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Artificial Intelligence in Demand Forecasting for Textile MSMEs Supply Chains in Indonesia: A Systematic Literature Review

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ABSTRACT

The Indonesian textile MSMEs industry faces significant challenges in demand forecasting due to high market volatility and limited resources. This study aims to examine the application of Artificial Intelligence (AI) in demand forecasting in the textile MSMEs supply chain through a Systematic Literature Review (SLR) approach. The review process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. A total of 347 articles were identified in the initial stage, which were then narrowed down to 286 articles after removing duplicates. Furthermore, 78 articles passed the title and abstract screening stage, and 25 articles met the full-text assessment criteria for analysis. The analysis was conducted through a thematic synthesis of AI methods, implementation success factors, and challenges faced. The study results indicate that AI-based forecasting methods, specifically Long Short-Term Memory (LSTM), Random Forest, and Neural Network, generally demonstrate higher accuracy levels than traditional forecasting methods based on the reviewed studies. Furthermore, 15 key factors for successful AI implementation were identified, encompassing four main dimensions: technology, organization, data, and environment. The study also found that the most frequently reported key obstacles to AI implementation in MSMEs include limited data infrastructure, lack of technical expertise, and limited financial resources. This research provides a conceptual framework and practical application of AI in demand forecasting in Indonesian textile MSMEs and offers recommendations for further research related to organizational readiness, data governance, and AI implementation strategies.

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INTRODUCTION

The textile industry is one of the strategic sectors of the Indonesian economy, making a significant contribution to job creation and foreign exchange earnings. According to data from the Ministry of Industry, more than 90% of businesses in Indonesia's textile and textile products (TPT) sector are Micro, Small, and Medium Enterprises MSMEs, making this segment the backbone of the national textile industry (Central Statistics Agency, 2023). The TPT industry itself encompasses the entire process of processing fibers into yarn, fabric, and finished textile products used for clothing and household needs, characterized by high product variety, relatively short product cycles, and dynamic demand patterns that are heavily influenced by market trends (Thomassey, 2010). In this context, textile MSMEs face serious challenges in supply chain management, particularly in the area of demand forecasting. Rapid changes in fashion trends, seasonal variations, and shifting consumer preferences create a high degree of demand uncertainty, making forecasting accuracy a critical factor for business sustainability. Inaccuracies in demand forecasting directly impact inventory management inefficiencies, suboptimal production planning, and inflated operational costs, which cumulatively threaten the competitiveness of MSMEs amid increasingly intense competitive pressures.

Conventional demand forecasting methods, such as moving averages and exponential smoothing, have proven to have limitations in capturing the complex patterns and nonlinear relationships that characterize textile market demand (Thomassey, 2010) This situation has driven the need for more adaptive and accurate approaches, particularly in light of the rapid advancements in artificial intelligence (AI) and machine learning.

Recent studies show that AI-based models are capable of processing large amounts of historical data and adapting to changing market conditions more effectively than traditional methods (Abbasimehr et al., 2020) On a large industrial scale, companies such as H&M have implemented AI-based forecasting systems to predict product demand and significantly optimize inventory management (Guan et al., 2025) On a smaller scale, a case study at CAHAYA SANDANG in Bandung demonstrates that the Long Short-Term Memory (LSTM) method can achieve higher forecasting accuracy than conventional approaches (Setiawan & Suryadi, 2024) However, this research is isolated and does not yet represent the broader conditions of Indonesia's textile MSMEs.

Literature mapping using bibliometric analysis with the VOSviewer tool (Figure 1.) confirms that research in this field remains concentrated in specific thematic clusters. The keyword co-occurrence map reveals the formation of four main clusters: (1) the red cluster linking artificial intelligence, supply chain management, and big data analytics; (2) the green cluster linking deep learning, predictive analytics, and business value; (3) the yellow cluster encompassing supply chain and supply chain activities; and (4) the blue cluster linking demand forecasting, demand, and retailers. A key finding from this map is the weak connection between the demand forecasting cluster (blue) and the AI and supply chain management clusters (red), indicating that the integration of AI technology and demand forecasting within the supply chain context particularly for MSMEs has not yet been comprehensively explored in the existing literature.

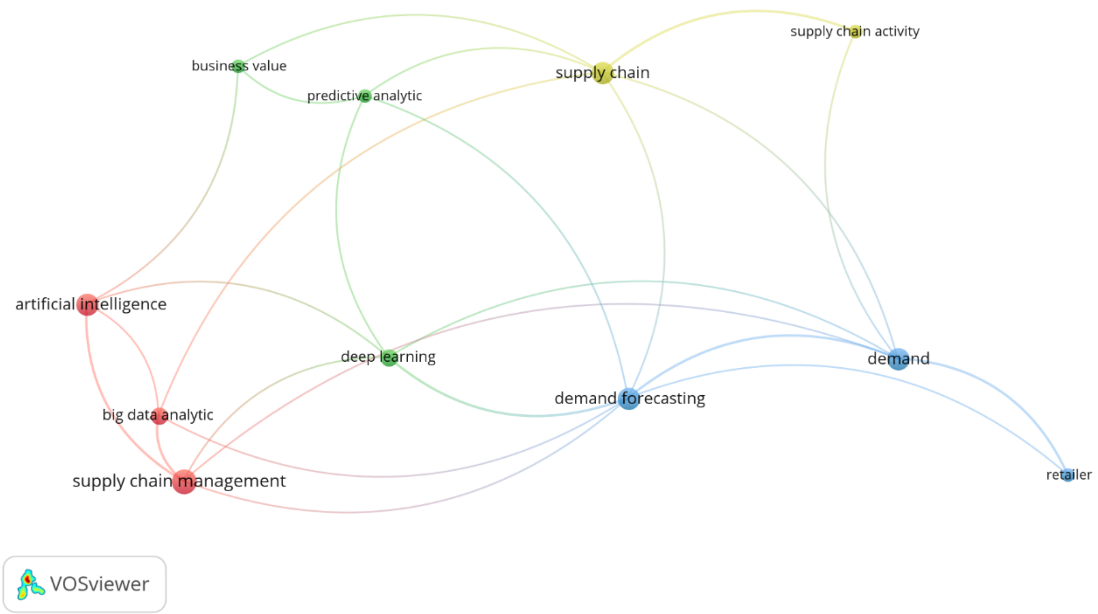

Figure 1. VOSviewer analysis results

This research gap is increasingly apparent from several interrelated perspectives. Technically, there has been no systematic comparison between traditional models and modern machine learning- or deep learning-based models such as XGBoost, LSTM, ARIMA, or hybrid approaches tested on local textile demand data with its nonlinear and complex characteristics. Existing models also rarely integrate exogenous variables relevant to the Indonesian context, such as seasonal demand patterns during religious holidays Eid al-Fitr, Christmas, domestic fast fashion trends, or social media signals that increasingly influence consumer behavior. Practically, most of the literature stops at the simulation or proof-of-concept stage without examining the real-world adoption challenges faced by MSMEs, ranging from limited structured historical data, low digital literacy, to implementation cost constraints. Appropriate approaches for limited data regimes, such as transfer learning and few-shot forecasting, are also rarely explored in this context.

At a more strategic level, demand forecasting is still often treated as a standalone function, separate from end-to-end production decisions, raw material management, and logistics. Furthermore, the aspect of explainability that is, the model's ability to generate predictions that can be understood by MSMEs stakeholders without a technical background is rarely discussed in the existing literature. This situation indicates that research specifically examining the application of AI in demand forecasting within the textile MSMEs supply chain in Indonesia taking into account the industry's unique characteristics, resource constraints, and the practical needs of business operators represents an urgent, unmet need.

The urgency of this research stems from the strategic role of MSMEs as the primary drivers of the national textile industry. Improving forecasting accuracy through AI will have a direct impact on production efficiency, the reduction of deadstock, and the business sustainability of MSMEs amid increasingly intense market competition and rapidly changing consumer preferences. Through this digital transformation, textile MSMEs can adopt more flexible and responsive supply chain management methods to enter the Industry 4.0 era. Therefore, this Systematic Literature Review was conducted to synthesize existing global and local literature, identify the most applicable AI models, and formulate a practical demand forecasting implementation framework that aligns with the resource constraints of the textile MSMEs supply chain in Indonesia.

METHOD

Systematic Literature Review

This study uses a Systematic Literature Review (SLR) method to synthesize empirical evidence and previous research on the implementation of Artificial Intelligence (AI) in demand forecasting in textile Micro, Small, and Medium Enterprises (MSMEs) supply chain management. The SLR protocol was conducted systematically in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement to ensure transparency, validity, and replicability.

Search Strategy and Protocol

A literature search was conducted in four high-impact academic databases: Scopus, ScienceDirect, IEEE Xplore, and Google Scholar. The search protocol was limited to peer-reviewed articles published within a 12-year period (2014–2025) to capture the latest advances in deep learning algorithms. To ensure comprehensive coverage, a formal Boolean search string was formulated and applied to the title, abstract, and keyword fields in each database: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "LSTM") AND ("demand forecasting" OR "sales forecasting" OR "inventory prediction") AND ("supply chain management" OR "SCM") AND ("MSMEs" OR "textile industry"). This string was adapted to the specific syntax requirements of each database (e.g., field-tag operators in Scopus and IEEE Xplore) while maintaining the same Boolean logic to ensure the consistency and replicability of the search process.

Inclusion and Exclusion Criteria

To filter the retrieved literature objectively, strict inclusion and exclusion criteria were established prior to the screening process, as outlined in Table 1.

Table 1. Inclusion and Exclusion Criteria

Criteria	Inclusion Criteria	Exclusion Criteria
Document Type	Peer-reviewed journal articles and indexed conference proceedings.	Book chapters, dissertations, theses, patents, editorials, and non-peer-reviewed publications.
Time Period	Published between 2014 and 2025	Published before 2014 or after 2025.
Language	Written entirely in English	Non-English articles.
Research Focus	Focuses on AI/ML/DL models for demand forecasting within supply chain or SME contexts	Focuses on general AI applications outside forecasting or large corporate logistics with infinite resources.

Criteria	Inclusion Criteria	Exclusion Criteria
Methodology	Provides empirical data, experimental results, simulation outputs, or clear framework validations	Conceptual frameworks without empirical data, reviews lacking methodology, and duplicates.
Accessibility	Full-text available	Abstract-only access or restricted access.

Study Selection and PRISMA Flow

The multi-stage selection process followed the PRISMA protocol to minimize bias. Initially, the comprehensive database search yielded 347 articles. After removing duplicate records, 61 duplicate entries were discarded, leaving 286 unique articles for the next phase.In the screening phase, titles and abstracts were independently evaluated based on the criteria in Table 1, which excluded 208 irrelevant studies, leaving 78 articles for full-text assessment. Finally, a rigorous full-text review was conducted, resulting in 25 final articles that met all qualitative and empirical benchmarks for data synthesis. The complete screening architecture is visualized in Figure 2.

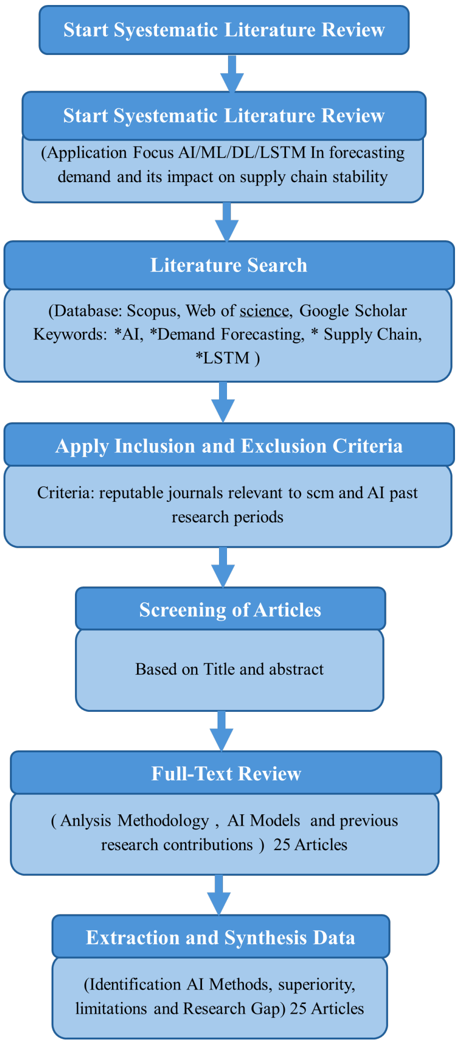

Figure 2. PRISMA Framework (AI in Supply Chain Demand Forecasting)

Quality Assessment (QA)

To secure analytical validity and address replication robustness, the 78 shortlisted full-text articles underwent a Quality Assessment (QA) protocol using a 3-point scoring system (0 = No, 0.5 = Partially, 1 = Yes) based on three critical checklist questions:

QA1 : Is the AI/ML/DL architecture and dataset characteristics explicitly described ?
QA2 : Does the study provide clear performance metrics (e.g., MAPE, RMSE, MAE) to evaluate forecasting accuracy?
QA3 : Are the operational barriers or supply chain implications for MSMEs critically discussed ?

Only articles scoring ≥ 2.0 were retained, ensuring that the final 25 selected studies possessed high methodological rigor.

Data Analysis and Synthesis Method

The data extracted from the final 25 articles were analyzed using four distinct, complementary analytical approaches to ensure a deep and critical synthesis:

Content Analysis: Extracting and tabulating explicit structural metadata from the selected studies, including specific AI methods (e.g., LSTM, XGBoost, ARIMA), dataset sizes, performance metrics, industry sectors, and company scales.

Thematic Analysis: Classifying qualitative insights into four interconnected core themes: technological capabilities of AI, organizational readiness factors, data quality/pipeline constraints, and downstream supply chain performance impacts.

Comparative Analysis: Critically cross-examining the operational trade-offs of modern deep learning models against traditional forecasting benchmarks in terms of algorithmic complexity, computational resource demands, and viability for small-data MSMEs regimes.

Framework Synthesis: Integrating the empirical findings from the previous three steps to construct a novel, phased implementation framework tailored specifically to the structural constraints and requirements of textile MSMEs in Indonesia.

RESULT AND DISCUSSION

Publication distribution showed: 2014–2016 had 4 articles (16%), 2017–2019 had 9 articles (36%), and 2020–2025 had 12 articles (48%). This increasing trend reflects the acceleration of AI adoption in supply chain management, indicating that AI-based demand forecasting has shifted from an emerging research topic into a strategic approach for improving supply chain responsiveness. The increasing number of studies after 2020 is strongly associated with the acceleration of digital transformation and the increasing availability of machine learning techniques for processing complex demand patterns. However, despite the growth of AI forecasting research, only a limited number of studies specifically address MSME contexts, where data availability, financial capability, and technological readiness remain major adoption constraints. Industrial context distribution: retail and e-commerce (32%), manufacturing (28%), fashion and textiles (20%), FMCG (12%), and multiple industries (8%). AI methodology distribution: deep learning (44%), traditional machine learning (24%), hybrid/ensemble methods (20%), and neural networks (12%). The dominance of deep learning approaches indicates a growing research interest in models capable of capturing nonlinear relationships and temporal dependencies in demand data. In particular, LSTM-based models are frequently adopted because textile and fashion demand characteristics are highly dynamic, influenced by seasonality, product life cycles, and changing consumer preferences. Nevertheless, the higher forecasting capability of deep learning does not automatically imply better suitability for MSMEs. Deep learning models generally require larger historical datasets, higher computational resources, and specialized technical expertise. Therefore, the selection of forecasting methods should consider the balance between prediction accuracy and organizational capability.

AI Technology Framework

Artificial intelligence (AI) is a branch of computer science focused on developing systems that mimic human cognitive abilities such as learning, reasoning, pattern recognition, and autonomous decision-making (Mikalef & Gupta, 2021) Based on the reviewed studies, AI application in supply chain demand forecasting consists of several interconnected components, including machine learning, deep learning, data analytics, and decision-support mechanisms. These components contribute not only to improving forecasting accuracy but also to supporting inventory planning, production scheduling, and supply chain risk management. The findings indicate that AI adoption in demand forecasting should be considered as a capability-building process rather than only a technology implementation. The effectiveness of AI depends on the integration between forecasting algorithms, data availability, organizational capability, and supply chain decision processes. This explains why some advanced models such as LSTM achieve high accuracy but remain challenging for MSMEs due to limited data infrastructure and technical expertise. In supply chain management (SCM), AI plays an important role in demand forecasting, inventory management, logistics optimization, and risk mitigation. (Makridakis et al., 2018) show that AI methods provide 20–40% accuracy improvement over conventional statistical methods. Comprehensively, the technology framework and main components of AI applied in supporting decisions and supply chain management are illustrated in Figure 3.

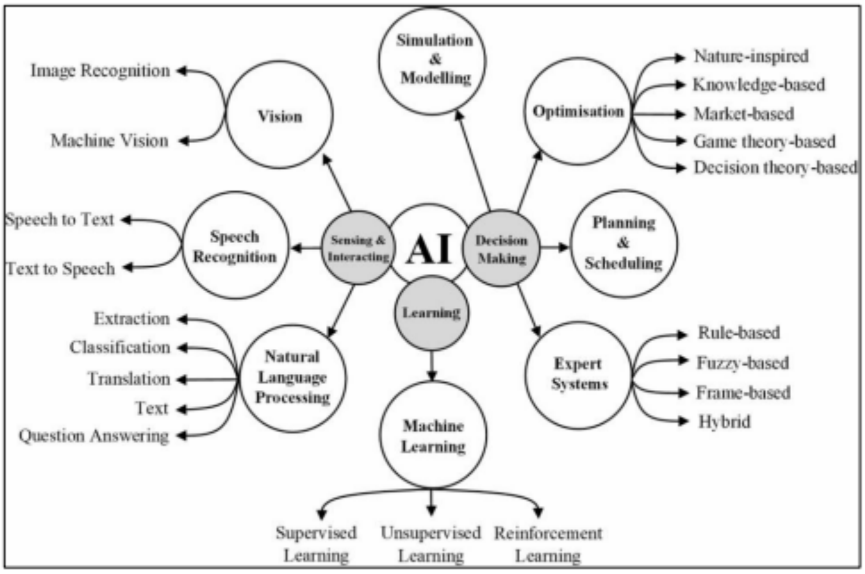

Figure 3. Application and Component Ai (Pournader et al, 2021)

As part of the Learning component in Figure 3, Machine Learning (ML) focuses on algorithms that learn from historical data without explicit programming (Makridakis,2018) Deep Learning (DL) extends traditional ANN with multiple hidden layers for hierarchical feature extraction (Abbasimehr et al., 2020). Long Short-Term Memory (LSTM) is an RNN variant overcoming gradient vanishing problems through input, forget, and output gates consistently achieving the highest forecasting accuracy for sequential demand data (Hochreiter, S., & Schmidhuber, 1997). Meanwhile, the Sensing & Interacting section in Figure 3 is represented by Natural Language Processing (NLP) extracts features from unstructured data such as reviews and social media, improving prediction accuracy in trend-sensitive markets (Boone et al., 2019).

Table 2. Categorization of AI Implementation Factors in Demand Forecast

No.	Internal Factors (Operational)	Strategic Factors (External)
1.	Quality Of Algorithms	Technology Vendor Support
2.	Computing Infrastructure	Regulation and Policy
3.	Top Management Support	Competitive Pressure
4.	HR Technical Expertise	Industry Ecosystem
5.	Historical Data Volume	Government Support
6.	Data Quality	Supply Chain Collaboration
7.	Data-Driven Culture	Technology Trend

No.	Internal Factors (Operational)	Strategic Factors (External)
8.	Financial Resources	Market Conditions
9.	Change Management	Customer Expectations
10.	System Integration	Industry Standard

Source: Systematic Literature Review Analysis (2024)

Comparative Analysis of AI Methods

Based on the reviewed studies, deep learning methods, particularly LSTM, frequently demonstrated superior forecasting performance compared with conventional forecasting approaches. Several studies reported significant improvements; however, the magnitude of improvement varied depending on dataset characteristics, forecasting horizon, evaluation metrics, and industry context. Although LSTM provides strong capability in modelling sequential demand patterns, its implementation in textile MSMEs requires careful consideration. Many MSMEs operate with limited historical sales data and lack advanced analytical capabilities, making simpler machine learning methods such as Random Forest or hybrid lightweight models potentially more practical during early adoption stages. LSTM is very effective for capturing temporal dependencies in time-series data, but requires a minimum of 2–3 years of historical data, specialized expertise, and significant computational resources, making it less suitable for resource-constrained MSMEs. Traditional machine learning methods such as Random Forest and SVM show a 15–22% improvement, are easier to implement, have better interpretability, and lower resource requirements making them more suitable for MSMEs. Hybrid or ensemble methods such as SARIMA-LSTM demonstrated excellent performance with 32% improvement but are highly complex, requiring multiple expertise.

Table 3. Comparison Results of AI Methods in Demand Forecasting studied in the article

No.	Method	Journal	Percentage
1.	LSTM	9	28-35%
2.	Random Forest	5	22%
3.	Ensemble Methods	3	18-25%
4.	Neural Networks	2	30%
5.	Hybrid SARIMA-LSTM	2	32%
6.	SVM	1	15%
7.	Deep Learning	1	24%
8.	Big Data Analytics	2	15-20%

Source: Comparative Analysis of Various Studies (2024)

Key Success Factors

Analysis of 25 articles identified 15 key success factors categorized into four dimensions. The identified success factors demonstrate that AI implementation success depends on the interaction between technological capability and organizational readiness. Algorithm quality alone is insufficient if MSMEs lack reliable historical data, digital infrastructure, and skilled human resources. This finding supports the Technology–Organization–Environment (TOE) perspective, where technology adoption is influenced by internal organizational capability and external environmental support. Therefore, AI implementation strategies for textile MSMEs should prioritize capability development before adopting advanced forecasting models. The technology dimension explains 32% of the variance algorithm quality appeared in 92% of the reviewed studies as the most critical factor; computing infrastructure is the primary constraint for MSMEs in 72% of studies, with cloud-based solutions as a potential enabler. The organization dimension explains 36% of variance top management support is a prerequisite in 84% of studies; HR technical expertise is the primary bottleneck in 80% of studies; data-driven culture development is needed in 68% of studies. The data dimension explains 26% of variance data volume and quality underpin all studies; multi-source integration in 64% of studies significantly improved accuracy; data cleaning takes 60–70% of total project time. The environmental dimension explains 6% of variance, with vendor/ecosystem support facilitating adoption. Taken together, these four dimensions indicate that successful AI adoption in textile MSMEs requires a balanced investment across technology, organization, data, and environmental support, rather than focusing solely on algorithmic sophistication.

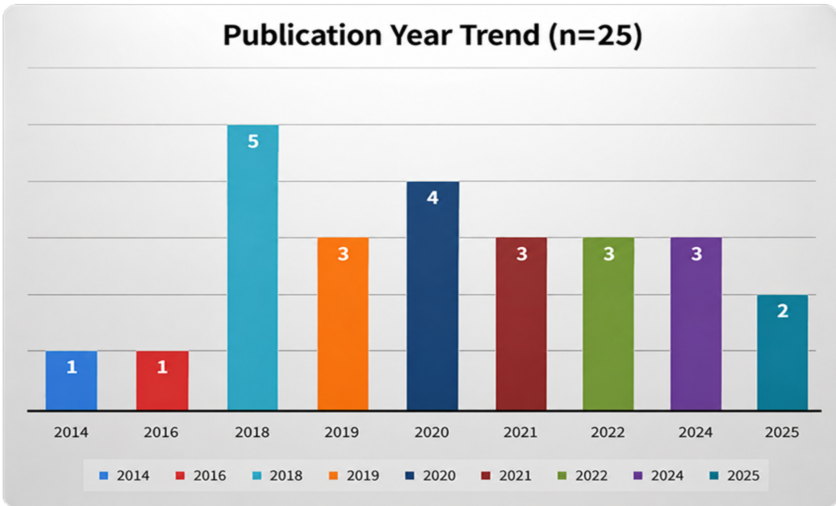

Figure 4. Publication Year Trend (n=25)

Figure 4 illustrates the distribution of the 25 reviewed articles published between 2014 and 2025. The number of publications increased noticeably from 2018 onward, reaching its highest level in 2018 with five articles. Publication activity remained relatively stable thereafter, with four articles published in 2020 and two to three articles annually during 2021–2025. This distribution indicates sustained academic interest in the application of artificial intelligence for demand forecasting across supply chain and textile-related contexts.

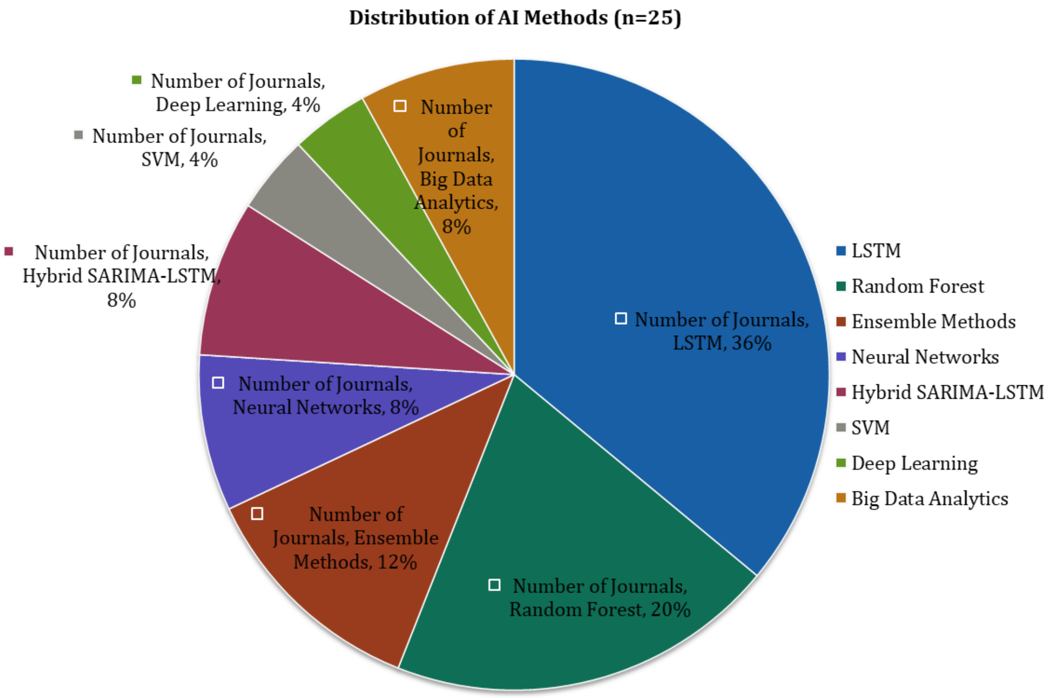

Figure 5. Distribution Methods (n=25)

Figure 5 illustrates the distribution of AI methods applied in demand forecasting across the 25 reviewed articles. LSTM emerged as the most frequently used method, appearing in 9 articles (36%), demonstrating its superiority in capturing temporal patterns and long-term dependencies in time-series demand data. Random Forest followed with 5 articles (20%), valued for its robustness and interpretability. Ensemble Methods were identified in 3 articles (12%), while Neural Networks and Hybrid SARIMA-LSTM each appeared in 2 articles (8%), reflecting interest in combining statistical and deep learning approaches. SVM and Deep Learning each accounted for 4%, and Big Data Analytics appeared in 2 articles (8%). These findings indicate that deep learning-based methods, particularly LSTM, dominate recent demand forecasting research, suggesting their strong potential for adoption in textile MSMEs supply chains.

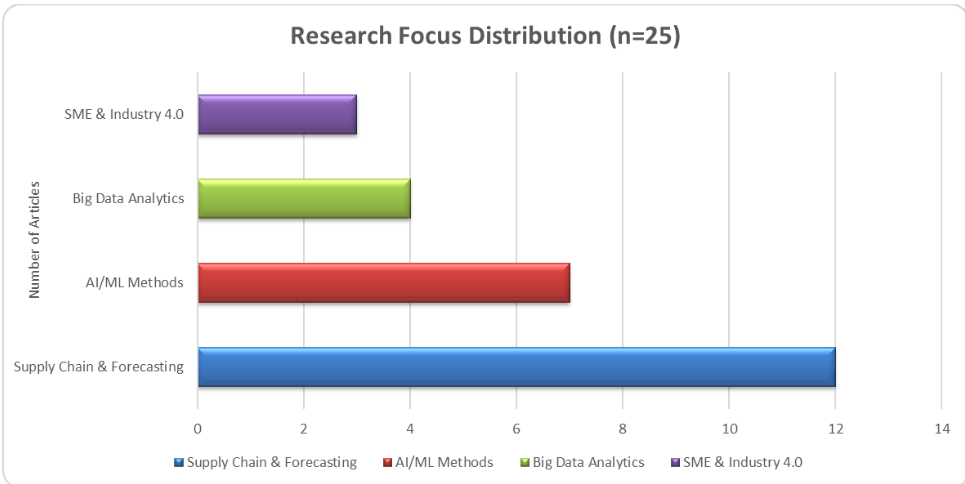

Figure 6. Research Focus Distribution (n=25)

Figure 6 presents the distribution of research focus across the 25 reviewed articles. Supply Chain & Forecasting constituted the largest category with 12 articles, reflecting the central role of demand forecasting within supply chain management research. AI/ML Methods followed with 7 articles, focusing on algorithm development and performance evaluation. Big Data Analytics appeared in 4 articles, highlighting the growing importance of large-scale data processing in forecasting accuracy. MSMEs & Industry 4.0 was addressed in 3 articles, indicating an emerging but still limited body of research specifically targeting small and medium enterprises. These findings suggest that while supply chain forecasting is well-studied, research focused on MSMEs contexts remains underexplored, reinforcing the need for studies specifically addressing the challenges faced by textile MSMEs in Indonesia.

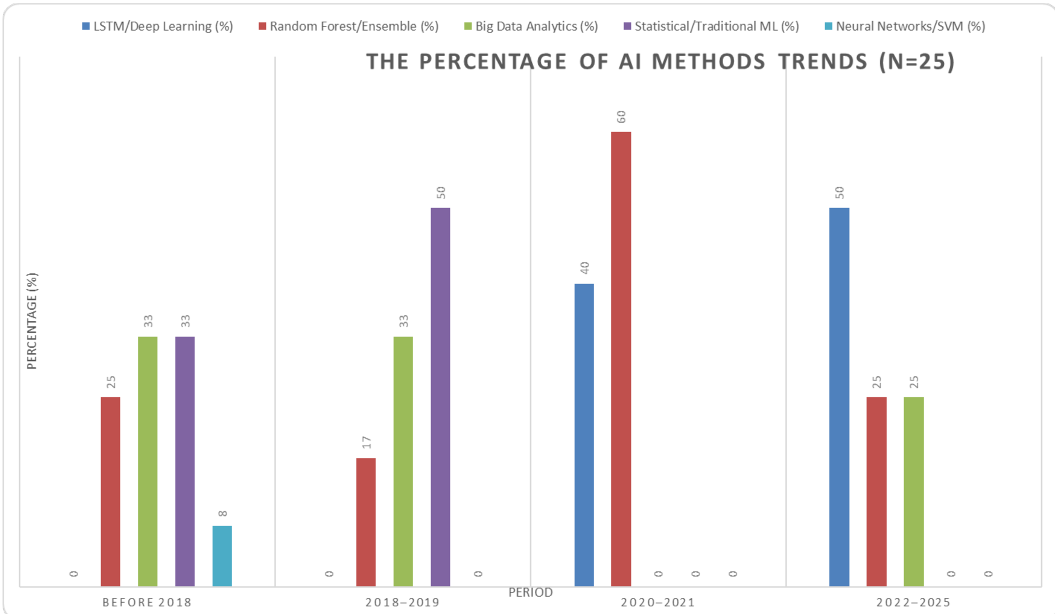

Figure 7. The Percentage Of AI Methods Trends (n=25)

Figure 7 illustrates the trends in AI methods usage across four publication periods. Prior to 2018, Statistical/Traditional ML methods dominated, reflecting the early reliance on conventional forecasting approaches. In the 2018–2019 period, Statistical/Traditional ML remained prominent while Random Forest/Ensemble methods began to emerge, indicating a transitional phase toward more advanced machine learning techniques. A significant shift occurred in 2020–2021, where LSTM/Deep Learning and Random Forest/Ensemble methods rose sharply, collectively accounting for the majority of studies, demonstrating the rapid adoption of deep learning in demand forecasting research. From 2022 to 2025, LSTM/Deep Learning continued to dominate, consolidating its position as the leading method, while Big Data Analytics maintained a steady presence. Overall, these trends confirm a clear evolution from traditional statistical methods toward deep learning approaches, with LSTM emerging as the preferred method for demand forecasting in supply chain contexts.

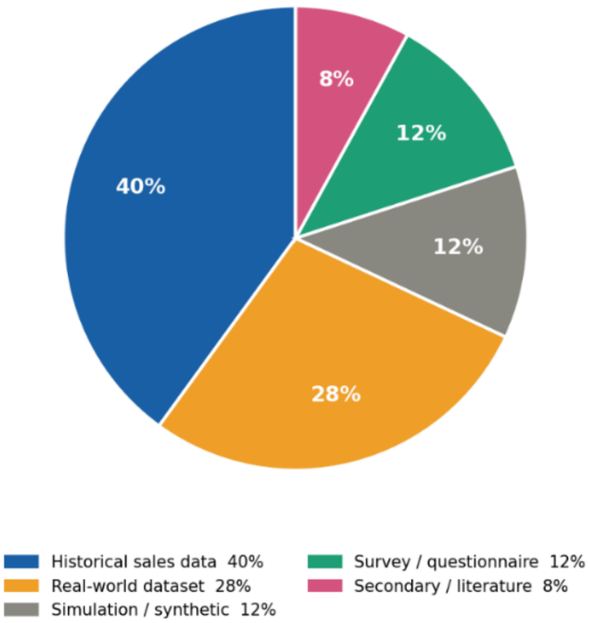

Figure 8. The percentage of data collection tools trends (n=25)

The data sources used in the reviewed articles varied according to the research objectives and context. As shown in Figure 8, historical sales data was the most frequently used data source, appearing in 10 articles (40%), indicating that most AI-based demand forecasting studies rely on actual transactional records from retail or manufacturing companies. Real-world datasets from specific companies or industries were utilized in 7 articles (28%), reflecting the growing trend of applying AI methods to authentic operational data. Simulation and synthetic data were used in 3 articles (12%), typically in studies that aimed to test algorithm performance under controlled conditions. Survey and questionnaire-based data collection was also found in 3 articles (12%), particularly in studies examining organizational readiness and barriers to AI adoption in SMEs. Finally, 2 articles (8%) relied on secondary data or existing literature to support conceptual and framework-based analyses. These findings suggest that empirical data-driven approaches dominate AI demand forecasting research, which underscores the importance of data availability as a key success factor for AI implementation in textile MSMEs in Indonesia.

Implementation Barriers

The main barriers to AI implementation in textile MSMEs are grouped into four categories: (1) Technological barriers (35% of total barriers) IT infrastructure limitations (68% of studies), algorithm complexity (56%), and integration with legacy systems (52%); (2) Organizational barriers (42%) lack of technical expertise (72%, highest barrier), limited financial resources (64%), and resistance to change (58%); (3) Data barriers (18%) poor data quality (60%), insufficient data volume (52%), and data silos (44%); (4) Environmental barriers (5%) lack of ecosystem support (32%) and regulatory uncertainty (24%). The findings reveal that organizational barriers represent the most significant challenge, particularly limited technical expertise and financial resources. This indicates that the primary difficulty in AI adoption is not only related to algorithm availability but also the ability of MSMEs to operate, maintain, and interpret AI-based forecasting systems. Therefore, future implementation strategies should emphasize gradual adoption, beginning with simple forecasting solutions before progressing toward advanced deep learning models.

Impact on Supply Chain Performance

AI implementation showed significant positive impact across all supply chain dimensions. The positive impact identified across supply chain dimensions suggests that AI-based forecasting contributes beyond improving prediction accuracy. Accurate demand forecasting enables better inventory decisions, reduces uncertainty in production planning, and improves responsiveness toward market changes. However, these benefits are highly dependent on data quality and implementation capability. Without proper data governance and operational integration, AI systems may fail to generate sustainable improvements despite high model accuracy. Inventory performance improved with 20–35% stockout reduction (Jaipuria & Mahapatra, 2014) and 15–30% inventory cost reduction (Fildes et al., 2022). Operational efficiency increased through a 25–40% improvement in production planning accuracy (Choi et al., 2018), 15–22% higher resource utilization (Dubey et al., 2020), and 12–20% lead time reduction (Wong et al., 2024). Customer service improved with a 15–20% service level increase (Khan et al., 2025). Financial performance improved with 8–15% revenue increases through better product availability (Boone et al., 2019) and 12–20% working capital optimization (Hofmann & Rutschmann, 2018).

Literature Review Summary

Table 4. Literature Review Results

No	Reference	Method	Research Focus	Type	Context	Key Findings
1.	(Abbasimehr et al., 2020)	LSTM	Optimization Demand Forecasting	Journal	Industrial	LSTM outperform 35%; Need 2-3 year data
2.	(Makridakis et al., 2018)	Hybrid ML	Comparative Forecasting	Journal	Multiple	Hybrid good; Improvement 18-25%
3.	(Agostini & Nosella, 2020)	-	Adoption Industri 4.0	Journal	Manufacturing MSMEs	Adoption 23-35%; not enough skills main obstacle
4.	(Wong et al., 2024)	Deep Learning	AI risk Management	Journal	Supply Chain MSMEs	AI upgrade agility 42%; Need readiness
5.	(Huber & Stuckenschmidt, 2020)	Random Forest	Retail Demand Forecasting	Journal	Retail	Accuracy goes up 28%; Handle seasonality good
6.	(Guan et al., 2025)	Integrated Deep Learning	Fast Fashion Demand Forecasting	Journal	Fashion Industry	Successfully improved the accuracy of demand prediction.
7.	(Kot et al., 2018)	-	Supply Chain SME	Journal	European MSMEs	Practice informal dominan; Adoption Low
8.	(Choi et al., 2018)	Big Data Analytics	Operation Management	Journal	Fashion	Big data supports real-time decision-making.

No	Reference	Method	Research Focus	Type	Context	Key Findings
9.	(Jaipuria & Mahapatra, 2014)	Neural Networks	Bullwhip Effect	Journal	Supply chain	ANN Reduce bullwhip 30%; Coordination good
10.	(Fildes et al., 2022)	Various ML	Retail Forecasting	Journal	Retail	Accuracy 10-20% = Cost saving 15-30%
11.	(Mikalef & Gupta, 2021)	-	AI Capability	Journal	Manufacturing	AI capability driving performance; Culture matters
12.	(Hofmann & Rutschmann, 2018)	Big Data Analytics	Big Data Framework	Journal	Supply chain	Quality data Critical; Integration challenging
13.	(Boone et al., 2019)	Consumer Anlytics	Demand Forecasting Using External Data	Journal	Retail	External data upgrade 15-20%
14.	(Dubey et al., 2020)	Big Data + AI	Operational Performance	Journal	Manufacturing	AI + orientation = performance
15.	(Kim et al., 2025)	Big Data	Supply Chain Analytics	Journal	Banking	Big data transformation SC; Skills gap significant
16.	(Gunasekaran et al., 2016)	Predictive Analytis	Supply Chain Predictive Analytics	Journal	Supply chain	Adoption grow; ROI positive
17.	(Raut et al., 2018)	MCDM	Technology Adoption	Journal	Agriculture	Cloud enable adoption; Cost-effective
18.	(Baryannis et al., 2019)	AI	Risk Management	Journal	Multiple	AI strengthens SCM risk management through better integration.
19.	(Ramdani et al., 2019)	-	Business Model	Journal	Entrepreneurship	Digital transformation requires strong organizational commitment.
20.	(Punia & Shankar, 2022)	SARIMA-LSTM	Time Series Forecasting	Journal	Operations	Hybrid SARIMA–LSTM improved time-series forecasting performance
21.	(Rožanec et al., 2021)	Time Series ML	Forecast Explanation	Journal	Manufacturing	Model explainability improves trust in AI- based forecasting
22.	(Setiawan & Suryadi, 2024)	LSTM	Fabric Demand Forecasting	Journal	Textile MSMEs (Indonesia)	LSTM outperformed conventional methods for

						textile demand forecasting
23.	(Terrada et al., 2022)	Deep Learning	Demand Forecasting for Supply Chain 4.0	Journal	Supply Chain Management 4.0	Deep learning improved demand forecasting in Supply Chain 4.0.
24.	(Pournader et al, 2021)	Artificial Intelligence	AI Applications in Supply Chain Management	Journal	Supply Chain Management	AI facilitates demand forecasting, inventory optimization, and logistics coordination within supply chain management
25.	(Anitha & Neelakandan, 2024)	Machine Learning	Demand Forecasting for New Fashion Products	Journal	Fashion Industry	Customer preference data improved fashion demand forecasting accuracy

Source: Systematic Analysis Review of Literature (2024)

Phased Implementation Framework

Based on the literature synthesis, a phased implementation framework is proposed for textile MSMEs. The proposed phased implementation framework contributes by translating AI adoption from a purely technical perspective into an operational roadmap suitable for resource-constrained textile MSMEs. Unlike previous studies that mainly focus on model performance evaluation, this framework emphasizes organizational readiness, gradual capability development, and alignment between forecasting technology and supply chain processes. The framework integrates the principles of TOE Framework, Resource-Based View, and Dynamic Capability Theory, suggesting that sustainable AI adoption requires not only technological availability but also the development of internal capabilities and continuous adaptation: (1) Foundation phase (3–6 months) data infrastructure development, data quality improvement, basic analytics capability building, and training programs;(2) Pilot implementation phase (6–12 months) starting with simple ML methods (Random Forest or Linear Regression), focusing on specific product categories, and measuring results; (3) Scale-up phase (12–24 months) expanding to more complex algorithms, integrating with broader supply chain systems, and continuous improvement; (4) Optimization phase (24+ months) deploying advanced AI methods such as LSTM, real-time forecasting, predictive analytics expansion, and competitive advantage development.

CONCLUSIONS

This systematic literature review of 25 journal articles (2014–2025) suggests that AI-driven demand forecasting has the potential to improve forecasting accuracy compared with conventional forecasting methods. Several reviewed studies reported accuracy improvements ranging from approximately 20% to 40%, depending on the dataset characteristics, forecasting horizon, evaluation metrics, and application context. Among the reviewed methods, LSTM was consistently reported as one of the highest-performing approaches for complex demand forecasting problems. For resource-constrained textile MSMEs, Random Forest and Support Vector Machine (SVM) appear to be practical alternatives because they require lower computational resources while still providing competitive forecasting performance compared with more complex deep learning models, offering a meaningful

15–22% accuracy gain with substantially lower computational and expertise requirements. The reviewed studies suggest that successful AI implementation may contribute to reductions in inventory costs (15–30%), improvements in service levels (10–25%), and gains in operational efficiency (20–35%), although the magnitude of these benefits depends on organizational readiness, data quality, and implementation context.

Realizing these benefits, nonetheless, remains conditional on addressing four intersecting barriers: technical expertise gaps (72% of studies), inadequate IT infrastructure (68%), limited capital (64%), and poor data quality (60%). The four-phase implementation framework proposed in this study spanning foundation, pilot, scale-up, and optimization is specifically designed to sequence these challenges in a financially and operationally feasible order for Indonesian textile MSMEs. Theoretically, this study advances AI adoption research by integrating the TOE Framework with the Resource-Based View and Dynamic Capabilities Theory, providing a unified lens for explaining why capability-building precedes technology deployment in MSME contexts. Practically, it offers the first context-specific roadmap consolidating 15 success factors and phased guidance for this sector. Future research should empirically validate the framework through longitudinal case studies, develop an AI readiness assessment instrument for textile MSMEs, and examine workforce and data privacy implications as adoption scales.

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AUTHOR CONTRIBUTION STATEMENT

IN conceived the study idea, designed the research framework, conducted the systematic literature review, performed the analysis, and wrote the original draft. G, JP, and MH provided academic supervision and guidance throughout the research process.

AI DISCLOSURE STATEMENT

The authors declare that this research was prepared, researched, written, and edited without the aid of artificial intelligence (AI) techniques.

REFERENCES

Abbasimehr, H., Shabani, M., & Yousefi, M. (2020). An optimized model using LSTM network for demand forecasting. *Computers and Industrial Engineering*, *143*(March). https://doi.org/10.1016/j.cie.2020.106435

Agostini, L., & Nosella, A. (2020). The adoption of Industry 4.0 technologies in SMEs: results of an international study. *Management Decision*, *58*(4), 625–643. https://doi.org/10.1108/MD-09-2018-0973

Anitha, S., & Neelakandan, R. (2024). A Demand Forecasting Model Leveraging Machine Learning to Decode Customer Preferences for New Fashion Products. *Complexity*, *2024*. https://doi.org/10.1155/2024/8425058

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. *International Journal of Production Research*, *57*(7), 2179–2202. https://doi.org/10.1080/00207543.2018.1530476

Boone, T., Ganeshan, R., Jain, A., & Sanders, N. R. (2019). Forecasting sales in the supply chain: Consumer analytics in the big data era. *International Journal of Forecasting*, *35*(1), 170–180. https://doi.org/10.1016/j.ijforecast.2018.09.003

Choi, T.-M., Wallace, S., & Wang, Y. (2018). Big Data Analytics in Operations Management. *Production and Operations Management*, *27*(10), 1868–1883. https://doi.org/10.1111/poms.12838

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics*, *226*, 107599. https://doi.org/10.1016/j.ijpe.2019.107599

Fildes, R., Ma, S., & Kolassa, S. (2022). Retail forecasting: Research and practice. *International Journal of Forecasting*, *38*(4), 1283–1318. https://doi.org/10.1016/j.ijforecast.2019.06.004

Guan, Y., Banerjee, S., Gogus, C., & He, A. (2025). Data-Driven Demand Forecasting in Fast Fashion Using Integrated Deep Learning Models. *Lecture Notes in Networks and Systems*, *1248 LNNS*, 271–281. https://doi.org/10.1007/978-981-96-1758-6_23

Gunasekaran, A., Kumar Tiwari, M., Dubey, R., & Fosso Wamba, S. (2016). Big data and predictive analytics applications in supply chain management. *Computers and Industrial Engineering*, *101*, 525–527. https://doi.org/10.1016/j.cie.2016.10.020

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation 9(8), 1735-1780*. https://doi.org/10.1162/neco.1997.9.8.1735

Hofmann, E., & Rutschmann, E. (2018). *Big data analytics and demand forecasting in supply chains : a conceptual analysis*. The International Journal of Logistics Management, 29(2), 739–766. https://doi.org/10.1108/IJLM-04-2017-0088

Huber, J., & Stuckenschmidt, H. (2020). Daily retail demand forecasting using machine learning with emphasis on calendric special days. *International Journal of Forecasting*, *36*(4), 1420–1438. https://doi.org/10.1016/j.ijforecast.2020.02.005

Jaipuria, S., & Mahapatra, S. S. (2014). An improved demand forecasting method to reduce bullwhip effect in supply chains. *Expert Systems with Applications*, *41*(5), 2395–2408. https://doi.org/10.1016/j.eswa.2013.09.038

Kim, S., Rahman, M. M., Nihal, I. A., Khan, Y., UddinHimel, H., & Sikder, M. S. (2025). Big data analytics for supply chain management. International Journal of Grid Computing & Applications, 16(3), 30–43. https://doi.org/10.5121/ijgca.2025.16302

Kot, S., Goldbach, I. R., & Ślusarczyk, B. (2018). Supply chain management in SMES – Polish and Romanian approach. *Economics and Sociology*, *11*(4), 142–156. https://doi.org/10.14254/2071-789X.2018/11-4/9

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and Machine Learning forecasting methods: Concerns and ways forward. *PLoS ONE*, *13*(3). https://doi.org/10.1371/journal.pone.0194889

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information and Management*, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Pournader, M., Ghaderi, H., Hassanzadegan, A., & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. International Journal of Production Economics, 241, 108250. https://doi.org/10.1016/j.ijpe.2021.108250

Punia, S., & Shankar, S. (2022). Knowledge-Based Systems Predictive analytics for demand forecasting : A deep learning-based decision support system. *Knowledge-Based Systems*, *258*, 109956. https://doi.org/10.1016/j.knosys.2022.109956

Ramdani, B., Binsaif, A., & Boukrami, E. (2019). Business model innovation: a review and research agenda. *New England Journal of Entrepreneurship*, *22*(2), 89–108. https://doi.org/10.1108/NEJE-06-2019-0030

Raut, R. D., Gardas, B. B., Kharat, M., & Narkhede, B. (2018). Modeling the drivers of post-harvest losses – MCDM approach. *Computers and Electronics in Agriculture*, *154*(February 2017), 426–433. https://doi.org/10.1016/j.compag.2018.09.035

Rožanec, J., Trajkova, E., Kenda, K., Fortuna, B., & Mladenić, D. (2021). Explaining bad forecasts in global time series models. *Applied Sciences (Switzerland)*, *11*(19). https://doi.org/10.3390/app11199243

Setiawan, G., & Suryadi, D. (2024). Design of an Information System for Forecasting Fabric Demand (Case Study At Cahaya Sandang). *International Journal of Economics, Business and Accounting Research (IJEBAR)*, *8*(2), 351–364. https://doi.org/10.29040/ijebar.v8i2.13055

Terrada, L., El Khaili, M., & Ouajji, H. (2022). Demand Forecasting Model using Deep Learning Methods for Supply Chain Management 4.0. *International Journal of Advanced Computer Science and Applications*, *13*(5), 704–711. https://doi.org/10.14569/IJACSA.2022.0130581

Thomassey, S. (2010). Sales forecasts in clothing industry: The key success factor of the supply chain management. *International Journal of Production Economics*, *128*(2), 470–483. https://doi.org/10.1016/j.ijpe.2010.07.018

Wong, L. W., Tan, G. W. H., Ooi, K. B., Lin, B., & Dwivedi, Y. K. (2024). Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis. *International Journal of Production Research*, *62*(15), 5535–5555. https://doi.org/10.1080/00207543.2022.2063089