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LLMs in Supply Chain Management: Opportunities and a Case Study

Ge Zheng * Sara Almahri * Liming Xu * Maria Minaricova ** Alexandra Brintrup *

* *Institute for Manufacturing, University of Cambridge, Cambridge CB3 0FS, UK (E-mail: gz305@cam.ac.uk)*
** *Fetch.ai, Cowley Rd, Cambridge CB4 0WS, UK*

Abstract: Large language models (LLMs) have garnered significant attention since OpenAI launched ChatGPT in November 2022, demonstrating immense potential across various domains, including education, healthcare, software engineering, and supply chain management (SCM). We further explore the potential of LLMs in SCM and examine the challenges associated with their adoption. Additionally, we present a pipeline case study to demonstrate the integration of LLMs with a decentralized agent-based system to effectively execute SCM tasks. By exploring these opportunities and providing a delivery prediction delay example, this study would inspire further leverage of LLMs for enhanced SCM operations. This study thus contributes to the growing body of research on the transformative impact of LLMs in the real-world SCM context.

Keywords: Large Language Models, ChatGPT, Supply Chain Management, Delay Prediction

1. INTRODUCTION

Since the launch of ChatGPT (OpenAI, 2022) in late November 2022, Large Language Models (LLMs), capable of performing a variety of Natural Language Processing (NLP) tasks, have gained significant popularity in both academia and industry. This surge in interest is largely attributed to the ability of LLMs to leverage extensive web-based data to contextualize and generate human-like responses to various prompts. Numerous studies (Bulian et al., 2023; Kasneci et al., 2023) have highlighted the transformative potential of LLMs across diverse domains, including healthcare, education, business management, marketing, tourism, and engineering.

Supply Chains emerge when various partners collaborate to produce and deliver a product or service to the end consumer. As in many other domains, researchers (Rathore, 2023; Li et al., 2023; Jackson and et al., 2024) suggested the potential of LLMs to improve supply chain performance. For example, Rathore (2023) mentioned that ChatGPT can be retrained using production process data for detecting production faults. Li et al. (2023) proposed an LLM-based framework, OptiGuide, which interprets and explains supply chain optimization outcomes through natural language queries while preserving proprietary data. Jain et al. (2023) adapted NLP foundation models to estimate supply chain carbon emissions. While these recent works show the promising potential of LLMs for SCM, the existing literature in this area remains limited. This paper thus aims to further study this emerging field by first categorising the existing research into key SCM topics and then exploring the opportunities for LLMs in SCM.

When implementing LLMs in SCM, researchers (Aguero and Nelson, 2024) found that current LLMs, such as ChatGPT, are generic and cannot function as experts in supply chain-specific domains. Similar limitations have been identified in other fields, including climate change (Bulian et al., 2023), education (Kasneci et al., 2023), and medical (Beaulieu-Jones et al., 2023).

To address this limitation, researchers (Lehman et al., 2023; Aggarwal et al., 2024) have explored adapting pre-trained LLMs to specific domains or tasks by retraining or fine-tuning them on domain-specific data, resulting in a significant performance improvement. Lehman et al. (2023) conducted an extensive empirical analysis of 12 language models across three clinical tasks. This study concludes that a smaller language model trained on domain-specific data and a fine-tuned pre-trained model with limited annotated data outperformed a large language model trained on general text. Companies, therefore, must incorporate explicit SCM domain knowledge into the model to develop an LLM capable of functioning as an SCM expert.

However, developing a SCM-specific LLM requires substantial data and significant computational resources, which poses three major challenges within SCM (Lehman et al., 2023; Jackson and et al., 2024). First, data in supply chain is distributed over various collaborative companies, which are often reluctant to share business sensitive information. Second, the majority of supply chains are composed of small and medium-sized enterprises, which typically lack the human and IT resources to support SC LLM training initiatives. Finally, effective training of SC LLMs requires collaboration among companies to centralize data. However, practical implementation of such collaboration is hindered by concerns about data security and privacy.

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To address these challenges, we introduce a decentralised agent-based system driven by LLMs, where the LLM interacts with users while decentralised agents handle domain-specific tasks. These agents can be machine learning models trained locally on proprietary supply chain data, eliminating the need for retraining or fine-tuning LLMs and avoiding data sharing concerns. We demonstrate this approach through a pipeline case study, showcasing how LLMs can facilitate SCM. Therefore, the main contributions of this paper are twofold:

- We explore the potential opportunities of LLMs for SCM.
- We present a pipeline case study to illustrate how LLMs can facilitate SCM.

The rest of this paper is organised as follows. Section 2 reviews related works and explores the opportunities of LLMs for SCM. Section 3 presents a pipeline case study, showing how LLMs can be used to facilitate SCM. Section 4 concludes the work.

2. LLMS IN SUPPLY CHAIN MANAGEMENT

This section reviews related work and examines the potential opportunities and applications for LLMs in SCM. It also discusses the challenges and limitations when employing LLMs for SCM tasks.

2.1 Literature Review and Opportunities

We use Google Scholar to search relevant literature, in which keywords "LLMs" (or "LMs" or "ChatGPT"), "Supply Chain", "Supply Chain Management" and "Supply Chain Risk Management" were used for the search. The searched articles were then categorised into several SCM themes, including visibility, inventory management, optimisation, demand planning, transportation, risk management, and customer service, since these areas directly leverage LLM's strengths in processing larger volumes of unstructured data and represent critical, high-impact challenges in SCM.

Visibility involves the entire SC and allows SC members to track the movements of goods, monitor inventory levels, and identify potential risks. Enhancing SC visibility can offer better SCM performance. An early research work by Wichmann et al. (2018) showcased the usage of language models to extract insights from openly available SC text data, facilitating SC mapping by processing unstructured data such as news and reports. AlMahri et al. (2024) advanced the application of LLMs by integrating them with knowledge graphs, enabling enhanced SC visibility without necessitating direct information exchange between stakeholders. These studies highlight LLMs' strengths in processing diverse unstructured data sources, including emails, social media posts, and reports, to generate actionable SC insights.

Inventory Management involves monitoring, controlling, and optimising a company's goods inventory level. Better inventory management represents a better balance between the costs of holding inventory and the benefits of having sufficient stock to meet customer demand. Recent studies have shown the significant potential of LLMs in revolutionizing inventory management. For example, Zhu et al. (2023) explored the use of LLMs for semantic parsing and text-to-SQL methodologies, illustrating their ability to enhance data processing for inventory optimization in real-world business settings. Quan and Liu (2024) advanced this application by introducing LLMs as autonomous agents in multi-agent systems for inventory management, improving the efficiency and resilience of supply chain networks. Similarly, Maichle et al. (2024) utilised the GPT architecture to develop a foundation model that reduces inventory distortion costs in retail environments, showcasing the practical impact of LLMs on cost management. Patil et al. (2024) further highlighted the value of LLMs in powering real-time inventory systems with generative interfaces, enhancing the usability of enterprise software for managers. These advancements underscore the benefits of LLMs in streamlining inventory control, reducing costs, and improving decision-making. Inspired by these works, one future exploration could be integrating LLMs with technologies, such as IoT devices for real-time inventory tracking, AI-driven demand forecasting, and dynamic stock replenishment, to redefine inventory management practices.

Optimisation aims to support decision-making and allows automation. LLM as a generated AI technology can be a promising tool for SC optimisation by enhancing decision-making and automating complex processes. Li et al. (2023) introduced a framework in which an LLM translates human queries into optimisation codes, allowing solvers to process scenarios and return results in human-readable language. For example, questions such as "How would the cost change if we used supplier B instead of supplier A?" can be directly addressed, helping in cost-efficient supplier selection. Shahini et al. (2024) applied LLMs for automating the categorisation of millions of invoices in the oil and gas industry. This approach not only streamlined SCM, but also uncovered significant cost-saving opportunities. These examples underline LLMs potential to simplify optimisation tasks, enhance analytical capabilities, and reduce human intervention in decision-making processes. Based on these works, future opportunities that could be explored include using LLMs for real-time scenario modelling, adaptive scheduling, and multi-criteria optimisation across global SC networks. Additionally, integration with other technologies, such as machine learning for predictive analytics or blockchain for secure decision tracking, could further elevate SC optimisation, allowing organisations to respond swiftly and effectively to dynamic market demands.

Demand Planning refers to forecasting customer demand to optimise inventory levels, production schedules, and supply chain activities, ensuring that products are available to meet customer needs efficiently and cost-effectively. LLMs with the ability to process unstructured data and generate actionable insights can be used to obtain demand-relevant information for effective demand planning. An early research work (Teo, 2020) integrated an NLP model with deep learning to enhance demand forecasting in long supply chains, showcasing the value of advanced linguistic capabilities in understanding demand trends. Nguyen et al. (2023) further refined this approach by fine-tuning CamemBERT, a monolingual variation of

BERT, using a dataset of 5,000 drug news headlines. By extracting relevant information from these headlines and combining it with structured drug demand data in a vector autoregressive (VARX) model, they provide accurate demand forecasting in the pharmaceutical sector. Meanwhile, other researchers, including Fosso Wamba et al. (2024) and Jackson et al. (2024), have highlighted the broader applicability of LLMs in demand planning, emphasizing their potential to analyse diverse data sources such as news articles, company updates, and online trends. These works underline the transformative role of LLMs in demand planning, where their natural language understanding and processing capabilities enable organisations to respond proactively to market changes. Furthermore, LLMs could integrate with real-time market monitoring systems to dynamically adjust forecasts. Besides, combining LLMs with predictive analytics and machine learning models can also help organisations achieve more accurate, adaptive, and efficient demand planning to meet customer needs and optimise supply chain activities.

Transportation refers to the movement of goods from one location to another within SC, including the movement of raw materials from suppliers to manufacturers, finished goods from manufacturers to distribution centres, and products from distribution centres to retailers or end customers. LLMs with the ability to analyse and interpret large volumes of unstructured data, such as shipment records, weather reports and customer communications, have shown promising potential in optimising transportation within SC logistics. Kleinová and Straka (2024) utilised LLMs like ChatGPT-3.5 to optimise distribution routes in micro-logistics systems, achieving substantial cost savings and operational efficiency improvements. Similarly, Li et al. (2024) demonstrated the application of LLMs in enhancing digital twins for urban freight transportation. Biswas (2023) and Wamba et al. (2023) further emphasized the potential of LLMs in addressing challenges in transportation. Based on these works, further work, such as integrating LLMs with IoT-enabled tracking systems to enhance real-time route optimisation, predict weather-related delay disruptions, and streamline last-mile delivery, can also be explored.

Risk Management involves identifying, assessing, and mitigating potential risks that affect the efficiency and effectiveness of SCs. Many studies have shown LLMs are a promising tool for SC risk management. Shahsavari et al. (2024a) used LLMs to power Bayesian Network-based agent models to determine the relevance of detected events to the targeted SC risks. Shahsavari et al. (2024b) adopted LLMs to autonomously learn event-related phrases from an event's name and analyse vast news data to identify risk events and their contributing factors. Sun et al. (2024) examined the utility of LLMs in media analysis to predict stock market risk. Zhao et al. (2024) introduced LLMs to automate the potential risk identification and categorisation in SCs from news and supplier databases. All these works benefit from the ability of LLMs to analyse news and media information. In addition, LLMs have been employed to support demand forecasting (Teo, 2020; Nguyen et al., 2023), which, in turn, facilitates organisations to anticipate and mitigate potential risks. Further opportunities could be the usage of LLMs on financial stability, reliability and vulnerability assessment by analysing company data, to provide critical insights for decision-making, such as determining lending arrangements or evaluating supplier health.

Customer Service involves a set of activities and processes to ensure that customers receive the right product with the right quantity and quality at the right time. LLMs can be used to optimise customer services by supporting order tracking, inventory management, order process automation, and communication with customers. Rojas (2024) used LLMs to automate customer service, leading to improved response times, enhanced customer satisfaction and reduced operational costs. Similarly, Pandya and Holia (2023) built a custom open-source GPT Chatbot to automate customer service. Slightly different to these two works, Praveen et al. (2024) provided strategic decision-making insights for customer services by fine-tuning LLMs using consumer reviews to understand their topics, emotions and sentiments. All these works pointed out that LLMs can significantly improve the efficiency and effectiveness of customer service. Particularly, human-machine communication, a primary core function of LLMs, can be used to develop an SC Chatbot that responds to specific needs such as finding new suppliers and sourcing raw materials.

2.2 Challenges and Limitations

While LLMs demonstrate tremendous potential in SCM, challenges and limitations must be addressed before these potential can be fully unleashed in practice. Key obstacles include the lack of SC-specific domain knowledge, limited interpretability and explainability, security and privacy concerns, the dynamic and rapid environmental changes in SC, integration challenges, and resource intensiveness (Aggarwal et al., 2024; Jackson and et al., 2024). Currently, LLMs are generic and lack SC domain knowledge, leading to potential inaccuracies in understanding SC information. Equipping LLMs with SC domain knowledge requires fine-tuning or retraining on specific SC data, which introduces additional challenges: 1) large and high-quality SC data collection, 2) data security and privacy concerns, and 3) expensive computation resources. In addition, LLMs operate as "black boxes", making their decision-making processes difficult to interpret or explain (Shahsavari et al., 2024a). This lack of transparency can undermine trust among supply chain operators. The SC landscape itself is dynamic, characterised by frequent changes in market conditions, regulations, and consumer preferences. LLMs may struggle to adapt quickly to these changes, potentially leading to inaccurate or outdated recommendations. Moreover, integrating LLMs into the current SCM systems presents significant challenges due to compatibility issues. Despite these hurdles, thoughtful and strategic approaches can help overcome these challenges. As suggested by Seifert and Markoff (2023), while LLMs offer substantial opportunities for SCM, their immediate impact may be limited, requiring time for refinement and adoption.

3. A PIPELINE CASE STUDY

In this section, we use a pipeline case study as an example to show how LLMs can facilitate SCM and address the

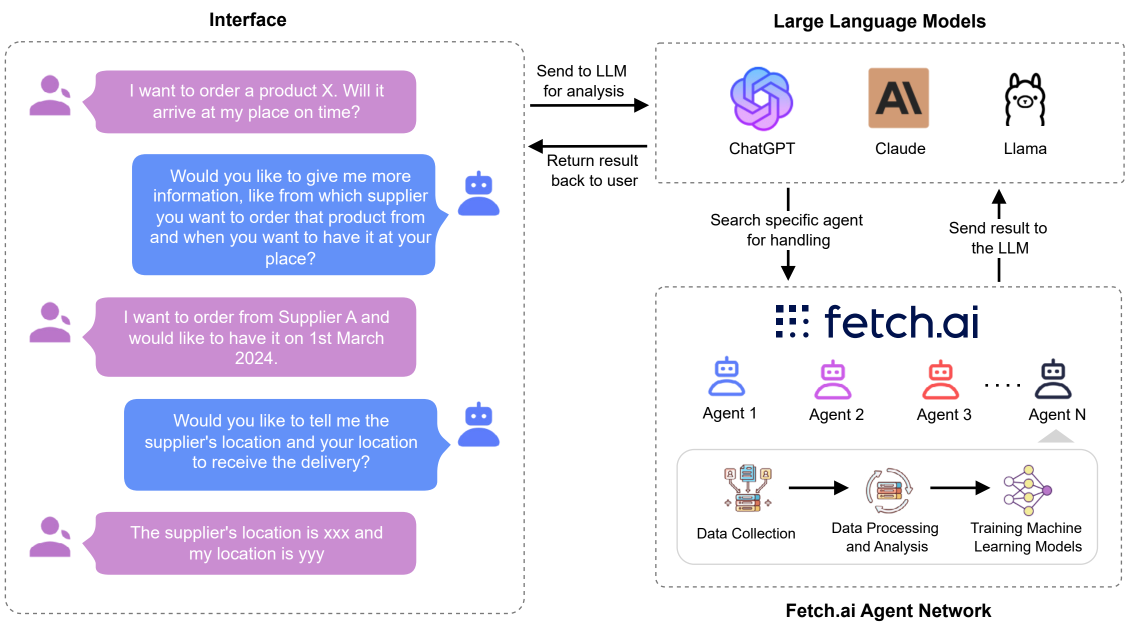

Fig. 1. The framework of LLM-driven AI agent system.

challenges mentioned in Section 1. This pipeline case study uses a decentralised agent-based system driven by an LLM to predict SC risks and communicate the predictions with users for risk mitigation. The following sections explain this system and demonstrate how it works by providing an example task of delivery delay prediction in SCM.

3.1 LLM-Driven Decentralised Agent-based System

Figure 1 presents the framework of the LLM-driven decentralised agent-based system. As shown in Figure 1, this system mainly consists of three parts: an user interface (UI), an LLM (e.g., ChatGPT or Llama) and a group of agents for specific SCM tasks, such as the agent to predict supply chain risks. The UI is designed as a conversional UI, where users can communicate with agents via natural languages. Users submit queries through the UI, which the LLM processes to extract key information and route to the appropriate agent capable of addressing the specific task in the query. In the system, agents can incorporate machine learning models trained for various SCM tasks, such as demand forecasting, delivery delay prediction, and product quality prediction. Each agent is specialised to handle a distinct task. These agents operate on a decentralised agent platform provided by Fetch.ai [1], an AI company focused on intelligent and connected systems through agent-based technology. Agents on this platform are decentralised, trained, and deployed locally by their respective owners, ensuring data privacy and security (Xu and et al., 2024).

3.2 Risk Prediction Agent

To demonstrate how the decentralised agent-based system facilitates SCM, we use an agent designed to predict supply chain risks—specifically delivery delay—as an example. This agent adopts a machine learning model trained on the local data of a company that procures various components and manufactures products for its buyers. The agent's task is to predict whether an order will be delivered on time to the expected location or delayed, a binary classification problem.

The training data consists of order records from 2014 to 2022. Each order includes product name, product description, the quantity of the product, order issue date, schedule lead time, supplier name, buyer name, supplier location, and buyer location. Since the raw data collected from the company's system often contains noise, data cleaning processing was applied. This involves removing noise, addressing missing data points, and filtering out irrelevant information. Furthermore, feature importance analysis was conducted using XGBoost (Chen and Guestrin, 2016) to identify the most important features for training the model. Because Convolution Neural Networks (CNNs) have demonstrated good performance in delivery delay prediction tasks (Zheng et al., 2023), CNNs were adopted as the machine learning model.

If a user wants to purchase a product and determine whether there is a risk of receiving it later than the expected delivery date, the user can query the system using this agent. First, the user interacts the system through the UI, specifying their request in natural language. The UI then sends the query to the LLM, which interprets the user's intent, identifies the requested task, and maps it to the appropriate agentin this case, the delivery delay prediction agent. Example queries could be: "*I need a delivery prediction for a product I want to buy;*" or "*I want to order a product. Will it arrive on time? Can you help with the delivery prediction?*", but not limited to.

After that, the prediction agent gathers additional details about the product and the order by asking the user the following questions:

- What is the date on which the order was officially placed or requested?

[1] `https://fetch.ai/`

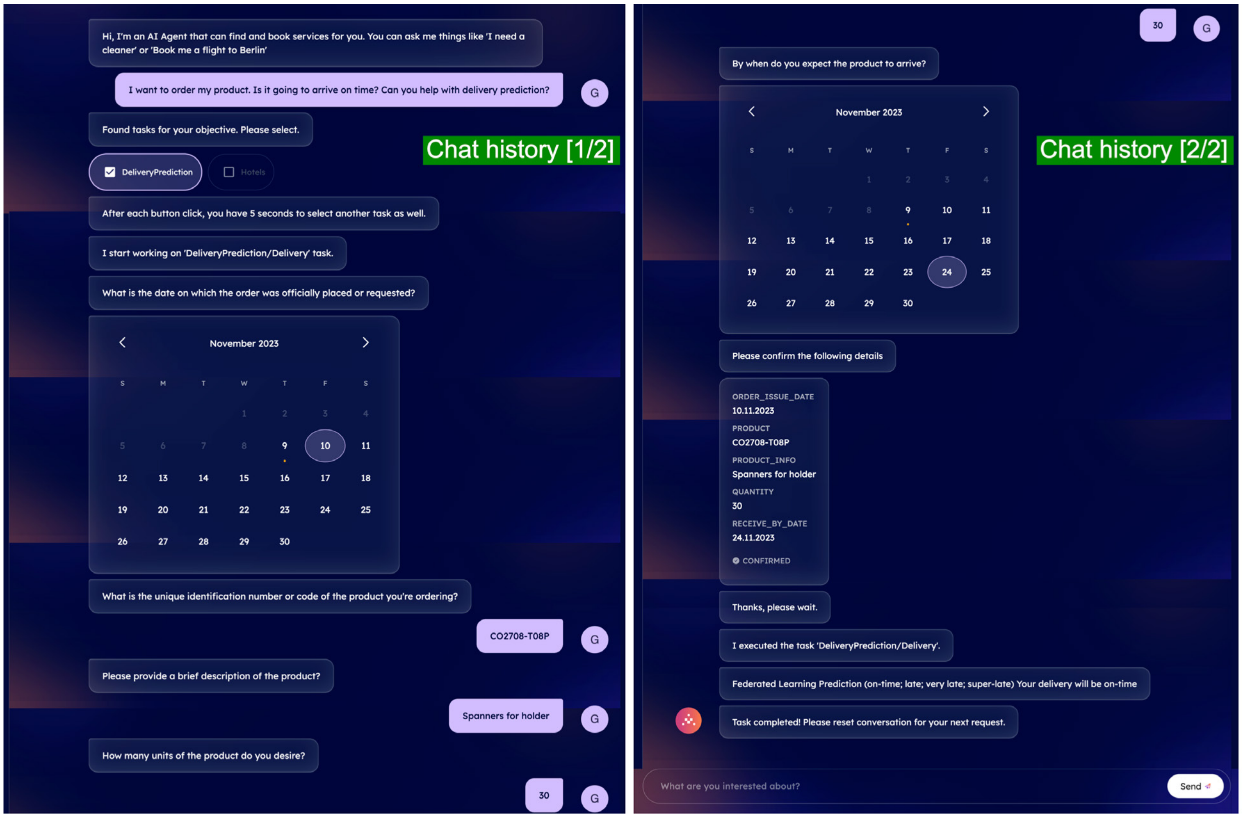

Fig. 2. Illustration of the delay prediction process performed by the LLM-driven decentralised agent-based system.

- What is the unique identification number or code of the product you are ordering?
- Can you provide a brief description of the product?
- How many units of the product are you ordering?
- By when do you expect the product to arrive?

Once the required details are provided, the order information is summarised for the user to review and confirm. After confirmation, the agent processes the data, executes the prediction, and returns the result to the user, as shown in Figure 1.

3.3 Showcase and Discussion

Figure 2 presents the result of the delivery delay prediction performed by the decentralised agent-based system. The process begins when the user queries the system with, "*I want to order my product. Is it going to arrive on time? Can you help with delivery prediction?*" Once the system is ready to assist, the request is sent to the LLM (e.g., ChatGPT) to interpret the query and route it to the appropriate agent. As shown in Figure 2, the system searched two relevant agents: `DeliveryPrediction` and `Hotels`. Since the users request pertains to predicting a delivery delay, the `DeliveryPrediction` agent is selected to handle the task. The agent then gathers essential details about the order by asking specific questions, as described in Section 3.2, such as order date, product code, product description, quantity and expected delivery date. After the user provides all the required information, the `DeliveryPrediction` agent summarises them for user confirmation. Once confirmed, the agent performs the prediction task, delivers the result to the user, and concludes the session. If the user wishes to perform another delivery delay prediction, they must reset the conversation to initiate a new query. Notes that the requests could be diverse and the LLM has ability to understand them and find the relevant agent for the requests.

By leveraging the advanced natural language understanding capabilities of LLMs, the system efficiently interprets complex user queries and seamlessly coordinates with relevant agents to execute SCM tasks. The decentralised agents, trained and managed locally to handle SC-specific queries, effectively address challenges, such as lack of specialised knowledge, data privacy and security concerns with applying LLMs in SCM.

This case study demonstrates the significant potential of LLMs like ChatGPT to enhance SCM by enabling intelligent, context-aware interactions between users and specialised agents. However, this study has also limitations. The reliance on LLMs introduces challenges related to computational resource demands and latency, which may affect performance in real-time applications. Ensuring the consistency and reliability of agent outputs is critical, as discrepancies or errors from individual could compromise the overall system's effectiveness. Additionally, integrating such a decentralized system into existing SCM infrastructures presents technical and organisational challenges, requiring substantial adaptation and investment.

4. CONCLUSION AND FUTURE WORK

In this paper, we explore potential opportunities for LLMs in SCM, drawing inspiration from relevant works in other domains such as education, healthcare, law, and software engineering. Moreover, we present a pipeline case study that demonstrates how LLMs can facilitate SCM through the introduction of a decentralised agent-based system, driven by ChatGPT, for SCM tasks.

This system allows users to interact with agents via natural language queries. As shown in the case study, the `DeliveryPrediction` agent can understand and analyse the order information provided by the user to predict delivery status. This highlights the significant potential of LLMs in handling various SCM tasks—not only for delivery delay prediction, but also for other applications such as demand forecasting, visibility, transportation, and even the realisation of a fully autonomous supply chains. A key limitation of our work is its reliance on a single pipeline case study, focused solely on delivery delay prediction, which limits the empirical evaluation and generalisability of the approach to other SCM tasks. Therefore, our future work will explore the potential LLMs in addressing SCM tasks beyond the delivery delay prediction.

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