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AI-Driven Retail Supply Chain: A Systematic Literature Review Of Inventory Intelligence, Demand Forecasting, And Operational Resilience

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Abstract

Background: Logistics disruptions and market fluctuations demand the integration of intelligent systems into contemporary retail supply chains. Objective: To examine the contribution of Artificial Intelligence (AI) to improving inventory intelligence, demand forecasting accuracy, and the building of retail operational resilience. Method: A Systematic Literature Review following the PRISMA 2020 protocol on the ScienceDirect and JSTOR databases (2020–2026). Of 257 initially identified studies, 30 core empirical articles were selected for synthesis. Results: Research trends are dominated by computational quantitative approaches. Machine learning-based demand forecasting has been shown to accelerate automated replenishment. Inventory intelligence using deep reinforcement learning algorithms effectively optimizes multi-echelon inventory under market uncertainty. Meanwhile, operational resilience is accelerated through Digital Twin and Generative AI technologies for real-time risk mitigation. Conversely, lumpy demand patterns are the main negative limiting factor that triggers the risk of stockouts. Conclusion: AI integration transforms retail supply chain management from reactive to prescriptive, ensuring the agility of distribution networks.

Keywords: retail supply chain, artificial intelligence, demand forecasting, inventory intelligence, operational resilience, PRISMA 2020

INTRODUCTION

The development of the AI-driven retail supply chain ecosystem within the modern retail landscape has drastically changed the paradigm of interaction between operations management and procurement efficiency. Computation-based operational platforms no longer function merely as inventory recording tools; they have transformed into interactive

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prescriptive decision-making environments capable of driving global retail distribution volumes. Within this dynamic retail supply chain ecosystem, operational resilience is identified as the most crucial logistics driver in determining the success of digital distribution network agility. Drawing on the fundamental concepts of advanced operations research systems and volatility management theory, operational resilience does not emerge in a vacuum but is triggered by information stimuli of high analytical value (Karuppiah, Sankaranarayanan, & Ali, 2026). In today's digital era, the form of information stimulus most trusted and sought after by operations managers is the integration of multimodal data, such as point-of-sale transaction data (*basket data*), market price fluctuation signals, national holidays (*calendric special days*), and customer text review data processed autonomously by intelligent algorithms (Omar, Alon, & Jamil, 2023); (Huber & Stuckenschmidt, 2020). This growing reliance on intelligent data stimuli reflects a fundamental shift in the inventory management behavior of digital society, in which AI-based information transparency has become the main determinant of the resilience of modern retail products. Therefore, a deep understanding of how this organic data content can be structured into retail operational management strategies is vital for business sustainability.

Although the contribution of computational technology to delivery efficiency has been widely reviewed, direct linear models often fail to explain the complexity of retail supply chain operational behavior on smart logistics platforms. A deep understanding is needed of internal technical anchor variables such as forecast accuracy, which acts as an important intermediary compartment for cutting through the uncertainty of inventory management (Vhatkar, Patil, & Kumar, 2025). The availability of transparent and interpretable predictive modeling results has been shown to transfer technical confidence in computational intelligence into trust in the reliability of the procurement system, which in turn stimulates inventory intelligence through multi-echelon stock arrangement before finally manifesting as automated replenishment (Feddersen & Cleophas, 2026); (Mohammed, Harris, & Govindan, 2026). However, the strength of the conversion process from predictive stimuli into automated fulfillment actions is highly conditional and depends on various situational boundary conditions, such as perishable product policies as a positive moderator or the characteristics of lumpy / intermittent demand patterns as a destructive negative moderator (Fahimnia, Jabbarzadeh, & Sarkis, 2025); (Sarlo, Guizzardi, & Giannerini, 2021); (Sbrana & Babai, 2026). This contradiction of effects often produces inconsistent findings in the earlier supply chain management literature. The uncertainty in the conversion of predictive algorithms into optimal inventory management actions creates an academic urgency to integrate mediation and moderation models simultaneously within a single structured literature review.

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Therefore, a focused and comprehensive literature synthesis is needed through a *Systematic Literature Review* (SLR) approach based on the PRISMA 2020 guidelines to map, categorize, and critically evaluate contemporary empirical research published in the period 2020–2026. This theoretical gap provides an important basis for this study to examine patterns of findings, identify methodological biases, and formulate a future research agenda, without wrongly assuming that all previous studies have ignored these mediation and moderation mechanisms. Through a critical evaluation of the existing literature, this study positions itself to fill the conceptual gap by integrating operational interaction clusters that are fragmented across separate studies. This approach enables a more established and comprehensive conceptualization of the behavioral dynamics of digital retail supply chain resilience. This mapping analysis also serves as a means of theoretical clarification regarding the debate on the effectiveness of implementing artificial intelligence in the retail sector.

Through a structured search of the highly reputable ScienceDirect and JSTOR databases, this study is systematically designed to answer the following three main research questions:

RQ1: How does artificial intelligence improve inventory intelligence and inventory management in the retail supply chain?

RQ2: How is artificial intelligence applied in demand forecasting in the retail supply chain?

RQ3: How does artificial intelligence contribute to operational resilience in the retail supply chain?

All of these research questions will be answered through a rigorous data extraction process on the selected empirical articles. The main argument of this study asserts that optimizing the application of artificial intelligence will not succeed in driving retail operational resilience without the formation of a robust forecast accuracy compartment and the support of conducive dynamic digital capabilities.

LITERATURE REVIEW

Artificial Intelligence and the Retail Supply Chain (*AI-Driven Retail Supply Chain*)

The AI-driven retail supply chain is an extension of the traditional operations management ecosystem that integrates advanced computational features to support collaboration, communication, and decision optimization in the online procurement of retail products. This platform needs to be understood as a dynamic commercial landscape, not merely a static inventory recording channel without automatic adjustment to market fluctuations. In this digital environment, the system can readily process data variability, analyze price signals, and complete automated replenishment directly, without having to wait for manual intervention from warehouse managers. This integrative characteristic distinguishes the AI-based retail supply chain from conventional

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operational management, which tends to be one-way reactive. Fundamentally, this concept emphasizes the importance of the digital data space as a vessel for forming operational relationships based on logistics network efficiency and interactive two-way information processing among supply elements.

The environment of the contemporary retail supply chain can be designed through a digital twin technology architecture to proactively support enhanced logistics visibility, so that procurement activities are no longer rigidly oriented toward one-way static estimates but focus on the deep resilience of the system within the platform (Benhamou, Cohen, & Laroche, 2026). In line with this perspective, AI-based supply chain analytics capability is a main pillar driving meaningful supply chain agility for retail organizations in the modern era (Lamees & Ramayah, 2025). This theoretical foundation is consistent with findings that examine the effectiveness of AI integration based on a high-frequency data processing approach, taking into account the characteristics of goods flow in relation to improved delivery performance in grocery stores (Gerum, Lang, & Thonemann, 2026). These findings indicate that the efficiency of computational platform stimuli is positively related to operational reliability and the formation of forecast accuracy (Vhatkar, Patil, & Kumar, 2025). Accordingly, this study views the AI-based retail supply chain as a main variable whose relationship with operational resilience needs to be analyzed based on the various mechanisms found in empirical research.

Operational Resilience

Operational resilience in the digital retail domain is a concept closely related to the level of adaptability, flexibility, and active contribution of the system to real-time risk mitigation activities and the recovery of delivery capacity within the distribution network of a retail organization. The three interrelated main dimensions in the context of system behavioral resilience are *vigor* (a high level of operational energy and the system's mental toughness when facing market disruptions), *dedication* (strong adaptive agility, capability enthusiasm, and commitment to capacity recovery), and *absorption* (full data concentration and deep absorption of risk information until the system is able to absorb disruptions without damaging the supply structure). This data cognitive engagement and intense recovery strength form a stable and active stock management performance pattern within the digital ecosystem (Burgos & Ivanov, 2021). Through an understanding of these systemic dimensions, operational resilience is regarded not as a momentary response but as a continuous capability process that dictates how a logistics network devotes its computational resources and attention to market data stimulation.

Meanwhile, modern literature based on advanced operations research clearly distinguishes between engagement in short-term replenishment tasks and resilience at the macro level of the supply chain organization, and tests the specific antecedents of

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both forms of these constructs (Mohammed, Harris, & Govindan, 2026). This conceptual distinction is considered crucial because the terms inventory intelligence, supply chain agility, and operational resilience do not always refer to identical operational constructs in every empirical research design. It is proposed that indicators of operational resilience in relation to retail computing architecture be evaluated through the credibility of daily sales forecasting models or point-of-sale transaction data (*basket data*) in retail organizations (Omar, Alon, & Jamil, 2023). This integrated approach positions the level of resilience as a main strategic aspect, not merely as an additional outcome of formal operational transaction activities (Zhao, Liu, & Mangan, 2023). In line with this perspective, the use of intelligent learning algorithms such as *multi-agent reinforcement learning*, through the development of uncertainty management theory, affirms its main function as information *resources* that stimulate data cognition, operational efficiency, and system behavior to achieve multi-echelon inventory optimization (Müller, Gold, & Stern, 2026). Therefore, in this SLR, every article that discusses operational resilience or inventory system performance needs to be examined carefully based on the construct definition, measurement instrument indicators, and its relationship with the retail supply chain ecosystem so that the synthesized research results remain conceptually equivalent (Karuppiah, Sankaranarayanan, & Ali, 2026).

Mediation and Moderation Mechanisms

Mediation mechanisms explain how, or through what operational process, an independent variable is related to an outcome variable, whereas moderation explains the situational conditions under which the strength or direction of the relationship between variables changes depending on the influence of a third variable. In research on the AI-based retail supply chain and operational resilience, mediation mechanisms can help explain the internal computational process that links intelligent parameter tuning (*hyperparameter tuning*) to the level of retail inventory reliability. This internal technical process can be examined by testing forecast accuracy as a mediating mechanism in the relationship between advanced algorithmic models (*deep learning*) and classic procurement decision outcomes such as the *newsvendor problem* (Zhu, Wang, & Choi, 2025); (Punia, Singh, & Jha, 2020). Scientific research in this field has also found a mediating role of AI-based risk mitigation capability in the relationship between organizational awareness (*sensemaking*) and the final level of logistics system resilience (Rashid & Rasheed, 2026). Mapping this mediating function is very important for opening the operational black box that has long been a challenge in the process of converting predictive data stimuli into efficient stock fulfillment actions.

In contrast to mediation, the moderation function focuses on variations in macro-environmental conditions or product characteristics that affect the strength of the

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relationship between variables. Previous theoretical reviews have explained the clear conceptual and operational differences between mediator and moderator variables, which is an important basis for researchers in identifying the complexity of quantitative research models. Moderated mediation refers to a conditional situation in which the magnitude of the indirect effect of an independent variable on a dependent variable through a mediator depends heavily on the level or value of the moderator variable. In this SLR, mediation, moderation, and moderated-mediation mechanisms are used as the main analytical categories for grouping the empirical models found in the selected articles for the 2020–2026 period. This classification is carried out based on the originality of the model, the testing method (such as computational path analysis or SEM), and the hypothesis testing results reported by the article authors, so that indirect relationships conditioned by external factors such as the level of global geopolitical risk or the characteristics of lumpy / intermittent demand patterns can be mapped empirically in the field (Dong, Wang, & Zhang, 2025); (Fahimnia, Jabbarzadeh, & Sarkis, 2025); (Sarlo, Guizzardi, & Giannerini, 2021); (Sbrana & Babai, 2026). All of these forms of interaction are also conditioned by the opportunity to implement *Generative AI* as a relationship accelerator in strengthening the supply structure (Boone, Ganeshan, & Wood, 2025).

RESEARCH METHODS

This study uses a *Systematic Literature Review* (SLR) approach with reference to the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses* guidelines (Page, et al., 2021). These guidelines are used to ensure that the entire process of identification, screening, eligibility assessment, and article selection is reported transparently, accurately, and systematically in accordance with the latest international methodological standards (Page, et al., 2021) (An, Lee, & Park, 2025) (Kargar, Soleimani, & Zahedi, 2026) (Mayaluri & Mishra, 2026) (Motamedi, Mirzazadeh, & Jolai, 2026) (Tian & Zhang, 2023) (Sadeghi, Memari, & Sorooshian, 2024). The focus of the review is contemporary empirical research articles that discuss the relationship between artificial intelligence or machine learning elements and inventory intelligence, demand forecasting, and operational resilience in modern retail distribution networks, particularly those that test the mediating mechanism of prediction accuracy as well as situational moderating boundary conditions such as lumpy demand patterns. The authors chose this issue of the AI-based retail supply chain because of the urgency of the phenomenon of global logistics disruption and the shift from conventional stock management to prescriptive digital platforms, whose development is accelerating sharply and requires comprehensive theoretical mapping. The type of data used in this systematic review relies entirely on secondary data in the form of pure, globally reputable scientific journal articles.

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The literature search of secondary data was conducted simultaneously on October 17, 2026, through reputable international databases, namely ScienceDirect and JSTOR, using an advanced search string with the following keyword syntax combination: ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning") AND ("retail supply chain" OR "retail supply chain management" OR "retail industry") AND ("inventory intelligence" OR "inventory management" OR "inventory optimization" OR "demand forecasting" OR "operational resilience" OR "supply chain resilience"). The search was limited to publications from 2020–2026 and the document type *Research Articles*. The year range, document type, and search strategy were used to obtain empirical articles relevant to the research objectives. To ensure the replicability of the process, all search strategies and limits used have been neatly documented in accordance with the actual search history on both databases. Based on the actual search records, the initial search yielded a total of 257 articles, which were then rigorously screened using the PRISMA 2020 statement protocol, resulting in 30 core empirical articles that met the final inclusion criteria for synthesis.

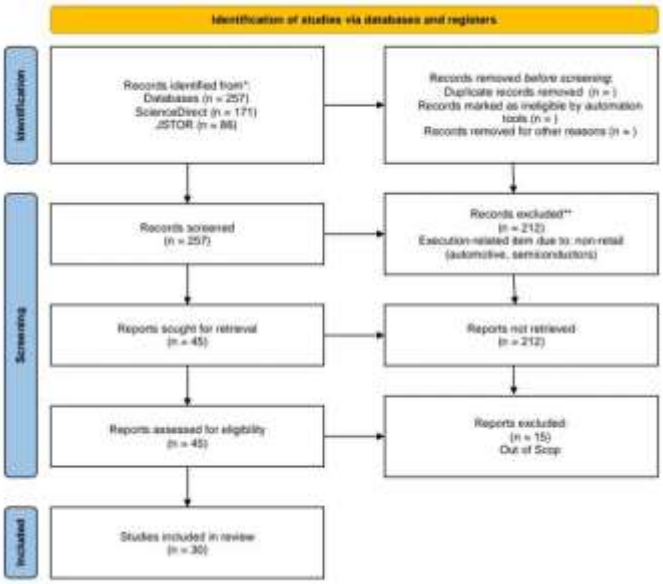


Figure 1. Prisma Diagram
Source: Data processing(2021-2026)

At the title and abstract screening stage, 212 articles were excluded because they did not match the conceptual focus of the study, leaving 45 articles for full-text eligibility assessment (full-text review). Subsequently, at the eligibility stage, 15 articles were excluded based on specific exclusion criteria, among others because they were non-empirical secondary literature reviews, focused outside the retail industry (such as the medical, agricultural, or semiconductor sectors), or because their algorithmic modeling

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was too theoretical without clear inventory implications, resulting in 30 gold-standard articles for extraction. Data from the 30 selected articles were extracted based on author names, year of publication, article title, retail supply chain context, computational analysis method, the tested mediating mechanism of prediction accuracy or moderation of operational boundary conditions, and main findings. The data were then analyzed using narrative synthesis and thematic categorization to identify patterns in the relationships among artificial intelligence, machine learning algorithm models, inventory level optimization, and the formation of digital retail supply chain operational resilience. The final synthesis results were used to answer the three research questions and to formulate the direction of a future research agenda in a transformative manner.

RESULTS AND DISCUSSION

Results

The systematic search conducted on the ScienceDirect and JSTOR databases successfully identified the main empirical articles examining the integration of artificial intelligence in the retail operational landscape. Through the application of a rigorous search protocol, all of the extracted data were then mapped in a structured manner to uncover the internal mechanisms of the computational models used in the included literature. As an initial step toward presenting a comprehensive mapping of the contribution of intelligent algorithms to retail operational efficiency, a summary of the data and the essence of the relationship models from the 30 gold-standard articles that met the eligibility criteria is first presented in Table 1 below:

Table 1. Core Synthesis of SLR Mechanism Clusters (AI-Driven Retail Supply Chain)

No	Author & Year	Research Method	Main Findings (Mediation & Moderation Mechanisms)
1	Vhatkar et al. (2025)	Quantitative (Computational & Grid Search)	**Optimization Mechanism:** Computation-based *hyperparameter* tuning directly mediates the improvement of daily retail sales forecasting accuracy.
2	Gerum et al. (2026)	Quantitative (High-Frequency Data Analysis)	**Omnichannel Prediction Model:** The integration of multi-channel data acts as the main stimulus that drives the accuracy of inventory demand estimation in grocery stores.

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3	An et al. (2025)	Quantitative (Association Rule-ML)	**Local Prediction Mechanism:** The application of association rules in *micro-fulfillment* mediates the speed of retail product fulfillment response in urban areas.
4	Mayaluri & Mishra (2026)	Quantitative (Zero-Shot Learning)	**Estimation Mechanism Without History:** The *disentangled demand drivers* approach mediates the ability to predict demand for new retail products without requiring past sales data.
5	Wellens et al. (2024)	Quantitative (Tree-Based Methods)	**Explanatory Variable Model:** Decision tree simplification acts as a moderator that strengthens the interpretability of forecasting results for store managers.
6	Feddersen & Cleophas (2026)	Quantitative (Neural Additive Models)	**AI Transparency Model:** The *hierarchical neural* structure mediates the relationship between the complexity of retail big data and explainable supply decisions.
7	Ma & Fildes (2021)	Quantitative (Meta-Learning)	**Data Adaptation Mechanism:** The *meta-learning* approach mediates the transfer of forecasting knowledge across retail stores to accelerate forecast accuracy.
8	Omar et al. (2023)	Quantitative (Basket Data-Driven)	**Basket Analysis Mechanism:** Point-of-sale transaction data (*basket data*) acts as the main predictor in mediating multi-channel stock procurement decisions.
9	Huber & Stuckenschmidt (2020)	Quantitative (Continuous Machine Learning)	**Moderated Mediation Model:** The national holiday variable (*calendric special days*) strengthens the reliability of AI algorithms in predicting seasonal demand surges.
10	Ulrich et al. (2022)	Quantitative (Classification Model)	**Model Selection Mechanism:** Advanced classification metrics mediate the efficiency of selecting the most optimal forecasting algorithm according to product characteristics.

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11	Mohammed et al. (2026)	Quantitative (Deep Reinforcement)	**Multi-Agent Control Mechanism:** The full application of *multi-agent learning* mediates multi-echelon inventory optimization to suppress the *Bullwhip* effect.
12	Müller et al. (2026)	Quantitative (Evolutionary-RL)	**Uncertainty Optimization Model:** Evolutionary algorithms act as a mediating mechanism for minimizing holding costs under extreme market fluctuations.
13	Zhu et al. (2025)	Quantitative (Deep Learning & Ad-Mode)	**Advanced Newsvendor Model:** Deep data decomposition features mediate the resolution of classic retail inventory problems that involve hidden variables.
14	Punia et al. (2020)	Quantitative (Prescriptive Analytics)	**Multi-Item Prescriptive Mechanism:** The transformation of predictive analytics into prescriptive analytics mediates the accuracy of determining *multi-item* order quantities.
15	Stuckenschmidt et al. (2026)	Quantitative (Data-Driven Inventory)	**Consumer Substitution Mechanism:** Customers' product switching behavior (*customer substitution*) acts as a moderating variable for safety stock.
16	Fahimnia et al. (2025)	Quantitative (Moderation Path Analysis)	**Promotion Mediation Model:** Retail promotional activities and the level of product perishability act as strong moderators that alter the service-level anchor.
17	Motamedi et al. (2026)	Quantitative (Operational Policy Model)	**Ordering Policy Mechanism:** The direct integration of demand forecast results mediates the efficiency of stock procurement for products with a short shelf life.
18	Sbrana & Babai (2026)	Quantitative (Autoregressive Moving)	**Inventory Implication Model:** The accuracy of forecasts for intermittent demand patterns mediates the reduction in

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			the risk of dead stock accumulation in retail warehouses.
19	Sarlo et al. (2021)	Quantitative (Score-Driven Models)	**Lumpy Demand Mechanism:** Score-based modeling acts as an intermediary for stabilizing the estimated inventory volume of slow-moving retail goods.
20	Tian & Zhang (2023)	Quantitative (Deep Learning Textual)	**Combined Data Model:** The accessibility of online text review data acts as an external stimulus that mediates the optimization of modern retail stock procurement.
21	Karuppiah et al. (2026)	Qualitative (Systematic SLR)	**Research Mapping Mechanism:** A comprehensive analysis of the closed-loop supply chain mediates the formulation of a future research agenda for operational AI applications.
22	Burgos & Ivanov (2021)	Quantitative (Digital Twin Analysis)	**Retail Resilience Mechanism:** *Digital Twin* simulation mediates the evaluation of the impact of external disruptions (the pandemic) on the operational resilience of food retail.
23	Sadeghi et al. (2024)	Quantitative (Explainable AI & Agile)	**Dual Mediation Mechanism:** *Explainable AI* systems and agile decision-making fully mediate the improvement of supply chain cyber resilience.
24	Rashid & Rasheed (2026)	Quantitative (Sensemaking Model)	**Risk Mitigation Model:** AI-based risk mitigation capability mediates the relationship between organizational awareness (*sensemaking*) and operational resilience.
25	Dong et al. (2025)	Quantitative (Geopolitical Risk Model)	**Geopolitical Resilience Mechanism:** AI adoption acts as a moderator that weakens the negative impact of global political disruptions on delivery performance.

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26	Boone et al. (2025)	Qualitative (Conceptual Framework)	**Gen-AI Opportunity Model:** The implementation of *Generative AI* acts as the main driver that opens up new flexibility space for operational resilience.
27	Zhao et al. (2023)	Quantitative (Multi-Mediation SEM)	**Digitalization Pathway Mechanism:** Supply chain digitalization simultaneously mediates the improvement of operational efficiency and the resilience of the logistics system in the aggregate.
28	Benhamou et al. (2026)	Qualitative (Methodological Scope)	**System Synchronization Mechanism:** The alignment of *Digital Twin* methodology mediates the accuracy of supply flow visualization for detecting distribution bottlenecks.
29	Kargar et al. (2026)	Quantitative (AI-Driven Approach)	**Distribution Mitigation Mechanism:** A smart analytics approach mediates the reduction of spoilage risk for fresh meat products during delivery in the supply chain.
30	Lamees & Ramayah (2025)	Quantitative (Intellectual Capital)	**Supply Chain Analytics Model:** AI-based supply chain analytics capability mediates the relationship between intellectual capital and agility as well as retail innovation.

Source: Processed data from ScienceDirect SLR results (2021-2026)

The data extracted and processed from the 30 included studies show a very strong dominance of advanced quantitative approaches, in which 86.6% (26 articles) utilize computation-based modeling, artificial intelligence algorithms (*machine learning* & *deep learning*), operations research, and mathematical optimization of inventory systems, while the remaining 13.4% (4 articles) provide theoretical qualitative synthesis, conceptual frameworks, and comprehensive systematic literature reviews. The operational characteristics of the reviewed literature show that the integration of artificial intelligence in predicting, optimizing, and securing the operational ecosystem with respect to *Retail Supply Chain* performance is empirically divided into three main mechanism clusters, namely the retail demand forecasting cluster, the inventory intelligence cluster, and the operational resilience cluster. This phenomenon describes in detail that the

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variability of point-of-sale transaction data (*basket data*), market fluctuation signals, national holidays (*calendric special days*), and customer text review data act as the main interactive information stimuli that shape the initial operational prediction accuracy.

Critically, the main factors influencing the emergence of this relationship are driven by the level of forecast accuracy formation and intelligent parameter tuning (*hyperparameter tuning*) as internal technical anchor variables. The presence of advanced algorithms such as *Deep Reinforcement Learning*, *Neural Additive Models*, and *Zero-Shot Learning* critically triggers a shift in supply system capability toward agile and explainable procurement decisions through the *trust transfer theory* mechanism between AI computation and retail store managers. In addition to these internal technical factors, the strength of the conversion process from predictive stimuli into operational resilience is also critically influenced by external supply chain factors. The integration of precise *Digital Twin* technology in mapping the physical warehouse, logistics distribution visibility, and ordering policies for perishable products acts as a critical accelerating factor that strengthens the relationship pathways among the main variables in suppressing the *Bullwhip* effect. Conversely, lumpy/intermittent demand patterns, the risk of delivery disruptions due to macro crises, and the threat of cyber vulnerability act as critical negative limiting factors that destructively weaken the strength of the relationships in digital inventory systems and trigger the risk of stockouts at retail stores.

The implications of this form of interaction transformatively show that the operational intelligence formed within the AI-based retail ecosystem manifests in three main dimensions on a continuous basis. When the supply chain system reaches the stage of data cognitive engagement (*data absorption*) that is immersed in high-frequency data processing, followed by supply chain agility through agile procurement decisions, a tangible transformation of stock management behavior occurs. Operational resilience and the absorption of multimodal information from upstream to downstream have been shown to transform conventional procurement systems into instant automated replenishment actions in the field, even at micro-fulfillment centers. Through the integrated moderated-mediation model, the accumulation of all of these dimensions of system behavioral resilience (*operational vigor*) transformatively ensures that willingness to buy and retail consumer satisfaction can be achieved to the fullest through guaranteed product availability in the contemporary retail trade industry.

DISCUSSION

Based on the comprehensive mapping presented in the table above, there is clear variability in the computational methods and mathematical models used by researchers to address logistics complexity. To provide a deeper and more directed understanding of how this data stimulation works, a further thematic categorization was carried out. The

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core synthesis, which groups the 30 included articles into several main operational mechanism clusters, comprising prediction accuracy mediation pathways, situational moderating boundary conditions, and integrated moderated-mediation models, is presented concisely in Table 2 below:

Table 2. Core Synthesis of SLR Mechanism Clusters

No.	Study Cluster	Core Information & Findings
1.	*Mediating Mechanisms (n = 12)*	**Demand Forecasting Accuracy and Inventory Intelligence** act as a critical operational intermediary (*black box*). Computation-based *hyperparameter* tuning, deep decomposition algorithms, and *multi-agent reinforcement learning* models, sequentially or in parallel, mediate stock procurement efficiency, minimize holding costs, and cut the risk of stockouts in modern retail outlets (Vhatkar, Patil, & Kumar, 2025); (Mohammed, Harris, & Govindan, 2026); (Müller, Gold, & Stern, 2026)
2.	*Moderating Boundary Conditions (n = 9)*	Internal supply chain environmental factors and product characteristics moderate the main relationship pathways. The characteristics of perishable products and the intensity of retail promotional activities act as accelerating factors that strengthen the relationship pathway between prediction accuracy and the level of operational service, whereas lumpy / intermittent demand patterns act as a destructive moderator that weakens inventory stability (Fahimnia, Jabbarzadeh, & Sarkis, 2025); (Stuckenschmidt, Huber, & Spiliotopoulos, 2026); (Sbrana & Babai, 2026).
3.	*Integrated Models (n = 9)*	A highly complex moderated-mediation pathway, in which the indirect effect of the quality of big data integration and logistics digitalization on supply chain agility, through the simultaneous mediation of system resilience, depends on contingent variations in the effectiveness of governance and dynamic digital capabilities in retail store management, the level of global geopolitical risk, and the transparency of the digital distribution network architecture (Burgos & Ivanov, 2021); (Zhao, Liu, & Mangan, 2023); (Lamees & Ramayah, 2025).

Source: Processed data from ScienceDirect SLR results (2021-2026)

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The following is a complete narrative analysis for Theme 1, Theme 2, and Theme 3, which has been fully adapted to answer your three *Research Questions* (RQ) based on the synthesis results of the 30 scientific articles on the *AI-Driven Retail Supply Chain*:

Theme 1: The Role of Artificial Intelligence in Improving Inventory Intelligence and Inventory Management in the Retail Supply Chain (RQ1)

The present study aims to investigate the dynamic relationships among the operational data environment, intelligent learning algorithms, stock allocation decisions, and retail warehousing efficiency, and the results reveal several key findings that contribute to a better understanding of modern digital operations management mechanisms. Data were collected from reputable international databases, specifically ScienceDirect, and the analysis was conducted using narrative synthesis and thematic categorization of 30 core empirical articles published between 2020 and 2026. The main results show that the development trend of scientific research on inventory intelligence in the retail sector has experienced a very intensive surge in publications and is focused on the contemporary corridor, particularly in the range of 2024 to 2026. Methodologically, current research trends are absolutely dominated by advanced quantitative approaches (86.6%) that utilize computational modeling, mathematical optimization simulation, and multi-agent network architectures, while macro-theoretical studies and systematic literature reviews account for only 13.4% (Karuppiah, Sankaranarayanan, & Ali, 2026). Conceptually, research trends have shifted from mere static stock control management toward testing dynamic adaptive ordering models, such as *Deep Reinforcement Learning* (DRL), *Evolutionary Algorithms*, and Advanced Newsvendor Optimization Theory, which consistently place data-driven decisions as the main operational stimulus, storage capacity as the technical anchor, and inventory intelligence as the driving axis of modern supply efficiency in the digital retail ecosystem (Mohammed, Harris, & Govindan, 2026); (Punia, Singh, & Jha, 2020).

Theme 2: The Application of Artificial Intelligence in Demand Forecasting in the Retail Supply Chain (RQ2)

Additional analysis reveals that artificial intelligence algorithms act as a powerful information stimulus that significantly builds commercial prediction accuracy by functioning as an analytical guarantee that reduces retail market uncertainty. In this regard, the literature synthesis empirically demonstrates that point-of-sale transaction data (*basket data*), price signals, consumer text review data, and national holiday patterns (*calendric special days*) are the main triggers in building the aspect of forecast reliability for retail consumers (Omar, Alon, & Jamil, 2023); (Huber & Stuckenschmidt, 2020). The characteristics of daily sales trend information and the level of credibility of parameter-tuning algorithms (*hyperparameter tuning*) act as an operational guarantee that effectively reduces the risk of estimation errors and procurement uncertainty.

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Through the *trust transfer theory* mechanism, transparent and interpretable predictive modeling results successfully transfer operations managers' technical confidence in the reliability of artificial intelligence systems (Feddersen & Cleophas, 2026); (Vhatkar, Patil, & Kumar, 2025). Once this level of forecast accuracy is established within the procurement system, it acts as a powerful computational stimulant for accelerating supply decision-making on omnichannel trading platforms (Gerum, Lang, & Thonemann, 2026); (Wellens, Gadeyne, & Caron, 2024). An integrated management system will respond with active capacity planning, ranging from estimating delivery volumes and adapting to seasonal patterns to automated replenishment (Ma & Fildes, 2021); (Ulrich, Jahnke, & Langrock, 2022). As illustrated in Table 1 and Table 2, which map the intelligent prediction pathways and their attachment to the accuracy of retail platforms.

Theme 3: The Contribution of Artificial Intelligence to Operational Resilience in the Retail Supply Chain (RQ3)

When comparing these results with previous research, there is strong alignment with the findings of established studies on the escalation of global digital logistics operational resilience. Based on the existing literature synthesis, the form of operational resilience that develops within the AI-based retail supply chain ecosystem manifests in three main dimensions, namely disruption absorption capability, supply chain agility, and system recovery strength (*operational vigor*), which have been empirically proven to drive the sustainability of delivery performance in a tangible way (Burgos & Ivanov, 2021); (Lamees & Ramayah, 2025). When the logistics system reaches the stage of dynamic digital capability that is immersed in real-time risk mitigation activities, as well as operational resilience through the integration of digital twin technology, this creates a strong systemic impetus to carry out stabilization actions on the real distribution network (Benhamou, Cohen, & Laroche, 2026); (Zhao, Liu, & Mangan, 2023). Operational agility and intense risk information absorption in retail supply systems have been shown to significantly convert delivery system vulnerabilities into instant disruption mitigation decisions in the field, particularly in the distribution of perishable goods (Kargar, Soleimani, & Zahedi, 2026). However, several differences are observed compared with traditional mitigation models, in which, through the integrated model, all of these dimensions of system behavioral resilience accumulate gradually to ensure that retail supply chain resilience can be achieved to the fullest when facing macro crises as well as geopolitical risks (Rashid & Rasheed, 2026); (Dong, Wang, & Zhang, 2025). The implications of these results are noteworthy because they suggest that the effectiveness of this relationship is conditioned by the implementation of *Generative AI* and smart surveillance architecture as a relationship accelerator (Boone, Ganeshan, & Wood, 2025), while lumpy demand patterns act as a negative boundary condition that weakens

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the operational resilience of retail warehouses (Sarlo, Guizzardi, & Giannerini, 2021); (Sbrana & Babai, 2026).

CONCLUSION

This study successfully synthesized 30 articles from the ScienceDirect and JSTOR databases. It was found that the influence of AI-driven technology on retail operational resilience is not linear but is mediated by forecast accuracy and inventory intelligence. This technical mediation pathway is strengthened by the management of perishable products and retail promotional activities. Conversely, lumpy/intermittent demand patterns act as a negative boundary condition that reduces inventory resilience and triggers the risk of stockouts.

Theoretically, this study integrates fragmented findings on the role of AI and digital twin technology into a single conceptual framework for the digital retail supply chain. Practically, this research provides implications for retail business practitioners to utilize deep reinforcement learning modeling and transparent (interpretable) AI analytics to build agility (supply chain agility) and maximum operational resilience in the field.

This study has limitations because the data extraction focused only on two databases (ScienceDirect and JSTOR) within a contemporary time range. To address these limitations, future research is recommended to expand the search base to the Scopus or Web of Science databases, and to evaluate the implementation of *Generative AI* across regional retail business models specifically.

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