiments with hosting AWS and Azure showed that the cost grew exponentially without robust management.
- Licencing Fees: Some LLMs are proprietary and require licencing fees for commercial use, which adds to the overall cost. The choice between a pay-by-token model and a hosting model needs to be considered carefully. The pay-by-token approach involves companies paying based on the amount of data processed by the model service, whereas hosting requires upfront infrastructure investment. The best option depends on the specific needs of the user, and for the purposes of this research, a pay-by-token model is chosen, due to the nature of the nodestream© and buttress products.

4.3.1. Sales of the Product

Several software packages, API, and other requirements are essential for leveraging advanced language models in this context. The discussion encompasses the development environment, programming language, and crucial packages necessary for implementing these models effectively. Additionally, a number of considerations, such as model cost, budgeting, and deployment intricacies specific to supply chain operations, are required to be explored. Table 7 presents a cost estimation for various LLMs, including OpenAI Azure, Anthropic Claude, Llama 2, Google PaLM 2, and Cohere LLM APIs. The pricing is determined based on an input of 10,000 tokens (equivalent to approximately 7500 words) and an output of 10,000 tokens per day, reflecting average token usage. The table provides insight into the calculated costs associated with the usage of these LLMs in terms of both input and output tokens.

To further ground the feasibility analysis, we constructed a real-world deployment scenario based on DPC's Q system, involving automated delivery manifest generation and validation using GPT models. This workflow reflects realistic usage volumes (50 manifests per day), with an estimated monthly token consumption of ~4 million tokens and a corresponding cost in the range of $70–100/month, depending on the model choice (GPT-3.5 or GPT-4). The scenario also includes optional embedding usage for historical manifest search and constraint matching. These estimates show that even modest-scale deployment of LLMs in operational logistics workflows is both technically feasible and economically viable, supporting our feasibility claim. While large-scale deployments would require additional robustness and cost-efficiency analysis, this scenario demonstrates the immediate utility and practical cost envelope for targeted integration in SME logistics processes (Table 8).

Table 7. LLM pricing cost estimation.

Provider	LLM	Context Length	Input/1K Tokens	Output/1K Tokens	Per Each Call/Request	Total Price (USD)
Chat Models						
OpenAI	GPT-3.5 Turbo	4K	$0.0015	$0.002	$0.0350	$3.50
OpenAI	GPT-3.5 Turbo	16K	$0.003	$0.004	$0.0700	$7.00
OpenAI	GPT-4	8K	$0.003	$0.06	$0.9000	$90.00
OpenAI	GPT-4	32K	$0.06	$0.12	$1.8000	$180.00
Anthropic	Claude Instant	100K	$0.00163	$0.00551	$0.0714	$7.14
Anthropic	Claude 2	100K	$0.01102	$0.03268	$0.4370	$43.70
Meta	Llama 2 70b	4K	$0.001	$0.001	$0.0200	$2.00
Google	PaLM 2	8K	$0.002	$0.002	$0.0400	$4.00
Cohere	Command	4K	$0.015	$0.015	$0.3000	$30.00
Fine-Tuning Models						
OpenAI	GPT-3.5 Turbo	4K	$0.012	$0.016	$0.2800	$28.00
Google	PaLM 2	8K	$0.002	$0.002	$0.0400	$28.00
Embedding Models						
OpenAI	Ada v2	—	$0.0001	—	$0.0010	$0.10
Google	PaLM 2 Embed	—	$0.0004	—	$0.0040	$0.40
Cohere	Embed	—	$0.0004	—	$0.0040	$0.40
Audio Models						
OpenAI	Whisper	—	—	—	$0.006/min	—

Table 8. Real-world deployment estimate: LLM-assisted manifest workflow for DPC's Q system.

Deployment Component	LLM Type	Usage Volume	Token Estimate	Monthly Token Total	Estimated Monthly Cost (USD)
Manifest generation and validation	Chat (GPT-4)	50 manifests/day	2000 input + 1500 output = 3500	3500 × 30 = 105,000 tokens/day × 30 = 3.15 M	~$63–95 (*GPT-3.5 to GPT-4*)
Partner-specific format transformation	Chat (GPT-4)	Integrated with above	Reuses prompt context	Included above	Included above
Constraint validation and reasoning	Chat (GPT-4)	Integrated with above	Reuses prompt context	Included above	Included above
Embedding of historical manifests (*initial*)	Embedding (OpenAI)	5000 manifests (one-off)	500 tokens × 5000 = 2.5 M tokens	One-time cost	~$5 (*OpenAI embedding*)
Daily manifest embedding (*ongoing*)	Embedding (OpenAI)	50 manifests/day	500 tokens × 50 = 25,000 tokens	750,000 tokens/month	~$1.50
Semantic search (e.g., delivery constraint matching)	Embedding search	Optional, ad hoc	Negligible (cached vector queries)	<100,000 tokens/month	<$1
Total deployment estimate	—	Operational scale (real-world)	~3.9–4 M tokens/month		**~$70–$100/month**

4.3.2. Maintain the Project's Financial Viability and Attractiveness

Our findings suggested that the following maintenance factors should be reviewed to ensure the project's financial viability and attractiveness. Here are the strategies for maintaining financial viability and their implications, drawing upon the research findings, as follows:

- Monitoring and review for adaptive financial management: The research underscores the necessity of continuous financial monitoring to ensure project viability. Regularly generating financial reports (monthly, quarterly, and yearly) is crucial for tracking project performance. However, simply generating reports is insufficient; these must be actively used to compare actual financial performance against predicted performance to identify deviations and their underlying causes. This analytical approach facilitates data-driven decision-making, allowing agile adjustments to financial strategy in response to evolving project needs. For example, if the cost of training the LLM exceeds the initial budget, this approach would allow the team to identify and address this overspending by either finding a more cost-effective solution or by adjusting the project's budget. This proactive financial management stance moves beyond a descriptive approach.
- User feedback integration for enhanced value: The study highlights the critical role of user feedback in maintaining the project's appeal and usefulness. Actively incorporating user input into the project's development ensures alignment with user needs and preferences. This feedback is not just about identifying bugs but about understanding how users interact with the system and what features add the most value. For example, the "Q" system, as described in the case study, highlights the complexities users face with manual processes in delivery manifest workflows, which can directly inform what aspects of the LLM-based system need to be prioritised. This user-centric approach drives continuous improvement and ensures the LLM-based solution remains relevant and effective. By understanding pain related to the LLM's responsiveness for specific supply chain management tasks, the development team can prioritise refining the model in that area, ultimately enhancing user satisfaction.
- Iterative improvement as a financial strategy: The research emphasises that continuous improvement is not merely about product development, but a financial necessity. Regularly gathering and analysing customer feedback directly feeds into product enhancements, addressing shortcomings promptly and improving the overall range. A commitment to quality and user responsiveness is not merely a customer service tactic; it also promotes loyalty and can act as a key differentiator in a competitive market. Furthermore, monitoring and reviewing available models will help with using the most cost-effective and efficient models. For instance, the use of the GPT-4 model might be more expensive than GPT-3.5, which can be a factor to be considered when a specific aspect of a project is being looked at in terms of cost-effectiveness. This iterative approach allows the business to grow by ensuring that the product delivers maximum value for money for its users.
- User satisfaction and engagement for Long-Term Viability: The research emphasises the importance of user engagement, suggesting that fostering a sense of ownership and investment in the project's user base is crucial to long-term financial health. When users are involved in the feedback process and feel their suggestions are considered, they develop a sense of ownership and loyalty, leading to higher engagement and satisfaction. For example, involving DPC employees, who use the "Q" system, in the development and feedback process for the LLM-based workflows can increase their satisfaction and adoption of the new system. This loyalty translates into sustained usage and a more reliable revenue stream. Active participation of users will also help in understanding the market and areas for enhancements. Encouraging a sense of ownership and investment within the project's user group involves actively listening to their input and integrating their suggestions into our project, if possible. This

promotes the belief that our company values and listens to the users, leading to increased satisfaction and loyalty among individuals.

- Building a reputation for future growth: By actively incorporating feedback and demonstrating a commitment to continuous improvement, the project can cultivate a reputation for responsiveness and customer-centricity. This reputation is crucial to attracting new users and can have a positive impact on the project's financial viability. A user-friendly and adaptable system attracts users, which drives up adoption rates and improves the revenue potential of the system.

4.3.3. Managing Financial Risks—Identification and Mitigation Strategies

This section provides an analytical discussion of financial risk mitigation, drawing upon the findings of our research.

The research indicates a significant risk of low turnover if the product is not adopted widely. To mitigate the risk of low turnover for the LLM-based solution, a robust marketing and promotion strategy is essential. Crafting a comprehensive plan to increase awareness and interest in the project is imperative. This entails leveraging a diverse array of channels, including social media platforms, targeted email campaigns, compelling content marketing initiatives, Search Engine Optimisation (SEO) techniques, and strategic advertising efforts. Furthermore, showcasing positive feedback from satisfied users through testimonials serves as crucial social proof, building credibility and reassuring potential users of the solution's value. For example, highlighting the efficiency gains that an organisation such as DPC might achieve from using the new LLM-based workflows would work as a valuable testament for other potential users. This goes beyond basic advertising to provide evidence of real-world benefits. This approach uses a data-backed strategy to demonstrate value and overcome user reluctance.

Additionally, addressing the challenge of post-paid billing, wherein users only pay if they utilise the service, requires careful consideration. While this billing model offers flexibility to users, it also poses the risk of limited revenue if adoption rates are low. To counteract this, the findings suggest implementing a range of flexible payment options, including monthly subscriptions or pay-per-use models, catering to diverse user preferences and budgets. For example, for companies that have a higher volume of transactions, pay-per-use might be more suitable, whereas companies with predictable needs might prefer a subscription model. Offering trial periods and discounts encourages initial adoption, allowing users to experience the product before making a full commitment. Transparent pricing and billing practices build trust, eliminating apprehension about hidden costs. Furthermore, features such as auto-pay options streamline transactions, and reward systems encourage continued engagement. This analytical approach does not merely list solutions but explains the need for a holistic and nuanced strategy to mitigate the risk associated with post-paid billing.

Furthermore, the research revealed significant hidden costs associated with LLM applications. These include the variability in the size of user input, the size of generated output, the complexity of application prompts, and the API calls that occur in the background. The research suggests that these are not minor factors but significant variables that impact the final cost. For example, an application that uses an LLM to create an entire workflow would have a much higher output of tokens in comparison to an application that simply provides a small piece of information. Acknowledging these complexities is crucial to developing a realistic pricing strategy. Without accounting for these hidden costs, pricing structures could be inaccurate and unsustainable.

5. Discussion

This section discusses the implications of the feasibility study findings, offering a critical analysis of the technical, operational, financial, and socio-technical considerations involved in implementing an LLM-powered workflow editor. The discussion contextualises these results within real-world constraints, addressing challenges such as scalability, user adoption, financial sustainability, and socio-technical alignment. Strategies for optimising performance, enhancing user engagement, and mitigating risks are explored, alongside reflections on broader organisational and societal impacts. Through this analysis, the chapter provides a roadmap for translating feasibility insights into actionable steps for successful implementation.

5.1. Enhanced Capabilities of LLMs in SCM

The results underscore the transformative impact of LLMs on inventory management and supply chain workflows. Unlike traditional methods, which rely heavily on numerical data, LLMs integrate qualitative and contextual information. This shift enables businesses to anticipate demand fluctuations influenced by external factors, creating a more responsive and proactive approach to inventory management. This section addresses the core question of how LLMs enhance SCM beyond traditional methods, linking findings to the gaps identified in the Section 1.

The study's findings demonstrate that LLMs offer a significant advantage over traditional SCM models by integrating qualitative and contextual information. Traditional methods typically rely on numerical data, whereas LLMs incorporate qualitative data such as customer feedback, market sentiment, and real-time events. This capability is critical for anticipating demand fluctuations influenced by external factors, enabling a more responsive and proactive approach to inventory management. For example, LLMs can analyse social media trends or geopolitical events to predict potential supply chain disruptions, a capability lacking in static, traditional models.

Furthermore, LLMs have shown the capacity to learn from the nuances of language and context, improving accuracy in areas such as demand forecasting and supplier communication. This is a crucial improvement over conventional models that often struggle with dynamic market conditions. The research shows how this enhanced analytical capability of LLMs directly addresses the need for more adaptable and intelligent SCM solutions. This adaptability ensures that the LLM-driven workflows can be continuously optimised according to the user's needs.

5.2. Implications of LLM Integration

The integration of LLMs into supply chain processes introduces a higher degree of efficiency and accuracy. The core aim of this research was to investigate the feasibility of employing LLMs in generating SCM-related processes and workflows. The development of the Chain-AI bot and the nodeStream© workflow editor, coupled with the case study at DPC, demonstrated that it is technically feasible to implement and integrate LLMs for automating key SCM workflows. In addition, the study addressed research questions concerning the technical, financial, and socio-technical feasibility of LLM implementation. The technical feasibility analysis assessed the potential capabilities of LLMs for automating workflows through prototype development. As this study focused on feasibility exploration rather than performance optimisation, benchmarking against existing SCM platforms was not within scope. However, the structured prompts and modular design of our prototypes lay the groundwork for such comparative evaluations in follow-up studies.

The operational feasibility was assessed by examining a detailed case study, while financial and socio-technical feasibilities were also rigorously evaluated. The financial analysis provided insights into cost factors and various models for cost management, and the socio-technical analysis shed light on potential organisational impacts. Furthermore, the study addressed gaps in the literature by focusing on process-related supply chain challenges such as the integration of technologies, data management, agile operations, supply chain visibility, and collaboration. The Chain-AI bot, with its RAG architecture, offers solutions to enhance supply chain visibility through better data integration and real-time insights. The system's ability to facilitate better communication through its chat interface addresses issues in collaboration and partnership.

5.2.1. Theoretical Implications

This study contributes to SCM theory [39] by demonstrating the feasibility of using LLMs to create dynamic, real-time workflows. This moves beyond the traditional focus on static models, introducing a framework for SCM that is adaptable and responsive to changing conditions. The findings support the notion that AI, particularly LLMs, can fundamentally alter how SCM is approached, offering a theoretical grounding for further exploration into AI-driven supply chain management. The research also provides theoretical insights into the specific capabilities of LLMs within the context of SCM. By analysing their performance in areas such as inventory management, demand forecasting, and supplier relationship management, this study establishes a foundation for understanding how LLMs can enhance various aspects of supply chain operations. This understanding helps in developing better strategies for the integration of AI in SCM and contributes to the body of knowledge around it.

These findings align with Dynamic Capabilities Theory (DCT), which highlights a firm's ability to sense, seize, and transform its resources in response to changing environments. In this study, LLMs facilitate the sensing of market shifts, such as demand fluctuations and potential disruptions, in real-time, enabling firms to adapt more efficiently. The seizing aspect is demonstrated through automated workflows powered by LLMs, which enhance operational efficiency by allowing rapid responses to emerging opportunities, such as supplier disruptions. Additionally, the transforming dimension of DCT is reflected in LLMs' ability to drive continuous evolution in SCM processes, offering flexibility and responsiveness in volatile environments.

In addition, the Resource-Based View (RBV) further supports these findings by positioning LLMs as valuable, rare, and inimitable resources that contribute to sustained competitive advantage in SCM. LLMs enhance the firm's capacity to process vast amounts of qualitative and quantitative data, providing actionable insights that traditional models cannot offer. Moreover, RBV emphasises the importance of capability-building, which is evident in how LLMs help firms continuously update their SCM practices in line with changing market demands. This research highlights that LLMs are not just technological tools but dynamic capabilities that enable firms to align their practices with emerging trends, thereby reinforcing their competitive edge.

5.2.2. Framework for Addressing SCM-Related Challenges Using LLMs

In addition, the research provides a novel framework for integrating LLMs into SCM workflows. This framework provides a holistic view of the technical, operational, financial, and socio-technical considerations that are necessary for successful implementation. It establishes a structured approach that helps researchers and practitioners to understand the complex relationships between various aspects of AI adoption in the supply chain.

The framework is a series of interconnected layers, each distinctively designed to orchestrate a harmonious interplay of data and insights. Tailored specifically for the multifaceted challenges and opportunities of the supply chain, the framework emphasises responsiveness and adaptability, especially in the context of inventory management. As illustrated in Figure 10, the envisioned framework integrates four layers (Data Source, Data Engineering, LLMs, and Applications) designed to address challenges in supply chain management.

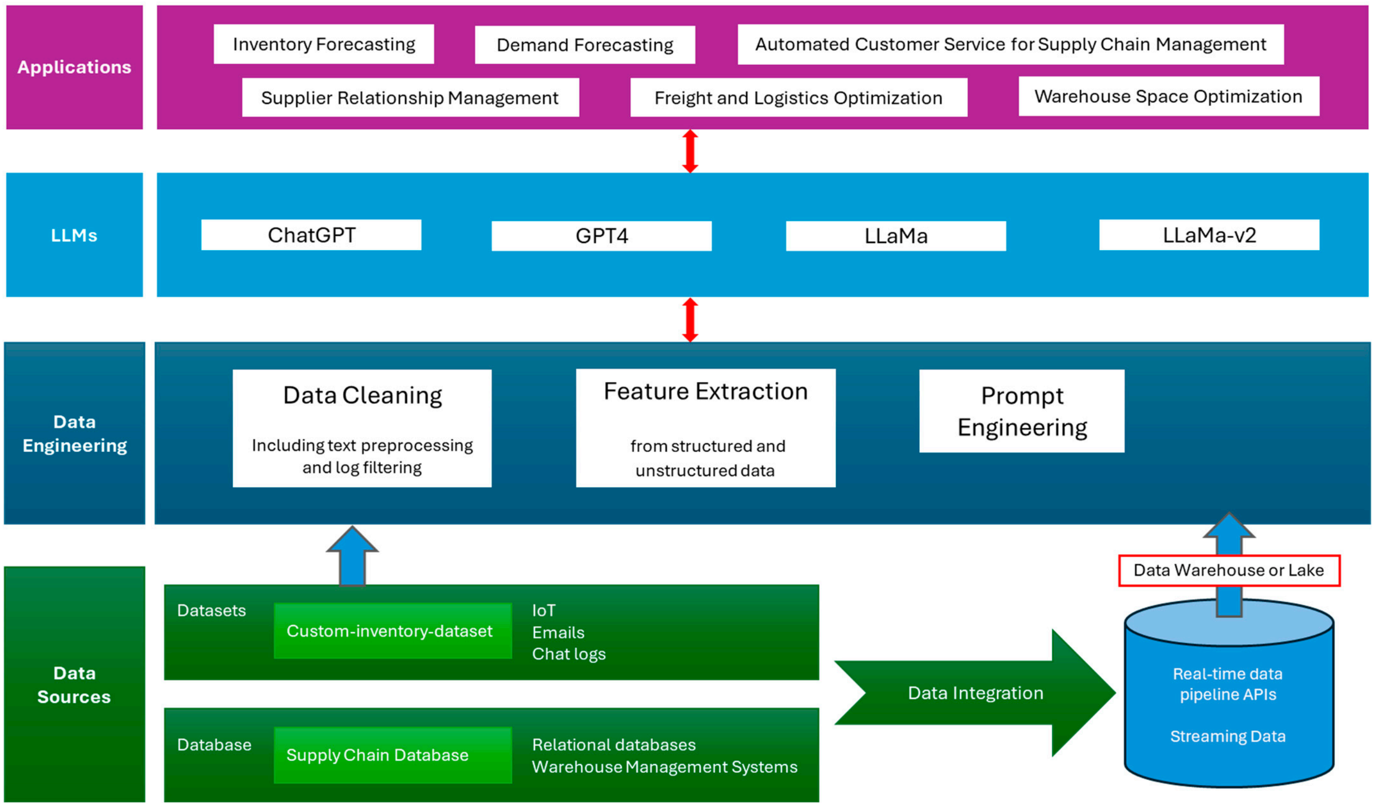

Figure 10. Proposed framework for addressing SCM-related challenges using LLMs.

Each layer contributes to achieving seamless data integration, real-time processing, and actionable insights:

1. Data Source Layer: Aggregates diverse sources like relational databases, warehouse management systems, IoT streams, and supplier communication platforms (e.g., emails and chat logs), ensuring real-time and comprehensive data access.
2. Data Engineering Layer: Processes both structured and unstructured data through advanced cleaning, log parsing, and NLP techniques. Unstructured SCM data, such as IoT device logs and supplier emails, is pre-processed and transformed using appropriate pipelines. Feature extraction accommodates heterogeneous data formats, enabling refined insights for downstream tasks.
3. LLM Layer: Fine-tunes LLMs for adaptability, ensuring accurate and relevant outputs aligned with evolving supply chain dynamics. and evolving supply chain contexts. The models are continuously improved using feedback loops, performance evaluation metrics (e.g., accuracy, response relevance, and latency), and retraining strategies to support ongoing learning and alignment with current supply chain data.
4. Application Layer: Demonstrates practical applications of LLMs, including inventory forecasting, demand sensing, and supply chain risk management. Figure 11 shows how LLMs revolutionise various facets of supply chain management:

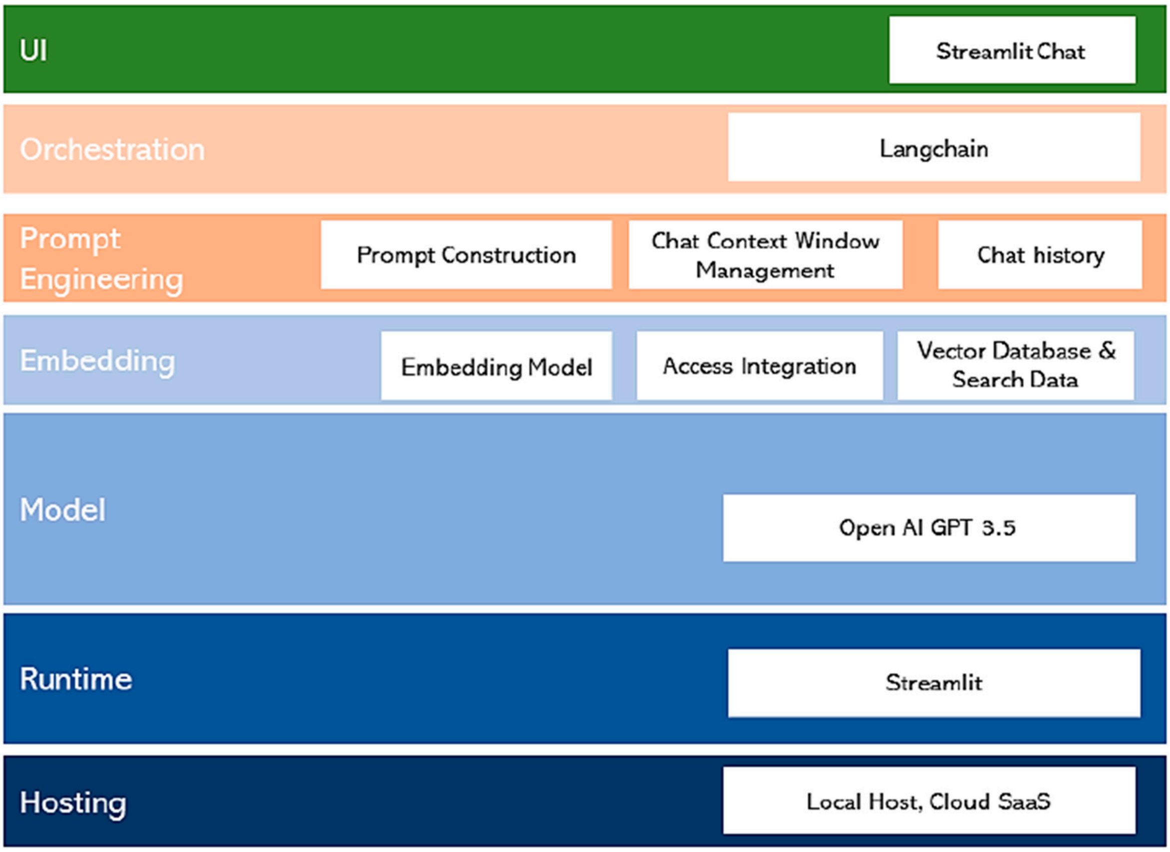

Figure 11. The application layered stack for the LLM-based bot solution.

In synthesising these multifaceted applications, the framework crystallises its vision of seamlessly melding AI with inventory management and the broader supply chain. This confluence is not just a harbinger of avant-garde research and innovation but also manifests as pragmatic tools and solutions, enabling businesses to redefine their operational trajectories. The framework offers a comprehensive solution for integrating AI into inventory management and supply chain. This not only facilitates cutting-edge research and innovation but also offers practical tools for businesses to streamline their operations.

5.2.3. Practical and Managerial Implications

The study demonstrates the practical implications of LLM integration, particularly in operational efficiency and cost optimisation. For example, the Chain-AI bot can automate repetitive tasks such as production scheduling and logistics data analysis, leading to reduced lead times and increased overall operational effectiveness. The study showed that this automation leads to fewer errors and a better flow of communication, which is beneficial in complex supply chains like that of DPC. The research findings suggest that implementing LLM-based systems can lead to considerable cost savings through improved forecasting, reduced stockouts, and optimised supplier management.

The ability of LLMs to analyse communication patterns and performance metrics enhances supplier collaboration and helps mitigate potential risks. This allows businesses to make strategic decisions by evaluating their suppliers based on data, leading to a more robust and efficient supply chain. This addresses a gap mentioned in the introduction regarding the need for better adaptability in the supply chain.

The development and evaluation of the Chain-AI bot demonstrate the feasibility of generating customised workflows dynamically, tailored to specific user requirements. The conversational interface of the Chain-AI simplifies the interaction between users and technology. This enhances accessibility and adaptability of the system to different types of users, making it user-friendly. By employing LLMs, the system bridges the gap between user requirements and technical capabilities, promoting adoption and enhancing the user experience.

In our case study, the issues highlighted in the "Q" inventory management case study show how complex it is to handle inventory, manage orders, maintain stock, oversee products and ranges, handle customer service cases, and deal with container logistics. These challenges include difficulties connecting different parts of the supply chain, adapting to different delivery company needs, performing manual work for container shipments, and working within a rigid workflow setup (Table 9).

Table 9. DPC's SCM challenges and LLM-based solutions.

Challenge	LLMs Solution
Supply Chain Connection	Assist in developing a secure data-sharing mechanism for retailers, suppliers, and delivery firms.
Delivery Manifest Customisation	Analyse commonalities across custom workflows and suggest a unified or modular approach.
Manual Work in Container Shipment	Contribute to automating manual work related to container shipment and status updates.
Generalised Workflow Framework	Aid in developing Data-Driven Workflows to automate and adapt workflows based on identified needs.

LLMs and our framework developed within this research (Table 9) bring powerful solutions to tackle these hurdles. To connect the supply chain better, LLMs can help create secure ways for retailers, suppliers, and delivery companies to share data. They can also design systems that make it easier for everyone to exchange information smoothly. However, most importantly, the findings of this study help address the latter challenge by developing a data-driven workflow generator to adapt and automate workflows based on identified needs.

During the implementation of the "Q" system, supported by LLM-enabled solutions, it demonstrates how AI-driven automation can enhance supply chain workflow generation. Our findings reveal that the integration of LLMs addresses key challenges in SCM, such as data standardisation, trust, and workflow automation. This discussion critically examines these contributions, situating them within the broader discourse on AI-driven SCM optimisation.

A major challenge in SCM is the lack of standardisation across data models used by different organisations. Our study demonstrates that embedding an LLM within the system enables seamless data transformation, where disparate data models are mapped onto a standard framework with minimal user intervention. This contributes to the broader understanding of how AI can enhance interoperability in SCM by automating data reconciliation—a persistent challenge in multi-enterprise collaborations.

Another critical issue is trust and secure data verification. Our findings indicate that the system's trust mechanisms, including identity verification workflows and document authentication, are significantly enhanced through LLM capabilities. By leveraging generative AI to validate uploaded documents and enforce authentication workflows, our research highlights the role of AI in strengthening data security and fostering trust in digital supply chain ecosystems. This aligns with contemporary discussions on the need for AI-driven verification mechanisms in decentralised supply chain networks.

Furthermore, our research confirms that LLMs facilitate data-driven workflows by generating automated supply chain processes tailored to user needs. The ability of the LLM to suggest predefined workflows or assist in the creation of new streamlined supply chain operations reduces the time and complexity involved in workflow generation. This finding underscores the transformative potential of LLMs in shifting SCM practices from manual and static workflows to adaptive, AI-driven processes that improve operational efficiency.

5.3. Financial Feasibility

The financial analysis indicates significant cost considerations but also provides avenues for cost control and revenue generation. Hence, based on these research findings, the following key strategies emerged:

- Utilising semi-automated annotation tools, data augmentation techniques, and crowdsourcing can significantly reduce annotation expenses while maintaining data quality.
- Choosing between pay-per-token models and hosting proprietary models depends on projected usage patterns. For enterprises with high transaction volumes, investing in proprietary hosting may offer better long-term financial feasibility.
- A horizontal scaling architecture, combined with robust resource management practices, was identified as essential for containing infrastructure costs.
- Strategies to maintain the project's financial attractiveness include regular financial performance reviews, customer feedback incorporation, and user-focused design principles. These align financial management with user satisfaction and product quality.

5.3.1. Pay Model

The study explored two primary pay models for LLM services: pay-by-token and self-hosting models. While the pay-by-token model offers simplicity and scalability, self-hosting provides control over data privacy and operational flexibility.

Based on the transactional nature of the case study, the research recommends a pay-by-token model as the preferred option. This model is well-suited for the dynamic usage patterns observed and helps to minimise upfront infrastructure costs. This addresses a key research question regarding the practical financial viability of the proposed solution.

The financial model developed in this research proposes a post-paid pricing system, where users are charged based on actual consumption. This approach provides flexibility to users while ensuring that revenue generation is directly tied to usage. This model aligns with the study's focus on delivering adaptable and user-centric solutions.

5.3.2. Risk Mitigation and Revenue Generation

Based on our findings from discussions with our case study stakeholders, it was concluded that to mitigate financial risks such as low turnover or high hidden costs, several strategic approaches are recommended.

To address the risk of low turnover for LLM-based solutions, the study emphasises the need for a robust marketing and promotion strategy, leveraging multiple channels such as social media, email campaigns, and SEO techniques. This directly responds to the identified gap in the introduction regarding the need for scalable and sustainable SCM solutions.

The challenge of post-paid billing, which introduces a risk of limited revenue if adoption rates are low, is addressed by implementing several factors aimed at increasing user engagement and satisfaction, as follows:

- Flexible payment plans, including subscription and pay-per-use models, cater to diverse user needs and budgets.
- Trial periods and introductory discounts encourage initial adoption and enable users to experience the benefits of the solution before full commitment.
- Transparent pricing and billing build trust by clearly communicating cost structures and avoiding hidden charges.

- Autopay and convenient billing features streamline transactions for users, promoting recurring payments.
- Rewarding systems, such as loyalty points, incentivize continued engagement.
- Social proof and testimonials build credibility by showcasing positive feedback from existing users.

In addition, the study recognised that a user-focused design approach, which ensures the project meets the needs of the users, coupled with continuous improvement based on customer feedback, is critical to maintain the project's financial viability and attractiveness. These strategies are practical examples of how financial feasibility can be achieved by focusing on user engagement and product quality.

Moreover, the research findings suggested that these strategies, along with an understanding of the hidden costs of LLM applications, are essential for managing financial risks and ensuring that the AI-enabled workflow editor is both financially sustainable and beneficial for its users. The strategic approach suggested ensures that the project maintains financial viability while meeting user needs.

5.4. Socio-Technical Aspects of Using LLMs for Inventory Management and Automated Workflow

In the pursuit of supply chain optimisation, the integration of Language Model-based workflow automation presents a socio-technical endeavour that requires careful consideration of both technological and human factors. This section analyses the socio-technical aspects of implementing LLMs within the Q inventory management system and nodeStream© framework, drawing insights from socio-technical systems theory. By examining the interplay between technology, organisational structure, human behaviour, and socio-cultural contexts, this analysis aims to provide a comprehensive understanding of the implications of LLM-based workflow automation for supply chain optimisation.

The integration of LLM-based workflow automation in Q and nodeStream© represents a socio-technical endeavour that requires careful consideration of both technical and human factors. By analysing the socio-technical implications of this integration, organisations can navigate the challenges and opportunities associated with adopting LLM technology in supply chain optimisation. By nurturing collaboration, promoting learning, embracing diversity, and upholding ethical standards, organisations can harness the full potential of LLM-based workflow automation to drive innovation, enhance efficiency, and achieve sustainable competitive advantage in the rapidly evolving digital landscape.

5.4.1. Social Aspects

At the social level, the integration of LLM-based workflow automation introduces changes in organisational dynamics, roles, and interactions. Key social aspects to consider include:

- **Organisational Structure:** The adoption of LLMs for workflow automation necessitates a re-evaluation of organisational structures to accommodate new roles and responsibilities. In the context of our project, integrating LLM-based automation into Q and nodeStream© requires a shift towards more agile and flexible organisational structures. This might involve flattening traditional hierarchies within DPC to promote cross-functional collaboration among teams working on supply chain optimisation. Additionally, decision-making processes may become more decentralised, allowing frontline employees to leverage LLM capabilities effectively in their day-to-day operations.
- **Stakeholder Engagement:** Effective stakeholder engagement is crucial for the successful implementation of LLM-based workflow automation within DPC's ecosystem. In our project, engaging stakeholders from various departments within DPC, as well as

external partners such as retailers, suppliers, and delivery companies, ensures buy-in and adopts a culture of collaboration and innovation. Clear communication channels established through Q and nodeStream© facilitate feedback and input, enabling stakeholders to actively participate in the optimisation of supply chain workflows. By involving stakeholders in the design and implementation process, we can tailor LLM-based solutions to meet their specific needs and address any concerns proactively.

- **Change Management:** The introduction of LLM-based workflow automation represents a significant change for employees accustomed to traditional manual processes within DPC. To effectively manage this transition, changing management strategies is essential. In our project, implementing training programmes and workshops on how to use LLMs within Q and nodeStream© equips employees with the necessary skills and knowledge to adapt to the new workflow automation tools. Ongoing support and guidance provided by the project team help address any resistance to change and promote acceptance of LLM-based solutions. Emphasising the benefits of LLMs, such as time savings, error reduction, and enhanced decision-making capabilities, encourages employees to embrace the new technology and leverage its potential to optimise supply chain operations.

5.4.2. Technical Aspects

From a technical perspective, the implementation of LLM-based workflow automation involves considerations related to system architecture, data integration, and algorithmic design. Key technical aspects include:

- Integrating LLMs within existing systems such as Q and nodeStream© requires careful planning and coordination to ensure compatibility and seamless interoperability. APIs and data exchange protocols play a crucial role in facilitating communication between different components of the system, enabling data sharing and workflow execution.
- As LLMs handle sensitive data related to supply chain operations, ensuring data privacy and security is paramount. Robust encryption mechanisms, access controls, and authentication protocols must be implemented to safeguard against unauthorised access, data breaches, and cyber threats. Compliance with regulatory requirements such as GDPR and CCPA is essential to maintain trust and credibility with stakeholders [40].
- The algorithms powering LLMs must be transparent and accountable to mitigate the risk of bias, discrimination, and unintended consequences. Transparency measures such as model documentation, explainability techniques, and audit trails enable stakeholders to understand how decisions are made and detect potential biases or errors. Accountability frameworks, including mechanisms for oversight, recourse, and redress, hold stakeholders accountable for the outcomes of LLM-based workflows [41].

5.4.3. Integration of LLM-Based Workflow Automation in the “Q” and nodeStream©

Building upon the socio-technical analysis, we examine the specific implications of integrating LLM-based workflow automation within the Q inventory management system and nodeStream© framework.

First, the Organisational impacts are discussed. The integration of LLMs in Q and nodeStream© requires organisations to adapt their structures, processes, and cultures to leverage the full potential of this technology. Key organisational impacts include the following:

- **Flattened Hierarchies:** LLM-based workflow automation promotes a more decentralised approach to decision-making, enabling employees at all levels to contribute to the design and execution of workflows [42]. Flattened hierarchies empower frontline workers to innovate and adapt workflows to meet specific operational needs, advancing a culture of continuous improvement and agility.

- **Cross-Functional Collaboration:** LLM-based workflow automation breaks down silos between departments and functions, facilitating cross-functional collaboration and knowledge sharing. By providing a common platform for workflow design and execution, NodeStream© raises collaboration among stakeholders across the supply chain, enabling real-time data exchange and collaboration.
- **Agile Work Practices:** The agility afforded by LLM-based workflow automation enables organisations to respond rapidly to changing market conditions, customer demands, and supply chain disruptions. Agile work practices, such as iterative development, rapid prototyping, and continuous improvement, allow organisations to experiment with new workflows, iterate based on feedback, and adapt to evolving business needs [43].

From a technical standpoint, integrating LLM-based workflow automation in Q and nodeStream© introduces several technical considerations related to system architecture, data management, and algorithm design. Key technical impacts include the following:

- **Scalability and Performance:** The scalability and performance of the system are critical factors to consider when integrating LLM-based workflow automation. As the volume of data and the complexity of workflows increase, the system must be able to scale horizontally to handle additional load and maintain responsiveness. Performance optimisation techniques, such as caching, parallel processing, and distributed computing, can help ensure that the system meets the demands of a growing user base and workload.
- **Data Integration and Interoperability:** Effective data integration and interoperability are essential for seamless communication and collaboration between different components of the system. APIs, data standards, and data exchange protocols play a crucial role in facilitating data sharing and interoperability between Q, nodeStream©, and other systems within the supply chain ecosystem. Ensuring compatibility and consistency of data formats and schemas is essential for avoiding data silos and enabling cross-system workflows.
- **Model Training and Tuning:** The performance and accuracy of LLMs depend on the quality of training data and the tuning of model parameters. Organisations must invest resources in curating high-quality training datasets that accurately reflect the domain-specific nuances of supply chain operations. Additionally, ongoing monitoring and tuning of LLMs are necessary to adapt to changing business requirements, evolving user needs, and shifts in market dynamics.
- **Algorithmic Fairness and Bias Mitigation:** Addressing algorithmic fairness and bias mitigation is crucial to ensure equitable outcomes and avoid unintended consequences. Organisations must implement measures to detect and mitigate bias in LLM-based decision-making processes, such as bias audits, fairness-aware training, and algorithmic transparency. Ethical considerations, including privacy preservation and consent management, are also paramount to uphold user trust and integrity.

Moreover, the integration of LLM-based workflow automation in Q and nodeStream© has far-reaching socio-technical implications that extend beyond the technical domain. Understanding these implications is essential for advancing adoption, promoting user acceptance, and maximising the potential benefits of this technology [44,45]. Key socio-technical implications include the following:

- **Human–Machine Interaction:** The interaction between humans and machines in LLM-based workflow automation systems is characterised by collaboration, coordination, and communication. Human operators rely on LLMs to assist them in decision-making, automate repetitive tasks, and augment their cognitive abilities. Effective human–machine interaction requires intuitive user interfaces, natural language processing capabilities, and feedback mechanisms to support seamless communication and collaboration [46].

- **Organisational Learning and Adaptation:** The adoption of LLM-based workflow automation forwards organisational learning and adaptation by enabling rapid experimentation, iterative improvement, and knowledge sharing. Organisations can leverage insights from LLM-generated workflows to identify patterns, optimise processes, and drive innovation. Learning organisations embrace a culture of continuous improvement, where employees are empowered to experiment with new ideas, learn from failures, and iterate based on feedback.
- **Socio-Cultural Impact:** The socio-cultural impact of LLM-based workflow automation extends to organisational culture, employee behaviour, and societal norms. Organisations must consider the socio-cultural context in which LLMs are deployed, recognising the potential implications for job roles, career paths, and work–life balance. Embracing diversity, equity, and inclusion principles is essential for adopting a supportive and inclusive workplace culture that values the contributions of all employees.
- **Ethical and Legal Considerations:** Ethical and legal considerations are paramount in the design, development, and deployment of LLM-based workflow automation systems [47]. Organisations must adhere to ethical principles, such as transparency, accountability, and fairness, to ensure responsible AI use. Legal compliance with regulations, such as data protection laws, intellectual property rights, and anti-discrimination statutes, is essential for mitigating legal risks and safeguarding against potential liabilities.

5.4.4. Actionable Workforce Training and Ethical Governance Strategies Informed by DPC Experience

Drawing on implementation insights from the DPC use case, two critical sociotechnical themes emerged: workforce readiness and the need for robust ethical AI governance. This section outlines actionable strategies rooted in the specific challenges DPC faced during early-stage adoption of LLM-based workflow automation as follows:

- **Workforce Training and Upskilling Strategies:** The transition to LLM-assisted workflows at DPC revealed several skill and adoption gaps, particularly in prompt design, interpretation of model outputs, and integration into legacy operations. Based on these insights, we propose the following phased training approach:
    - Foundational AI Literacy (All Staff): Short, domain-relevant sessions introducing core LLM concepts, risks (e.g., hallucination), and appropriate use cases. These were essential to demystify the technology and promote user acceptance.
    - Role-Specific Prompting Workshops (Operations/Tech Leads): Practical training in designing effective prompts, evaluating model outputs, and using Q/nodeStream© with LLMs. DPC staff benefited from hands-on experimentation during early prototypes.
    - Cross-Functional Collaboration Labs (Managers, Logistics, IT): Facilitated sessions where different departments co-designed automated workflows, discussed constraints, and identified edge cases. These labs helped translate tacit domain knowledge into usable prompt frameworks.
- **Ethical AI Governance Measures:** While DPC's deployment remained exploratory, governance gaps quickly emerged around data sensitivity, output accountability, and system auditing. To address these, we propose the following initial governance scaffolding:

- ○ AI Use Policy and Access Controls: Defining appropriate use cases for LLMs, who can run workflows, and how sensitive data (e.g., customer info, pricing) is handled. DPC implemented role-based access in nodeStream© to restrict certain operations.
- ○ Human-in-the-Loop Verification Points: Embedding human checkpoints before critical actions, e.g., validating auto-generated delivery manifests before submission. This strategy balanced efficiency with control and auditability.
- ○ Ethical Review Board or Steering Group: As workflows scale, DPC would benefit from a small multi-role advisory group to periodically review LLM outputs, assess drift or bias, and recommend updates to training data or prompting strategies.

These measures reflect feasible, lightweight steps that can evolve into a more formal AI governance structure over time. Importantly, they are informed by operational realities at DPC rather than abstract compliance goals.

5.5. Strategic Market Landscape and Positioning

Referring to the [48] report, our analysis of the global SCM market, extrapolating trends, growth trajectories, and emerging opportunities, our research serves as a strategic compass for businesses seeking to align their trajectories with the evolving dynamics of the global SCM market is certainly required. By understanding the larger landscape, our findings enable businesses to anticipate shifts and proactively position themselves for future success.

The review of the market in this study identified the key drivers propelling the growth of the SCM market. Beyond generic observations, we illuminate how the escalating demand for real-time visibility, supply chain analytics, and the optimisation of big data utilisation are reshaping the industry. The key insights from the analysis are as follows:

- Understanding Market Dynamics: Through industry reports and expert insights, we examine market size, growth trajectories, and major players in the SCM industry.
- Identifying Emerging Trends: The analysis highlights trends such as increased AI adoption, sustainability practices, and demand for tailored solutions, guiding our research objectives.
- Assessing Market Demand: Surveys and interviews with industry stakeholders inform us of our understanding of the demand for AI-enabled workflows and pain points in SCM.
- Analysing Competitive Landscape: We study competitors' strategies, product offerings, and customer feedback to identify strengths and weaknesses related to our solution.
- Evaluating Market Readiness: Factors like technological infrastructure and regulatory landscape are evaluated to assess the market's readiness for AI-driven solutions.
- Forecasting Future Trends: Insights from the analysis help forecast future market shifts and technological advancements, guiding strategic research positioning.

This feasibility study serves as a guide for businesses to strategically align their AI-enabled solutions with the core drivers steering the market's trajectory. UK businesses stand to benefit from AI-based solutions by enhancing operational efficiency and streamlining processes.

Potential clients for the Chain-AI Bot include the following:

- Manufacturing Powerhouses: Large-scale manufacturers with intricate supply chains.
- Logistics and Transportation Enterprises: Companies engaged in transportation, warehousing, and distribution.
- E-commerce Enclaves: E-commerce platforms with complex supply chain needs.
- Retail Prowess: Extensive retail chains managing diverse product portfolios.

- Pharmaceutical Guardians: Industries governed by stringent regulatory frameworks.
- Tech and Electronics Manufacturers: Companies with rapid product cycles and global supply chains.
- Food and Beverage Stewards: Companies dealing with perishable goods.
- Automotive Visionaries: The automotive industry with complex assembly processes.

Key competitors in the AI-enabled SCM market include IBM Watson Supply Chain, Oracle SCM Cloud, SAP Integrated Business Planning, Blue Yonder, Kinaxis RapidResponse, Microsoft Dynamics 365 SCM, Llamasoft Supply Chain Guru, and Elementum. By understanding the market dynamics, emerging trends, and competitive landscape, the Chain-AI Bot can be strategically positioned to meet specific client needs and gain a competitive edge.

5.6. Roadmap for Implementing an LLM-Powered Workflow Editor

The following roadmap (Figure 12) outlines a comprehensive strategy for implementing an AI-enabled workflow editor powered by LLMs. The roadmaps have been designed according to the findings of this study to translate feasibility insights into actionable steps, addressing key feasibility dimensions, including technical, operational, financial, and socio-technical dimensions. It serves as a practical guide for translating feasibility insights into actionable steps.

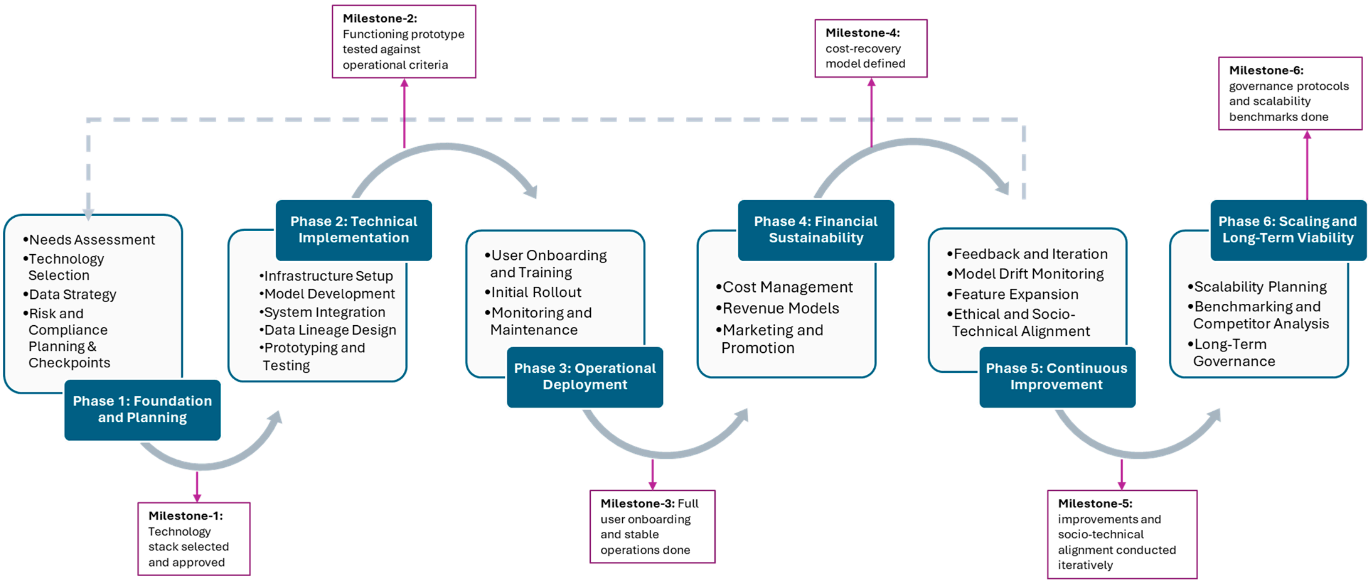

Figure 12. Roadmap for Implementation of an LLM-Powered Workflow Editor.

As illustrated in this diagram, the journey to implementing an LLM-powered workflow editor begins with a robust foundation and careful planning. In the first phase, organisations focus on assessing their needs by engaging with stakeholders through interactive workshops. These discussions bring to light the objectives, constraints, and priorities for the workflow editor. The next step involves evaluating the technological landscape to select the most suitable large language model platform. Here, criteria such as scalability, cost-effectiveness, and customisation options guide the decision-making process. Simultaneously, a comprehensive data strategy is developed to ensure high-quality datasets are available for training and fine-tuning the model. This includes curating existing datasets, identifying gaps, and planning for ongoing annotation efforts. Additionally, risk and compliance planning are prioritised to address potential issues such as data privacy violations, bias in model outputs, or regulatory concerns. By conducting risk analysis, organisations can devise mitigation strategies that lay the groundwork for an ethical and secure implementation.

Furthermore, the planning process includes the definition of risk-mitigation checkpoints, where technical, operational, and ethical risks are periodically reviewed by designated task forces. These checkpoints ensure early identification of drift, non-compliance, or performance degradation. Data-lineage controls are also established at this stage, ensuring traceability of training data sources, annotations, and usage policies. These controls support transparency and accountability, especially in regulated environments.

In the technical implementation phase, the focus shifts to establishing the necessary infrastructure. Organisations deploy scalable cloud-based solutions, such as AWS or Azure, to accommodate the computational demands of LLMs while maintaining flexibility. Once the infrastructure is in place, the selected LLM undergoes fine-tuning with domain-specific data, ensuring its output is relevant and aligned with organisational needs. Techniques such as prompt engineering or embedding customisation are employed to enhance the model's functionality for workflow scenarios. System integration follows, where the LLM is connected to enterprise systems via APIs, enabling it to interact seamlessly with tools like databases or CRM platforms. After integration, a prototype is developed and rigorously tested in controlled environments. This stage involves iterative feedback loops with users to identify and address performance bottlenecks or usability issues.

The operational deployment phase marks the transition from testing to real-world application. Here, organisations prioritise user onboarding and training to ensure smooth adoption. Comprehensive user manuals, interactive tutorials, and role-specific training sessions are provided to empower users. Workshops are conducted to showcase the tool's capabilities and gather additional feedback, fostering user confidence. Deployment is carried out in phases, starting with a pilot rollout in select departments or user groups. During this phase, the tool's performance is monitored closely to identify any adjustments needed. Once validated, the deployment is scaled to the entire organisation. Simultaneously, systems for real-time monitoring are established to ensure ongoing operational health and reliability. This phase also initiates baseline monitoring for model drift, with thresholds and alerting systems set up to detect significant deviations in model behaviour over time. Mechanisms are established for both manual audits and automated alerts to safeguard against performance loss or bias re-emergence in production environments.

Financial sustainability becomes a key focus as the system matures. Cost management strategies are implemented to monitor and optimise resource allocation, particularly for hosting and computational demands. Organisations explore revenue models, such as subscription-based or pay-per-use plans, to generate consistent income while accommodating diverse user needs. Marketing efforts are ramped up, leveraging SEO, content marketing, and social media campaigns to reach potential users. Success stories and user testimonials are highlighted to build credibility and drive adoption.

Continuous improvement forms the backbone of long-term success. Organisations establish feedback loops that enable users to provide insights into system performance and suggest new features. Based on this input, iterative updates to the model and software are prioritised, ensuring the system remains responsive to emerging trends and user needs. Advanced features, such as predictive analytics or multi-language support, are introduced to enhance the tool's value proposition. Organisations also maintain a strong focus on ethics, periodically reviewing outputs for unintended consequences and promoting inclusivity through diverse stakeholder involvement. Part of the continuous improvement effort includes refinement of data-lineage tracking as new data sources and user interactions are integrated. Additionally, drift monitoring dashboards are refined using user feedback and system logs to ensure sustained performance and relevance of the LLM outputs in dynamic environments.

The final phase involves scaling and ensuring long-term viability. As user demand grows, architecture is optimised to handle increased workloads without compromising performance. Strategic partnerships and collaborations are explored to expand the tool's applications across industries. Benchmarking against competitors helps identify areas for innovation and improvement, keeping the system at the cutting edge of AI development. A governance model is established to oversee technical, financial, and operational aspects, ensuring the system's sustainability. A steering committee composed of technical experts, business leaders, and user representatives guides these decisions, safeguarding the project's alignment with organisational goals. The long-term governance framework incorporates regular risk reviews aligned with the earlier checkpoints, and it mandates compliance audits that revisit both data provenance and model behaviour. This governance model also includes provisions for adapting drift thresholds, updating lineage documentation, and evaluating mitigation strategies as the system scales and evolves.

Through this six-phase roadmap, organisations systematically transform feasibility insights into a fully operational and sustainable LLM-powered workflow editor, ensuring long-term impact and value creation. In addition, each phase in the roadmap is designed to conclude with specific milestones that signal readiness to advance.

6. Conclusions

In this paper, we have undertaken a comprehensive exploration of integrating LLMs and chatbot technology into the nodeStream© platform to optimise supply chain workflows. The primary objective was to harness these cutting-edge technologies to improve efficiency and streamline operations, ultimately empowering organisations to achieve a competitive advantage in their supply chain management practices.

Beginning with an overview of the nodeStream© platform as a case study and its relevance in supply chain management, we examined the theoretical foundations and practical implications of embedding LLMs and chatbots within the platform.

Our financial feasibility analysis delved into the potential costs associated with implementing an AI-enabled workflow editor using LLMs. Key considerations included data preparation, model training, infrastructure, licencing fees, and maintenance. By offering a meticulous cost breakdown and exploring different pricing models, we equipped organisations with a robust understanding of the investments required for adopting LLM-based solutions effectively.

Moreover, we underscored the socio-technical dimensions of the integration process. By addressing organisational impacts, technical considerations, and socio-cultural implications, this paper highlighted the critical importance of collaborative, adaptive, and ethical approaches to implementing such technologies. These considerations ensure that both technical and human factors are holistically addressed to maximise value and mitigate potential risks.

Building on these insights, the paper also presented a detailed roadmap to guide organisations through the implementation of an LLM-powered workflow editor. This roadmap outlined a phased approach, from assessing organisational needs and establishing technical infrastructure to operational deployment, financial sustainability, continuous improvement, and long-term scaling. By offering this structured framework, we aimed to translate the feasibility insights into actionable steps, supporting organisations in navigating the complexities of integrating advanced AI technologies into supply chain systems.

In conclusion, the findings presented in this paper contribute to advancing the understanding of how LLMs and chatbots can be leveraged to optimise supply chain workflows.

Our findings indicated that these technologies not only enhance operational efficiency and streamline workflows but also offer a pathway for organisations to achieve a significant competitive edge. By elucidating the challenges, opportunities, and best practices associated with this integration, we aim to empower organisations to make informed decisions and embark on successful digital transformation journeys in the dynamic landscape of supply chain management. The detailed roadmap, grounded in rigorous research, enables organisations to navigate the complexities of AI adoption and implement these solutions successfully. Ultimately, this research paves the way for a more agile, responsive, and resilient supply chain landscape.

6.1. Research Contributions

In summary, the contributions of this research lie in several key areas that advance the understanding and application of LLMs in SCM, as follows:

1. **Prototype Development**: The research presents the development of innovative prototypes, such as the Q inventory management system and the nodeStream© workflow editor, which leverage LLM technology to automate and optimise supply chain workflows. These prototypes not only demonstrate the feasibility of using LLMs to streamline complex processes but also set a precedent for how AI can reshape operational efficiencies and enhance organisational competitiveness.
2. **Integration of Cutting-Edge Technologies**: By integrating cutting-edge technologies, including chatbots and LLMs, this research offers a multifaceted solution to address various aspects of SCM. The seamless integration of these technologies raises enhanced communication, collaboration, and decision-making capabilities within supply chain workflows, providing a robust framework for organisations to navigate the complexities of modern SCM.
3. **Financial Feasibility Analysis**: The research explores the socio-technical implications of integrating LLM-based workflow automation within supply chain operations. By addressing technical, organisational, and socio-cultural dimensions, this study highlights critical human–machine interaction dynamics and ethical considerations. The analysis underscores the importance of collaborative, adaptive, and inclusive approaches to the deployment of LLMs in real-world settings.
4. **Socio-Technical Implications**: The paper explores the socio-technical implications of integrating LLM-based workflow automation within supply chain operations. By considering both technical and social factors, the analysis highlights the organisational impacts, human–machine interactions, and ethical considerations associated with deploying LLMs in real-world environments.
5. **Development of a Roadmap for Implementation:** As a pivotal output of this research, a detailed roadmap has been developed to guide organisations through the implementation of an LLM-powered workflow editor. This roadmap offers a structured and actionable framework for organisations, addressing technical, financial, operational, and socio-technical challenges across distinct phases of implementation. It bridges the gap between theoretical feasibility and practical execution, ensuring that organisations can navigate the complexities of AI integration with confidence and clarity.

6.2. Recommendations for Further Research

Moving forward, there are several promising avenues for research and development that can enhance the prototypes presented in this paper and further validate their effectiveness in real operational workflows. One crucial area of focus is the refinement and expansion of the prototypes' knowledge base to encompass a broader range of supply chain scenarios and domain-specific knowledge. This involves collecting and annotating real-world data to train the LLMs on a diverse set of supply chain processes, challenges, and best practices. Expanding the knowledge base will ensure that the LLMs are not only applicable to a wide variety of industries but also adept at handling the dynamic and evolving nature of supply chain environments.

Additionally, conducting rigorous testing and validation of the prototypes in live operational environments is essential for demonstrating their practical utility and value proposition. Collaborating with industry partners and deploying the prototypes in real supply chain settings will enable researchers to gather invaluable feedback, assess how LLM-based customised workflows impact productivity, efficiency, and decision-making, and refine the prototypes to meet the needs of diverse supply chain stakeholders. This empirical evidence will be crucial for building confidence in the efficacy of LLM-based solutions and accelerating their widespread adoption across various sectors.

Future research should also focus on understanding how LLM-based customised workflows can transform supply chain operations to drive tangible business outcomes. This includes conducting comprehensive case studies and performance evaluations to quantify the impact of LLMs on KPIs such as lead times, inventory turnover, order fulfilment rates, and cost reduction. By analysing the before-and-after effects of implementing LLM-based workflows, researchers can identify specific areas where LLMs add value, pinpoint inefficiencies, and uncover opportunities for further optimisation. This will contribute to a better understanding of how LLMs can directly influence supply chain performance and help organisations realise substantial business value.

Moreover, integrating LLM-based workflows with advanced analytics and optimisation techniques presents a rich area for future exploration. By combining the predictive and prescriptive capabilities of LLMs with data analytics platforms, machine learning algorithms, and optimisation techniques, organisations can unlock additional value by improving decision-making agility, forecasting accuracy, and strategic planning. This integrated approach would enable proactive risk management, demand forecasting, resource allocation, and the identification of supply chain bottlenecks. This synergy between LLMs and analytics can further enhance the resilience, efficiency, and competitiveness of supply chains in an increasingly complex and volatile global marketplace.

While this study demonstrates technical feasibility and prototype utility, we did not benchmark LLM-based performance (e.g., response accuracy, latency) against traditional SCM tools. This decision reflects the exploratory nature of our work and the absence of standardised conversational datasets tailored to SCM tasks. However, future research will involve quantitative benchmarking using synthetic supply chain workflows and open-source benchmarks to validate performance claims more rigorously.

Future work will also include rigorous testing of the prototype's robustness under adversarial prompting conditions and noisy or incomplete input data. We aim to evaluate workflow reliability by introducing malformed prompts, corrupted datasets, and stress scenarios such as conflicting instructions or ambiguous supply chain conditions. These tests will help establish the resilience of LLM-generated workflows and provide quantitative insights into their operational reliability prior to scaled deployment.

Furthermore, future studies should consider the socio-technical aspects of LLM implementation in more detail. This includes investigating the organisational impact, changing management strategies, and user acceptance of LLM-based systems in supply chain environments. Understanding human–machine interactions, user trust, and ethical considerations in LLM adoption will be crucial in ensuring that such systems are implemented in a way that aligns with the cultural and operational dynamics of organisations. These socio-technical factors should be integrated into the roadmap for future LLM deployment, ensuring that technological adoption is both effective and responsible. Additionally, future work will include the development of a more comprehensive cost model that accounts for broader financial implications of LLM-based systems, including prompt engineering effort, vector-database maintenance, compliance processes, and long-term scalability. A sensitivity analysis will also be undertaken to evaluate how these cost components impact overall ROI under various operational conditions. Moreover, future work will explore socio-technical impacts in greater depth, including assessments of role displacement, employee sentiment and resistance metrics, and the design of governance frameworks aligned with responsible AI principles. These aspects are critical for ensuring that LLM-based systems are implemented in an ethical, inclusive, and sustainable manner.

For the roadmap, Future research should focus on automated and auditable risk-mitigation pipelines, particularly for dynamic environments where LLMs are embedded into evolving enterprise processes. Additional attention is required to formalise data-lineage frameworks and develop robust, real-time drift detection systems that can feed directly into model re-tuning or rule adjustments. Such mechanisms will play a pivotal role in ensuring responsible and resilient AI deployment at scale.

Finally, as part of the ongoing development of AI-powered supply chain systems, further research should also explore the potential for continuous learning in LLMs. This involves creating mechanisms where LLMs can evolve, learning from new data, changing market conditions, and evolving business strategies. Developing adaptive LLM systems that can continuously learn and improve will ensure that supply chain workflows remain optimised and relevant in the face of rapid technological and market changes.

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Conflicts of Interest: Author B.B. was our partner in undertaking this research project, and he is CEO of DPC-ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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