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Artificial Intelligence Applications in Supply Chain Management: A Review

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Abstract:

Supply chain management (SCM) connects various organizations that perform operations such as financing, sourcing, production, distribution, and retail. Artificial intelligence (AI) techniques like machine learning, deep learning, optimization, and robotics can assist this balancing act. A growing number of companies have adopted AI-enabled tools and systems to manage supply chains more effectively and gain competitive advantage. Intelligent and flexible decision-support systems have been developed for forecasting, inventory management, logistics, and supplier selection. By improving consistency and accuracy across multiple decision-making levels, such systems can lead to lower costs, reduced inventory, and greater service flexibility. Comparing traditional decision-support systems with AI-augmented tools highlights the complementarity between AI and other decision-support methods. Although organizations have invested heavily in enterprise resource planning, material requirements planning, and other systems that facilitate business process integration, additional improvement opportunities remain. AI and traditional systems are compatible, as AI principles can enhance capabilities through existing data channels and processes. This compatibility facilitates adoption; traditional systems remain viable while organizations explore AI applications and experiment with emerging paradigms and technologies.

Keywords — **Put your keywords here, keywords are separated by comma. Supply chain management (SCM); Artificial intelligence (AI), demand forecasting; Logistics; transportation**

I. INTRODUCTION

Supply chain management (SCM) plays an indispensable and pivotal role for both private and public organizations, especially in an era characterized by increasingly global operations amid constrained resources[1]. In today's competitive landscape, every company must prioritize the efficient management of its supply chains to sustain and significantly improve their unique competitive advantages[2]. The surge of interest in Artificial Intelligence (AI) is noteworthy, particularly due to its remarkable ability to enhance productivity levels by harnessing unclear and disparate data sets, automating repetitive and time-consuming tasks, and enabling quicker and more effective decision-making processes[3].

A well-managed and efficiently handled supply chain is fundamental in facilitating the automation of various processes, including freight document processing, shipment planning and execution, freight payment processing, as well as ongoing shipment tracking[4]. Supplychain-oriented AI can provide invaluable assistance in several key areas such as value chain modeling and the thorough evaluation of end-to-end supply chain processes. Furthermore, it supports interaction graph-based supply chain modeling, alongside digital twin-driven supply chain modeling[5]. In this context, a digital twin involves linking the model of the actual supply chain with the model of the planned supply chain, allowing for the tracking of events that occur in either system independently and simultaneously[6]. Moreover, many studies have proven that artificial intelligence applications contribute significantly to supporting supply chains due to their high capability in data analysis and making high-quality decisions[7], [8], [9]. In addition, Intelligent Augmented Analytics stands to significantly support supply chains by offering comprehensive capabilities in network connectivity modeling, conducting design analyses of bottom-up heterogeneous supply chain networks, optimizing channel placement strategies, managing risk division and undertaking route balancing for a defined resource transportation site[10]. It can also suggest a priority ranking for logistic orders based on invoice-related data, enhancing the overall operational efficiency and responsiveness of supply chains in today's dynamic market environment[11]. Through these advancements, organizations can better navigate the complexities of modern supply chains and leverage AI to drive more effective and strategic outcomes.

Based on the relevant literature, Supply Chain Management is closely associated with a diverse and influential set of core functions that constitute a highly important element in the sustainability of the operations related to it. Where its success depends largely and mainly on the high integration and coordination between these components. And from these basic components: Firstly, Demand Forecasting and Inventory Optimization, as they significantly influence and contribute to achieving a balance between supply and demand and reducing the waste that may occur during the process[12]. Secondly: Logistics and Transportation Optimization work on ensuring the acceptable level of goods flow with high efficiency and at the specific and appropriate time for them[13]. Thirdly: Supply Chain Risk Management and the enhancement of Supply Chain Resilience play a pivotal, primary, and fundamental role in addressing disruptions and fluctuations that may face supply chains, especially in the current crisis represented by the ongoing war in the Middle East and its impact on the Strait of Hormuz[14]. Fourthly: the practices of Supplier Selection and Supplier Relationship Management contribute to building and establishing sustainable strategic partnerships of importance in supply chains[15].Fifthly: Both Production Planning and Scheduling are considered a basis and a primary element in supply chains to organize production operations with high efficiency[16]. Finally, the important and fundamental role of Quality Assurance and Compliance in developing and ensuring an acceptable level of product quality and their conformity with the required standards[17].

In light of what has been explained above, the importance of employing modern and innovative technologies such as Artificial Intelligence clearly emerges as a main and pivotal enabling factor that significantly contributes to improving and enhancing the accuracy of forecasting for activities related to supply chains. Moreover, supporting and enhancing the efficiency of related operational decisions, and which is raising the level of flexibility and responsiveness in various supply chain activities. Accordingly, this research will shed light on the impact of artificial intelligence applications in developing these vital areas, which supports achieving high performance in supply chains and sustainability in modern business environments, especially with the challenges facing supply chains currently in light of the disruptions in navigation in the Middle East and particularly in the Strait of Hormuz (see figure 1 below).

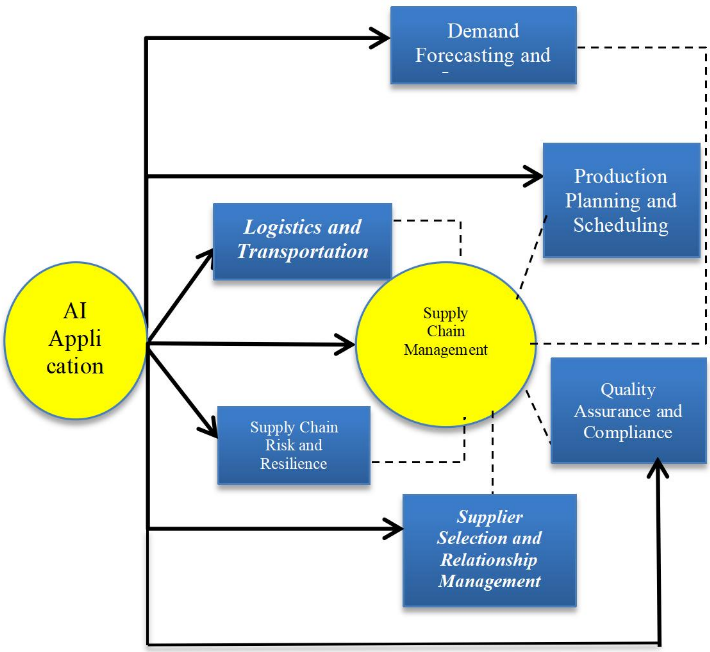

Fig. 1. Research Design

II. Related Work

Artificial Intelligence (AI) has emerged as the key enabler for digitalization, allowing organizations to modify their business strategies with better data-driven solutions. AI encompasses a range of technologies, spanning data mining, machine learning (ML), natural language processing, the Internet of Things (IoT), deep learning (DL) and robotics[18],[19]. Efficiency enhancements, predictive analytics, process automation and intelligent connected operations are obtainable benefits by deploying AI and ML methodologies. AI has a profound impact throughout the entire supply chain[20]. For example, on the planning side, AI supports operational procurement through smart data and conversations with chatbots. It also assists in supply chain planning to forecast supply and demand, using sales data, influencing factors, climate, and social activities. On the inventory management side, AI optimizes warehouse management for inventory volume, location, and shelf life[21]. In transportation, AI enables faster and more accurate shipping by providing various transportation options and scheduling recommendations, receiving current orders, specifications, and frequently used suppliers. AI also facilitates supplier selection by maintaining up-to-date data on suppliers[22]. Machine learning enhances supply chain planning and logistics by refining data-driven decision-making and optimization strategies such as warehouse optimization and daily operational improvements in inventory management, transportation, and supplier coordination[23].

A. Demand Forecasting and Inventory Optimization

Efficient and accurate demand forecasting is crucial for inventory optimization in supply chain management. Supply chain optimization systems use only data regarding the present demand to forecast future demand, which frequently leads to inaccurate forecasts. Demand management systems that integrate data regarding future planned sales with the present demand improve forecasting accuracy[24].Demand forecasting models can be classified into three categories: classical statistical, machine learning (ML), and hybrid statistical–ML models. Statistical models such as simple exponential smoothing (SES) have a long track record in forecasting practice. ML model implementation, however, requires meeting a series of conditions such as a given forecast horizon and supply-demand policy. Statistical demand forecasting remains an indispensable component of demand-forecasting systems, used instead of or in conjunction with ML models, depending on the state of the item in its product life cycle[7].

Demand-forecast-driven inventory management policies take a forecasted demand signal as input, regardless of forecasting model type. Based on such demand-forecast-driven control policies, a safety stock optimization framework expresses the inventory problem as a constrained optimization problem with a service level as an objective, which is not solvable in closed form under continuous demand assumptions[25]. The definition of service level varies across industries, inventory management systems, and regulatory frameworks. For instance, in retails and fast-moving consumer goods businesses, stock-out avoidance is key. In such contexts, the service level cm is defined as the fraction of demand that is fulfilled directly from stock on hand, capturing the frequency of stock-outs over time[26].

B. Logistics and Transportation Optimization

Routing of vehicles, selection of transport mode, and planning of freight capacity all benefit substantially from Artificial Intelligence (AI) methods in logistics and transportation[27]. The routing of a fleet of vehicles involves the solution of the well-known Vehicle Routing Problem. The aim is to cover a set of customer requests (each associated with a specified volume of goods) with a minimal number of vehicles and by adhering to various constraints such as time windows and driver working hours[28]. Schedule planning, typically made in a dispatching context, is another challenging category of problems involving the assignment of resources to activities over time. Its objectives include minimizing tardiness, driver work time, or distance travelled, combining a rich variety of hard and soft constraints concerning capacities, precedence relationships, the compatibility of drivers and freight such as dangerous goods, and so on[29]. The medium-term planning of freight capacity has also seen the introduction of AI methods. It involves predicting the future operational situation over one or two days and optimizing freights, taking account of price policies[30].

The management of real-time tracking, dynamic re-routing, and last-mile automation is further enhanced through AI. Real-time tracking concerns the monitoring of the location of freight and vehicles, and of the various activities that take place in a logistics supply chain[31]. Although it is not a routing problem, it deserves to be mentioned here as it fosters improvements and refinements of real-time routing algorithms whenever new information becomes available. Dynamic re-routing follows on from this last point. As new tracking information is received, not only can the schedule be updated, but the route itself can also be adjusted. Dynamic rerouting concern taking into account that, while driving the scheduled route, a driver may encounter certain events such as traffic saturation, line closure, or accident, thus leading to revised routes. Automation of last-mile logistics refers to automated delivery and pick-up processes at customer locations[32].

C. Supply Chain Risk and Resilience

Supply chain risk is defined as the likelihood of an event occurring that disrupts the ordinary course of business[33]. The fundamentals of supply chain risk management consist of the identification of risk, the assessment of risk exposure and impact, and the development of tactics to avoid or mitigate risk and to recover after a risk event occurs[34]. AI technologies impact all these fundamentals. AI techniques can support detection of risk signals in supply chain operations, such as when on-time delivery decreases or product quality deteriorates, and they are often utilized generically to detect anomalies when operating data differs from typical patterns, regardless of the underlying cause[35]. Text mining and topic modeling can analyze unstructured documents, such as customer complaints, service call logs, and internal reports, to detect emerging issues. AI can aid in forecasting the possible escalation of a risk situation and in generating simulations of potential future scenarios[36].

Supply chain resilience is defined as the ability of a supply chain to prepare for unexpected disruptions and recover from them rapidly. An organization seeking to assess the resilience of its supply chain can define its need in terms of resilience metrics such as recovery time, capacity to absorb a hit, or coverage of alternative supply sources[37]. If a supply chain disruption occurs, a collection of escalation protocols can describe how the organization responds, specifying indicators that reveal the emergence of a disruptive event, determinants characterizing the nature of the disruption, and a sequence of countermeasures or a predefined contingency plan[38]. AI-based forecasting and scenario generation can help determine the supply chain evolution and the probable course of events [39].

D. Supplier Selection and Relationship Management

Suppliers' strategic importance has prompted an increasing focus on selection and collaboration. Supplier-scoring approaches to contracts, negotiations, and joint projects provide managers with crucial information to support decisions and improve performance[40]. Supplier evaluation and scoring methods systematically address technical, operational, financial, and strategic criteria, providing quantitative grading for informed decision-making[41]. To enhance operational efficiency and aid sourcing, AI-based models for supplier capability assessment, performance tracking, and cost analysis have been developed . Offering scalable and smart collaboration options, digital platforms facilitate deep engagement, transcending traditional transactional exchanges[42]. AI techniques bolster supplier collaboration by enhancing supplier selection, risk evaluation, negotiation, and interaction design. Contract negotiation is critical for regulating firm-supplier relationships, with AI applications assisting in contract content and pricing, activating pre-defined clauses, and implementing smart contracts. AI-based models examine large sets of historical situations to ascertain stakeholder preferences[42].

E. Production Planning and Scheduling

Production planning in supply chain management is a challenge characterised by high uncertainty and complexity[43]. Uncertainty stems from unpredictable demand, faulty equipment, unreliable suppliers, and sudden accidents. Complexity arises from diverse products with varying prices and margins, numerous materials, intricate product structures, changing capacity and lead times, multiple production modes, and intricate bill of materials[44]. Consequently, many supply chain companies resort to sophisticated planning tools. These traditional planning tools enable planners to optimise daily production planning while considering various constraints, including product delivery times, batch sizes, minimum changeover times between different products, and production capacities[45]. However, the strategies and methodologies of traditional planning tools have remained unchanged for years.

Many supply chain companies adopt classical planning approaches due to the challenges associated with the overall digitalisation of production[46]. Nevertheless, the concerns and prerequisites for incorporating classical and modern planning simultaneously have received insufficient attention. The new-fashioned approach, which utilises company-specific production scenarios and enables a gradual progression from classical to modern planning, yields reasonable subsequent benefits[47]. During an AI planning project, large segments of relevant planning data, such as production targets and run times, are transferred into a database to create a standardised basis for AI intervention. Simulation models capable of representing the company's unique process flows and requirements are integrated into the digital twin. As project objectives change, different algorithms can be analysed on the same data by adjusting the defined objective functions[48] .

F. Quality Assurance and Compliance

Many organizations strive for consistent product quality and compliance with regulations, particularly in sectors such as automotive, semiconductor, and pharmaceuticals. Quality Assurance (QA) can ensure suitable quality control and avoid problems like defective products, service failures, fraud, and environmental mishaps[49]. Automation can aid activities such as defect prediction, isolated process audit, and analysis of a common root cause while improving efficiency in many tasks[50].Statistical methods have been extensively utilized for anomaly detection in various domains[51]. Modern supervised machine learning approaches and related techniques can be adopted in several applications of Supply Chain Quality Assurance (SCQA). Maintenance strategy analysis is important to avoid failures during units' operation. Based on historical data, machine learning can help predict failure occurrences accurately. Data-based predictive maintenance recommends and investigates how long maintenance should be conducted before units mistakenly fail. Machine learning can also quantify degradation and classify operation modes. Corporate compliance with required policies strives to uphold enterprise objectives and customer trust[52]. Several quality management strategies have been proposed. A vast array of academic and industrial literature support a mix of modelling, monitoring, and controlling aspects[53],[54].

III. Methodological Considerations and Evaluation Metrics

Supply chain management (SCM) is a dynamic field in which the objectives, constraints, and evolving conditions frequently change. Designers of AI methods who wish to impact SCM positively must acknowledge this complexity and employ methodological rigor that corresponds with its operational intricacies. Many researcher provides a framework guidance for improving the methodological foundations of AI applications in SCM[55]. This framework articulates three ”Methodological Dimensions” and three ”Methodological Levels.” On the dimensional side, the relevant categories include Causality, Experimental Design, and Validation. The three levels indicate increasing sophistication in model development, experimentation, and evaluation: a system is described, an experiment is designed for a decision-maker using this system, and evaluation logic capable of assessing a broad class of alternative systems is expressed. Many publications in SCM concentrate chiefly on the system description aspect and provide little insight on experimentation, leaving large swathes of the discipline disconnected. Further development and deepening of applied AI contributions are essential to facilitate broader AI deployment in supply chains[56].

Favoring a restricted definition of AI that emphasizes its analytical character streamlines discourse around methodological considerations. Accordingly, it is proposed that the term AI centres on the analysis of data to yield quantities deemed important. This perspective steers attention away from the mechanistic and physical features of the supply operations themselves. A second specification adopts a narrower expert-centric view, focusing on contributions with the potential to enhance the decision-making process of an expert rather than claiming to supplant the expert entirely. It follows that major advances in AI-level applications defined exclusively in this limited sense will be the most powerful catalyst for overall AI penetration within SCM. Both these positions are reasonably positioned: an assessment of the general science machine learning publications across all fields including academics, the broader literature, and commercial activity at large—can locate assessments of AI-level contributions occupying positions ranging from several months to several years apart from supply chains .

Evaluating the impact of AI contributions poses a significantly understudied challenge. Traditional metrics encompass accuracy, precision, recall, and F1; however, taking a decidedly SC-centric position leads to alternative formulations of evaluation heavily linked to the overall objective of the enterprise establishment, namely the total cost of ownership. Profit-maximizing enterprises investment total cost of ownership—across alternative upgrades to their infrastructure or even the acquisition of other ventures—and discounting periodic cash flows at the enterprise pre-tax cost of capital in order to assess net present value. Companies increasingly pay attention not only to direct monetary considerations but also to the risk associated with implementing various changes. An explicit parameterization of risk—even lienarly coalescing all different dimensions into a single number—becomes a key approach. The risk-adjusted ROI is derived from the standard ROI computation, whereby consequently guidelines are in general adviced for equipment and software purchases as much as the smoother data required for AI implementations.

IV. Conclusion, Limitations, and Future Directions

Artificial intelligence in supply chain management can enable autonomous drones or highly automated vehicles to comply with dynamic transportation and delivery requests[1]. Automated drones and vehicles in logistics can independently track and regulate supply, delivery, and recycling cycles. AI-enabled robots can automate tedious labor-intensive tasks such as stocktaking, inspections, and accidents in factories and warehouses.

The implementation of AI-related technologies in supply chain networks has its challenges. Supply chain managers deploying AI must be aware of the maturity level of their existing technologies. There are gaps in the “people” and “processes” dimensions that necessitate acquiring new talents and reworking processes. For those using machine learning (ML) tools for automation, data quality remains a challenge. A high failure rate in deployment is often due to issues related to data quality, whether the data are easily accessible or other obstacles. The extract-transformed-load layer for transforming data may not even exist or be poorly set up. Low-quality data can severely limit AI and ML activities.

Artificial intelligence must be ethical and compliant with regulations and local laws. The practices within AI need more compliance, control, and supervision. Although the supply chain network operates at a system level, AI should delve into the optimization of subcomponents, be they facility layout, strategic procurement of raw material, or resource allocation to support production planning and control. Advanced explaining AI is also critical for effective design. The training of AI cannot be a one-shot task; continued training is needed to prevent the model from deteriorating or degrading with the new data that occur over time. A seamless integration pathway should be created for building, deploying, and evolving AI/ML pipelines over the entire life cycle across components. High-dimensional data generation, such as image, video, and voice input for maximizing production planning and control or logistics optimization, is on the rise. Self-supervised or semi-supervised ML approaches remain an active area of research; data generation aids both model training and deeply understanding physical processes. With the rise of self-supervised and multi-modal ML, the generation of education materials to facilitate the adoption of AI may proliferate further, along with pre-trained, foundation-sized models.

Standard data formats along the supply chain enable data aggregation and offer broad data sources for improved modeling, training, and sharing. Multi-organization data-sharing platforms for collaborative modeling and fine-tuning are under investigation. Data platforms for a particular, wide-spread supply chain pattern or domain could also benefit broader sharing and reusage of both multi-organizational and single-organization supply chain data, such as digital twins, supply chain simulations, supply chain regulatory frameworks, compliance definitions, and templates for enhanced supply chain networking. Artificial Intelligence (AI) offers significant benefits and risks within supply chains. AI enhances planning, sourcing, manufacturing, warehousing, distribution, and customer interface processes. It enables automation, predictive analytics, and cognitive robotics, improving efficiency and decision-making. Nonetheless, AI adoption poses challenges and risks that require careful management to maximize benefits and mitigate potential downsides.

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Recommended font sizes are shown in Table 1.

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Title must be in 24 pt Regular font. Author name must be in 11 pt Regular font. Author affiliation must be in 10 pt Italic. Email address must be in 9 pt Courier Regular font.

TABLE I
FONT SIZES FOR PAPERS

Font Size	Appearance (in Time New Roman or Times)		
	Regular	**Bold**	**Italic**
8	table caption (in Small Caps), figure caption, reference item		reference item (partial)
9	author email address (in Courier), cell in a table	abstract body	abstract heading (also in Bold)
10	level-1 heading (in Small Caps), paragraph		level-2 heading, level-3 heading, author affiliation
11	author name		
24	title		

All title and author details must be in single-column format and must be centered.

Every word in a title must be capitalized except for short minor words such as "a", "an", "and", "as", "at", "by", "for", "from", "if", "in", "into", "on", "or", "of", "the", "to", "with".

Author details must not show any professional title (e.g. Managing Director), any academic title (e.g. Dr.) or any membership of any professional organization (e.g. Senior Member IEEE).

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3) ***Level-3 Heading:*** A level-3 heading must be indented, in Italic and numbered with an Arabic numeral followed by a right parenthesis. The level-3 heading must end with a colon. The body of the level-3 section immediately follows the level-3 heading in the same paragraph. For example, this paragraph begins with a level-3 heading.

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Figures and tables must be centered in the column. Large figures and tables may span across both columns. Any table or figure that takes up more than 1 column width must be positioned either at the top or at the bottom of the page.

Graphics may be full color. All colors will be retained on the CDROM. Graphics must not use stipple fill patterns because they may not be reproduced properly. Please use only *SOLID FILL* colors which contrast well both on screen and on a black-and-white hardcopy, as shown in Fig. 1.

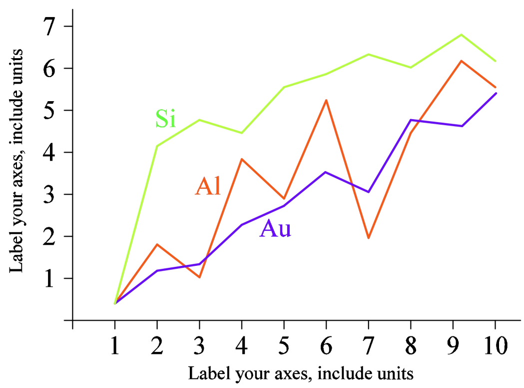

Fig. 1 A sample line graph using colors which contrast well both on screen and on a black-and-white hardcopy

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Figures must be numbered using Arabic numerals. Figure captions must be in 8 pt Regular font. Captions of a single line (e.g. Fig. 2) must be centered whereas multi-line captions must be justified (e.g. Fig. 1). Captions with figure numbers must be placed after their associated figures, as shown in Fig. 1.

Fig. 2 Example of an unacceptable low-resolution image

Fig. 3 Example of an image with acceptable resolution

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CONCLUSIONS

The version of this template is V2. Most of the formatting instructions in this document have been compiled by Causal Productions from the IEEE LaTeX style files. Causal Productions offers both A4 templates and US Letter templates for LaTeX and Microsoft Word. The LaTeX templates depend on the official IEEEtran.cls and IEEEtran.bst files, whereas the Microsoft Word templates are self-contained. Causal Productions has used its best efforts to ensure that the templates have the same appearance.

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Causal Productions wishes to acknowledge Michael Shell and other contributors for developing and maintaining the IEEE LaTeX style files which have been used in the preparation of this template. To see the list of contributors, please refer to the top of file IEEETran.cls in the IEEE LaTeX distribution.

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