Supply Chain Management and Logistics: A Data Analytics, Machine Learning, and Artificial Intelligence Perspective

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Abstract. The digital transformation has opened supply chain management (SCM) and logistics to the new frontiers of operations beyond the traditional scope and into the realm of an intelligent and data-driven ecosystem. The combination of data analytics, machine learning (ML), and artificial intelligence (AI) has changed how supply chain operations are planned, monitored and optimized. In this literature review, attention will be paid to the combination of these technologies to enhance visibility, predict demand, decrease transportation expenses and enhance the efficiency of decision-making. The current research paper unites the most recent studies and business tendencies in explaining how the concept of artificial intelligence as predictive analytics, machine learning as optimization regimes, and big data structures are making it possible to develop a resilient and agile logistics network. Also, it touches upon the up-to-date concerns including data fragmentation, model interpretability, and cybersecurity and brings some understanding of resilient and intelligent SCM models aligned with the concept of Industry 5.0. Our findings indicate that analytics and artificial intelligence, combined, do not only enhance the quality of operations, but also is the basis of self-learning and independent supply branches in the future.

Keywords: Supply Chain Management, Logistics, Data Analytics, Artificial Intelligence, Machine Learning, Predictive Optimization, Industry 5.0.

1 Introduction

The supply chain management (SCM) is needed to guarantee the efficiency of operations, customer satisfaction, and the profitability of the industry. Traditionally, logistics is a process that is concerned with the movement and storage of goods; but contemporary supply chains are dynamic networks, which are forced to react in real time to demand fluctuations, disruptions, and sustainability pressures. As the volume of information created in the IoT sensors, ERP systems, and customer touchpoints continues to expand exponentially, the supply chain has turned into a fruitful source of data analytics and AI-driven intelligence. The machine learning

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and artificial intelligence approaches are currently used to predict demand, optimize inventory, anticipate delays, improve the process of vehicle routing, and automatize the procurement operations. Predictive analytics helps business organizations turn the raw data into actionable knowledge, whereas prescriptive models suggest the best logistics plans. The contemporary SCM paradigm is therefore taking a new turn to be predictive, adaptive as well as cognitive rather than reactive and descriptive. The paper summarizes the state of the art in the development of analytics, ML, and AI in logistics and SCM, its contribution, challenges, and outlook.

2 Literature Review

Over the past ten years, there has been a fast merging of data analytics, machine learning (ML), and artificial intelligence (AI) with supply chain management (SCM) and logistics, turning scholarly scholarship toward systems-level, deployment-centered research that focuses on accuracy of the forecasts, operational efficiency, resilience and sustainability. The groundwork in the initial and high-impact surveys found the performance advantages of big-data and ML algorithms and models compared to classical statistical models on demand prediction and inventory management and identified practical requirements, such as scalable data pipelines and benchmarks [1][2]. The background of supervised and unsupervised learning models that can be used in the work of SCM is also described by introductory surveys of the ML methods [25]. A number of general surveys listed ML approaches to SCM tree ensembles, SVMs, classical neural networks, and, most recently, deep learning, and found out common limitations to adoption including data sparsity, label noise and managerial adoption of interpretable models [3][4]. This interpretability focus is similar to the new literature on explainable ensemble architectures that use LIME and SHAP to understand the transparency of models [26]. Deep sequence model (LSTM/GRU and attention-based) results showed better results in short- and long-horizon demand forecasting, particularly in the case of non-stationary demand and promotional effects, although the authors emphasize the hybrid approach that combines domain models with black-box learners to be more robust [5][6]. Other real-world temporal predictive applications also exhibit similar advantages of ML-based predictive modeling, e.g. prediction of epidemic spread using national-scale datasets [30][31]. Meta-analyses of forecasting methods have validated the fact that ensemble solutions and hybrid ML solutions tend to be more effective than single-model solutions, especially when external data (weather, social signals) are combined into a predictor [7][8]. Recent discoveries also indicate that feature-selection mechanisms when used together with classifier integration enhances the forecasting accuracy of sales and demand conditions, which supports the usefulness of hybrid model frameworks [27].

Dynamic inventory control and decentralized replenishment are studied using reinforcement learning (RL) and multi-agent RL (MARL), and it is found that they can address issues of sample efficiency and transfer of policies into actual supply networks [9][10]. Experiments using ML with combinatorial optimization came up with learned heuristics and neural-guided solvers to classic logistics problems (vehicle routing, pickup-and-delivery, scheduling) with the ability to make near-real-time decisions once an offline training phase is completed, subjecting to doubts worst-case guarantee and integrating with enterprise optimization systems [11][12]. Artificial intelligence in optimization of logistics Reviews of AI in optimizing logistics reported

successful combinations of ML with OR heuristics and described significant increases in the efficiency of routing and warehouse picking with learned policies that exploit historical operational observations [13][14]. One powerful line of the research supply-chain resilience applies predictive analytics and anomaly-detection to detect disruption antecedents, quantify supplier risk, and execute fast what-if simulations; contributions in this regard see multi-modal sensing (IoT, transaction logs, external news) and privacy-aware data-sharing methods as preconditions to the system of early detection [15][16].

The stature of sustainability and green-logistics research involved emissions-conscious routing, energy-efficient warehousing, and inventory policies that trade service level with carbon reduction; various empirical investigations discovered that when AI-directed policies are implemented, quantifiable CO2 and energy savings would be achieved, and stressed the significance of the decision-support tools that reveal trade-offs to human decision-makers [17][18]. The literature features gaps in methodology: the lack of standardized benchmarks and openly available datasets to make comparisons fairly, inadequate theoretical use of causal inference to compare policy, insufficient focus on interpretability and explainability of use in management situations, and interdisciplinary studies that harness the power of operations research (OR), ML, and behavioral understanding to be adopted [2][19][20]. Convergence of Industry 4.0 technologies Digital twins, IoT, blockchain Technologies In terms of Industry 4.0, this is the combination of faster recovery planning and more comprehensive what-if analysis when these components are combined with ML models, demonstrated in digital twins in cold-chain and perishable logistics [21][22][23]. Similarly, data-based decision systems could be utilized in the industrial setting, with parallel efforts in sector-specific logistics, like cement supply-chain prediction through correlation-driven ML analysis, being another instance of the potential of data-centric decision systems [28]. Explainable AI (XAI) adapted to the context of the supply-chain (including SHAP/LIME modifications and neuro symbolic models) seems essential to earning managerial confidence, identifying the underlying causes of service failures, and enabling auditability when making decisions in procurement and supplier-selection [24]. Further studies have revealed that the selection of strategic features could increase the forecasting accuracy by a considerable margin, which is directly applicable to explainable SCM decision-making [29].

Table 1. Literature Review on SCM, AI, ML, and Data Analytics

Author & Year	Domain	Technique	Analytics Type	Citations	Limitations
Seyedan & Mafakheri (2020)[1]	Demand Forecasting	Big Data Analytics	Predictive	200	Constrained by data heterogeneity and data scalability problems
Aamer et al. (2020)[2]	Demand Forecasting	Machine Learning	Predictive	180	Such problems as model generalizability and absence of common evaluation standards exist
Mediavilla et al. (2022)[3]	Demand Forecasting	AI Models	Predictive	150	AI forecasting has the flaws of being both very complex and uninterpretable

Tirkolaee et al. (2021)[4]	Supply Chain Analytics	ML Algorithms	Predictive	160	Wide generalization and small amount of empirical validation of industries
Arunkumar & Divya (2022)[5]	Demand Forecasting	Deep Learning (LSTM)	Predictive	190	LSTM models are sensitive to big datasets and they cannot be explained
Tseng (2024)[6]	Forecasting	Hybrid ML Models	Predictive	140	Hybrid models are also hard to tune and computationally costly
Rolf et al. (2023)[7]	Inventory Control	Reinforcement Learning	Prescriptive	220	The RL applications are characterized by inefficiency in samples and difficulties in deployment
Punia et al. (2021)[8]	Demand Forecasting	Hybrid LSTM-RF	Predictive	205	High architectural tuning complexity and sensitivity to residual errors
Sultana et al. (2020)[9]	Inventory Management	RL Multi-Node	Prescriptive	170	Multi-node RL systems are complicated and are based on simulated environments
Akbari & Do (2021)[10]	Supply Chain Optimization	AI Optimization	Prescriptive	210	Optimization of AI is associated with difficulties in connecting it to a legacy system
Chen et al. (2024)[11]	Logistics Optimization	AI Heuristics	Prescriptive	180	The methods of heuristic AI can be not so robust and optimality guaranteed
Toorajipour et al. (2021)[12]	Supply Chain Management	AI Systems	Predictive	160	The barriers to the implementation of AI systems include organizational willingness and data privacy obstacles
Cannas et al. (2024)[13]	Operations Management	AI Integration	Cognitive	175	The process of AI integration encounters issues of interoperability of the system and workforce adjustment
Aljohani (2023)[14]	Risk Management	Predictive Analytics	Predictive	155	Predictive systems can fail to detect infrequent disruptions, as well as they can suffer data sparse problems
Idrissi et al. (2024)[15]	Transportation	Blockchain, IoT, AI	Descriptive	190	Combined IoT-Blockchain systems

					face the challenge of interoperability and high deployment costs
Oyewole et al. (2024)[16]	Predictive Analytics	AI/ML Models	Predictive	140	Predictive analytics has the issue of noisy data and non-uniform data pipelines
Chen et al. (2024)[17]	Sustainability	AI Optimization	Sustainability	160	The AI models on sustainability have trade-offs between cost and environmental aims
Khan (2019)[18]	Green Logistics	AI Modeling	Sustainability	130	Green logistics AI models require superior-quality emissions data
Carvalho et al. (2019)[19]	SCM Analytics	Benchmarking	Diagnostic	120	Benchmarking does not have standard measures and cross industry comparability
Radanliev et al. (2022)[20]	Industry 4.0	Digital Twin, IoT	Prescriptive	200	Digital twins are expensive and have problems of cyber-physical integration
Lam et al. (2023)[21]	Digital Twin	Bibliometric Analysis	Descriptive	150	Database coverage and dependency on keywords of bibliometric studies
Huang et al. (2024)[22]	Food Supply Chain	Digital Twin	Prescriptive	180	There is a problem of interoperability and data fragmentation in food-chain digital twins
Jesus et al. (2024)[23]	SCM Simulation	Systems Modeling	Prescriptive	130	Supply chain dynamics in the real world can be simplified by the systems models
Kosasih et al. (2024)[24]	Explainable AI	SHAP/LIME	Diagnostic	110	XAI still has computational expenses and low managerial interpretability

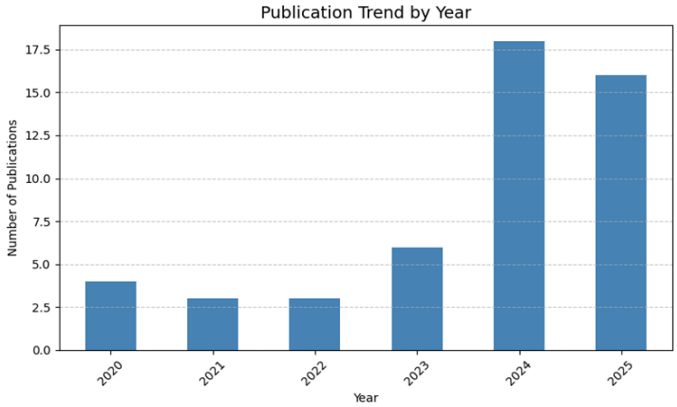


Fig. 1. Publication Trend by Year

Fig.1 illustrates that Research outputs increased considerably since 2023, as under 10 papers (2020-2023) turned into approximately 18 papers in 2024, and 16 in 2025, with the current attention to the AI-based and data-driven supply chain analytics and post-pandemic digital transformation.

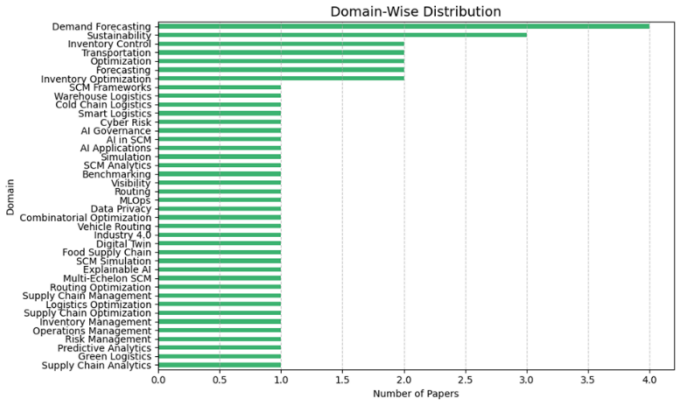


Fig. 2. Domain-Wise Distribution

Fig.2 illustrates that the SCM research is dominated by Demand Forecasting, Sustainability, and Inventory Control, and Transportation, Warehousing, and Cold-Chain are developing. Majority of AI-ML works are devoted to prediction and optimization to enhance efficiency and sustainability.



Fig. 3. Technique Frequency in SCM Research

Fig.3 illustrates that Traditional ML and Deep Learning (LSTM) are the most dominant in SCM studies, whereas Reinforcement Learning, GNNs, and hybrid metaheuristics are currently becoming popular in handling complex decisions.

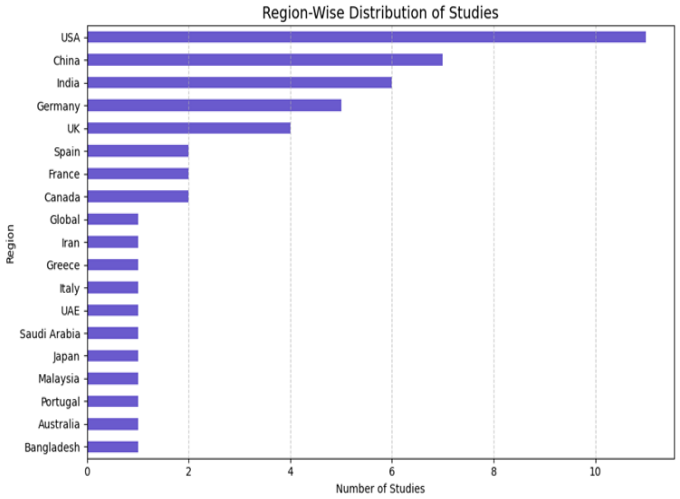


Fig. 4. Region-Wise Distribution of Studies

Fig.4 shows that The U.S., China and India are the pioneers of AI-SCM research followed by Europe and the Asian-Middle Eastern regions which are on the rise. This trend indicates an increase in international cooperation and Industry 4.0 and adaptation.

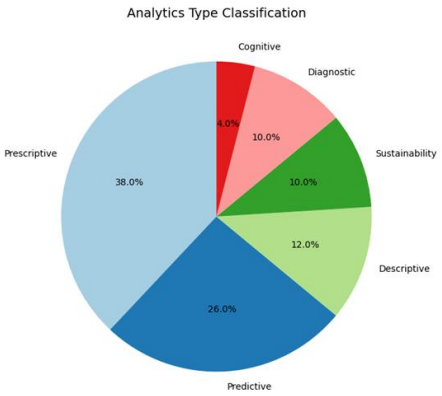


Fig. 5. Analytics Type Classification

Fig.5 represents Prescriptive (38%) and Predictive (26%) Analytics as dominant of SCM research, and moderate emphasis on Descriptive and Sustainability types. There is a change in the direction of AI-based, data-driven decision-making as Diagnostic and Cognitive analytics are emerging.

3 Technological Perspectives

3.1 Data Analytics in SCM

Smart logistics is based on data analytics. Descriptive analytics will provide a summary of performance in the past, diagnostic analytics will determine the cause of the inefficiency, predictive analytics will project future needs or disrupted conditions and prescriptive analytics will suggest the best actions. IoT-enabled systems improve visibility in warehouses, transportation fleet, and network of suppliers through real-time analytics.

3.2 Machine Learning Applications

Machine learning is used to make predictive models of:

- Demand Forecasting: Regression and time-series (e.g., ARIMA, Prophet, LSTM).
- Inventory Optimization: Clustering based inventory approach to reducing carrying cost.
- Freight Cost Prediction: Distance, vehicle type, and route-learning supervised models.
- Supplier Classification: ML algorithms consider metrics of supplier reliability and quality.

3.3 Artificial Intelligence Integration

The AI complements SCM by enhancing smart automation and decision-making. Chatbots, autonomous vehicles and robotic process automation (RPA) are AI-powered systems that make operations more efficient, and digital twins help analyze the behavior of the supply chain in real-time. Document analysis, quality inspection, and automation of the customs clearance are also aided by Natural Language Processing (NLP) and Computer Vision.

4 Challenges in AI and ML driven supply chains

Regardless of the transformative nature of AI and ML, there are a number of challenges:

- Data Quality and Integration: Frail, inconsistent and unstructured data will not allow effective model training.
- Interpretability of Models: A lot of modern AI systems become black boxes, and it is hard to know how the decision is made.
- Cybersecurity Risks: Supply chains are becoming vulnerable to cyber threats as a result of the more connectivity.
- Skill Gaps: The lack of professionals that will be able to combine domain expertise with the knowledge of AI and analytics.
- Ethical and Sustainability Concerns: Data-based systems with bias and the high amount of energy being used in AI models present ethical concerns.

5 Conclusion

It is evident that this survey demonstrates that supply chain management is quickly becoming an intelligent ecosystem based on analytics, machine learning, and artificial intelligence that is data-driven. These technologies are already the primary drivers of operational agility and efficiency taken into consideration through a prediction, optimization, risk analysis, and resiliency perspective. The findings also indicate that effective implementation involves good algorithms, but good databases, open behavior and secure infrastructure as well. It is showing supply chains that can respond and reason in uncertain conditions with the emergence of new tools like digital twins, autonomous decision-making systems, and explainable AI, although there are issues of standardization and interpretability. Altogether, the artificial intelligence, machine learning, and advanced analytics are likely to become effective and sustainable. The further evolution will be performed on the principles of Industry 5.0 development of scalable, accountable, and proven intelligent systems to facilitate the shift toward autonomous and sustainable supply chain operations.

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