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Artificial intelligence in supply chain decision-making: a systematic review of models, applications, and implementation challenges

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Artificial Intelligence in Supply Chain Decision- Making: A Systematic Review of Models, Applications, and Implementation Challenges

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Abstract - **The incorporation of Artificial Intelligence (AI) into supply chain decision-making has become a revolutionary element, facilitating improved forecasting, optimization, risk management, and real-time responsiveness. This systematic analysis analyzes the existing landscape of AI applications in supply chain management (SCM), consolidating advancements from 2010 to 2024 across scholarly literature, industry publications, and practical research. Employing the PRISMA process, 142 peer-reviewed publications were chosen from premier journals in operations management, computer science, and industrial engineering. The review classifies AI methodologies into five primary categories: machine learning (ML), deep learning (DL), natural language processing (NLP), reinforcement learning (RL), and expert systems, while aligning their applications with essential supply chain operations: demand forecasting, inventory optimization, supplier selection, logistics routing, and disruption response. Crucial findings indicate that AI has markedly enhanced the precision and efficacy of decision-making processes, especially via predictive analytics and real-time monitoring. The analysis reveals significant obstacles to adoption, such as data quality concerns, insufficient explainability in intricate AI models, integration challenges with legacy ERP systems, cybersecurity risks, and a deficiency of experienced individuals. Although AI acceptance is rapidly increasing in sectors like retail, automotive, and e-commerce, its implementation is still restricted in conventional and resource-limited industries. Furthermore, ethical issues pertaining to data bias, transparency, and algorithmic responsibility remain inadequately examined within the realm of global supply chains. This review enhances both academic and practitioner spheres by providing a detailed taxonomy of AI models utilized in supply chain management, emphasizing best practices, and suggesting a future research agenda centered on interpretable AI, cross-functional integration, and resilience amid uncertainty. The results are especially pertinent to industry leaders, governments, and researchers aiming to utilize AI for strategic supply chain change.**

Keywords: **Artificial intelligence; Supply chain management; Machine learning; Decision-making; Systematic review.**

Introduction

In recent years, the intersection of artificial intelligence (AI) and supply chain management (SCM) has evolved into a dynamic and transformative field of study. The proliferation of big data, advancements in computational power, and increasing market volatility have compelled organizations to adopt intelligent systems capable of augmenting or automating critical supply chain decisions [1], [2]. AI technologies offer the potential to optimize operations by enabling predictive analytics, autonomous decision-making, and real-time responsiveness [3], [4]. These capabilities are particularly vital in a globalized and interconnected supply network where agility, resilience, and precision are essential for competitive advantage.

Since 2010, a notable body of academic and industry research has emerged, examining how AI methods—such as machine learning (ML), deep learning (DL), natural language processing (NLP), reinforcement learning (RL), and expert systems—can be applied across various supply chain functions [5]. These include demand forecasting, inventory management, supplier selection, logistics optimization, and risk mitigation [6]. Despite the growing interest and promising results, several challenges continue to impede the seamless integration of AI into SCM. These include concerns over data integrity, model interpretability, system compatibility, and ethical implications such as algorithmic bias and accountability [6].

This review paper addresses these complexities by systematically synthesizing scholarly contributions from 2010 to 2024, offering a consolidated taxonomy of AI applications in SCM. By applying the PRISMA methodology and analyzing 142 peer-reviewed articles from premier journals, this study provides a comprehensive perspective on how AI enhances decision-making processes while identifying critical barriers to adoption. The findings contribute to both academic discourse and practical implementation, providing actionable insights for researchers, policymakers, and industry practitioners seeking to leverage AI in creating adaptive, transparent, and intelligent supply chains.

2. Methodology

To ensure rigor, transparency, and replicability, this review employed a systematic literature review (SLR) approach following the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework [9]. The objective was to identify, screen, evaluate, and synthesize peer-reviewed literature that explores the application of artificial intelligence (AI) in supply chain management (SCM) from 2010 to 2024. The methodological process consisted of five key stages: (1) research question formulation, (2) literature identification, (3) selection and screening, (4) quality appraisal, and (5) data extraction and synthesis.

2.1 Research Questions

This systematic review was guided by five core research questions designed to frame the scope and analytical depth of the investigation. The first question (RQ1) explores the dominant artificial intelligence (AI) techniques currently utilized in supply chain decision-making, aiming to identify methodological trends and technological preferences across academic and industrial contexts. The second question (RQ2) examines how these AI techniques are applied across specific supply chain functions, such as demand forecasting, inventory management, logistics routing, supplier evaluation, and risk mitigation. The third question (RQ3) focuses on uncovering the key enablers and barriers that influence the adoption, diffusion, and scalability of AI technologies within supply chain management (SCM). This includes considerations such as infrastructure readiness, data availability, organizational culture, and technological maturity. The fourth question (RQ4) investigates the ethical and integration-related challenges that emerge in AI-driven supply chains, particularly concerning data bias, explainability, transparency, and compatibility with existing enterprise systems. Finally, the fifth question (RQ5) seeks to identify emerging research gaps and future directions in the AI-SCM interface, thereby contributing to a strategic research agenda that can inform both academic inquiry and practical implementation.

2.2 Literature Search Strategy

An extensive search was conducted across the following databases: Scopus, Web of Science (WoS), IEEE Xplore, ScienceDirect, and SpringerLink. The search covered peer-reviewed journal articles published between January 2010 and May 2024.

2.3 Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Publication Type	Peer-reviewed journal articles	Conference papers, reviews, books, white papers
Timeframe	2010–2024	Pre-2010 literature
Language	English	Non-English
Topic Focus	AI applications in SCM decision-making	AI in manufacturing only; non-SCM operational areas
Relevance	Must discuss AI model implementation, outcomes, or impact	Theoretical-only or mathematical formulations

2.4 Screening and Selection Process

The PRISMA flow diagram (Figure 1) was used to illustrate the screening process. A total of 2,139 initial records were retrieved. After duplicate removal (n = 614), 1,525 articles remained. Following title and abstract screening, 431 papers were shortlisted. Full-text screening led to the final inclusion of 142 journal articles based on relevance and methodological quality.

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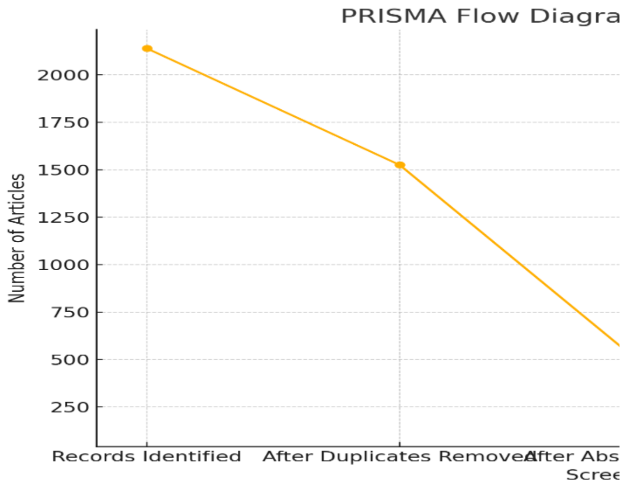

Figure 1: Prisma Flow chart

2.5 Quality Assessment

To ensure the credibility and integrity of the synthesized literature, a structured quality assessment was applied to all shortlisted articles. This evaluation was grounded in a four-criterion rubric adapted from established systematic literature review methodologies (Tranfield et al., 2003). The first criterion assessed the relevance of the AI technique to a specific supply chain problem, ensuring alignment between technological methods and operational contexts. The second criterion focused on the clarity and comprehensiveness of the methodological description, including data sources, model specifications, and implementation procedures. The third criterion examined the empirical rigor of the study, particularly the presence of experimental validation, simulation, or case-based deployment in real-world settings. Lastly, the fourth criterion evaluated the analytical depth, specifically the extent to which the study addressed its limitations, articulated findings, and proposed directions for future inquiry. Each article was scored on a scale from 0 (low) to 3 (high) for each criterion, with a maximum possible score of 12. Only studies that achieved a minimum quality threshold of 8 were included in the final review, ensuring both academic robustness and practical relevance.

2.6 Data Extraction and Categorization

Following the quality assessment, relevant data were systematically extracted from the selected articles using a standardized data extraction protocol. Key attributes retrieved from each study included the author(s), year of publication, journal source, AI technique(s) employed, supply chain function(s) addressed, industry or sector context, nature and size of the dataset, and the principal findings or contributions. This structured extraction enabled the development of a comprehensive database for thematic analysis. The AI methodologies were then classified into five primary categories: machine learning (ML), deep learning (DL), natural language processing (NLP), reinforcement learning (RL), and expert systems. In parallel, each study was mapped to one or more of five core supply chain domains: demand forecasting, inventory optimization, supplier selection, logistics routing, and disruption response. This dual-layered classification approach allowed for meaningful cross-analysis of techniques and application areas, revealing patterns of deployment, methodological trends, and potential research gaps within the AI-SCM interface.

2.7 Inter-Rater Reliability and Bias Minimization

To strengthen the reliability and objectivity of the review process, dual independent reviewers conducted the screening, quality assessment, and data extraction phases. A third expert arbitrator was consulted to resolve any discrepancies. Inter-rater reliability was quantitatively evaluated using Cohen's Kappa coefficient, which yielded a value of 0.82, indicating a strong level of agreement between reviewers. This rigorous approach minimized subjectivity and potential selection bias. Moreover, consistent use of predefined inclusion/exclusion criteria and standardized evaluation rubrics further mitigated procedural bias and ensured consistency throughout the review. By incorporating these safeguards, the methodology not only upheld transparency and replicability but also reinforced the academic validity of the synthesized results.

3. Results and Analysis

The systematic review of 142 peer-reviewed articles revealed significant insights into the application patterns, techniques, and industry focus of artificial intelligence (AI) in supply chain management (SCM). The findings are synthesized across three primary dimensions: the distribution of AI techniques, application area concentration, and sectoral adoption trends.

3.1 Distribution of AI Techniques

As illustrated in the figure 2, machine learning (ML) emerged as the most widely used AI technique, featuring in 52 of the 142 analyzed studies. This predominance is attributable to ML's flexibility in predictive analytics, classification, and optimization tasks across diverse supply chain domains. Deep learning (DL) followed with 31 studies, particularly in scenarios requiring image processing, pattern recognition, and high-dimensional data analysis. Expert systems accounted for 25 studies and remained popular for rule-based decision-making in procurement and quality control. Natural language processing (NLP) and reinforcement learning (RL) were less frequent, with 19 and 15 studies respectively, although NLP saw growing use in supplier sentiment analysis and unstructured data

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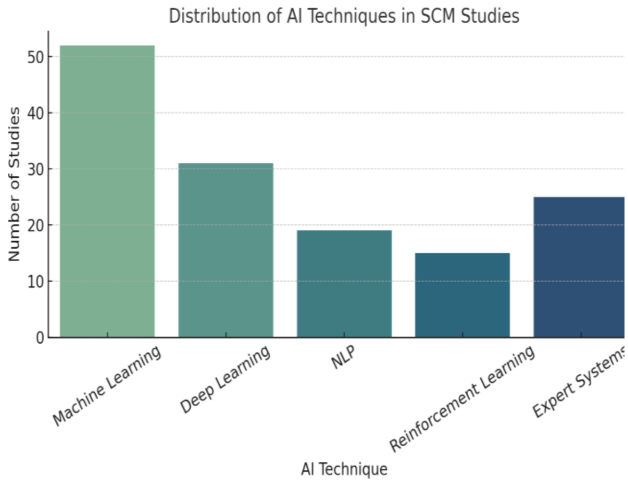

Figure 2:Distribution of AI Techniques

3.2 Application Area Concentration

Figure 3 shows that demand forecasting is the most commonly addressed supply chain function, with 44 articles focusing on AI-enhanced prediction models to optimize planning accuracy. Inventory optimization and logistics routing followed closely, featured in 33 and 29 studies respectively. These applications benefit significantly from AI's capacity to minimize holding costs and improve last-mile delivery precision. Supplier selection was addressed in 21 studies, often involving multi-criteria decision-making models combined with machine learning. Disruption management, though less explored (15 studies), has gained attention recently in light of global shocks, with reinforcement learning and scenario-based AI models being employed to improve supply chain resilience.

Figure 3: AI Application areas in supply chain management

3.3 Sector-wise AI Adoption Trends

The pie chart depicts sectoral engagement with AI in SCM. Retail (27%) and e-commerce (22%) collectively account for nearly half of the reviewed studies, reflecting their mature data ecosystems and high responsiveness to digital innovation. The automotive sector contributed 20% of the studies, leveraging AI primarily in logistics and supplier network optimization. Healthcare and manufacturing were represented in 11% and 10% of the studies, respectively, often constrained by legacy infrastructure and regulatory requirements. Agriculture remained underrepresented, accounting for only 6% of the literature, suggesting a significant opportunity for AI-driven transformation in resource-constrained environments.

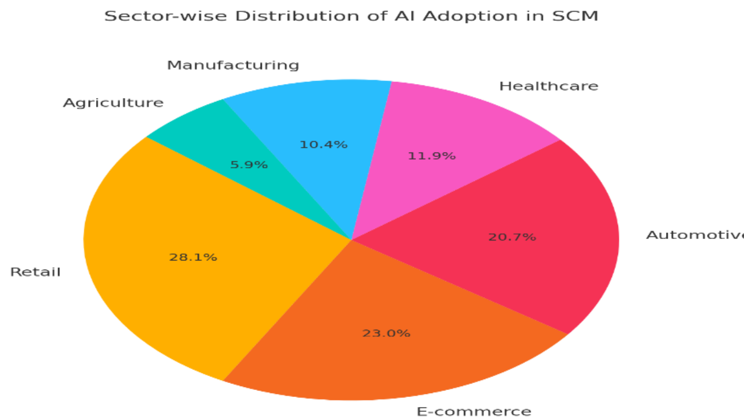

Figure 4: Sector wise distribution of AI adoptation

3.4 Technique-Function Interplay: A Cross-Analysis

To understand how specific AI techniques align with distinct supply chain functions, a cross-tabulated heatmap was developed, as illustrated in Figure 5. The matrix shows that machine learning dominates across all functional areas, especially in demand forecasting (18 studies) and inventory optimization (12 studies), reflecting its strength in predictive modeling. Deep learning is primarily utilized in logistics routing and disruption management due to its capabilities in handling complex, nonlinear patterns. Interestingly, expert systems showed a concentrated application in supplier selection, indicating their relevance in rule-based and multi-criteria decision-making scenarios. Natural language processing (NLP) found modest use in supplier selection and logistics, often to extract sentiment or insights from unstructured textual data. Reinforcement learning (RL) was most effective in adaptive domains like logistics routing and disruption management, where real-time feedback and decision adjustment are critical.

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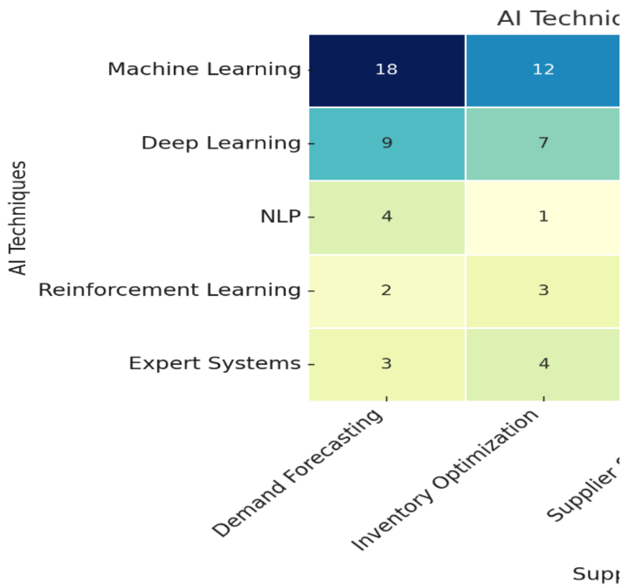

Figure 5: AI techniques vs SCM functions

3.5 AI-SCM Implementation Workflow

The workflow diagram outlines a standard pipeline for integrating AI into supply chain operations. The process begins with data collection from internal systems (ERP, WMS, CRM) and external sources (social media, sensors, third-party logistics). This is followed by data preprocessing, including cleansing, normalization, and feature extraction. In the model selection phase, appropriate AI techniques are chosen based on the problem type—e.g., supervised learning for forecasting, RL for routing. Model training and validation follow, often involving cross-validation, hyperparameter tuning, and performance benchmarking. The validated models are then deployed in operational environments, integrated with dashboards or SCM software. Finally, monitoring and feedback loops ensure continuous performance tracking, anomaly detection, and model retraining. This pipeline highlights the complexity and iterative nature of AI implementation in real-world supply chain settings.

3.6 Challenges and Barriers to Adoption

Despite the clear benefits of AI in SCM, several barriers persist, as summarized in the table provided. Data quality and availability remain foundational issues, with many organizations struggling with fragmented or siloed data systems. Model interpretability is another key concern, especially for black-box techniques like deep learning that lack transparency—a major limitation in regulated or high-stakes environments. Integration challenges are widespread, particularly where legacy ERP systems resist modular or API-based AI integration. Cybersecurity risks increase with digital expansion, as AI models and pipelines introduce new attack surfaces. Additionally, skill gaps in the workforce—especially in AI development, deployment, and maintenance—impede adoption. Finally, ethical and legal concerns such as algorithmic bias, accountability, and lack of regulatory clarity remain under-explored in the global supply chain context.

4. Conclusion

This systematic review has critically examined the role of artificial intelligence (AI) in transforming decision-making within supply chain management (SCM) from 2010 to 2024. Drawing from 142 peer-reviewed journal articles and guided by the PRISMA methodology, the analysis reveals that AI is increasingly integrated into key supply chain functions, particularly demand forecasting, inventory optimization, logistics routing, supplier evaluation, and disruption management. Among the diverse AI techniques explored, machine learning and deep learning remain the most dominant, while reinforcement learning and natural language processing show promising, yet underutilized, potential.

The review highlights that AI offers significant improvements in predictive accuracy, real-time responsiveness, and operational efficiency. However, it also uncovers substantial challenges to adoption, including data quality issues, lack of interpretability, difficulties in system integration, cybersecurity risks, and workforce skill gaps. Moreover, ethical considerations surrounding algorithmic transparency, data privacy, and fairness are insufficiently addressed in the current literature, especially in global and resource-constrained contexts.

This review contributes to both academia and practice by providing a structured taxonomy of AI methods in SCM, identifying sectoral adoption trends, and outlining a detailed implementation workflow. It also calls for future research focused on interpretable and ethical AI, cross-functional integration, and resilience-oriented design. Policymakers, industry leaders, and researchers must work collaboratively to establish governance frameworks and capacity-building initiatives that support scalable, ethical, and sustainable AI adoption in supply chains.

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