ACCSCIENCE PUBLISHING

Supply Chain Management Research

REVIEW ARTICLE

Artificial intelligence for demand forecasting in manufacturing supply chains: A systematic literature review, research gap analysis, and future directions

Attia Hussien Gomaa*

Mechanical Engineering Department, Faculty of Engineering, Benha University, Shubra, Cairo, Egypt

Abstract

Artificial intelligence (AI) has become a transformative technology for demand forecasting in manufacturing supply chains, improving forecasting accuracy, production planning, inventory optimization, and demand–supply synchronization in increasingly dynamic and data-intensive environments. Despite the rapid advancement of AI-driven forecasting, existing review studies remain fragmented, primarily focusing on forecasting algorithms and predictive performance while providing limited synthesis of methodological developments, implementation challenges, and emerging research gaps. Consequently, a comprehensive understanding of the evolution, adoption, and future trajectory of AI-enabled demand forecasting remains lacking. This work addresses these limitations through a systematic literature review, research gap analysis, and future research agenda on AI applications for demand forecasting in manufacturing supply chains. Following the PRISMA 2020 guidelines, this review systematically analyzes studies published between 2010 and 30 May 2026 to examine the evolution of AI methodologies, identify research trends and implementation barriers, evaluate unresolved theoretical and practical gaps, and propose strategic directions for future research. The findings reveal a clear transition from conventional machine learning to deep learning, reinforcement learning, hybrid intelligence, transformer-based architectures, and foundation AI, reflecting a broader shift from predictive analytics toward intelligent and autonomous decision-making. Although these advances have significantly enhanced forecasting performance and supply chain responsiveness, their industrial adoption remains constrained by challenges related to data quality, interoperability, model explainability, organizational readiness, enterprise system integration, scalability, AI governance, cybersecurity, and cross-organizational collaboration. The review further identifies critical research gaps, including the limited adoption of explainable AI, inadequate integration of foundation models and digital twins, fragmented evaluation frameworks, and insufficient real-world validation. It proposes a future research agenda centered on explainable and trustworthy AI, AI-driven decision intelligence, autonomous forecasting, responsible AI governance, sustainable AI, and autonomous manufacturing systems. This review contributes an integrated synthesis and research roadmap that advances both academic understanding and the practical implementation of intelligent, resilient, and sustainable manufacturing supply chains.

Keywords: Artificial intelligence; Demand forecasting; Manufacturing supply chains; Machine learning; Deep learning; Reinforcement learning; Industry 4.0

***Corresponding author:**
Attia Hussien Gomaa
(attia.goma@feng.bu.edu.eg)

Citation: Gomaa AH. Artificial intelligence for demand forecasting in manufacturing supply chains: A systematic literature review, research gap analysis, and future directions. *Supply Chain Manag Res*. 2026;1(3):026270018. doi: 10.36922/SCMR026270018

Received: July 3, 2026

Revised: August 6, 2026

Accepted: August 13, 2026

Published online: August 24, 2026

Copyright: © 2026 Author(s). This is an Open-Access article distributed under the terms of the Creative Commons Attribution License, permitting distribution, and reproduction in any medium, provided the original work is properly cited.

Publisher's Note: AccScience Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

1. Introduction

Demand forecasting is a strategic capability in manufacturing supply chains, underpinning production planning, inventory management, procurement, distribution, capacity allocation, and operational decision-making. Accurate demand forecasts enable manufacturers to align supply with market demand, improve resource utilization, minimize waste, enhance customer service, and strengthen supply chain agility and resilience.[1,2] However, increasing market volatility, shorter product life cycles, global supply chain disruptions, and rapidly evolving customer preferences have made demand forecasting considerably more complex while simultaneously increasing its strategic importance for maintaining operational efficiency and competitive advantage.[3-5]

The digital transformation associated with Industry 4.0 has fundamentally reshaped manufacturing through the integration of cyber–physical systems, the Industrial Internet of Things (IIoT), cloud–edge computing, and advanced analytics. These technologies continuously generate vast volumes of heterogeneous and real-time data, creating unprecedented opportunities for intelligent decision-making across manufacturing operations. Within this evolving landscape, artificial intelligence (AI) has emerged as a key enabler of data-driven manufacturing, transforming demand forecasting from a traditional statistical planning activity into an intelligent, adaptive capability that supports real-time operational and strategic decision-making.[6,7]

Traditional forecasting techniques, including autoregressive integrated moving average (ARIMA), exponential smoothing, and regression models, continue to be widely adopted because of their simplicity, transparency, and interpretability. Nevertheless, their reliance on assumptions of linearity, stationarity, and stable historical relationships limits their ability to capture the complex and dynamic demand patterns characteristic of modern manufacturing environments, where intermittent demand, structural market shifts, and unexpected disruptions are increasingly common.[8] In contrast, AI-based approaches can learn complex nonlinear relationships from heterogeneous data, continuously adapt to changing operating conditions, and exploit multiple information sources simultaneously. These capabilities make AI particularly well suited to addressing the uncertainty, volatility, and complexity that characterize contemporary manufacturing supply chains.[9-11]

The rapid advancement of AI has generated a substantial and diverse body of research on demand forecasting in manufacturing supply chains. Although several review studies have examined AI-enabled forecasting, machine learning techniques, or broader AI applications in supply chain management, most emphasize forecasting methods or predictive performance while providing limited synthesis of methodological evolution, manufacturing-specific implementation challenges, and emerging AI paradigms. Moreover, existing reviews rarely present a comprehensive analysis of theoretical, methodological, and practical research gaps or establish a structured research agenda for future investigation. Consequently, a holistic understanding of the current state of AI-enabled demand forecasting and its future development remains limited, highlighting the need for a comprehensive and up-to-date systematic literature review.

1.1. AI-enabled demand forecasting in manufacturing supply chains

AI has fundamentally transformed demand forecasting by integrating diverse data sources—including historical sales, production records, inventory levels, promotional activities, economic indicators, weather conditions, and social media signals—to capture complex demand dynamics and evolving market conditions.[12-14] Compared with conventional forecasting techniques, AI-based approaches consistently improve forecasting accuracy, reduce prediction errors associated with demand spikes and disruptions, and enhance production planning, procurement, inventory optimization, capacity management, and supply chain risk mitigation.[15-17] Enhanced demand visibility further strengthens coordination among supply chain partners, mitigates the bullwhip effect, and improves overall supply chain responsiveness, resilience, and competitiveness.[18]

Recent developments indicate a clear evolution from conventional predictive analytics toward intelligent decision support. Deep learning architectures—including recurrent neural networks (RNNs), long short-term memory (LSTM) networks, gated recurrent units (GRUs), and transformer-based models—effectively capture complex nonlinear temporal dependencies within manufacturing data, enabling more accurate and robust forecasting across dynamic operating environments.[19] Beyond improving predictive performance, hybrid forecasting models combine complementary analytical techniques to enhance both accuracy and interpretability, while probabilistic forecasting explicitly quantifies uncertainty to support more informed decision-making. Furthermore, emerging paradigms—including causal machine learning, foundation models, and generative AI—are extending forecasting capabilities through improved scalability, transferability, adaptability, and explainability.[20-22]

The role of AI is increasingly extending beyond

prediction toward autonomous and collaborative decision-making. Reinforcement learning integrates demand forecasting with inventory and production optimization through continuous interaction with dynamic manufacturing environments, although its industrial deployment remains constrained by computational complexity and implementation challenges.[23] Similarly, explainable artificial intelligence (XAI) enhances model transparency and strengthens managerial trust by improving the interpretability of AI-generated predictions.[24] At the same time, federated learning, blockchain, and secure multi-party computation facilitate collaborative forecasting across organizational boundaries while preserving data privacy and confidentiality.[24] Figure 1 summarizes the principal AI technologies and their applications in manufacturing demand forecasting.

1.2. Research gap, objectives, and contributions

Despite the rapid growth of AI-enabled demand forecasting research, the existing review literature remains fragmented. Previous reviews have predominantly focused on forecasting techniques, machine learning algorithms, or predictive performance, with limited attention to the evolution of AI methodologies, manufacturing-specific applications, implementation challenges, and emerging AI paradigms. Furthermore, few reviews systematically identify theoretical, methodological, and practical research gaps or provide a comprehensive future research agenda tailored to manufacturing supply chains. These limitations underscore the need for an updated systematic literature review that integrates current knowledge, critically evaluates the existing literature, and identifies priorities for future research.

To address these limitations, this study conducts a systematic literature review (SLR) of AI applications for demand forecasting in manufacturing supply chains, covering the period from 2010 to 30 May 2026 and following the PRISMA 2020 guidelines. Unlike previous reviews, this paper combines a systematic synthesis of AI methodologies with a comprehensive analysis of research trends, implementation challenges, research gaps, and future research directions. The review is guided by five research questions addressing the evolution of AI-enabled demand forecasting, AI methods and models, application trends and evaluation practices, implementation challenges and research gaps, and future research directions.

The research questions of this paper are as follows:

RQ1: How has AI-based demand forecasting research evolved in manufacturing supply chains?
RQ2: What AI methods, models, and approaches have been applied to demand forecasting?
RQ3: What are the key application trends, data characteristics, and evaluation practices?
RQ4: What challenges and research gaps constrain AI forecasting adoption?
RQ5: What future research directions can advance AI-enabled demand forecasting systems?

Research objectives include:

RO1: To examine the evolution of AI-based demand forecasting research.
RO2: To identify AI methods, models, and forecasting applications.
RO3: To synthesize application trends, data characteristics, and evaluation practices.
RO4: To identify major challenges and research gaps.
RO5: To propose future directions for reliable and adaptive AI-enabled forecasting systems.

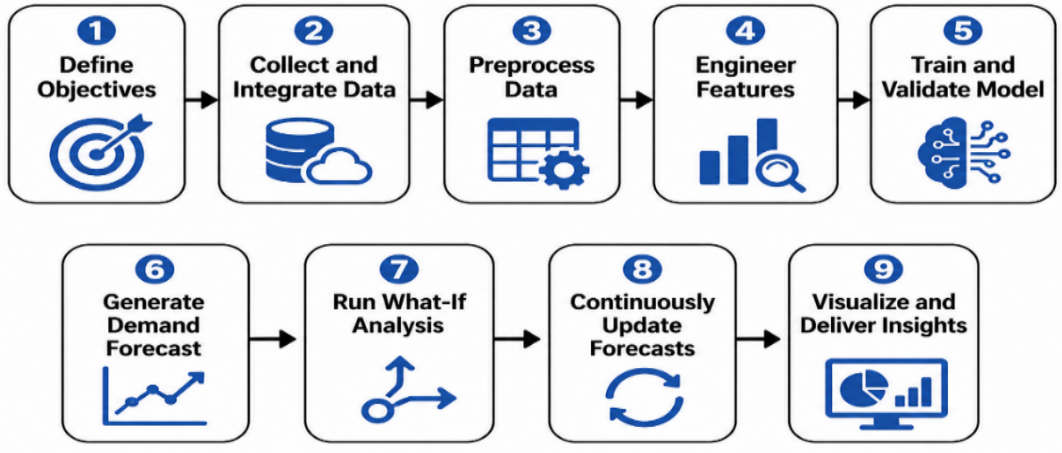


Figure 1. How does AI-based demand forecasting work?

This study makes three principal contributions to the literature. First, it provides a comprehensive and up-to-date systematic synthesis of AI-enabled demand forecasting research in manufacturing supply chains published between 2010 and 30 May 2026, offering an integrated perspective on the evolution of the field. Second, it identifies and analyzes the theoretical, methodological, and practical research gaps while developing a systematic taxonomy that links AI forecasting methods with manufacturing applications, data characteristics, evaluation practices, and implementation challenges. Third, it proposes a structured future research agenda highlighting emerging opportunities in explainable AI, causal learning, foundation models, uncertainty-aware forecasting, federated intelligence, and real-time decision support, thereby providing valuable guidance for researchers, practitioners, and policymakers seeking to develop intelligent, trustworthy, resilient, and sustainable manufacturing supply chains.

The remainder of this paper is organized as follows. Section 2 describes the PRISMA 2020-based review methodology. Section 3 presents the results of the literature synthesis and the proposed taxonomy. Section 4 discusses the key findings and future research directions. Finally, section 5 concludes the paper by summarizing the main contributions and outlining implications for both research and industrial practice.

2. Literature review

This study adopts a Systematic Literature Review (SLR) following the PRISMA 2020 guidelines to ensure methodological rigor, transparency, and reproducibility.[25] The review protocol comprised four sequential phases: identification, screening, eligibility assessment, and study inclusion. To enhance the reliability and reproducibility of the review, a predefined search strategy, explicit inclusion and exclusion criteria, a structured quality assessment framework, and a transparent screening process were employed. The selected studies were systematically synthesized to examine the evolution of AI-enabled demand forecasting in manufacturing supply chains, classify AI methodologies and applications, identify implementation challenges and research gaps, and propose future research directions.

(a) **Data sources and search strategy:** A comprehensive literature search was conducted across Scopus, Web of Science, IEEE Xplore, ScienceDirect, and SpringerLink, selected for their broad coverage of high-quality research in artificial intelligence, manufacturing, operations management, and supply chain management. The search covered publications from January 2010 to May 30, 2026. A standardized Boolean search strategy combined three groups of keywords related to AI technologies (*e.g.*, AI, machine learning, deep learning, reinforcement learning, neural network, transformer, and foundation model), forecasting (*e.g.*, demand forecasting, sales forecasting, time-series forecasting, and demand prediction), and manufacturing supply chains (*e.g.*, manufacturing supply chain, industrial supply chain, and production planning). The search syntax was adapted to the indexing requirements of each database while preserving equivalent search logic.

(b) **Eligibility criteria:** Explicit inclusion and exclusion criteria were established *a priori* to ensure methodological consistency and domain relevance. Studies were included if they (i) were peer-reviewed journal articles or high-quality conference papers, (ii) were published in English between 2010 and 30 May 2026, (iii) investigated AI-enabled demand forecasting in manufacturing or closely related supply chain contexts, and (iv) reported empirical, computational, simulation-based, or experimental validation. Studies were excluded if they were books, book chapters, editorials, theses, reports, or other non-peer-reviewed publications; unrelated to manufacturing demand forecasting; purely conceptual without empirical validation; or lacked sufficient methodological or evaluation details. These predefined criteria ensured that only methodologically rigorous and practically relevant studies were retained for analysis.

(c) **Screening process and PRISMA workflow:** The study selection process followed the PRISMA 2020 framework. From the 412 records initially retrieved, 64 duplicate records were removed, resulting in 348 unique studies. Title and abstract screening excluded 196 studies that did not satisfy the eligibility criteria, leaving 152 studies for full-text assessment. Following detailed evaluation, 63 studies were excluded because of insufficient methodological rigor, inadequate empirical validation, or limited relevance to the review scope. Consequently, 89 studies were included in the final synthesis, representing an inclusion rate of 21.6%. To improve transparency and reproducibility, studies were screened independently using the predefined eligibility criteria, and any disagreements regarding inclusion were resolved through discussion until consensus was reached. The complete selection process is illustrated in the PRISMA 2020 flow diagram (Figure 2).

(d) **Quality assessment:** To ensure the credibility and methodological robustness of the synthesized evidence, all eligible studies were evaluated using a structured quality assessment framework adapted

from established SLR practices. Each study was assessed against six predefined criteria: (i) research objectives and design, (ii) dataset transparency and adequacy, (iii) AI model specification, (iv) validation methodology, (v) performance evaluation and reporting, and (vi) reproducibility of findings. Studies failing to satisfy the minimum quality requirements, particularly those with inadequate methodological reporting or insufficient empirical validation, were excluded from the final review. This process ensured that the synthesized evidence was derived from high-quality and methodologically sound studies.

(e) **Data synthesis:** The final dataset of 89 studies was synthesized using a structured thematic analysis complemented by descriptive quantitative analysis. The studies were systematically classified according to AI methodology (machine learning, deep learning, reinforcement learning, hybrid intelligence, and emerging AI paradigms), manufacturing application, forecasting horizon, data characteristics, evaluation metrics, implementation challenges, and research outcomes. This multidimensional synthesis enabled comprehensive comparisons across studies, identified methodological developments and emerging research trends, revealed persistent theoretical and practical research gaps, and supported the development of a structured taxonomy of AI-enabled demand forecasting in manufacturing supply chains.

(f) **Methodological positioning:** This review adopts a socio-technical systems perspective, positioning AI-enabled demand forecasting as an intelligent decision-support capability that integrates advanced AI methods, heterogeneous data ecosystems, organizational capabilities, and digital infrastructure within manufacturing supply chains. Beyond synthesizing forecasting algorithms, the review systematically integrates methodological advances, manufacturing applications, implementation challenges, organizational considerations, and emerging AI paradigms. This holistic analytical perspective provides a comprehensive understanding of the evolution of AI-enabled demand forecasting, identifies unresolved theoretical, methodological, and practical research gaps, and establishes a robust foundation for future research and industrial implementation.

AI has redefined demand forecasting in manufacturing supply chains by transforming it from a statistical prediction task into an intelligent decision-support capability.[26] Unlike conventional forecasting approaches, AI integrates heterogeneous data—including historical sales, production records, inventory levels, promotional activities, economic indicators, weather conditions, and social media signals—to capture nonlinear demand patterns, adapt to evolving market conditions, and continuously improve forecasting performance. As a result, AI consistently outperforms

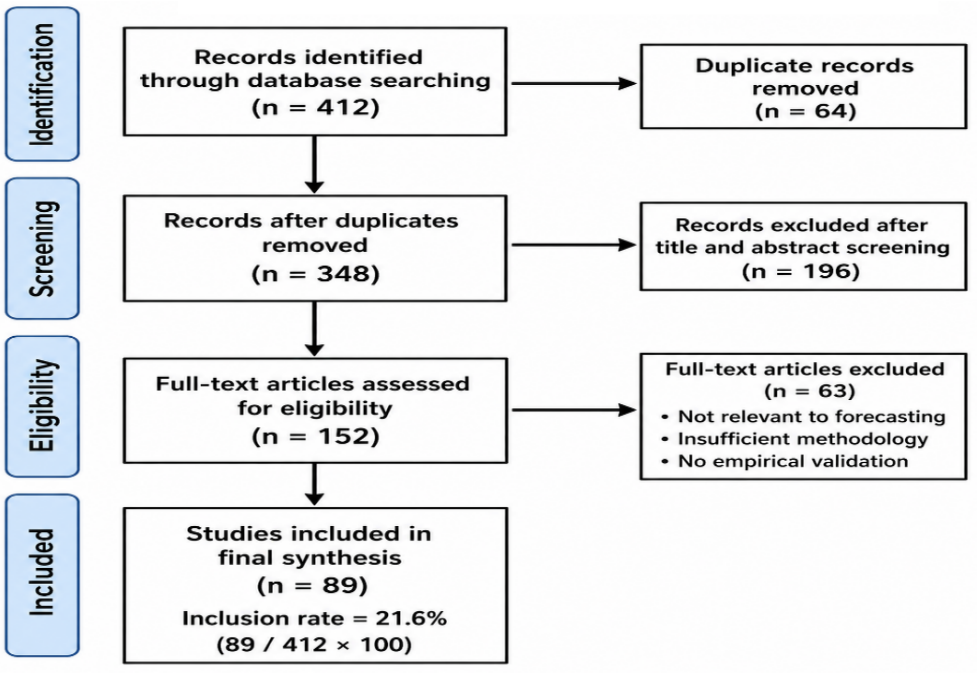


Figure 2. PRISMA flow diagram (January 2010 to May 30, 2026)

traditional forecasting methods by reducing forecasting errors, including mean absolute percentage error (MAPE), while improving the prediction of demand spikes and market disruptions.[27]

The benefits of AI extend well beyond predictive accuracy. More reliable forecasts improve production planning, procurement, inventory optimization, capacity allocation, and supply chain risk management while enhancing coordination across suppliers, manufacturers, distributors, and retailers. By increasing demand visibility and reducing information distortion, AI strengthens supply chain synchronization, mitigates the bullwhip effect, and enhances operational agility, resilience, and competitive performance, positioning demand forecasting as a strategic capability rather than a purely operational function.[16-18]

The evolution of AI has also expanded forecasting from prediction to intelligent decision support. Deep learning architectures—including recurrent neural networks (RNNs), long short-term memory (LSTM) networks, gated recurrent units (GRUs), and transformer-based models—have substantially improved the modeling of nonlinear temporal dependencies in manufacturing data.[19] Complementary advances in hybrid forecasting, probabilistic forecasting, causal machine learning, foundation models, and generative AI have further improved interpretability, uncertainty quantification, knowledge transfer, and scalability, reflecting a broader shift toward adaptive and context-aware forecasting systems.

A parallel stream of research focuses on making AI forecasting systems more autonomous, transparent, and collaborative. Reinforcement learning integrates demand forecasting with inventory and production optimization through continuous interaction with dynamic manufacturing environments, although industrial implementation remains constrained by computational complexity, reward-function design, parameter tuning, and validation requirements.[23] Likewise, XAI addresses the limited transparency of high-capacity models by improving interpretability, managerial trust, and decision accountability.[24] Beyond organizational boundaries, federated learning, blockchain, and secure multi-party computation enable collaborative forecasting while preserving data privacy and ownership, although technical and governance challenges continue to limit widespread implementation.[24]

Despite rapid methodological progress, the literature consistently indicates that successful AI-enabled forecasting depends on more than algorithmic sophistication. Forecasting performance remains highly sensitive to data quality, noisy and incomplete observations, heterogeneous industrial datasets, and concept drift, requiring robust data governance, continuous model monitoring, adaptive retraining, and close collaboration among data scientists, operations managers, and domain experts.[7,8,28] Furthermore, organizational capabilities—including digital maturity, AI expertise, governance mechanisms, and strategic alignment—are critical determinants of industrial adoption, indicating that sustainable value creation depends on integrating technological innovation with organizational readiness.[13,14]

2.1. Limitations of traditional inventory forecasting and inventory management systems

Inventory management plays a strategic role in manufacturing supply chains by balancing inventory availability with operational efficiency, customer service, and financial performance. Maintaining sufficient inventory supports uninterrupted production and timely deliveries, whereas excessive inventory increases holding, storage, insurance, and obsolescence costs. Conversely, insufficient inventory results in stockouts, production disruptions, and lost sales. These challenges are amplified in multi-stage production systems, diverse product portfolios, and globally distributed supply networks, making effective inventory management essential for supply chain resilience and competitiveness.[29-31] Because inventory represents a significant proportion of current assets, efficient inventory control also improves liquidity, profitability, and resource utilization.[32]

Manufacturing organizations have traditionally relied on a range of inventory planning and control techniques to improve operational performance. Classical methods such as Economic Order Quantity (EOQ), ABC analysis, safety stock, and reorder-point systems optimize inventory levels by balancing ordering and holding costs.[33-35] These approaches are complemented by Just-in-Time (JIT), the Toyota Production System (TPS), Materials Requirements Planning (MRP I/II), Distribution Requirements Planning (DRP), and integrated materials management systems, which improve production coordination, procurement, and inventory control.[36-42] Process improvement frameworks, including Lean Six Sigma (LSS), DMAIC, FMEA, SPC, and ISO 9001, further enhance inventory accuracy, process stability, and continuous improvement.[43-50]

These conventional approaches have contributed significantly to improving inventory turnover, reducing operational costs, shortening lead times, and enhancing production efficiency.[51-55] Nevertheless, they are primarily designed for relatively stable operating environments and depend heavily on historical data, predefined decision

rules, and periodic review policies. Consequently, their ability to capture nonlinear demand patterns, rapidly changing customer preferences, and external disruptions is limited. Their reliance on manual processes and isolated information systems further reduces real-time visibility, scalability, and responsiveness in complex manufacturing supply chains.[56-58]

The limitations of traditional inventory systems become more pronounced under demand volatility, supply uncertainty, geopolitical disruptions, and increasingly digital manufacturing environments. Conventional models often struggle to integrate heterogeneous data sources, adapt to changing market conditions, and support timely decision-making across multi-echelon supply chains.[59] Although they remain relatively inexpensive and straightforward to implement, their limited analytical capability constrains forecasting accuracy and operational agility. These challenges have accelerated the transition toward AI-enabled inventory management, where machine learning, predictive analytics, automation, and real-time data integration enable adaptive inventory optimization, intelligent replenishment, and resilient decision-making in dynamic manufacturing environments.[42]

2.2. AI-based inventory optimization and supply chain performance

Demand forecasting and inventory optimization represent interconnected capabilities within intelligent manufacturing systems. Accurate AI-based forecasts provide the foundation for adaptive inventory strategies by enabling organizations to balance holding costs, stockout risks, and service-level requirements under uncertain operating conditions. Recent studies demonstrate that AI-enabled inventory optimization improves decision quality by integrating predictive analytics with advanced optimization methods capable of addressing stochastic demand patterns and supply variability.[60-62] Unlike traditional inventory approaches based on fixed assumptions, AI-driven systems continuously analyze operational data and generate adaptive replenishment decisions that better reflect dynamic supply chain conditions.

Conventional inventory management techniques, such as Economic Order Quantity (EOQ) models and reorder point systems, remain important due to their simplicity, transparency, and ease of implementation. However, these approaches generally assume stable demand, fixed lead times, and predictable supply conditions, limiting their effectiveness in modern manufacturing environments characterized by volatility, short product life cycles, and complex multi-echelon networks.[63] AI-based inventory models overcome these limitations by incorporating real-time data, probabilistic forecasts, and continuous learning mechanisms to improve replenishment decisions and operational responsiveness.[64,65]

AI and machine learning techniques have significantly enhanced inventory management by enabling organizations to identify complex patterns within large-scale supply chain datasets. Machine learning models improve demand prediction, inventory visibility, and resource allocation by integrating historical sales data, production information, sensor data, market conditions, and external variables.[66,67] Unlike conventional statistical models that rely on predefined assumptions, AI algorithms learn directly from data and continuously improve their performance as additional observations become available. This capability enables manufacturers to achieve more accurate inventory decisions under uncertain and rapidly changing market conditions.

Among AI methodologies, deep learning approaches have demonstrated strong potential for inventory intelligence due to their ability to capture nonlinear relationships and temporal dependencies. Architectures such as artificial neural networks (ANNs), deep neural networks (DNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks have been widely applied in demand forecasting and predictive inventory control problems. Furthermore, convolutional neural networks (CNNs) and advanced sequential learning architectures effectively identify complex demand fluctuations and improve forecasting robustness in dynamic supply chain environments.[68,69] These developments have enabled inventory systems to move from reactive control mechanisms toward predictive and adaptive decision-support platforms.

Hybrid and probabilistic forecasting approaches have further strengthened AI-based inventory optimization by addressing uncertainty and improving decision reliability. Hybrid models combine statistical forecasting techniques with machine learning algorithms to achieve a balance between predictive accuracy and interpretability. For example, the Hidden Markov Model Newsvendor (HMMNV) integrates neural networks with Hidden Markov Models to improve inventory decision performance, achieving a 27% improvement in cost-related metrics. Similarly, probabilistic forecasting enables organizations to evaluate multiple future demand scenarios rather than relying solely on deterministic predictions, supporting improved safety stock decisions, risk management, and contingency planning.[70] These approaches are particularly valuable in manufacturing environments where demand uncertainty and supply disruptions significantly influence inventory performance.

Reinforcement learning has emerged as one of the most promising AI approaches for adaptive inventory optimization because of its ability to learn optimal policies through interaction with dynamic environments. Unlike traditional optimization models that depend on predefined rules, reinforcement learning–based systems continuously adjust inventory decisions according to changing demand conditions, supply constraints, and operational objectives. Studies demonstrate that Deep Q-Network (DQN) and Proximal Policy Optimization (PPO) approaches can achieve near-optimal performance in multi-item inventory systems involving stochastic demand, capacity limitations, shelf-life constraints, and product interactions.[71] Similarly, reinforcement learning has demonstrated superior performance compared with conventional replenishment strategies in healthcare inventory systems.[72] However, practical adoption remains challenging due to computational complexity, reward-function design, parameter tuning requirements, and the need for extensive industrial validation.[23] Additional studies highlight the importance of reward shaping for improving learning stability in perishable inventory systems and provide structured research directions for broader reinforcement learning implementation.[73,74]

AI-based inventory optimization provides significant operational benefits by improving production planning, procurement coordination, inventory utilization, and supply chain responsiveness. By enhancing demand visibility, AI systems enable manufacturers to reduce excess inventory, minimize stockout risks, optimize replenishment decisions, and improve service levels. Recent studies confirm that AI-driven inventory approaches contribute to lower operational costs, improved resource utilization, and enhanced supply chain performance.[75,76] Furthermore, improved information availability strengthens coordination among suppliers, manufacturers, distributors, and retailers by reducing information distortion and mitigating the bullwhip effect. Through improved demand sensing and information exchange, AI systems support greater synchronization and responsiveness across supply chain networks.[77,78]

Beyond operational improvements, AI-enabled inventory systems support strategic decision-making by providing predictive and prescriptive insights. Organizations can use AI-generated forecasts to perform scenario analysis, evaluate alternative strategies, and develop contingency plans for disruptions such as supplier failures, transportation interruptions, and demand shocks. Consequently, AI transforms inventory management from a transactional control activity into a strategic capability that supports resilience, agility, and long-term competitiveness.

The application of AI has also expanded inventory management beyond forecasting and replenishment toward intelligent monitoring and autonomous decision systems. Inventory visibility has become a critical capability for improving transparency and operational efficiency. Decision-support systems based on machine learning improve item tracking and reduce inefficiencies, while computer vision technologies enable automated inventory monitoring and warehouse intelligence. For example, Decision Tree–based systems have been developed to improve inventory visibility in constrained environments.[79] CNN-based approaches have achieved low detection error rates in inventory monitoring applications, while real-time out-of-stock detection systems and UAV-assisted recognition frameworks further enhance automated inventory control capabilities.[80-82]

The integration of AI with digital twin technologies represents another important advancement in intelligent inventory and manufacturing systems. Digital twins provide virtual representations of physical processes, enabling real-time monitoring, simulation, and predictive analysis. When combined with AI forecasting models, digital twins allow organizations to evaluate alternative production and inventory strategies before implementing operational changes, thereby improving decision quality and reducing uncertainty.[7] This integration supports the development of more adaptive and autonomous manufacturing ecosystems.

AI-driven inventory optimization also contributes significantly to sustainability and supply chain resilience. Accurate forecasting reduces overproduction, unnecessary inventory accumulation, material waste, and inefficient resource utilization by aligning production activities with actual market requirements. These capabilities support lean manufacturing principles and improve environmental performance through reduced energy consumption, transportation requirements, and resource waste.[8] Furthermore, AI improves resource planning by enabling more accurate procurement, workforce allocation, production scheduling, and capacity utilization, supporting more sustainable manufacturing practices and circular economy objectives.[18]

In addition to sustainability benefits, AI strengthens supply chain resilience by enabling organizations to anticipate disruptions and develop proactive response strategies. Manufacturing networks increasingly face uncertainty from geopolitical instability, supplier failures, economic fluctuations, and rapid changes in customer demand. AI forecasting systems provide early-warning capabilities by analyzing historical patterns, real-time

operational data, and external environmental factors to identify potential risks and recommend adaptive responses.[14] Advanced AI approaches, including probabilistic forecasting and multi-agent reinforcement learning, further enhance resilience by enabling organizations to evaluate alternative strategies and optimize inventory policies under uncertain conditions.

At the supply chain network level, AI enables collaborative intelligence among interconnected partners while addressing challenges related to data sharing and confidentiality. Technologies such as federated learning, blockchain, and secure multi-party computation allow organizations to benefit from shared analytical capabilities without directly exposing proprietary information. Federated learning supports collaborative model development while preserving data privacy, whereas blockchain enhances transparency and trust in information exchange. However, successful implementation requires effective governance mechanisms, cybersecurity practices, and inter-organizational coordination.

Empirical studies across multiple industrial sectors demonstrate the practical value of AI-based inventory optimization. Applications in automotive, electronics, consumer goods, and high-technology industries show improvements in inventory utilization, order fulfillment, production efficiency, and responsiveness to market changes. Cross-country evidence further indicates improvements in inventory accuracy and efficiency in the UK, forecasting and resilience in India[83], profitability and customer satisfaction in Germany[84], and operational performance in automotive manufacturing. AI applications have also been demonstrated in large-scale retail and industrial environments, where organizations such as Walmart use external signals including social trends, weather conditions, and local events to optimize inventory decisions[85], while Amazon applies predictive analytics to improve inventory positioning and logistics efficiency.[86]

Despite these benefits, AI adoption in inventory management remains constrained by several technological, organizational, and governance challenges. Financial limitations arise from high infrastructure investments, software requirements, and the need for specialized human expertise, particularly among small and medium-sized enterprises.[87] Data-related challenges, including fragmented information systems, poor-quality datasets, and insufficient data availability, can reduce model reliability and forecasting performance. Organizational barriers include limited analytical skills, workforce resistance, and difficulties integrating AI-generated insights into existing decision-making processes. Furthermore, technological challenges related to legacy enterprise resource planning systems, cybersecurity risks, transparency, and ethical concerns continue to influence adoption decisions.[88]

Overall, the literature demonstrates that AI has transformed inventory management from a traditional control function into an adaptive, predictive, and strategic capability. Through the integration of machine learning, deep learning, reinforcement learning, digital twins, and collaborative intelligence, AI-enabled systems improve forecasting accuracy, inventory efficiency, resilience, and sustainability. However, achieving long-term value requires a holistic implementation approach combining technological investment, workforce development, data governance, organizational readiness, and continuous system adaptation. Such integration is essential for developing intelligent manufacturing supply chains capable of responding effectively to increasing uncertainty and complexity.

2.3. Artificial intelligence for demand forecasting in manufacturing supply chains

Demand forecasting has evolved from conventional statistical estimation to intelligent, data-driven decision support as manufacturing systems become increasingly digitalized. Traditional forecasting methods, including moving averages, exponential smoothing, and autoregressive integrated moving average (ARIMA), have long been adopted because of their simplicity, interpretability, and computational efficiency. However, these approaches rely on assumptions of linearity, stationarity, and stable historical relationships, limiting their ability to capture nonlinear demand behavior, structural market changes, and rapidly evolving customer preferences in modern manufacturing environments.[89-91]

The emergence of Industry 4.0 and smart manufacturing has accelerated the adoption of AI-based forecasting approaches capable of learning complex relationships directly from data. Machine learning, deep learning, reinforcement learning, and hybrid AI models provide adaptive forecasting capabilities that continuously improve as new information becomes available, enabling more accurate prediction under conditions of demand volatility, supply uncertainty, and production complexity.[70,92] Consequently, demand forecasting has evolved from a standalone analytical task into a strategic capability supporting production planning, inventory management, procurement, and supply chain coordination.[93]

The effectiveness of AI-based forecasting depends fundamentally on its ability to exploit diverse sources of manufacturing data. Unlike traditional methods that primarily rely on historical demand observations, AI integrates heterogeneous information from enterprise

systems, production records, IoT sensors, market indicators, macroeconomic variables, customer sentiment, online reviews, and social media to improve forecasting accuracy and responsiveness.[66,94]

Recent studies further demonstrate that ensemble learning enhances forecasting robustness by combining multiple predictive models to capture seasonal effects, promotional activities, and unexpected demand fluctuations. However, forecasting performance depends not only on algorithm selection but also on data quality. Missing values, noisy observations, inconsistent records, and heterogeneous data structures remain major challenges, highlighting the importance of preprocessing, feature engineering, and robust data governance for reliable AI deployment.[95]

Rapid advances in AI have significantly expanded forecasting capabilities beyond conventional machine learning. Deep learning architectures—including recurrent neural networks (RNNs), long short-term memory (LSTM) networks, gated recurrent units (GRUs), attention mechanisms, and transformer-based models—have demonstrated superior performance in modeling nonlinear temporal dependencies and long-range patterns within complex manufacturing time-series data.[19,96]

Beyond deep learning, hybrid forecasting models integrate statistical methods, machine learning algorithms, and optimization techniques to improve predictive performance while maintaining interpretability.[97] Probabilistic forecasting further extends decision support by explicitly quantifying uncertainty and enabling the evaluation of alternative demand scenarios.[70] More recently, causal machine learning, foundation models, and generative AI have emerged as promising approaches for identifying demand drivers, transferring knowledge across manufacturing contexts, and developing scalable forecasting systems capable of adapting to diverse industrial environments.

The role of AI has expanded beyond demand prediction toward supporting operational and strategic decision-making. Reinforcement learning integrates forecasting with inventory control, production scheduling, and supply chain optimization by enabling intelligent agents to learn optimal policies through continuous interaction with dynamic manufacturing environments. Despite its considerable potential, industrial implementation remains constrained by computational complexity, reward-function design, parameter tuning, and validation requirements.[23]

Similarly, XAI addresses the limited transparency of high-capacity AI models by improving interpretability, accountability, and managerial trust. Combined with interpretable optimization frameworks, XAI enables practitioners to understand forecast drivers, validate AI recommendations, and support more transparent operational decisions.[24] In parallel, digital twins extend forecasting capabilities by integrating real-time simulation, predictive analytics, and scenario evaluation, enabling manufacturers to optimize production strategies before implementation.[7]

As manufacturing supply chains become increasingly interconnected, AI is evolving from organization-specific forecasting toward collaborative intelligence. Technologies such as federated learning, blockchain, and secure multi-party computation enable multiple organizations to jointly develop forecasting models while preserving data privacy, ownership, and security. These approaches enhance forecasting accuracy, coordination, and trust across supply chain partners, although challenges related to interoperability, governance, and implementation complexity continue to limit large-scale adoption.[24,98]

The literature demonstrates a clear progression from conventional statistical forecasting to AI-enabled forecasting systems that integrate advanced learning models, heterogeneous data, uncertainty quantification, explainability, and collaborative intelligence. Accordingly, demand forecasting has evolved from a predictive function into a strategic capability that supports real-time planning, operational optimization, and coordinated decision-making across manufacturing supply chains. Despite these advances, future progress depends on addressing persistent challenges related to data quality, model transparency, interoperability, governance, organizational readiness, and scalable industrial deployment.

Despite the significant advancements achieved in AI-enabled demand forecasting and inventory optimization, widespread industrial adoption remains constrained by a range of interconnected technological, organizational, and implementation challenges. Existing research demonstrates that AI models can improve forecasting accuracy, inventory decisions, and supply chain responsiveness; however, translating these benefits into sustained industrial value requires alignment among data capabilities, digital infrastructure, organizational readiness, human expertise, and governance mechanisms. Accordingly, AI-based forecasting should be viewed as a comprehensive socio-technical capability that integrates technological innovation with operational processes and managerial decision-making.

A primary challenge influencing AI forecasting effectiveness is the quality, availability, and integration of industrial data. Smart manufacturing environments generate large volumes of heterogeneous data from IoT

devices, sensors, enterprise resource planning systems, production monitoring platforms, customer databases, and external market sources. However, these datasets frequently suffer from missing values, inconsistent structures, measurement errors, duplicated records, and temporal inconsistencies, which may negatively affect model accuracy and reliability. Therefore, effective data preprocessing, validation, and governance frameworks are essential to ensure that AI models can generate dependable forecasting insights.[99]

In addition to data quality issues, the complexity of industrial datasets introduces challenges related to feature engineering, variable selection, and knowledge representation. Although advanced AI algorithms are capable of extracting complex patterns from large datasets, forecasting performance remains dependent on the availability of meaningful input variables and sufficient contextual information. Limited historical data, poorly structured datasets, and inadequate integration of internal and external demand drivers may reduce model generalization and limit transferability across manufacturing environments. Consequently, future AI forecasting systems require improved data architectures, standardized information structures, and robust analytical approaches to support reliable decision-making.[95]

Another major challenge is the dynamic and uncertain nature of manufacturing demand. Modern supply chains operate under continuously changing conditions driven by evolving customer preferences, market volatility, economic fluctuations, technological developments, and unexpected disruptions. These conditions create concept drift, where the relationships between input variables and demand outcomes change over time, gradually reducing model performance. Maintaining forecasting effectiveness therefore requires adaptive learning mechanisms, continuous monitoring, automated retraining, and uncertainty-aware forecasting approaches capable of responding to changing operational environments.[13,28]

Beyond technological limitations, organizational readiness significantly influences the success of AI implementation. Many manufacturing organizations continue to operate with fragmented information systems, legacy technologies, and limited integration between operational and enterprise platforms. Such constraints restrict data accessibility and reduce the ability to exploit AI-generated insights effectively. Successful implementation requires investment in digital infrastructure, interoperable systems, and scalable analytical platforms that enable continuous data exchange and real-time decision support.

Human capabilities and organizational culture represent additional barriers to effective AI adoption. Manufacturing firms often face shortages of expertise in AI, machine learning, and data analytics, as well as resistance to changes in established decision-making practices. Since AI forecasting requires cooperation between technical specialists and operational experts, interdisciplinary collaboration among data scientists, supply chain managers, production engineers, and domain specialists is essential. Organizations with stronger digital maturity, innovation capabilities, and strategic alignment between technology initiatives and business objectives are more likely to achieve sustainable benefits from AI forecasting systems.[100,101] Moreover, collaboration between technical and operational teams improves model relevance, user acceptance, and practical implementation outcomes.[102]

Trust, transparency, and interpretability remain critical challenges as AI forecasting models become increasingly sophisticated. Advanced deep learning architectures often achieve superior predictive performance but operate as complex black-box systems, making it difficult for decision-makers to understand the factors influencing generated forecasts. This limitation may reduce managerial confidence and hinder adoption, particularly in manufacturing environments where forecasting decisions directly affect production planning, inventory investment, and supply chain performance.

Explainable artificial intelligence (XAI) provides a promising approach for addressing these limitations by improving transparency while maintaining predictive capability. XAI techniques enable managers to interpret forecasting outcomes, identify influential factors, and validate AI recommendations against operational knowledge. Consequently, explainability enhances accountability, trust, and acceptance of AI-driven decision support systems.[90,101] Recent studies further emphasize that explainability represents both a technical requirement and an organizational necessity for responsible AI adoption and effective governance.[103]

Industrial deployment and scalability represent further unresolved challenges. Although many AI forecasting models demonstrate strong performance in experimental studies, their transition into real manufacturing environments is often limited by computational requirements, cybersecurity concerns, interoperability issues, and difficulties integrating AI outputs with existing operational systems. To generate measurable value, AI forecasting solutions must be connected with production planning, inventory management, procurement, and supply chain decision-support processes. Therefore, AI adoption should be embedded within broader digital transformation strategies involving process redesign,

workforce development, governance structures, and organizational change management.[66,101]

A continuing research challenge is achieving a balance between predictive capability and operational interpretability. While highly complex AI models can capture nonlinear relationships and improve forecasting accuracy, their limited transparency may restrict practical adoption. Hybrid AI approaches provide an effective pathway by combining machine learning algorithms with optimization techniques and domain knowledge. These frameworks enable organizations to benefit from advanced prediction capabilities while maintaining managerial control over operational decisions. Previous studies indicate that hybrid approaches can improve inventory performance, service levels, and responsiveness under uncertain manufacturing conditions.[90,97,104]

Governance and responsible AI implementation represent additional areas requiring further investigation. As AI systems become increasingly embedded within supply chain decision-making, organizations must address issues related to ethical use, cybersecurity, model risk management, regulatory compliance, and accountability. Effective governance frameworks are necessary to ensure that AI forecasting systems remain reliable, transparent, and aligned with strategic objectives throughout their operational lifecycle.

Beyond operational improvements, AI-enabled forecasting contributes to sustainability and supply chain resilience by improving demand visibility, reducing waste, and enabling more efficient resource allocation. Accurate forecasting reduces excess inventory, unnecessary production, and inefficient resource consumption, thereby supporting sustainable manufacturing practices.[8,18] Furthermore, AI-based predictive capabilities enable organizations to identify potential disruptions, evaluate alternative scenarios, and develop proactive mitigation strategies. These capabilities strengthen resilience by improving preparedness for supply shortages, transportation interruptions, and demand uncertainty.[13,14]

Emerging AI approaches, including probabilistic forecasting, multi-agent reinforcement learning, and collaborative intelligence, provide additional opportunities for developing more adaptive supply chain systems. These approaches enable organizations to model complex uncertainties, optimize inventory policies, and improve responsiveness under volatile conditions.[15,101] However, further research is needed to evaluate their industrial applicability, scalability, and integration within existing manufacturing ecosystems.

Collaborative forecasting across supply chain networks represents another important research direction. Modern manufacturing ecosystems require effective information exchange among suppliers, manufacturers, logistics providers, and customers; however, concerns related to data ownership, privacy, security, and trust continue to limit collaboration. Technologies such as federated learning, blockchain, and secure data-sharing frameworks provide potential solutions by enabling shared intelligence while preserving confidential information. Nevertheless, challenges related to governance structures, interoperability, and coordination mechanisms remain unresolved.

Overall, the literature indicates that AI-enabled demand forecasting has evolved from a predictive analytics technique into a strategic capability supporting intelligent manufacturing transformation. However, existing studies remain fragmented across algorithms, datasets, evaluation criteria, and industrial contexts. Current research has primarily emphasized forecasting accuracy, while comparatively less attention has been given to implementation challenges, organizational capabilities, governance requirements, and long-term sustainability impacts.

Future research should therefore focus on developing integrated AI forecasting ecosystems that combine predictive accuracy with adaptability, transparency, scalability, and strategic decision support. Key research priorities include explainable and trustworthy AI, adaptive learning under uncertainty, causal forecasting approaches, foundation models, collaborative intelligence, and practical industrial deployment frameworks. Addressing these gaps will support the development of reliable, resilient, and sustainable AI-enabled forecasting systems capable of enhancing manufacturing supply chain performance.

3. Challenges and research gaps analysis

The literature reviewed demonstrates that AI has substantially improved demand forecasting in manufacturing supply chains by enhancing predictive accuracy, operational responsiveness, and decision-making capabilities. However, despite these technological advances, the widespread industrial adoption of AI-enabled demand forecasting remains limited. The evidence indicates that implementation challenges extend well beyond algorithmic performance, encompassing a complex interplay of technological, organizational, managerial, and governance-related factors. Consequently, the successful deployment of AI should be viewed as a multidimensional socio-technical transformation that requires the alignment of advanced analytical capabilities with high-quality data ecosystems, robust digital infrastructure, organizational

readiness, responsible governance, and collaborative supply chain practices.

Importantly, these challenges are not independent. Poor data quality undermines model reliability and generalizability, limited explainability reduces managerial trust and decision confidence, inadequate organizational capabilities constrain implementation, and fragmented digital infrastructures hinder enterprise-wide integration and scalability. These interdependencies restrict organizations' ability to translate AI-generated forecasts into effective operational and strategic decisions. Therefore, advancing AI-enabled demand forecasting requires an integrated approach that simultaneously addresses technological innovation, organizational transformation, governance, and supply chain collaboration.

Figure 3 presents a conceptual synthesis of the principal challenges and research gaps identified in the literature on AI-enabled demand forecasting in manufacturing supply chains. The framework highlights critical barriers related to data quality and integration, demand uncertainty, model explainability, organizational readiness, enterprise system integration, scalability, AI governance, and cross-organizational collaboration. It also identifies emerging research directions, including explainable and adaptive AI, hybrid forecasting models, secure collaborative intelligence, and scalable, resilient, and sustainable AI-driven forecasting systems. By integrating these interconnected dimensions, Figure 3 provides a structured roadmap for guiding both future research and industrial implementation.

Table 1 summarizes the principal challenges identified in the literature, together with their operational implications and strategic recommendations. The synthesis demonstrates that realizing the full potential of AI-enabled demand forecasting requires more than advances in forecasting algorithms. Sustainable implementation depends on coordinated progress in data governance, model robustness, enterprise system integration, organizational capabilities, responsible AI governance, and collaborative supply chain ecosystems. Collectively, these findings underscore that future research should prioritize integrated, trustworthy, adaptive, and scalable AI solutions capable of delivering sustained operational value and strengthening the resilience and competitiveness of next-generation manufacturing supply chains.

(a) **Data quality, availability, and integration limitations:**

Data quality remains one of the most fundamental determinants of the reliability and effectiveness of AI-enabled demand forecasting systems. Manufacturing enterprises continuously generate large volumes of heterogeneous data from sensors, Internet of Things (IoT) devices, enterprise information systems, production platforms, and external market sources. However, these datasets frequently exhibit missing values, inconsistent formats, noise, duplication, and limited standardization, thereby reducing model reliability, generalizability, and forecasting accuracy. Poor data quality limits the ability of AI models to learn representative demand patterns and undermines their performance in real-world manufacturing environments.[99]

Beyond data quality, data fragmentation across

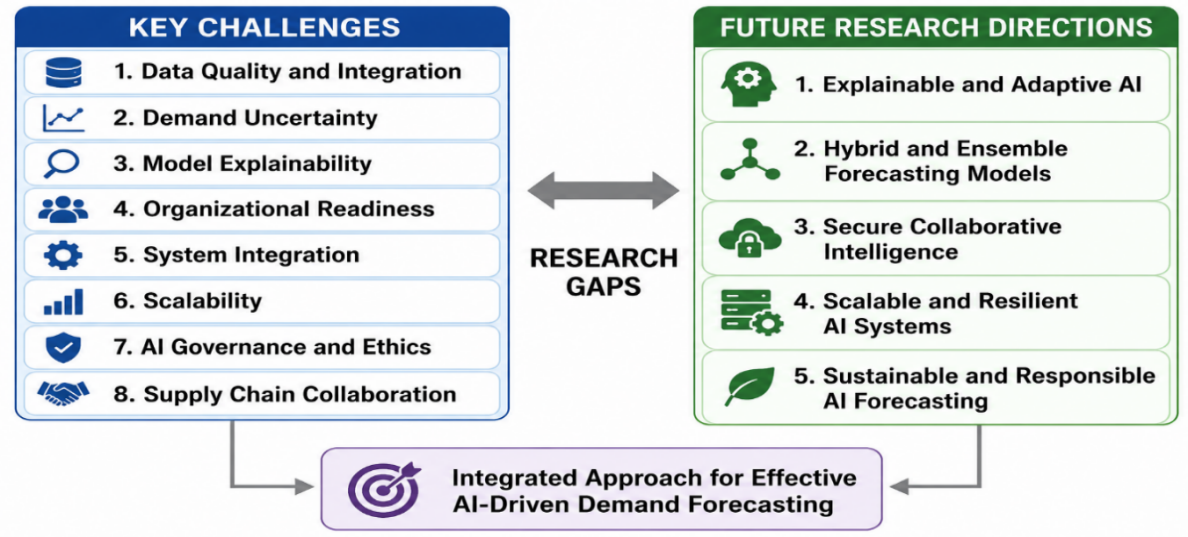


Figure 3. Key challenges and research gaps in AI-driven demand forecasting

organizational functions and supply chain partners remains a significant obstacle to effective AI deployment. Disconnected information systems and inconsistent data standards restrict interoperability and hinder the integration of diverse data sources required for intelligent forecasting. Consequently, AI implementation should be supported by comprehensive data governance frameworks, standardized data architectures, and robust data management practices that ensure data consistency, accessibility, and interoperability throughout the manufacturing supply chain.[95]

Although considerable progress has been made in developing increasingly sophisticated forecasting algorithms, comparatively limited attention has been devoted to establishing resilient data ecosystems capable of supporting large-scale industrial AI applications. Future research should therefore prioritize data-centric AI, automated data quality assessment, semantic interoperability, and real-time data integration to enhance the robustness and scalability of AI-enabled demand forecasting.

(b) **Dynamic demand patterns and concept drift:**
Manufacturing supply chains operate within highly dynamic environments characterized by rapidly changing customer preferences, technological innovation, market volatility, and recurring supply disruptions. These evolving conditions introduce concept drift, whereby the relationships between explanatory variables and demand outcomes change over time, gradually degrading the predictive performance of models trained on historical data. Consequently, static forecasting models often struggle to maintain their effectiveness under changing operational conditions.[28]

The literature indicates that maintaining forecasting accuracy increasingly depends on the ability of AI systems to continuously adapt to evolving demand patterns rather than relying solely on periodic model retraining. Adaptive learning, online learning, continual learning, and uncertainty-aware forecasting therefore represent important research directions for improving model robustness under non-stationary environments. These capabilities enable forecasting systems to detect structural changes, update model parameters dynamically, and respond more effectively to unexpected market events.

Despite growing interest in adaptive AI, relatively few studies have examined the integration of concept drift detection, continual learning, and autonomous model adaptation within industrial manufacturing environments. Future research should therefore focus on developing self-adaptive forecasting frameworks capable of maintaining reliable performance under persistent uncertainty while supporting resilient and agile manufacturing supply chains.

(c) **Model complexity and limited interpretability:**
The increasing adoption of advanced AI models, particularly deep learning architectures, has substantially improved forecasting performance but has also introduced significant challenges related to model transparency and interpretability. Although these models effectively capture complex nonlinear relationships, their "black-box" nature often obscures the reasoning underlying forecasting outputs, limiting managerial understanding and confidence. This lack of transparency is particularly problematic in manufacturing environments, where demand forecasts directly influence production planning, inventory investment, procurement strategies, and resource allocation.[103]

Model interpretability has therefore emerged as a critical prerequisite for organizational trust and effective human–AI collaboration. XAI provides mechanisms for interpreting model predictions, identifying influential variables, and improving transparency, thereby enabling managers to better understand, validate, and utilize AI-generated recommendations.[62] However, existing studies predominantly evaluate explainability from a technical perspective, while comparatively limited attention has been devoted to assessing how explainability influences managerial decision-making, organizational trust, and AI adoption within manufacturing environments.

Future research should move beyond algorithmic interpretability by developing human-centered explainability frameworks that balance predictive performance with transparency, usability, and managerial decision support. Integrating explainability into AI system design will be essential for promoting responsible AI adoption and strengthening confidence in intelligent forecasting systems.

(d) **Limited organizational readiness and AI capabilities:**
The successful implementation of AI-enabled demand forecasting depends not only on technological capability but also on organizational readiness, digital maturity, and human expertise. Many manufacturing organizations continue to face substantial barriers related to limited AI knowledge, fragmented business processes, insufficient analytical capabilities, and resistance to organizational change. These limitations frequently prevent organizations from translating AI-generated forecasts into measurable operational improvements, even when forecasting models demonstrate strong predictive performance.[100]

The literature increasingly recognizes that AI implementation is fundamentally an organizational

transformation rather than a purely technological initiative. Effective deployment requires cross-functional collaboration among data scientists, supply chain managers, manufacturing engineers, and information technology specialists to ensure that forecasting solutions align with operational objectives and organizational requirements.[102] Furthermore, leadership commitment, continuous workforce development, and an organizational culture that supports data-driven decision-making are critical enablers of long-term AI success.

Despite growing recognition of organizational factors, existing research continues to prioritize algorithm development over organizational capability building. Future research should therefore investigate AI maturity models, change management strategies, workforce capability development, and governance structures that facilitate sustainable AI adoption across manufacturing organizations.

(e) **Integration with existing manufacturing systems:**
The operational value of AI-enabled demand forecasting depends on its seamless integration with enterprise-wide manufacturing and supply chain systems. Although standalone AI models can generate highly accurate forecasts, their practical impact remains limited unless forecasting outputs are effectively embedded within production planning, inventory management, procurement, and enterprise decision-support processes. Consequently, the benefits of AI are realized only when predictive intelligence is translated into coordinated operational actions.

The literature highlights enterprise system integration as a persistent challenge, particularly within heterogeneous digital environments characterized by legacy information systems and fragmented data architectures. Integrating AI forecasting with enterprise resource planning, manufacturing execution systems (MES), and broader supply chain platforms is essential for enabling real-time information exchange, synchronized planning, and data-driven operational coordination.[66] Such integration enhances organizational responsiveness by ensuring that forecasting insights directly support planning and execution activities throughout the manufacturing supply chain.[101]

Future research should extend beyond algorithm development to investigate interoperable AI architectures, standardized integration frameworks, digital twins, and service-oriented system designs capable of supporting scalable AI deployment across complex manufacturing ecosystems. Strengthening enterprise-wide interoperability will be fundamental to realizing the full operational value of AI-enabled demand forecasting.

(f) **Computational complexity and scalability challenges:**
Although many AI-based forecasting models demonstrate excellent predictive performance under controlled experimental conditions, their deployment in large-scale manufacturing environments remains a significant challenge. Industrial applications require forecasting systems capable of processing high-dimensional, real-time data across multiple products, production facilities, and geographically distributed supply chain networks. However, substantial computational requirements, infrastructure constraints, interoperability issues, and increasing model complexity often limit the scalability and operational feasibility of advanced AI solutions.[97]

The literature suggests that scalability should be considered a fundamental design objective rather than a post-deployment consideration. Advances in cloud–edge computing, distributed AI architectures, model compression, and parallel computing provide promising opportunities for improving computational efficiency while maintaining forecasting performance. Nevertheless, existing research has primarily emphasized algorithm development, with comparatively limited attention devoted to scalable deployment strategies within industrial manufacturing settings.

Future research should investigate resource-efficient AI architectures, standardized benchmarking frameworks, and scalable deployment models capable of supporting real-time forecasting across complex manufacturing ecosystems. Such developments are essential for bridging the gap between laboratory-scale research and enterprise-wide industrial implementation.

(g) **Governance, security, and responsible AI concerns:**
The growing reliance on AI-enabled demand forecasting introduces important challenges related to governance, cybersecurity, transparency, accountability, and regulatory compliance. As forecasting models increasingly influence strategic and operational decisions, organizations must ensure that AI systems operate reliably, ethically, and consistently throughout their lifecycle. Inadequate governance may result in biased predictions, model degradation, cybersecurity vulnerabilities, and unclear accountability, thereby reducing organizational trust and increasing operational risk.

The literature increasingly recognizes that responsible AI extends beyond technical reliability to encompass ethical decision-making, transparency, human oversight, and regulatory compliance. Consequently, governance frameworks should incorporate continuous model validation, performance monitoring, cybersecurity protection, auditability, and clearly defined decision

ownership to ensure that AI-generated recommendations remain trustworthy and aligned with organizational objectives.

Despite growing interest in responsible AI, governance frameworks specifically designed for manufacturing supply chain forecasting remain relatively underdeveloped. Future research should therefore focus on integrating responsible AI principles into forecasting system design while developing governance models that balance predictive performance, transparency, security, accountability, and regulatory compliance.

(h) **Balancing predictive accuracy and operational decision support:**

A persistent challenge in AI-enabled demand forecasting is balancing predictive accuracy with practical decision support. Although increasingly sophisticated AI models often achieve superior forecasting performance, their operational value depends on the extent to which forecasting outputs can be translated into effective production planning, inventory management, capacity allocation, procurement, and risk management decisions. High predictive accuracy alone is insufficient if model outputs are difficult to interpret or cannot be readily incorporated into managerial decision-making processes.[97]

Recent studies suggest that forecasting should be viewed as an integral component of intelligent decision support rather than an isolated prediction task. Hybrid AI frameworks that combine machine learning with optimization techniques provide a promising approach by integrating predictive capabilities with operational decision models, thereby improving both forecasting performance and managerial applicability.[104] Such approaches enable organizations to align forecasting outputs more effectively with operational objectives and strategic planning.

Future research should prioritize the development of integrated forecasting and optimization frameworks that explicitly connect AI-generated predictions with real-time operational decision-making. Strengthening this integration will enhance the practical value of AI forecasting and support more intelligent, adaptive, and autonomous manufacturing systems.

(i) **Limited cross-organizational collaboration and data sharing:**

Modern manufacturing supply chains increasingly rely on collaboration among suppliers, manufacturers, logistics providers, distributors, and customers to improve forecasting accuracy and operational coordination. However, collaborative AI-enabled forecasting remains constrained by concerns related to data ownership, privacy, cybersecurity, competitive sensitivity, and the absence of trusted data-sharing mechanisms. These barriers limit the ability of organizations to exploit collective intelligence and develop coordinated forecasting strategies across supply chain networks.

Emerging technologies such as federated learning, blockchain, and secure data-sharing mechanisms offer promising solutions by enabling collaborative model development while preserving data privacy, confidentiality, and organizational autonomy.[24] Nevertheless, the literature remains largely focused on technological feasibility, with comparatively limited attention devoted to governance structures, incentive mechanisms, and inter-organizational coordination required to support sustainable collaborative forecasting.

Future research should therefore investigate integrated technological and governance frameworks that facilitate secure, trustworthy, and scalable cross-organizational AI collaboration. Such efforts will be essential for improving demand visibility, mitigating the bullwhip effect, and enhancing resilience across interconnected manufacturing supply chains.

(j) **Insufficient evidence of sustainability and resilience impacts:**

Although AI-enabled demand forecasting has demonstrated substantial benefits in improving forecasting accuracy, inventory utilization, and operational responsiveness, its broader contributions to sustainability and supply chain resilience remain insufficiently understood. Existing studies predominantly evaluate forecasting performance using technical metrics such as prediction accuracy and cost reduction, while comparatively fewer investigations assess how AI contributes to resource efficiency, waste reduction, circular economy initiatives, environmental sustainability, and long-term resilience.

As manufacturing organizations increasingly pursue sustainable and resilient operations, future AI forecasting systems should be evaluated using multidimensional performance frameworks that incorporate economic, environmental, and social outcomes alongside conventional forecasting metrics. Such an approach would provide a more comprehensive assessment of AI's strategic contribution to sustainable manufacturing.

Future research should therefore examine the role of AI-enabled demand forecasting in supporting circular manufacturing, disruption preparedness, decarbonization strategies, and long-term supply chain resilience. Expanding evaluation frameworks beyond predictive performance will provide a more holistic understanding of how AI contributes to sustainable competitive advantage and responsible manufacturing practices.

In summary, the analysis presented in Table 1 demonstrates that the successful implementation of AI-enabled demand forecasting extends far beyond improvements in forecasting algorithms. Although advances in machine learning, deep learning, reinforcement learning, and foundation AI have significantly enhanced predictive capabilities, their practical impact depends on addressing a broader set of interconnected technological, organizational, and governance-related challenges. The literature consistently indicates that limitations in data quality, model explainability, organizational readiness, enterprise system integration, scalability, governance, and cross-organizational collaboration collectively constrain the industrial adoption of AI-enabled forecasting systems.

Importantly, these challenges should not be considered in isolation. Reliable AI forecasting requires high-quality and interoperable data to support robust model development, explainable models to enhance managerial trust, scalable digital infrastructures to enable enterprise-wide deployment, and effective governance frameworks to ensure transparency, accountability, security, and regulatory compliance. Likewise, organizational capabilities and collaborative supply chain ecosystems play a critical role in translating AI-generated predictions into coordinated operational and strategic decisions. Consequently, future progress depends on adopting an integrated socio-technical perspective that recognizes the interdependence of technological innovation, organizational transformation, and supply chain integration.

The review also reveals several important research gaps. Existing studies continue to emphasize improvements in predictive performance, whereas comparatively limited attention has been devoted to adaptive learning under concept drift, human-centered explainability, enterprise-scale deployment, collaborative intelligence, responsible AI governance, and multidimensional evaluation frameworks that simultaneously consider operational performance, resilience, and sustainability. Furthermore, relatively few studies investigate how emerging technologies—including foundation models, generative AI, digital twins, federated learning, and autonomous decision-making—can be systematically integrated into manufacturing demand forecasting.

Overall, the evidence suggests that the next generation of AI-enabled demand forecasting should evolve from standalone predictive models toward intelligent, adaptive, explainable, collaborative, and autonomous decision-support ecosystems. Advancing this transition requires multidisciplinary research that integrates AI, operations and supply chain management, information systems, organizational behavior, and responsible AI. The future research directions presented in the following section build upon these identified challenges and research gaps to outline a strategic roadmap for developing intelligent, trustworthy, scalable, resilient, and sustainable demand forecasting systems for next-generation manufacturing

Table 1. Challenges, implications, and strategic recommendations

#	Challenge	Implications	Strategic recommendations
1	Data quality and integration	Poor and fragmented data reduce forecasting accuracy.	Strengthen data governance and integrate heterogeneous data.
2	Demand uncertainty	Dynamic demand patterns reduce model performance.	Adopt adaptive learning and continuous model updating.
3	Model explainability	Limited transparency reduces trust and adoption.	Implement explainable AI (XAI) and hybrid models.
4	Organizational readiness	Limited digital maturity and AI capabilities hinder adoption.	Build AI skills and strengthen digital readiness.
5	System integration	Poor integration limits operational effectiveness.	Integrate AI with enterprise resource planning, planning, and inventory systems.
6	Scalability	Computational complexity constrains industrial deployment.	Develop scalable architectures and deployment frameworks.
7	AI governance	Weak governance increases ethical, security, and compliance risks.	Establish responsible AI governance and continuous monitoring.
8	Decision intelligence	Accurate forecasts alone do not support effective decisions.	Integrate forecasting with optimization and decision support.
9	Supply chain collaboration	Data-sharing barriers limit collaborative forecasting.	Enable secure collaborative AI and data sharing.
10	Sustainability and resilience	Long-term strategic impacts remain underexplored.	Evaluate AI contributions to sustainability and resilience.

supply chains.

4. Future research directions

The systematic review demonstrates that AI is redefining demand forecasting in manufacturing supply chains from a predictive analytical function into a strategic capability that enables intelligent planning, autonomous decision-making, and digitally integrated manufacturing operations. Although recent advances in machine learning, deep learning, reinforcement learning, and foundation AI have significantly improved forecasting performance, the findings presented in **Section 3** indicate that several technological, organizational, and governance-related challenges continue to limit large-scale industrial adoption. Consequently, future research should extend beyond incremental improvements in predictive accuracy and focus on developing AI-enabled forecasting systems that are intelligent, adaptive, explainable, trustworthy, scalable, and seamlessly integrated across manufacturing and supply chain processes.

Building on the research gaps identified in this review, the future evolution of AI-enabled demand forecasting is expected to be driven by three complementary transformations. First, forecasting will evolve from predictive analytics toward AI-driven decision intelligence capable of supporting autonomous and real-time operational decision-making. Second, AI systems will progress from isolated forecasting models toward collaborative and interconnected intelligence supported by secure data sharing, enterprise-wide digital integration, and distributed learning. Third, advances in responsible AI, governance, and sustainable manufacturing will facilitate the transition from algorithm-centric forecasting toward intelligent, trustworthy, and autonomous manufacturing ecosystems. Together, these transformations establish a comprehensive research agenda that integrates technological innovation with organizational capabilities, digital transformation, and strategic supply chain management.

Figure 4 illustrates this conceptual framework by synthesizing ten interconnected research streams that collectively define the future landscape of AI-enabled demand forecasting in manufacturing supply chains. These research streams encompass data-centric AI, explainable AI, adaptive AI, foundation AI, AI-driven decision intelligence, autonomous inventory optimization, collaborative AI, responsible AI governance, sustainable AI, and autonomous manufacturing. Rather than representing independent research topics, these streams constitute an integrated innovation ecosystem in which advances in one domain reinforce progress across the others, thereby accelerating the development of intelligent, trustworthy, resilient, scalable, and autonomous forecasting systems.

Table 2 complements this framework by mapping each research stream to its corresponding knowledge gaps, theoretical foundations, methodological approaches, and research priorities. The proposed agenda highlights that future advances in AI-enabled demand forecasting will depend not only on methodological innovation but also on the convergence of AI, manufacturing systems, operations and supply chain management, information systems, digital transformation, and responsible AI. The following research directions therefore provide a structured roadmap for advancing both scholarly research and industrial practice.

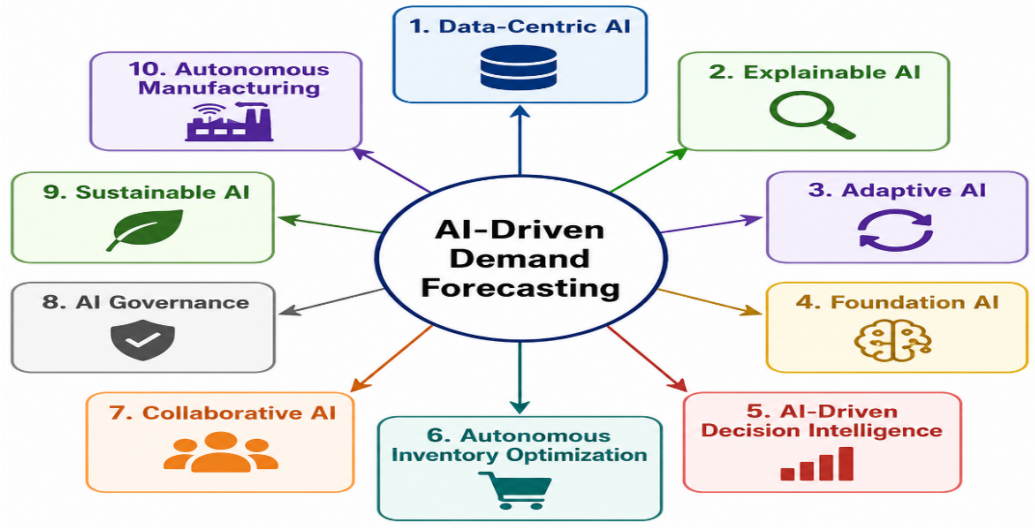


Figure 4. Future research directions for AI-driven demand forecasting

(a) **Data-centric AI:** Future progress in AI-enabled demand forecasting depends fundamentally on the quality, consistency, interoperability, and governance of manufacturing data. While existing research has predominantly focused on improving forecasting algorithms, comparatively limited attention has been devoted to developing resilient data ecosystems that support scalable industrial AI. Future studies should investigate intelligent data management frameworks incorporating IoT-enabled sensing, multimodal data fusion, semantic interoperability, automated data quality assessment, synthetic data generation, and advanced feature engineering. Strengthening data-centric AI will improve model robustness, scalability, and transferability across diverse manufacturing environments.

(b) **Explainable AI:** As AI increasingly influences strategic and operational decisions, model transparency has become a prerequisite for industrial adoption. Future research should advance human-centered XAI capable of balancing predictive accuracy with interpretability, enabling managers to understand model behavior, validate AI-generated recommendations, and strengthen organizational trust. Integrating explainability into decision-support systems will facilitate responsible AI adoption while improving collaboration between human expertise and intelligent forecasting models.

(c) **Adaptive AI:** Demand patterns are inherently dynamic, reflecting changing customer preferences, market volatility, technological innovation, and supply chain disruptions. Consequently, future forecasting systems should evolve from static predictive models toward adaptive learning architectures capable of continuously responding to changing operating environments. Research should investigate online learning, continual learning, transfer learning, meta-learning, and uncertainty-aware AI to improve robustness under concept drift and maintain long-term forecasting performance.

(d) **Foundation AI:** Foundation AI represents a transformative opportunity for manufacturing demand forecasting. Future research should explore the application of large language models, multimodal foundation models, generative AI, and domain-specific foundation models capable of learning transferable knowledge across products, production facilities, and supply chain networks. Such developments have the potential to improve scalability, reduce model retraining requirements, and enable generalized forecasting intelligence within complex manufacturing environments.

(e) **AI-driven decision intelligence:** Future research should reposition demand forecasting as an integral component of intelligent operational decision-making rather than an isolated predictive task. Integrating AI forecasting with mathematical optimization, digital twins, simulation, prescriptive analytics, and multi-agent systems can support production scheduling, procurement planning, inventory optimization, capacity allocation, and disruption management. This integration will transform forecasting into an intelligent decision-support capability that continuously optimizes manufacturing operations under uncertainty.

(f) **Autonomous inventory optimization:** Although reinforcement learning has demonstrated significant potential for inventory management, its industrial implementation remains limited. Future research should develop autonomous inventory optimization frameworks capable of continuously learning from operational data and dynamically adapting replenishment policies to changing demand and supply conditions. Integrating reinforcement learning with forecasting, optimization, digital twins, and real-time sensing will enable more resilient, efficient, and intelligent inventory management systems.

(g) **Collaborative AI:** Future manufacturing supply chains will increasingly depend on collaborative intelligence across organizational boundaries. Research should therefore investigate secure collaborative forecasting frameworks that integrate federated learning, blockchain, privacy-preserving machine learning, secure multi-party computation, and decentralized AI architectures. These technologies can facilitate trusted information sharing, collective learning, and coordinated forecasting while preserving data privacy, confidentiality, and organizational autonomy.

(h) **Responsible AI governance:** Responsible AI governance will become a critical enabler of sustainable industrial AI adoption. Future research should establish comprehensive governance frameworks encompassing ethical AI, transparency, accountability, cybersecurity, regulatory compliance, organizational readiness, digital maturity, and continuous model lifecycle management. Such frameworks will help ensure that AI-enabled forecasting systems remain reliable, trustworthy, and aligned with organizational and societal expectations.

(i) **Sustainable AI:** The contribution of AI-enabled demand forecasting should be evaluated beyond predictive accuracy by explicitly incorporating sustainability and resilience objectives. Future research should integrate environmental, economic,

and social performance indicators into forecasting models to support resource efficiency, waste reduction, circular manufacturing, carbon mitigation, and resilient supply chain operations. Developing multidimensional evaluation frameworks will enable a more comprehensive assessment of AI's long-term strategic value.

(j) **Autonomous manufacturing:** The long-term evolution of AI-enabled demand forecasting lies in its integration within autonomous manufacturing ecosystems. Future research should investigate intelligent architectures that combine AI forecasting with digital twins, the Industrial Internet of Things (IIoT), cyber–physical systems, edge AI, robotics, and autonomous control technologies. Such ecosystems will support continuous sensing, real-time forecasting, adaptive optimization, and closed-loop decision-making, ultimately enabling self-learning manufacturing systems capable of autonomously responding to changing operational and market conditions.

Collectively, these research directions indicate that the future of AI-enabled demand forecasting extends beyond developing increasingly sophisticated forecasting algorithms. Instead, future progress will depend on establishing integrated AI ecosystems that combine advanced analytical capabilities with robust data infrastructures, enterprise-wide digital integration, organizational readiness, collaborative intelligence, and responsible governance. Advancing this interdisciplinary research agenda will accelerate the transition from predictive analytics to autonomous decision intelligence, enabling manufacturing supply chains that are more adaptive, explainable, resilient, sustainable, and capable of supporting the next generation of smart manufacturing.

Table 2. Future research agenda for AI-based demand forecasting

#	Research stream	Key gap	Theoretical lens	Research methods	Future focus	Expected contribution
1	Data-centric AI	Poor data quality and fragmented data integration	Data governance	Data fusion, IoT analytics, feature engineering	Intelligent data ecosystems	Robust and reliable forecasting
2	Explainable AI	Limited model transparency and trust	Explainable AI (XAI)	SHAP, LIME, interpretable AI	Transparent forecasting models	Improved trust and adoption
3	Adaptive AI	Concept drift and dynamic demand	Adaptive learning theory	Online, continual, and transfer learning	Self-learning forecasting systems	Long-term forecasting accuracy
4	Foundation AI	Limited industrial application of foundation models	Foundation AI	LLMs, multimodal AI, generative AI	Scalable forecasting intelligence	Transferable AI capabilities
5	AI-driven decision intelligence	Weak integration with operational planning	Decision support theory	AI–optimization, digital twins, simulation	Forecasting-driven decision support	Smarter operational planning
6	Autonomous inventory optimization	Limited industrial validation of reinforcement learning	Reinforcement learning	Deep RL, multi-agent RL	Adaptive inventory policies	Autonomous inventory management
7	Collaborative AI	Data privacy and interoperability constraints	Collaborative intelligence	Federated learning, blockchain	Secure collaborative forecasting	Enhanced supply chain coordination
8	AI Governance	Limited organizational readiness and governance	TOE framework	Case studies, maturity models	Responsible AI implementation	Scalable industrial adoption
9	Sustainable AI	Limited sustainability and resilience assessment	Sustainable supply chain management	Multi-objective optimization, scenario analysis	Sustainable forecasting systems	Resilient and sustainable supply chains
10	Autonomous Manufacturing	Fragmented AI applications across manufacturing	Industry 5.0	Digital twins, IIoT, edge AI	Intelligent manufacturing ecosystems	End-to-end autonomous operations

Abbreviations: AI: Artificial intelligence; IIoT: Industrial Internet of Things; LLM: Large language model; RL: Reinforcement learning; TOE: Theory of everything.

5. Conclusion

As manufacturing systems become increasingly digitalized, interconnected, and data-driven, AI has become a strategic enabler of demand forecasting, supporting more accurate, adaptive, and intelligent decision-making across manufacturing supply chains. In this context, a systematic literature review of research published between 2010 and 30 May 2026 was conducted to synthesize the evolution of AI methodologies, examine manufacturing applications, identify implementation challenges and research gaps, and establish future research directions for AI-enabled demand forecasting.

The review reveals a clear progression from conventional statistical forecasting techniques to advanced AI paradigms, including machine learning, deep learning, reinforcement learning, hybrid intelligence, transformer-based architectures, and foundation AI. These developments have substantially enhanced forecasting accuracy, production planning, inventory optimization, demand–supply synchronization, and overall supply chain responsiveness. However, the findings also demonstrate that advances in AI algorithms alone are insufficient to ensure successful industrial implementation. Persistent challenges—including fragmented data ecosystems, poor data quality and interoperability, concept drift, limited model explainability, enterprise system integration, organizational readiness, cybersecurity, AI governance, and cross-organizational collaboration—continue to hinder the effective deployment of AI-enabled forecasting systems. Consequently, realizing the full value of AI requires an integrated socio-technical approach that combines advanced analytical capabilities with robust data governance, interoperable digital infrastructure, organizational capabilities, and responsible governance frameworks.

Beyond providing a comprehensive synthesis of the literature, this review advances the field by systematically identifying unresolved theoretical, methodological, and practical research gaps while positioning AI-enabled demand forecasting as a strategic socio-technical capability rather than merely a predictive modeling task. From this perspective, demand forecasting is conceptualized as an intelligent decision-support ecosystem that integrates predictive intelligence, operational optimization, organizational capabilities, digital infrastructure, and collaborative supply chain processes to support continuous, adaptive, and data-driven decision-making. This perspective extends previous reviews that have primarily emphasized forecasting techniques and predictive performance, offering a more holistic understanding of how AI creates operational and strategic value across manufacturing supply chains.

Building on the identified research gaps, the review proposes a structured future research agenda encompassing data-centric AI, explainable and trustworthy AI, foundation models, AI-driven decision intelligence, autonomous forecasting, digital twins, responsible AI governance, sustainable AI, and autonomous manufacturing systems. Collectively, these research directions highlight the evolution of AI-enabled demand forecasting from standalone prediction models toward intelligent, trustworthy, adaptive, and autonomous decision-support ecosystems capable of supporting resilient, sustainable, and digitally integrated manufacturing supply chains.

This study makes three principal contributions to the literature. First, it provides a comprehensive and up-to-date systematic synthesis of AI-enabled demand forecasting research in manufacturing supply chains, consolidating a rapidly expanding body of knowledge into a coherent evidence base. Second, it develops an integrated conceptual framework that links AI methodologies with manufacturing applications, implementation challenges, organizational capabilities, governance requirements, and supply chain integration while systematically identifying the key research gaps that remain unresolved. Third, it proposes a structured future research agenda that offers a strategic roadmap for advancing both academic research and industrial practice in AI-enabled manufacturing supply chains.

The findings also provide important implications for theory and practice. From a theoretical perspective, this review contributes to the literature on intelligent manufacturing by integrating insights from artificial intelligence, manufacturing systems, operations and supply chain management, information systems, and responsible AI into a unified conceptual framework. By bridging methodological, technological, and organizational perspectives, it provides a stronger foundation for future theory development and interdisciplinary research. From a practical perspective, the findings demonstrate that successful AI implementation requires substantially more than deploying advanced forecasting algorithms. Manufacturing organizations should invest in high-quality data ecosystems, interoperable digital infrastructure, organizational capabilities, enterprise-wide AI integration, and governance mechanisms that promote transparency, accountability, security, and trust. These complementary capabilities are essential for translating AI-enabled forecasting into measurable operational improvements, strategic agility, and long-term competitive advantage.

This review is subject to several limitations. The analysis is restricted to studies published between 2010 and 30 May 2026 and selected in accordance with the

PRISMA 2020 guidelines. Furthermore, the review relies primarily on qualitative synthesis and does not incorporate bibliometric, scientometric, or meta-analytic techniques that could provide complementary quantitative insights into the intellectual structure and evolution of the field. Given the rapid pace of AI innovation, future reviews should periodically update the evidence base, integrate quantitative evidence synthesis where appropriate, and further investigate emerging AI paradigms, industrial applications, and governance frameworks to ensure that the proposed research agenda remains aligned with continuing advances in intelligent manufacturing.

Despite the limitations, this paper has dual implications, both theoretical and managerial. Regarding the theoretical implications, this review advances the literature by systematically synthesizing AI-enabled demand forecasting research and developing an integrated conceptual framework that connects AI methodologies, manufacturing applications, implementation challenges, organizational capabilities, governance requirements, and supply chain integration. By conceptualizing AI-enabled demand forecasting as a strategic socio-technical decision-support capability, the study extends existing theory and establishes a robust foundation for future interdisciplinary research on intelligent manufacturing and AI-enabled supply chains. Regarding the managerial implications, the findings demonstrate that successful AI adoption depends on an integrated organizational approach that combines advanced forecasting models with high-quality data ecosystems, interoperable digital infrastructure, organizational readiness, enterprise-wide AI integration, and responsible AI governance. Embedding AI-enabled demand forecasting within strategic and operational decision-making can improve forecasting accuracy, optimize production planning and inventory management, enhance organizational agility, strengthen supply chain resilience, and support sustainable competitive advantage.

Acknowledgments

None.

Funding

None.

Conflict of interest

The author declares no conflicts of interest.

Author contributions

This is a single-authored article.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

All data supporting this work are contained within the article.

Further disclosure

The author acknowledges that ChatGPT (OpenAI) was used exclusively for language editing and stylistic refinement of the author's text, including improvements to clarity, grammar, and academic tone. The tool was not used to generate original scholarly content, data, analyses, or references. The author has carefully reviewed and verified the final manuscript and accept full responsibility for its content.

References

1. Abbasimehr H, Shabani M, Yousefi M. An optimized model using LSTM network for demand forecasting. *Comput Ind Eng.* 2020;143:106435.

   doi: 10.1016/j.cie.2020.106435

2. Korcari A, Saridi M, Koumpoti A, Anastasiadis F. AI-Driven Demand Planning: A Systematic Review of Adoption, Barriers and Strategic Implications. *Adm Sci.* 2026;16(6):260.

   doi: 10.3390/admsci16060260

3. Boone T, Ganeshan R, Jain A, Sanders NR. Forecasting sales in the supply chain: Consumer analytics in the big data era. *Int J Forecast.* 2019;35(1):170-180.

   doi: 10.1016/j.ijforecast.2018.09.003

4. Mediavilla MA, Dietrich F, Palm D. Review and analysis of artificial intelligence methods for demand forecasting in supply chain management. *Procedia CIRP.* 2022;107:1126-1131.

   doi: 10.1016/j.procir.2022.05.119

5. Biadigilign TM, Tagele MJ, Wondimu A, Ayenew W. The prediction of essential medicine demand using machine learning and traditional methods on EPSS Gondar hub 2018-2022 data. *Explor Res Clin Soc Pharm.* 2026;23:100801.

   doi: 10.1016/j.rcsop.2026.100801

6. Chen Y, Biswas MI, Talukder MdS. The role of artificial intelligence in effective business operations during COVID-19. *IJOEM.* 2022;18(12):6368-6387.

   doi: 10.1108/ijoem-11-2021-1666

7. Xin L, Yiming W, Bonaglia M. How to Motivate Enterprises to Use New Technologies: From the Perspective of Digitalization Cost in Digital Supply Chain Finance. *R&D Manag.* 2025;56(2):385-409.

doi: 10.1111/radm.70024

8. Rohrschneider D, Pehlke M, Handmann U, Jansen M. LLM-based JSON Mapping and Blockchain Integration for Digital Product Passports. *Digit Bus.* 2026;6(1):100167.

doi: 10.1016/j.digbus.2026.100167

9. Xiaoying W, Hassan H, Sampene AK, Xu L. Driving environmental sustainability: The effects of sustainable supply chain management, fossil fuel consumption, and trade openness. *Environ Sustain Indic.* 2026;29:101112.

doi: 10.1016/j.indic.2025.101112

10. Mohammad AA, Al Oraini B, Mohammad SI, Alenazi SA, Al-Fawwaz TM, Vasudevan A. Mathematical and statistical modelling of electricity demand forecasting using artificial neural networks and SARIMA: Implications for energy supply chain planning. *Alex Eng J.* 2026;139:98-108.

doi: 10.1016/j.aej.2026.01.046

11. Prastuti M, Pujawan IN, Widodo E, Kuswanto H. A predictive analytics method for multiregional supply chain demand forecasting with spatial time series and machine learning. *Decis Anal J.* 2026;19:100706.

doi: 10.1016/j.dajour.2026.100706

12. Nguyen T. Applications of artificial intelligence for demand forecasting. *Oper Supply Chain Manag.* 2023;16(4):424-434.

doi: 10.31387/oscm0550401

13. Chen P, Yunsheng Z, Liubin L. A dual-path driving mechanism study of digital transformation on supply chain adaptation from the asymmetric network power perspective. *Technol Soc.* 2025:103081.

doi: 10.1016/j.techsoc.2025.103081

14. Liu Z, Meng F, Li B, Li Y. Investment Efficiency-Risk Mismatch and Its Impact on Supply-Chain Upgrading: Evidence from China's Grain Industry. *Sustainability.* 2026;18(3):1293.

doi: 10.3390/su18031293

15. Nozari H, Yordanova Z. An intelligent digital twin approach for optimizing multi-channel supply chains in uncertain environments. *Green Technol Sustain.* 2025:100309.

doi: 10.1016/j.grets.2025.100309

16. Potgieter S, Oosthuizen-Vosloo S, Langenfeld K, et al. Biofiltration, seasonality, and distribution system factors influence nitrifier communities in a full-scale chloraminated drinking water system. *Water Res.* 2025:125288.

doi: 10.1016/j.watres.2025.125288

17. Hossen A, Arafat Y, Sarker MdN, Jamil MH, Islam MA, Hasan R. A Predictive Framework for Financial Crashes Using Advanced Time Series Techniques. In: *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS).* IEEE; 2024:476-483.

doi: 10.1109/icpids65698.2024.00080

18. Ellahi RM, Wood LC, Bekhit AEDA. A multi-layer Industry 4.0 framework for ensuring halal integrity in NZ meat supply chains. *Food Control.* 2026;182:111880.

doi: 10.1016/j.foodcont.2025.111880

19. El-Meehy AO, El-Kharbotly AK, El-Beheiry MM. Systematic hyperparameter analysis of GRU and LSTM across demand pattern types: a demand-characteristic-driven meta-learning framework for rapid optimization. *Sci Rep.* 2025;15(1).

doi: 10.1038/s41598-025-31508-x

20. Sajja GS, Addula SR, Meesala MK, Ravipati P. Optimizing inventory management through AI-driven demand forecasting for improved supply chain responsiveness and accuracy. In: *AIP Conference Proceedings.* Vol 3306. AIP Publishing; 2025:050003.

doi: 10.1063/5.0275697

21. Fares L, El Kharrim M, Dakkon M. Data-Driven Forecasting of Urban Electricity Demand: A Comparison of Machine Learning and Deep Learning Models. *Int J Stat Econom Data Anal Appl.* 2026;1(1). https://journals.imist.ma/index.php/IJSEDAA/article/view/9413

22. Patil S, Patil M, Thakur K, Pimple R, Patil S. AI-Driven Demand Forecasting and Inventory Optimization Using Prophet-Based Time Series Modelling. *Int Res J Innov Sci Technol.* 2026;1(2):1-7.

doi: 10.67308/irjist.009

23. Ning Z, Zhang J, Wu N, et al. From empirical to physical constraints: Revisiting the structure of monthly water balance models with global evaluation. *J Hydrol.* 2026;667:134916.

doi: 10.1016/j.jhydrol.2026.134916

24. Tian G, Chen Z, Xia Z, Abbas H, Liu W. Facilitation mechanisms for supply chain resilience-oriented inputs: a digitalization and enterprise alliance based perspective. *Int J Prod Econ.* 2026:109962.

doi: 10.1016/j.ijpe.2026.109962

25. Page MJ, McKenzie JE, Bossuyt PM, et al. Updating guidance for reporting systematic reviews: development of the PRISMA 2020 statement. *J Clin Epidemiol.* 2021;134:103-112.

doi: 10.1016/j.jclinepi.2021.02.003

26. Baryannis G, Validi S, Dani S, Antoniou G. Supply chain risk management and artificial intelligence: state of the art and future research directions. *Int J Prod Res.* 2019;57(7):2179-2202.

doi: 10.1080/00207543.2018.1530476

27. Chaudhary R, Mittal M, Arora HD, Jindal K, Chaudhary NK. AI-driven demand forecasting for sustainable inventory model in fuzzy environment. *Sustain Futures.* 2026;11:101752.

doi: 10.1016/j.sftr.2026.101752

28. Jamil MH, Hossen A, Talukder SI, Arafat Y, Sozib HM. Big Data Analytics and Its Usage on Financial Fraud Detection in the USA. *Adv Mach Learn IoT Data Secur.* 2025;1.

doi: 10.63471/amlid25001

29. Hong C. Implementing Lean Six Sigma to achieve inventory control in supply chain management. In: *AIP Conference Proceedings.* Vol 1902; 2017:020037.

doi: 10.1063/1.5010654

30. Gomaa AH. Enhancing Inventory Performance in Manufacturing Supply Chains Through Lean Six Sigma: A Case Study. *J Decis Sci Optim.* 2026;2(2):77-96.

doi: 10.55578/jdso.2605.006

31. Aruleswaran A, Muraliraj J, Zailani S. Lean six sigma and sustainable supply chain management: A case study in electric vehicle parts manufacturing. *Int J Lean Six Sigma.* 2026;17(1):147-169.

doi: 10.1108/IJLSS-04-2024-0069

32. Golas Z, Bieniasz A. Empirical analysis of the influence of inventory management on financial performance in the food industry in Poland. *Eng Econ.* 2016;27(3):264-275.

doi: 10.5755/j01.ee.27.3.5933

33. Emar W, Al-Omari ZA, Alharbi S. Analysis of inventory management of slow-moving spare parts by using ABC techniques and EOQ model-a case study. *Indones J Electr Eng Comput Sci.* 2021;23(2):1159-1169.

doi: 10.11591/ijeecs.v23.i2.pp1159-1169

34. Haekal J, Setiawan I. Comparative analysis of raw materials control using JIT and EOQ method for cost efficiency of raw material supply in automotive components company Bekasi, Indonesia. *Int J Eng Res Adv Technol.* 2020;6(10):76-82.

doi: 10.31695/IJERAT.2020.3661

35. Kumar G, Nebhnani R, Sharma R. Inventory Management of Automotive Industries using ABC Analysis: A Systematic Approach. *J Ind Eng Int.* 2022;4(3):27.

doi: 10.30495/jiei.2023.1954649.1212

36. Geng X, Li Y, Wang L, et al. Spatiotemporal multi-graph convolution network for ride-hailing demand forecasting. In: *Proceedings of the AAAI Conference on Artificial Intelligence.* 2019;33(01):3656-3663.

doi: 10.1609/aaai.v33i01.33013656

37. Schmidt MC, Veile JW, Müller JM, Voigt KI. Industry 4.0 implementation in the supply chain: a review on the evolution of buyer-supplier relationships. *Int J Prod Res.* 2023;61(17):6063-6080.

doi: 10.1080/00207543.2022.2120923

38. Mazanai M. Impact of just-in-time (JIT) inventory system on efficiency, quality and flexibility among manufacturing sector, small and medium enterprise (SMEs) in South Africa. *Afr J Bus Manag.* 2012;6(17):5786.

doi: 10.5897/AJBM12.148

39. Letunovska N, Offei FA, Junior PA, Lyulyov O, Pimonenko T, Kwilinski A. Green supply chain management: The effect of procurement sustainability on reverse logistics. *Logistics.* 2023;7(3):47.

doi: 10.3390/logistics7030047

40. Patrucco A, Ciccullo F, Pero M. Industry 4.0 and supply chain process re-engineering: A coproduction study of materials management in construction. *Bus Process Manag J.* 2020;26(5):1093-1119.

doi: 10.1108/BPMJ-04-2019-0147

41. Relich M, Nielsen I, Gola A. Reducing the total product cost at the product design stage. *Appl Sci.* 2022;12(4):1921.

doi: 10.3390/app12041921

42. Kumar P, Choubey D, Amosu OR, Ogunsuji YM. AI-enhanced inventory and demand forecasting: Using AI to optimize inventory management and predict customer demand. *World J Adv Res Rev.* 2024;23(1):1931-1944.

doi: 10.30574/wjarr.2024.23.1.2173

43. Pfeifer MR. SMEs in automotive supply chains: a survey on six sigma performance perceptions of Czech supply chain members. *Processes.* 2022;10(4):698.

doi: 10.3390/pr10040698

44. Snee RD. Lean Six Sigma-getting better all the time. *Int J Lean Six Sigma.* 2010;1(1):9-29.

doi: 10.1108/20401461011033130

45. Hu B, Tian Y. Six Sigma applied in inventory management. In: *Advanced Engineering Forum.* Vol 1. Trans Tech Publications Ltd; 2011:355-359.

doi: 10.4028/www.scientific.net/AEF.1.355

46. Rifqi H, Zamma A, Souda SB, Hansali M. Lean manufacturing implementation through DMAIC approach: A case study in the automotive industry. *Qual Innov Prosper.* 2021;25(2):54-77.

doi: 10.12776/qip.v25i2.1576

47. Puiu IR, Petre IM, Boșcoianu M. Targeting Toward Optimal Inventory in Automotive Industry-An Analysis Based on Six Sigma Methodology. *Logistics.* 2025;10(1):8.

doi: 10.3390/logistics10010008

48. Marques P, Requeijo J, Saraiva P, Frazão-Guerreiro F. Integrating six sigma with ISO 9001. *Int J Lean Six Sigma.*

2013;4(1):36-59.

doi: 10.1108/20401461311310508

49. Amjad MHH, Shovon MSS, Hasan ASMM. Analyzing Lean Six Sigma Practices In Engineering Project Management: A Comparative Analysis. *ITEJ.* 2024;1(01):245-255.

doi: 10.70937/itej.v1i01.27

50. Yang K, Wu Q, Cormican K. From the Great Wall to great workflow: lean six sigma in Chinese listed companies. *Int J Lean Six Sigma.* 2025;16(4):946-971.

doi: 10.1108/IJLSS-07-2024-0152

51. Kinney MR, Wempe WF. Further evidence on the extent and origins of JIT's profitability effects. *Account Rev.* 2002;77(1):203-225.

doi: 10.2308/accr.2002.77.1.203

52. Chen H, Frank MZ, Wu OQ. What actually happened to the inventories of American companies between 1981 and 2000? *Manage Sci.* 2005;51(7):1015-1031.

doi: 10.1287/mnsc.1050.0368

53. Koumanakos DP. The effect of inventory management on firm performance. *Int J Product Perform Manag.* 2008;57(5):355-369.

doi: 10.1108/17410400810881827

54. Muchaendepi W, Mbohwa C, Hamandishe T, Kanyepe J. Inventory management and performance of SMEs in the manufacturing sector of Harare. *Procedia Manuf.* 2019;33:454-461.

doi: 10.1016/j.promfg.2019.04.056

55. Mishra U, Wu JZ, Sarkar B. Optimum sustainable inventory management with backorder and deterioration under controllable carbon emissions. *J Clean Prod.* 2021;279:123699.

doi: 10.1016/j.jclepro.2020.123699

56. Gudavalli S, Ayyagari A. Inventory forecasting models using big data technologies. *Int Res J Mod Eng Technol Sci.* 2022;4(2):1654-1671. https://ssrn.com/abstract=5068357

57. Elbegzaya B, Tsedendorj S, Batbold B, Orkhontuul B. Application of strategic stockpile for ore quality stabilization at Erdenet open pit mine. *Mong Geosci.* 2025;30(60):46-54.

doi: 10.5564/mgs.v30i60.3747

58. Singh DK. Streamline and Save: AI-Driven Cartridge Inventory Management and Optimization. *IJMRSET.* 2022;05(10).

doi: 10.15680/ijmrset.2022.0510002

59. Raja Santhi A, Muthuswamy P. Pandemic, war, natural calamities, and sustainability: Industry 4.0 technologies to overcome traditional and contemporary supply chain challenges. *Logistics.* 2022;6(4):81.

doi: 10.3390/logistics6040081

60. Ejjami R. Optimizing in-store logistics: How AI enhances inventory management and space utilization. *J Next-Gen Res 5.0.* 2024;1(1).

doi: 10.70792/jngr5.0.v1i1.10

61. Liu B. The Ripple Effect: Does Digital Transformation Spark Enterprises' Technological Innovation in Supply Chains? *Technol Soc.* 2025:103155.

doi: 10.1016/j.techsoc.2025.103155

62. Emon MM, Rahman KM, Ahmed M, et al. AI Enabled Industry 4.0 Practices for Enhancing Sustainability Performance: Evidence from Manufacturing Firms in an Emerging Economy. In: *2026 5th International Conference on Electrical, Computer & Telecommunication Engineering (ICECTE).* IEEE; 2026:1-6.

doi: 10.1109/ICECTE69292.2026.11429215

63. Wen CM, Ierapetritou M. Multi-Criteria Decision-Making and Multi-Objective Optimization of a Sustainable Bio-Based Isopropanol Supply Chain. *Comput Chem Eng.* 2025:109487.

doi: 10.1016/j.compchemeng.2025.109487

64. Jiang Z, Dan W, Yu-Fei C. New-generation AI-driven intelligent decision-making and inventory optimization in the full lifecycle of complex product manufacturing integrating LSTM and Q-learning. *Sci Rep.* 2026;16(1):11077.

doi: 10.1038/s41598-026-41629-6

65. Mwove RM, Kithandi CK. Effect of AI-Inventory Management on Supply Chain Performance of Large Supermarkets in Nairobi City County, Kenya. *Afr J Commer Stud.* 2026;7(1).

doi: 10.59413/ajocs/v7.i1.16

66. Wang T, Wang P, Sun Z. Supply Chain Digitalization and Corporate Carbon Emissions: A Quasi-Natural Experiment Based on Pilot Policies for Supply Chain Innovation and Application. *Sustainability.* 2026;18(4).

doi: 10.3390/su18041868

67. Peddi S, Valivarthi DT, Narla S, Kethu SS, Nataraja DR, Kurunthachalam A. Artificial Intelligence (AI) and Machine Learning in Supply Chain Management. In: *Advances in Computational Intelligence and Robotics.* IGI Global Scientific Publishing; 2026:31-72.

doi: 10.4018/979-8-3373-3648-0.ch002

68. Sarker IH. Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions. *SN Comput Sci.* 2021;2(6):1-20.

doi: 10.1007/s42979-021-00815-1

69. Su Y, Wang MC, Liu S. Automated machine learning algorithm using recurrent neural network to perform

long-term time series forecasting. *Comput Mater Contin.* 2024;78(3):3529-3549.

doi: 10.32604/cmc.2024.047189

70. Sharma A, Singh SP, Nunkoo R, Mahadeva R. A review of research on the role of emerging technologies in digital globalization. *Res Global.* 2026:100342.

doi: 10.1016/j.resglo.2026.100342

71. Meisheri H, Sultana NN, Baranwal M, et al. Scalable multi-product inventory control with lead time constraints using reinforcement learning. *Neural Comput Appl.* 2022;34(3):1735-1757.

doi: 10.1007/s00521-021-06129-w

72. Abu Zwaida T, Pham C, Beauregard Y. Optimization of inventory management to prevent drug shortages in the hospital supply chain. *Appl Sci.* 2021;11(6):2726.

doi: 10.3390/app11062726

73. De Moor BJ, Gijsbrechts J, Boute RN. Reward shaping to improve the performance of deep reinforcement learning in perishable inventory management. *Eur J Oper Res.* 2022;301(2):535-545.

doi: 10.1016/j.ejor.2021.10.045

74. Boute RN, Gijsbrechts J, Van Jaarsveld W, Vanvuchelen N. Deep reinforcement learning for inventory control: A roadmap. *Eur J Oper Res.* 2022;298(2):401-412.

doi: 10.1016/j.ejor.2021.07.016

75. Rammo JP, Bouhadjer Y, Rouvelle CR, et al. Manufacturing change management–an AI-and data-enhanced Delphi study and algorithm to support change process tailoring and the identification of suitable methods and digital tools. *Prod Eng.* 2026;20(2):43.

doi: 10.1007/s11740-026-01422-w

76. Ahmed M, Ahmed MJ. Sustainable Industrial Operations Through IoT-Generated Big Data Insights. In: *Advances in Computational Intelligence and Robotics.* IGI Global Scientific Publishing; 2026:37-82.

doi: 10.4018/979-8-2600-0216-2.ch002

77. Huda SS, Akhtar A, Ahmed E, Hoq KM, Islam MN. Artificial intelligence in agriculture across south Asia: Technology adoption, improvements, and sustainability outcomes. *Sustain Futures.* 2026;11:101620.

doi: 10.1016/j.sftr.2025.101620

78. Zhou Y, He W, Tang H, Liu Y. From complexity to strength: how digital transformation and innovation enhances agricultural supply chain resilience? *J Innov Knowl.* 2026;15:100985.

doi: 10.1016/j.jik.2026.100985

79. Demey YT, Wolff M. SIMISS: a model-based searching strategy for inventory management systems. *IEEE Internet Things J.* 2016;4(1):172-182.

doi: 10.1109/JIOT.2016.2638023

80. Tabernik D, Skočaj D. Deep learning for large-scale traffic-sign detection and recognition. *IEEE Trans Intell Transp Syst.* 2019;21(4):1427-1440.

doi: 10.1109/TITS.2019.2913588

81. Merrad Y, Habaebi MH, Islam MR, Gunawan TS. A Real-time Mobile Notification System for Inventory Stock out Detection using SIFT and RANSAC. *Int J Interact Mob Technol.* 2020;14(5).

doi: 10.3991/ijim.v14i05.13315

82. Kalinov I, Petrovsky A, Ilin V, et al. Warevision: Cnn barcode detection-based uav trajectory optimization for autonomous warehouse stocktaking. *IEEE Robot Autom Lett.* 2020;5(4):6647-6653.

doi: 10.1109/LRA.2020.3010733

83. Mukherjee AK, Gallo M, Roy SK, He S, Weber GW. Machine learning-driven demand forecasting for multi-objective sustainable inventory control under uncertainty. *Int J Manag Sci Eng Manag.* Published online April 25, 2026:1-18.

doi: 10.1080/17509653.2026.2658608

84. Alomar MA. Performance optimization of industrial supply chain using artificial intelligence. *Comput Intell Neurosci.* 2022;2022(1):9306265.

doi: 10.1155/2022/9306265

85. Arestov D. Management accounting tools for inventory in the modern business environment. *ChSTU Repos.* 2024;25(2):81-95.

doi: 10.24025/2306-4420.73(2).2024.321518

86. Nweje U, Taiwo M. Leveraging Artificial Intelligence for predictive supply chain management, focus on how AI-driven tools are revolutionizing demand forecasting and inventory optimization. *Int J Sci Res Arch.* 2025;14(1):230-250.

doi: 10.30574/ijsra.2025.14.1.0027

87. Singh N, Adhikari D. AI in inventory management: Applications, challenges, and opportunities. *Int J Res Appl Sci Eng Technol.* 2023;11(11):2049-2053.

doi: 10.22214/ijraset.2023.57010

88. Mhaskey SV. Integration of artificial intelligence (AI) in enterprise resource planning (ERP) systems: Opportunities, challenges, and implications. *Int J Comput Eng Res Trends.* 2024;11(12):1-9.

doi: 10.22362/ijcert/2024/v11/i12/v11i1201

89. Kumar V, Goyal S. AI-driven forecasting and optimization for inventory control in manufacturing supply chain. *Adv Consum Res.* 2025;2(4):5085-5091.

90. Li J, Song H, Ma Y. The mechanism and impact of

digital transformation on supply chain resilience in the manufacturing industry. *Sci Rep.* 2026.

doi: 10.1038/s41598-026-38930-9

91. Ahmed M, Amareen OSA, Arafat Y. Harnessing Big Data for Reverse Logistics and Waste Management. In: *Enhancing Sustainability in Global Supply Chains with Big Data Analytics*. IGI Global Scientific Publishing; 2026:175-210.

    doi: 10.4018/979-8-3373-6896-2.ch006

92. Abdulhussain R, Muhamad H, Fiza T, et al. The integration of artificial intelligence through quality by digital design for sustainable pharmaceutical manufacturing. *Int J Pharm.* 2026:126682.

    doi: 10.1016/j.ijpharm.2026.126682

93. Scarton G, Benini N, Formentini M. AI-enhanced demand forecasting: an organizational information processing view. *Int J Phys Distrib Logist Manag.* 2026;56(4):485-508.

    doi: 10.1108/IJPDLM-01-2025-0022

94. Phan VT, Nguyen DT, Nguyen NXQ, Huynh XH. Application of Statistical and Machine Learning Models in Vietnam's Energy Consumption Demand Forecasting. *Appl Math.* 2026;6(5):71.

    doi: 10.3390/appliedmath6050071

95. Emon MMH, Chowdhury MostSA. AI and IoT-Powered Smart Logistics. In: *Emerging Trends in Smart Logistics Technologies*. IGI Global Scientific Publishing; 2025:45-72.

    doi: 10.4018/979-8-3373-2434-0.ch002

96. Haggag M, Abdelhady K, Guirguis M, Saudy M, Dakhakhni WE. Machine learning long-term electricity demand forecasting system for strategic energy investments. *Sci Rep.* 2026;16(1).

    doi: 10.1038/s41598-026-45123-x

97. Fernando A, Siriwardana C, Law D, Gunasekara C, Zhang K, Gamage K. A scoping review and analysis of green construction research: a machine learning aided approach. *Smart Sustain Built Environ.* 2026;15(1):62-91.

    doi: 10.1108/SASBE-08-2023-0201

98. Jwakle DJ, Bolaji FU, Aruwa SA. Effect of AI and machine learning-driven demand forecasting on retail performance of Jumia Nigeria. *GAS J Arts Humanit Soc Sci.* 2026;4(1):113-134.

    doi: 10.5281/zenodo.18323624

99. Kręt-Grześkowiak A, Baborska-Narożny M. Investigation of stakeholder perspectives and mobile app potential to mainstream CE strategies in single family housing sector. *Environ Impact Assess Rev.* 2026;117:108229.

    doi: 10.1016/j.eiar.2025.108229

100. Li B, Xiong X. Digital government development, supply chain finance, and the business environment for enterprises. *Finance Res Lett.* 2026;90:109138.

    doi: 10.1016/j.frl.2025.109138

101. Emon MMH. Ethical Intelligence in Motion. In: *Advances in Computational Intelligence and Robotics*. IGI Global Scientific Publishing; 2025:207-240.

    doi: 10.4018/979-8-3373-3104-1.ch008

102. Gong B, Xu S, Xu Z, Cheng C. Digital supply chain finance, government-business relationship and ESG performance: Evidence from the ZARFS platform in China. *J Int Account Audit Tax.* 2026;60:100754.

    doi: 10.1016/j.intaccaudtax.2026.100754

103. Zhang X, Liu L, Zhang S. Empowering effect of big data policies on enterprise technological innovation: Evidence from China. *Technol Soc.* 2026;85:103224.

    doi: 10.1016/j.techsoc.2026.103224

104. Shen L, Shi Q, Panda D, Parida V. Digital technology diffusion through supply chain orchestration. *Technol Forecast Soc Change.* 2026;225:124554.

    doi: 10.1016/j.techfore.2026.124554