

A Review of Artificial Intelligence in Inventory Management: Methods, Applications and Directions

Jinjin Li¹, Huijun Huang^{2*}, Yuping Gong³, Lei Wang⁴, Xiangui Yin⁵, Yichang Liu⁶
Metering Center, Guangxi Power Grid Co., Nanning, China^{1,2,3,4}
Inspur Group, Jinan, China^{5,6}

Abstract—Effective inventory management is fundamental to supply chain resilience and efficiency. Artificial intelligence (AI) has emerged as a transformative solution that enables more dynamic and data-driven inventory strategies. To map the latest advancements in this rapidly evolving field, this study presents a systematic literature review (SLR) of AI techniques in inventory management. The review was conducted following the PRISMA 2020 guidelines, through which 87 high-quality articles published between 2021 and 2025 were systematically analyzed. Our review identifies machine learning (ML), deep learning (DL), reinforcement learning (RL), and hybrid methods as the predominant AI technologies. These techniques primarily address three foundational tasks. In demand forecasting, they improve prediction accuracy and mitigate stockout and overstock risks. For inventory control, they balance costs with service levels and optimize replenishment strategies. In inventory classification, they facilitate targeted resource allocation. Despite these advancements, AI research confronts significant challenges, particularly in data dependency, model interpretability, and implementation overhead. To address these gaps, we suggest future research focused on data-efficient learning, explainable AI, and lightweight, integrated frameworks to lower adoption barriers. This review provides a timely and holistic overview of the current research landscape, which serves as a reference for academics to identify research directions.

Keywords—Inventory management; artificial intelligence; demand forecasting; inventory control; inventory classification; machine learning

I. INTRODUCTION

Effective supply chain management (SCM) plays a critical role in modern corporate strategy by optimizing resource allocation, enhancing market responsiveness, and mitigating operational risks [1], [2]. Inventory management is a core component of SCM that is crucial for balancing supply and demand. It directly impacts key performance indicators such as operational costs and customer satisfaction [3], [4]. The strategic importance of inventory management is particularly evident in high-stakes sectors, such as the power grid sector. In this domain, managing inventories of critical assets, such as transmission components and essential spare parts, is paramount for ensuring grid stability and operational reliability, especially amidst the growing integration of volatile renewable energy sources [5], [6]. Traditional inventory management methods, reliant on static models and historical data, are ill-equipped for the volatility of modern supply chains [7], [8]. These methods exhibit inherent limitations in timeliness, flexibility, and predictive accuracy. Consequently, there is a growing demand

for advanced solutions, and AI is a particularly promising approach [9], [10].

AI leverages big data and intelligent algorithms to enable scientific forecasting and dynamic optimization in inventory management, improving efficiency, reducing costs, and enhancing supply chain flexibility [11], [12]. For instance, machine learning (ML) can perform demand forecasting based on historical sales and market trends [13]. Deep learning (DL) is capable of processing complex nonlinear data for anomaly detection and defective product identification [14]. Natural language processing (NLP) can analyze supplier and customer information to support market fluctuation prediction [15]. Reinforcement learning (RL) can optimize replenishment strategies in dynamic environments [16]. The Internet of Things (IoT) combined with computer vision (CV) enables real-time monitoring, automated stocktaking, and visualization management [17]. These techniques significantly improve forecasting accuracy, inventory turnover, and anomaly detection, while supporting strategic supply chain planning and promoting intelligent manufacturing and digitalized supply chains [18][19][20].

Although artificial intelligence is rapidly transforming inventory management, the field lacks a current, unified map of these advancements, creating a research gap. To the best of our knowledge, there is a notable scarcity of comprehensive systematic reviews on this topic published after 2023. This gap is particularly critical for two reasons. On one hand, recent years have witnessed unprecedented progress in AI, with the emergence of large language models (LLMs) and the maturation of deep reinforcement learning and Transformers opening new paradigms. On the other hand, existing research has become increasingly fragmented. Studies often focus on narrow problems, such as demand forecasting or stock control, using isolated techniques, without providing a holistic view. Consequently, a systematic synthesis is urgently needed to answer critical questions regarding the current research landscape, the primary application topics, the comparative advantages and limitations of different AI techniques, and the challenges and future directions.

To address this clearly defined gap, this study presents a systematic literature review of AI in inventory management focused on the crucial 2021 to 2025 period. By synthesizing the latest advancements, we provide an updated and holistic framework of the current research status, topics, techniques, and future directions. This study, therefore, offers significant contributions. For the academic community, it maps the fragmented research landscape, identifies critical knowledge

*Corresponding author.

gaps, and outlines promising avenues for future inquiry. For practitioners and industry leaders, it serves as a practical guide, demystifying the capabilities and limitations of various AI methods and offering evidence-based insights to support strategic technology adoption. Ultimately, this review acts as a timely and essential reference, empowering researchers to navigate the new frontier and enabling practitioners to implement state-of-the-art solutions that enhance supply chain resilience and efficiency.

The remainder of this study is structured as follows: Section II introduces the research methodology employed for this review. Section III presents a descriptive analysis of the collected literature over the past five years. Section IV provides a detailed technical analysis based on the literature review. Section V discusses the findings in relation to the key research questions posed in this study. Finally, Section VI concludes the study.

II. RESEARCH METHODOLOGY

Due to its rigor, transparency, and reproducibility, the systematic literature review (SLR) enables a comprehensive and evidence-based synthesis of AI techniques and applications in inventory management. To further enhance the transparency and scientific rigor of this study, the entire process follows the preferred reporting items for systematic reviews and meta-analyses (PRISMA 2020) guidelines as shown in Fig. 1. The research began by outlining four research questions to explore the state, main topics, applied methods, and future directions of AI in inventory management. Subsequently, literature searches were conducted across databases. The retrieved articles were then filtered according to specific inclusion criteria. Studies unrelated to the topic, non-academic sources, and those outside the publication window were excluded. Finally, the selected literature was systematically analyzed to identify major findings, research trends, challenges, and recommendations for future research.

A. Research Questions

In the context of AI applications in inventory management, this study addresses the following research questions:

- RQ1: What is the current state of research on AI technologies in inventory management?
- RQ2: What are the primary topics in inventory management that AI is applied to solve?
- RQ3: What are the key AI techniques and algorithms applied in inventory management, and what are their respective advantages and disadvantages?
- RQ4: What challenges does AI face in inventory management, and what directions can be explored in future research?

B. Literature Search Strategy

To ensure comprehensive coverage of this interdisciplinary topic, our literature search utilized several major academic databases. The chosen platforms, IEEE Xplore, ScienceDirect, Springer, Wiley, Taylor & Francis, and MDPI, were selected

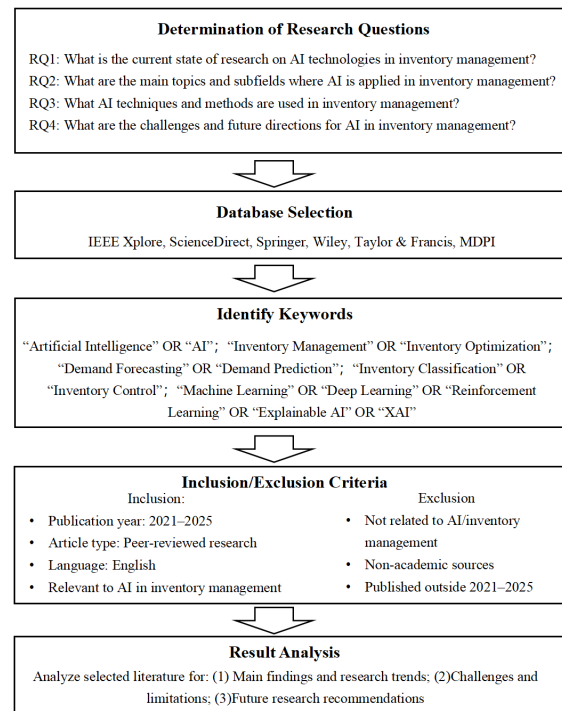


Fig. 1. Flowchart of the proposed method.

as they collectively represent the primary, high-quality publication venues for research spanning artificial intelligence, engineering, and supply chain management. This multi-database strategy was crucial for minimizing selection bias and capturing a broad spectrum of relevant studies.

A combination of subject terms and free-text keywords are used: (‘Artificial Intelligence’ OR ‘AI’) AND (‘Inventory Management’ OR ‘Inventory Optimization’) AND (‘Demand Forecasting’ OR ‘Demand Prediction’ OR ‘Inventory Classification’ OR ‘Inventory Control’) AND (‘Machine Learning’ OR ‘Deep Learning’ OR ‘Reinforcement Learning’ OR ‘Explainable AI’ OR ‘XAI’). Only English-language papers were considered. After initial screening, a total of 3,085 publications related to the above topics were identified.

C. Inclusion and Exclusion Criteria

The inclusion criteria required that studies focus on the application or methodology of AI in inventory management and related domains, covering techniques such as ML, DL, RL and other related methods. Only peer-reviewed research papers published between 2021 and 2025, with sufficient methodological or practical details, were included. Studies unrelated to AI in inventory management, non-academic publications, or published outside the specified period were excluded.

D. Quality Assessment

To ensure the scientific rigor and reliability of the systematic literature review, all included studies were subjected to a structured quality assessment based on established SLR frameworks [21]. The assessment focused on the clarity of research objectives, the appropriateness of the AI techniques employed, the transparency of data and experimental procedures,

the completeness and reliability of results, and the practical relevance of the study. Finally, 87 publications remained for further research.

III. RESULTS

Following the research protocol described above, the literature relevant to the topic was selected and analyzed from four perspectives: publication trends, resource distributions, most cited papers, and keyword analysis.

A. Publication Trend

Fig. 2 presents the publication trend in the field over the past five years using a line chart. Overall, the number of publications increased significantly from 6 in 2021 to 22 in 2025, with a particularly notable surge in 2022, reflecting the rapid growth of academic interest in this topic. The number of publications remained relatively stable in the subsequent years, indicating sustained attention from the research community.

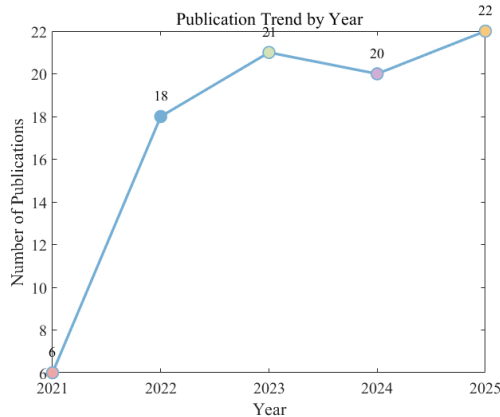


Fig. 2. Number of publications by year.

B. Resource Distributions

The distribution of publications across academic databases reflects the accessibility and concentration of research in this field. As shown in Fig. 3, *IEEE Xplore* hosts the largest number of publications (24 papers), followed by *ScienceDirect* (21 papers) and *Springer* (16 papers). This uneven distribution indicates that *IEEE Xplore*, *ScienceDirect*, and *Springer* serve as the primary sources of relevant studies, while *MDPI*, *Wiley*, *Taylor & Francis* and *Others* play a supplementary role.

At the journal level, the selected publications are relatively concentrated. Among the source journals, *Applied Sciences* contributed the most articles (8 papers), followed by *IEEE Access* with 7 papers. Additionally, *Annals of Operations Research* and *International Journal of Production Research* each published 4 relevant articles. Other contributing journals include *Sustainability* (3 papers), *Journal of Intelligent Manufacturing* (2 papers), *Expert Systems with Applications* (2 papers), *European Journal of Operational Research* (2 papers), *Production and Operations Management* (2 papers), and *IEEE Transactions on Engineering Management* (2 papers).

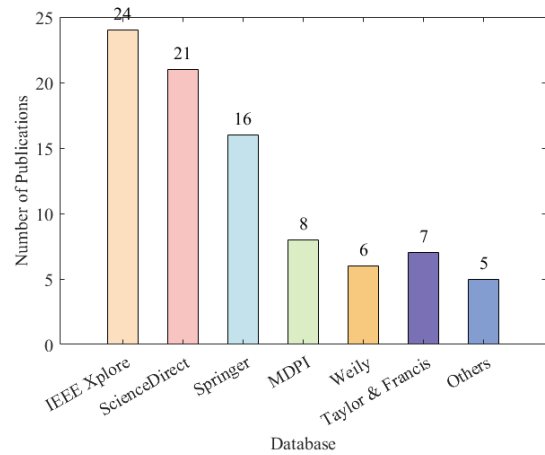


Fig. 3. Distribution of screened publications across databases.

C. Most Cited Papers

To illustrate the recent activity in this research area, Table I lists the top ten most cited papers. Leading publications received over 100 citations within a short period. For instance, the paper by Moor [22] has 126 citations, and the paper by Goncalves [23] has 115 citations. The high citation counts of recent publications further demonstrate the active research in this field.

TABLE I. TOP 10 MOST CITED PAPERS

Rank	Authors	Reference	Citations
1	Moor et al.	[22]	126
2	Goncalves et al.	[23]	115
3	Wang et al.	[24]	114
4	Meisheri et al.	[25]	111
5	Abu Zwaide et al.	[26]	109
6	Selukar et al.	[27]	94
7	Tang et al.	[28]	85
8	Jahin et al.	[29]	85
9	Shajalal et al.	[30]	79
10	Xu et al.	[31]	78

D. Keyword Analysis

As shown in Fig. 4, the keyword frequency analysis indicates that research in this field primarily focuses on the application of AI in inventory management. 'Inventory management' (21 occurrences) appears most frequently, followed by key methodological terms such as 'machine learning' (15 occurrences), 'deep learning' (10 occurrences), and 'reinforcement learning' (8 occurrences). Additionally, high-frequency terms like 'inventory control' (13 occurrences) and 'demand forecasting' (12 occurrences) further confirm that AI techniques are actively applied to address core challenges in this domain.

IV. REVIEW OF LITERATURE

This section provides a comprehensive review of the core literature identified through a systematic search, with a focus on the AI techniques in inventory management. To clearly present the research landscape, the studies are categorized according to the main tasks of inventory management, including demand forecasting, inventory control, inventory classification,

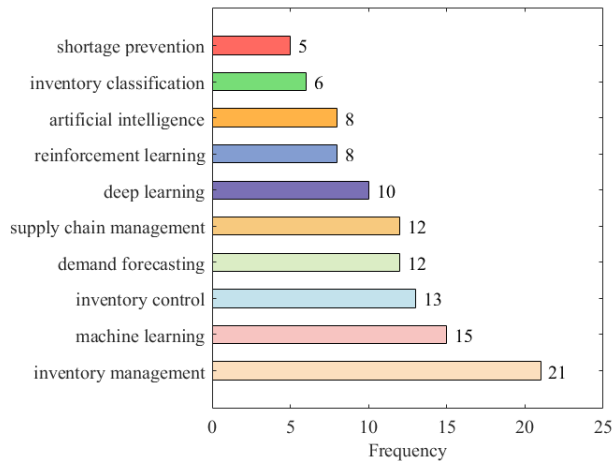


Fig. 4. Top 10 keywords by frequency.

and other related topics and application examples. Within each topic, the methods and algorithms such as ML and DL are reviewed. As this section contains a substantial number of technical acronyms, a table of abbreviations and their full names is provided in Appendix A for easy reference [see Table V].

A. Demand Forecasting

Accurate demand forecasting is central to inventory management, as it guides stock level decisions and mitigates the risks of stockouts and overstocking. A summary of works in this area is provided in Table II. Furthermore, demand forecasting can be broken down into more specific tasks, such as demand forecasting, inventory level prediction, and sales and price prediction.

1) *Demand forecasting*: Demand forecasting represents a core task in inventory management, aiming to predict future product or service demand based on historical data and relevant influencing factors. In existing research, mainstream approaches primarily encompass ML and DL techniques.

ML provides a simple and efficient way to predict the demands. Sathish [40] compared Exponential Smoothing (ES) with Gradient Boosting (GB), and found that ES outperformed GB in both forecasting accuracy and inventory optimization. Goncalves [23] compared ML methods with the statistic based ARIMAX, and proved that ML models achieve superior results in later stages. Manos [49] developed a dynamic demand forecasting platform with XGBoost and SVR to process the multiple data source and then improve the prediction accuracy. Yang [44] developed a dynamic forecasting platform that combines XGBoost and SVR, which leverages multi-source data to significantly enhance forecasting accuracy and operational efficiency.

DL models have shown remarkable success in supply chain forecasting, with predictive power scaling alongside model complexity. Foundational architectures like LSTM networks, have been widely adopted. For instance, Deng [32] utilized LSTMs to capture long-term temporal dependencies and achieved prediction accuracies exceeding 80%. The versatility

of LSTMs is further demonstrated in specialized applications, such as the hybrid LSTM variant proposed by Hasni [33] for intermittent medical supply demand, and the integration with customer segmentation by Jauhar [39], which slashed prediction errors by 74.14%. Building on this foundation, more sophisticated models are proposed to further enhance forecasting accuracy. Liu [45] developed a BO-CNN-LSTM model where Bayesian optimization fine-tunes a combined CNN-LSTM architecture. Seyedan [50] employed an ensemble DL method to forecast online retail demand, and the predictions are further used to optimize safety stock. Jin [51] integrated an attention-based Temporal Convolutional Network (ATCN) into their system. Abualroug [43] proposed the MMCW-BiLSTM model which leverages multi-dimensional collaborative attention. For industry-specific challenges, models like the NARXNN have also been effective, and the accuracy reaches 96.24% in food demand forecasting [41]. In addition, the Transformer architecture is also gaining traction. Yang et al. [44] combined a Transformer with multi-agent RL, and yielded an 18.2% reduction in prediction error.

2) *Inventory level prediction*: Predicting inventory levels and stockout risks is crucial for optimizing inventory control and minimizing costs. Researchers have applied a range of ML and DL models to this task.

As to ML methods, tree-based ensemble models like XGBoost have proven effective for direct inventory level prediction [28] and related tasks such as order quantity forecasting [47]. DL, on the other hand, provides more powerful tools to capture complex nonlinear patterns. For instance, a hybrid Multi-MLP and LightGBM model yielded a significantly lower prediction error with an MAE of 0.2331 [34]. Novel architectures target specific challenges: QAmplifyNet, a quantum-classical hybrid network, was designed to handle data imbalance in stockout prediction and achieved 90% accuracy [29]. To address the need for model transparency, an explainable CNN framework [30] was proposed, which delivered both high performance (AUC = 0.9489) and valuable interpretability.

3) *Sales and price prediction*: Accurate sales and price prediction is fundamental to developing effective commercial strategies, enabling businesses to forecast product demand and establish optimal pricing. Both ML and DL have been extensively applied to address these interconnected challenges.

For prediction tasks, ML models like SVR, MLR, and MNLR have demonstrated high accuracy of 95.63% [36], while more advanced hybrid kernel models such as IMOHHO-AHK-ELM have been developed for specialized areas like wine price forecasting [46]. DL architectures offer further improvements. BPNs have been used for daily sales prediction of perishable goods [35], and integrated CNN-LSTM models have proven effective for complex forecasting, leading to inventory cost savings of over 20% [38]. A real-time automatic pricing system was built using a Dueling DQN algorithm. This system [37] successfully tackled multi-period pricing challenges, securing 91.58% of the returns achievable by an optimal strategy.

B. Inventory Control

The central challenge in inventory control is to guarantee product availability while keeping total costs to a minimum.

TABLE II. LITERATURE FOR DEMAND FORECASTING

Study	Citations	Type	Algorithms	Method
[32]	78	DL	LSTM	Inventory management is optimized by using LSTM for demand prediction in this paper.
[33]	8	DL	LSTM	The challenge of accurately forecasting medical item demand in humanitarian operations is tackled using a hybrid LSTM method.
[23]	109	ML	VAR, ARIMAX, ANN	Multi-step demand forecasting in an automotive supply chain is tackled with a multivariate approach to improve prediction accuracy.
[34]	8	DL	MLP	Future inventory levels in manufacturing are predicted by employing a multi-MLP model.
[28]	69	ML	XGBoost	Inventory forecasting for cross-border e-commerce is enhanced using XGBoost to predict demand, with the aim of improving service automation and reducing costs.
[35]	13	DL	BPN	The daily sales quantity for short-shelf-life cream puffs is predicted using DL in this model, in order to reduce food waste.
[36]	79	ML	SVR, MLR, MNLR	The monthly demand for construction machinery spare parts (specifically manifold products) is predicted with ML and regression methods.
[37]	9	DL	DQN, DRL	The optimal real-time price for retailers in presale e-commerce environments was predicted using deep RL.
[38]	8	DL	DNN, CNN, LSTM	A dynamic sales prediction model (DSP-FAE) is proposed to forecast product sales volumes for inventory optimization, by which costs are reduced by over 20% using auto-learning and elastic-adjustment mechanisms.
[39]	15	DL, ML	K-means, Regression, LSTM	An explainable AI framework is proposed to predict wine sales volume (MntWines) for perishable supply chains by segmenting customers and forecasting demand per segment, resulting in a 74.14% reduction in forecasting errors.
[40]	115	DL	ES/GB	A material demand prediction task is solved to forecast material requirements through a comparative analysis of forecasting methods.
[41]	33	DL	NARXNN	A food demand prediction task is solved using a NARXNN model to forecast the daily sales volume of processed foods.
[42]	28	DL	LSTM	The inventory demand prediction task for volatile SME data is solved using LSTM and 2D kernel density estimation.
[43]	2	DL	BiLSTM	The inventory demand prediction task is solved using a novel MMCW-BiLSTM model, by which future product demand is predicted.
[44]	27	DL	MARL, Transformer, DQN	A multi-agent deep RL framework is proposed to solve demand prediction tasks in retail supply chains, achieving an 18.2% lower forecast error and 23.5% reduced stockout rates.
[45]	28	DL	CNN, LSTM	Demand forecasting is solved with BO-CNN-LSTM to predict demand accurately, which leads to improved inventory optimization and cost control.
[31]	14	DL, ML	LSTM, PSO	The demand prediction task in supply chains is solved using AI, specifically by forecasting future demand quantities to achieve higher accuracy and optimize resource allocation.
[46]	6	ML	IMOHHO-AHK-ELM	An IMOHHO-AHK-ELM prediction model is proposed to achieve accurate point and interval forecasting of wine prices using AI techniques.
[29]	34	ML	Quantum Neural Network	Supply chain backorders are predicted with 90% accuracy by QAmplifyNet using a hybrid quantum-classical neural network.
[47]	85	ML/DL	XGBoost, LSTM	The task of forecasting the number of meal orders for the next 10 weeks is addressed using time series analysis to minimize waste.
[30]	85	DL	CNN	A CNN-based explainable framework for product backorder prediction in inventory management was proposed in this paper.
[48]	-	DL	RNN, LSTM, GRU, CNN	A DL framework is proposed to predict supply chain risks; specifically, drug delivery status, food demand quantities, car prices, and electricity volumes are forecasted.

This involves a continuous balancing act between the costs of holding inventory, placing orders, and running out of stock. The primary tools for managing this balance are the optimization of order quantities, reorder points, and safety stock. A well-designed inventory system prevents stockouts, which directly improves customer satisfaction, operational efficiency, and overall profitability. In this section, we summarize the recent methods compiled in Table III. The task of inventory control can be further divided into three sub-categories: single-echelon inventory control, multi-echelon inventory control, and control strategies for special scenarios.

1) *Single-echelon inventory control*: The single-echelon inventory control task aims to determine the optimal replenishment policy for a single inventory node. Singh [62] combined decision trees with symbolic distance methods to defuzzify the fuzzy total cost of seasonal demand and imperfect perishable products, and the method achieved precise inventory control under uncertainty. Mo [64] proposed an online RL approach that dynamically adjusts inventory policies under non-stationary stochastic market demand without requiring prior knowledge of demand patterns.

2) *Multi-echelon inventory control tasks*: The multi-echelon supply chain inventory control task, which is significantly more complex than its single-echelon counterpart, aims to coordinate inventory decisions across multiple tiers such as factories, distributors, and retailers. This process involves optimizing inventory levels and replenishment policies at each

tier to minimize total supply chain costs and mitigate systemic issues like the bullwhip effect.

ML approaches continue to offer solutions. For instance, Preil [53] developed a MCTS based algorithm for both offline and online models. Their method is designed to determine optimal inventory decisions under stochastic demand and lead times and also helps to alleviate the bullwhip effect. Zietsmann [68] introduced an integrated inventory management framework. This framework, built upon a computer-aided decision support system, cohesively handles product selection, demand forecasting, and procurement to optimize inventory under multi-objective constraints.

On the other hand, DL methods, particularly RL one, have become a cornerstone of modern multi-echelon inventory control, because they can handle more complex and dynamic cases. Zhang [52] proposed an improved SAC-AlphaLR algorithm to optimize replenishment policies in the supply chains of multi-tier fast-moving consumer goods. Addressing systemic challenges like the bullwhip effect is another critical application. Liu [63] utilized a HAPPO algorithm within a multi-agent deep RL framework. Their goal was to mitigate the bullwhip effect in distributed multi-echelon systems. Scalability is a major advantage offered by DL. Meisheri [25] developed a scalable deep RL approach that leverages a single-product meta-model to manage the inventory of hundreds of products in parallel. This method effectively handles multi-period constraints and demonstrates the potential of DL in

TABLE III. LITERATURE FOR INVENTORY CONTROL

Study	Citations	Type	Algorithms	Goals/Approach
[52]	34	DL	SAC-AlphaLR, DRL	A DRL-based ME-DRFO model is proposed for multi-echelon FMCG inventory optimization, whereby total costs are minimized under demand uncertainty and supply chain constraints.
[53]	94	ML	MCTS	An MCTS approach is proposed for multi-echelon inventory optimization to reduce total supply chain costs and mitigate the bullwhip effect.
[54]	14	Hybrid	GBDT, ANN	Inventory, ordering, and financing decisions are optimized using data-driven methods under capital constraints and demand volatility.
[55]	12	DL	DRL	High-stochasticity inventory optimization is addressed using a tailored DRL algorithm.
[56]	5	DL	PPO, DRL	A DRLOM is proposed for multi-echelon inventory control, by which system-wide costs under stochastic demand and lead times are minimized.
[57]	2	Others	System Dynamics	Replenishment is optimized using system dynamics, leading to a reduction in stockouts and lost sales.
[58]	11	DL	LSTM, PSO	Inventory errors and operational costs are minimized through Transformer-based forecasting and PSO.
[59]	17	DL/ML	DQN, LSTM, SVR	SME inventory is optimized through joint demand forecasting and replenishment policies.
[27]	28	DL	DQN	Multi-perishable inventory is optimized using deep RL, with lead times, lifecycles, and demand being considered.
[60]	76	DL	DRL, BNN, MAML	New-product inventory across multiple stores is optimized under demand uncertainty and short life cycles.
[61]	28	ML	IPSO, BPNN	Green supply chain inventory is optimized using an IPSO-BPNN algorithm to reduce costs and improve environmental efficiency.
[62]	17	ML	DTL	Deteriorating product inventory is optimized using ML forecasts and fuzzy variables to minimize cost and emissions.
[63]	17	DL	MADRL	Decentralized multi-echelon inventory optimization is addressed using multi-agent DRL with limited information sharing.
[64]	10	ML	RL	Online RL methods are proposed for inventory control under nonstationary demand, through which costs are saved and service levels are improved.
[65]	29	DL	DRL	Apparel inventory control is optimized using DRL, where demand volatility, service level, and sell-through rate are considered to minimize costs and improve efficiency.
[26]	126	DL	DRL	A DRL method is proposed for hospital drug inventory optimization, aimed at minimizing refilling costs under demand uncertainty and storage constraints.
[66]	25	DL	PPO, DRL	DRL is applied to two-echelon inventory control with stochastic seasonal demand and multiple warehouses, minimizing total costs.
[67]	45	ML	KNN, DT, RF, XG-Boost	Hospital drug inventory is optimized using ML and stochastic optimization to reduce stock levels and emergency orders.
[22]	111	DL	DQN, TL	The problem of perishable inventory optimization under lead time and demand uncertainty is solved using DRLs with reward shaping.
[25]	41	DL	DQN	A DRL method is proposed for scalable multi-product inventory control with lead time constraints to optimize replenishment and reduce costs.
[24]	114	DL	DQN	The problem of inventory optimization for lost-sales and multi-echelon systems is solved using DRL, which minimizes costs under lead times and demand uncertainty.

large-scale supply chains. Beyond algorithmic development, researchers have also explored hybrid models. Xie [69] introduced the NFDIRM, which combines a RBF neural network with fuzzy logic. This fusion enhances both forecasting accuracy and decision flexibility in intelligent warehousing. Finally, providing a broader perspective, Boute [70] summarized key design choices in this domain and outlines promising directions for future research.

3) *Inventory control in special scenarios*: Inventory control in specialized contexts, such as for perishable goods and healthcare supplies, introduces distinct challenges due to strict temporal and safety constraints. RL has emerged as a powerful tool for addressing these complex problems.

For perishable goods, research has focused on dynamic policy learning to minimize spoilage and other losses. For instance, Selukar [27] developed a multi-product DQN model that dynamically learns optimal replenishment policies. Building on this foundation, De [22] improved the training stability of such models by incorporating reward shaping and transfer learning techniques. To better manage inherent uncertainties, Singh [62] adopted a fuzzy logic approach, which treats key parameters like deterioration and defect rates as fuzzy variables rather than fixed values.

Healthcare inventory management places a high premium on safety, and preventing stockouts is often a higher priority than minimizing costs. Addressing this critical balance, Abu [26] employed a deep RL framework for automated replenishment, which successfully reduced both operational costs and stockout incidents. Galli [67] integrated multiple

ML algorithms with stochastic optimization, where the system leverages daily ward-level data to optimize inventory.

C. Inventory Classification

Inventory classification is a systematic methodology that categorizes inventory items based on criteria such as value, demand patterns, and criticality. This approach enables organizations to allocate resources efficiently by applying differentiated management policies to distinct categories. Table IV summarizes recent research on inventory classification.

1) *Multi-criteria inventory classification*: Although the traditional ABC classification method remains widely adopted, its reliance on a single metric, such as annual usage value, often neglects other critical operational factors [80]. To overcome this limitation, multi-criteria inventory classification (MCIC) has been introduced as a more robust approach. This paradigm integrates multiple indicators and thus provides a more detailed and effective basis for decision support.

One major research stream of MCIC involves clustering algorithms. For example, Keskin [72] combined an autoencoder with K-means, incorporating sustainability indicators such as carbon emissions alongside traditional measures like order fulfillment and inventory turnover. Similarly, Khanorkar [84] applied K-means to simultaneously optimize usage value, delivery time, and unit cost. Another important line of work involves multi-criteria decision-making (MCDM) techniques. Kaabi [77] integrated genetic algorithms with TOPSIS to systematically generate optimal weights for multiple objectives. Furthermore, to address inherent uncertainties, Yung

TABLE IV. LITERATURE FOR INVENTORY CLASSIFICATION

Study	Citations	Type	Algorithms	Goals/Approach
[71]	10	ML	K-means Clustering	The inventory classification problem for impulse purchase products is solved by grouping SKUs via unsupervised clustering (K-means).
[72]	1	ML	Autoencoder/K-means	The problem of inaccurate multi-criteria inventory classification in the white goods industry is solved by hybridizing autoencoders with clustering methods.
[73]	34	ML	SVM, MNB, DT, RF, GB, KNN	Inventory classification in blood bank supply chains is addressed using ML to automate data handling, with big data and security factors being considered.
[74]	2	DL	CapsNet	Automated consumer product identification and classification for inventory management is solved, with noise reduction, feature extraction, hyperparameter tuning, and ensemble learning being considered to maximize accuracy.
[75]	26	ML	SHAP	The lack of explainability in multi-criteria ABC inventory classification is addressed by proposing an XAI-based approach using SHAP values, optimizing both classification accuracy and interpretability.
[76]	8	ML	CNN	Inventory classification challenges in electrical warehouses are solved by blending RGB and depth CNN pipelines with synthetic and real data; classification accuracy is optimized to 95.23% while domain shifts are addressed.
[77]	15	ML	Genetic Algorithm	Multi-criteria inventory classification (ABC analysis) is addressed by integrating metaheuristics (AI) for criteria weighting and TOPSIS (MCDM) for scoring; total safety stock cost and service level are optimized.
[78]	19	DL	CNN	The problem of fabric type classification for inventory management is solved using YOLOv10.
[79]	10	ML	BPNN	An objective spare parts importance evaluation method is proposed to optimize inventory strategies and reduce subjectivity.
[80]	13	ML	SHAP/K-means	The lack of Pareto compliance and explainability in multi-criteria ABC inventory classification is solved by integrating semi-supervised clustering and XAI to provide interpretable results.
[81]	50	ML	Fuzzy Logic	A fuzzy ABC classification system for space mission components is proposed, which incorporates multi-attribute criteria to optimize purchasing decisions.
[82]	1	DL	CNN/Transformer	Fine-grained product recognition for inventory classification is addressed. High interclass similarity and large intraclass variation are tackled, and accuracy is optimized with self-supervised learning to reduce annotation dependency.
[83]	28	DL	CNN/Transformer	Multi-criteria spare parts classification problems are solved by transforming hierarchical criteria into visual graphs, and inventory strategies are optimized through a modified CNN.
[84]	34	ML	K-means	The problem of inaccurate inventory classification is solved by incorporating criteria like annual usage value, lead time, and unit cost with K-Means clustering.
[85]	30	ML	GA/DT	A cost-driven ML classification method is proposed, integrating demand patterns and replenishment policies to minimize inventory costs.

[81] employed fuzzy logic, which allowed them to manage variability in delivery times and supplier risks, thereby improving classification robustness. Khan [86] proposed a fuzzy set enhanced VIKORSort method that uses trapezoidal fuzzy membership functions to improve classification flexibility and decision-making efficiency. In addition, Medina [87] applied a genetic algorithm for ABC classification of raw material inventory in a jewelry company, and the method reduced the total inventory costs across multiple criteria and established differentiated inventory policies.

2) *Enhanced classification interpretability:* The ‘black box’ nature of learning algorithms presents a challenge in inventory classification. Although these models can achieve high accuracy, their opaque decision-making processes hinder trust and adoption. This is particularly critical in multi-criteria ABC analysis, where stakeholders must understand the reasoning behind classifications. Enhanced classification interpretability directly addresses this problem.

Research in this area primarily focuses on explainable artificial intelligence (XAI) and advanced visualization. The SHAP framework is an example of XAI. As demonstrated by Qaffas [75], its primary function is to quantify the contribution of each input feature to a model’s final prediction. This allows for explanations at both the local level for individual items and the global level for the overall model. In their study [80], Qaffas further enhanced this approach by integrating semi-supervised clustering. This integration not only provides granular, multi-level explanations but also ensures that the classification results adhere to Pareto principles. Meanwhile, visualization techniques aim to make complex multi-criteria relationships intuitively understandable. For example, Yang [83] transformed hierarchical data structures into images and employed an improved CNN architecture to visualize decision boundaries and feature importance, and this method enhanced

the transparency of the classification process. Moreover, Medina [88] proposed an integrated inventory management model that combines ABC-AHP classification, holt forecasting, and cycle counting. The model is designed to optimize inventory control and minimize stock discrepancies for distributors.

3) *Classification in specified scenarios:* Beyond the foundational principles of inventory classification, many sectors present unique operational requirements. In the healthcare sector, studies focus on managing life-critical items. For example, Maathavan [73] proposed a machine learning framework for blood banks that integrates parameters like expiration dates and storage protocols. This approach serves to minimize human error in high-stakes environments. In retail, the primary challenge stems from demand volatility. Garcia [71] addressed this with a customized K-means clustering method. The approach groups SKUs by demand and cost patterns to effectively manage unpredictable impulse-buy categories and optimize total relevant costs. In manufacturing and warehousing, object detection techniques are pivotal for real-time classification. For instance, the YOLOv10-based textile inventory system from Mao [78] reached 85.6% mAP. Similarly, to handle uncontrolled environments, Piratelo [76] used a hybrid of RGB and depth CNNs for warehouse classification. Their model proved highly robust, with an accuracy of 95.23% despite domain shifts.

D. Other AI Techniques in Inventory Management

AI in inventory management typically focuses on core tasks like demand forecasting, inventory control, and inventory classification. However, researchers are also applying AI to a wider range of research. This section explores several of these novel topics.

1) *Automated simulation modeling:* Traditional logistics simulation modeling heavily depends on close collaboration

between domain experts and specialized engineers, which creates barriers to its widespread adoption in inventory management. To address this issue, Jackson [89] developed a system based on an enhanced GPT-3 Codex model. This system utilizes advanced NLP and Transformer architectures to translate natural language descriptions into executable Python simulation code, which simplified the model development process.

2) *3D inventory positioning*: The objective of 3D inventory positioning is to achieve precise automatic localization of inventory items in unstructured warehouses with flexible storage layouts. Traditional marker-based systems are often unsuitable for such dynamic environments due to their rigid infrastructure requirements. To overcome this limitation, Yoon [90] proposed a DL framework that processes drone-captured video from a single QR-coded camera. The framework integrates U-Net++ for image segmentation with epipolar geometry, resulting in a 17% improvement in coordinate estimation accuracy.

3) *Robot navigation and task management*: Efficient robot navigation and task management are crucial for automating modern warehouse operations. Research in this area addresses challenges ranging from physical pathfinding and environmental perception to high-level strategic decision-making.

One key challenge is maintaining mutual visibility and occlusion-free paths for cooperative autonomous systems, particularly for small UAVs with limited hardware. To address this problem, a visibility-aware framework was developed. Their system employs a cross-entropy method and a conditional variational autoencoder, which together significantly reduce occlusion and collision rates while maintaining real-time performance on embedded hardware. Beyond physical navigation, optimizing robot decision-making for tasks such as shelf reallocation is essential for adapting to dynamic inventory levels and traffic patterns. In [91], a DQN framework was proposed that integrates task assignment with shelf reallocation. This approach enables robots to optimize both task selection and storage repositioning concurrently, which resulted in a 17-23% increase in throughput and a 30% reduction in runtime compared to conventional methods.

4) *Fruit quality monitoring*: Food spoilage in micro-cold storage is a critical challenge for small-scale agriculture, where post-harvest losses can reach 35 to 40% due to inadequate quality monitoring. To mitigate such losses, Arun et al. [92] have proposed an AI-based system for real-time fruit freshness classification. Their approach utilizes the Inception architecture to analyze produce, and it demonstrated a classification accuracy of 99.78% under controlled laboratory conditions on apples, bananas, and oranges.

E. Application Examples

Beyond research, AI-driven solutions are being actively deployed to industries to solve problems. This section highlights specific applications of AI models across sectors such as energy, retail, manufacturing, healthcare, and agriculture. These examples showcase how AI-driven approaches address domain-specific challenges.

1) *Energy sector*: The energy sector faces challenges in material scheduling and managing demand uncertainty. To

optimize material scheduling, Hu [93] proposed an NSGA-II algorithm that integrates non-dominated sorting with rough vector feature decomposition. This method reduced convergence iterations from 460 to 65 and improved dispatch reliability. In addressing demand uncertainty, Thoummala [94] developed a two-stage DL framework. The model employs an LSTM network for forecasting to determine optimal inventory levels, resulting in inventory cost reductions ranging from 4.16% to 12.10%.

2) *Retail sector*: In the retail sector, key challenges include multi-echelon inventory coordination and the implementation of dynamic pricing strategies. To address coordination, Kaynov [95] proposed a DRL solution based on a PPO framework. This approach reduced network complexity and alleviated shortage bias, leading to cost reductions of 1 to 3% in lost-sales scenarios and 10 to 20% in backordering scenarios. For dynamic pricing, Liang [37] introduced a system based on DQN, modeling sales cycles as a Markov decision process. By decoupling the value and action-advantage functions, the algorithm achieved 91.58% of the optimal theoretical performance.

3) *Manufacturing sector*: Manufacturing supply chains are often hindered by demand information asymmetry, high inventory costs, and response delays. To mitigate the bullwhip effect, Sardar [96] developed a system that integrates an LSTM model with RFID tracking and a consignment strategy. This system enabled precise inventory control, and brings profit increase of 43%. In specialized fields such as pharmaceuticals, where historical data is limited, Zhu [97] leveraged multi-product data and grouping strategies to capture complex demand patterns more effectively.

4) *Healthcare sector*: Inventory management in healthcare must address the challenges of perishable resources, such as blood products and pharmaceuticals, where demand uncertainty and static policies can cause costly expirations or critical shortages. To optimize blood inventory, Mohamadi [98] developed a framework based on an A2C RL algorithm. This framework enabled dynamic distribution policies that achieved a zero-expiration rate while maintaining an 85% service level. To mitigate drug shortages, Abu [26] proposed a DQN-based replenishment model that formulates the problem as a Markov decision process. The model balances routine inventory with emergency demand, which reduced the shortage rate to 2.21% and the overall costs by 12.31%. Additionally, Adedugba [99] developed a dual-scenario deterministic inventory model for a pharmaceutical manufacturer in Lagos, Nigeria, using mathematical optimization to improve inventory hierarchies, lead times, and shortage management.

5) *Agriculture sector*: Agricultural supply chains face severe challenges, including perishable product losses of up to 35-40% and significant seasonal imbalances between supply and demand. For freshness monitoring, Arun [92] developed an Inception v3-based algorithm to process sensor-captured images, achieving 99% classification accuracy. This enabled more precise harvest timing and contributed to price stabilization. To optimize seasonal inventory, Wang [100] proposed a DQN framework integrated with real-time IoT data. The model incorporates reward shaping and cosine functions to effectively capture seasonal demand patterns.

V. DISCUSSION

A. RQ1: What is the Current State of Research on AI Technologies in Inventory Management?

To address this question, in Section III, this study analyzed publication trends, source distributions, and high-impact studies using a predefined set of subject terms, keywords, and application domains.

Publication trends indicate a continuous increase in AI-driven inventory optimization research from 2020 to 2025. As shown in Fig. 2, a substantial surge in publications occurred in 2022, followed by stable growth over the next three years. This trajectory reflects the growing recognition of AI's potential to enhance inventory performance, while rapid technological advancements have further promoted practical adoption.

An analysis of keywords reveals the field's main research areas. The most prominent topics are demand forecasting and inventory management, which together account for nearly 28% of the research. This high percentage shows the foundational role of forecast accuracy in effective inventory optimization. Next, inventory control and optimization make up another 24%, which indicates that translating forecasts into actionable strategies is still a central research challenge. Other major research topics include dynamic pricing, replenishment, and supply chain resilience, with each representing about 12% of the literature. This focus reflects significant scholarly attention on profit maximization and risk mitigation. In contrast, topics like multi-criteria classification, warehouse automation, and new technologies such as AI and RL currently represent a smaller but growing area of research.

Several studies have demonstrated significant influence in this domain (see Table I). For instance, [22] has garnered substantial attention with 126 citations, followed by [23] (115 citations) and [24] (114 citations). These highly cited works underscore the importance of forecasting and advanced optimization strategies. Overall, the top ten cited articles primarily focus on optimization algorithms, DL, and explainable AI, reflecting sustained efforts to leverage advanced technologies for improved inventory management efficiency and decision support.

B. RQ2: What are the Primary Topics in Inventory Management that AI is Applied to Solve?

Although AI has been widely applied to a wide range of topics, this study finds that its most significant impact is on three core challenges: demand forecasting, inventory control, and inventory classification. These domains form the operational foundation of modern inventory strategies, where AI demonstrates the greatest value in overcoming the limitations of traditional methods.

1) *Demand forecasting*: Demand forecasting aims to predict future demand accurately by modeling complex patterns, such as nonlinear trends and temporal dependencies, from historical data and diverse features. A key aspect of modern forecasting is not only to provide point estimates but also to quantify uncertainty through techniques like interval prediction [48], [46], [42], allowing for robust adaptation across various industries and contexts.

However, achieving this goal in practice faces fundamental challenges. A primary issue is that these models often fail to capture the complex nonlinearities and multivariate dependencies that drive demand [33], [43]. Second, their single point estimates neglect the quantification of forecast uncertainty, which is a critical input for robust inventory and risk management [46]. Finally, their effectiveness is frequently undermined by the practical realities of sparse, incomplete, or low-quality data.

To address these forecasting challenges, recent research has shifted towards AI-driven methods capable of capturing complex demand patterns. Deep learning models, particularly LSTM networks and their variants, have proven effective at modeling long-term temporal dependencies. For instance, Hasni [33] demonstrated that a hybrid LSTM model could reduce prediction errors for intermittent medical supplies by 74.14%.

Further advancements include the integration of attention mechanisms and sophisticated optimization algorithms. A notable example is the BO-CNN-LSTM model, which employs Bayesian optimization to automatically fine-tune the model architecture, simultaneously enhancing forecasting precision and inventory cost control [45]. Beyond improving accuracy, researchers have also tackled data scarcity. Generative AI and transfer learning are now being explored to augment sparse datasets [42], which is crucial for ensuring robust predictions for new products or in settings with limited historical data.

2) *Inventory control*: Inventory control dynamically determines optimal ordering and stocking policies to balance the trade-off between minimizing costs and maximizing service levels, while adapting to complex constraints and demand uncertainties across the supply chain [53], [52], [27], [22].

However, traditional inventory control methods are often ill-equipped for modern complexities. They struggle with diverse, non-stationary demand patterns, and a structural disconnect between forecasting and control allows prediction errors to propagate directly into costly stock imbalances [53], [52], [59]. These demand-side issues are further amplified by supply chain dynamics. Within the supply chain, information asymmetries can fuel instabilities such as the bullwhip effect. Furthermore, a complex web of real-world constraints often renders simple optimization models ineffective.

To address these challenges, DRL has emerged as a powerful paradigm for developing dynamic ordering policies that sense and adapt to non-stationary demand in real time. These policies have shown superior performance over static models [52], [53]. A key architectural innovation is the integrated forecast-and-optimize framework. In this framework, deep learning models first capture complex demand patterns. Their outputs then directly inform optimization algorithms, which prevents the propagation of prediction errors [58], [59]. This principle of integration extends to multi-echelon systems. Here, multi-agent RL allows for the development of collaborative policies that coordinate decisions across all supply chain nodes. This approach effectively dampens the bullwhip effect and aligns local actions with global system efficiency.

3) *Inventory classification*: Inventory classification is a critical process that segments items based on multiple criteria to align management strategies with their strategic importance.

However, conventional methods face significant practical limitations. First, they are constrained by an over-reliance on single or subjective criteria. Classic ABC analysis, for instance, uses a single metric and neglects critical operational factors from supplier risk to sustainability [72]. Even multi-criteria approaches often depend on subjective expert weights, which undermines objectivity and auditability [77]. Second, their effectiveness is compromised by opaque “black-box” logic. As models grow in complexity, their internal decision-making becomes unintelligible to managers, eroding trust and hindering practical adoption [80]. Third, they exhibit poor adaptability to real-world data, and are difficult to manage the uncertainty, noise, or sparsity common in modern inventories.

To overcome these challenges, AI-driven methods offer targeted advancements. To counter subjective bias, AI employs data-driven multi-objective optimization. Techniques like K-means clustering and genetic algorithm-enhanced MCDM autonomously learn the importance of diverse metrics, establishing an objective, evidence-based framework [72], [77]. To resolve the ‘black-box’ problem, AI incorporates eXplainable AI (XAI) techniques. Frameworks such as SHAP deconstruct model decisions, and provides transparent, quantifiable justifications for item categorization that enhance trust and stakeholder buy-in [80]. Finally, to tackle poor data adaptability, AI leverages advanced data processing. Fuzzy logic [81], [72] is used to effectively integrate mixed criteria, while feature enhancement tools like autoencoders ensure model robustness against noise and data sparsity.

C. RQ3: What are the Key AI Techniques and Algorithms Applied in Inventory Management, and What are their Respective Advantages and Disadvantages?

According to the review, AI techniques in inventory management can be categorized into traditional ML, DL, RL, and hybrid algorithms.

1) *ML methods*: Algorithms such as KNN, DT, RF, XGBoost, LightGBM, SVR, ANN have been widely adopted in inventory management. These methods are primarily applied to demand forecasting and can handle volatile demand [23], [29], [36]. They also support basic inventory decisions, such as optimizing replenishment quantities for profit maximization [61], [67]. The main advantages of ML algorithms lie in their low computational costs and fast inference speeds. In addition, they provide good interpretability and can clearly identify the contribution of each feature. However, their ability to capture long-term dependencies is limited. For example, SVR often performs poorly in modeling multi-period demand for short-shelf-life products [47]. In addition, ML models frequently require substantial manual intervention [34], including parameter tuning and feature engineering, and their generalization ability is constrained.

2) *DL methods*: Models including LSTM, CNN, Transformers, and AEs are increasingly applied to complex inventory management problems. They are primarily used for advanced demand forecasting, capable of handling non-stationary, intermittent, and multi-factor-driven demand patterns, such as forecasting procurement needs for perishable goods [35], and multi-category inventory requirements influenced by factors like weather and promotions [45]. DL

models excel at high-dimensional feature extraction, automatically capturing temporal dependencies and multi-feature interactions. For instance, MMCW-BiLSTM [43] captures bidirectional temporal relationships, while Transformers identify long-range nonlinear dependencies.

The main advantage of DL lies in its superior predictive accuracy, which significantly outperforms traditional statistical methods. For example, in [58], a Transformer model reduced the MAE of the predicted values from 15.8 to 8.2 and RMSE from 22.3 to 11.5. DL models also demonstrate strong adaptability to complex demand patterns. In [43], BiLSTM can process nonlinear time-series data with MAE as low as 1.75. Their generalization ability is also notable, with MMCW-BiLSTM and BO-CNN-LSTM achieving high accuracy across diverse datasets and scenarios [45].

However, compared with ML methods, DL models have high computational costs, and higher dependence on large-scale, high-quality datasets. Moreover, the ‘black-box’ nature of these models makes decision logic difficult to trace, which restrict their applicability in regulated fields such as healthcare.

3) *RL methods*: The RL algorithms, such as PPO, A2C, DDPG, and DQN, have emerged as powerful tools for dynamic inventory control. RL is particularly well-suited for multi-echelon supply chain management, perishable and multi-category inventory control, and joint inventory-financing decision-making under constraints [26], [55]. A key application is mitigating the bullwhip effect by promoting coordination and information sharing among supply chain nodes. For instance, the HAPPO [44] model can reduce demand amplification by 20%.

The core advantage of RL is its strong dynamic adaptability. It provides responses to stochastic demand, lead-time variability, and changing inventory states to achieve significant cost optimization. For example, in [53], the supplier order variability is reduced by 21%. In addition, its high-dimensional handling capability enables scalability for large-scale SKU management, with inference speeds one to two orders of magnitude faster than linear programming [53]. However, RL comes with substantial challenges: training costs are high, with models such as PPO and A2C requiring millions of iterations and several hours to converge [27] [56]. Additionally, multi-agent coordination in multi-echelon supply chains remains a challenge, as MARL models often exhibit slow convergence and struggle to balance the objectives of individual nodes with the global optimum.

4) *Hybrid algorithms*: Hybrid algorithms combine the strengths of multiple AI techniques to create more powerful and flexible solutions. Examples include LSTM-PSO [60], IPSO-BPNN [61], and joint ‘prediction + inventory’ frameworks such as W-LSTM + Q-learning [59]. These models are designed for ‘forecast-then-optimize’ workflows, bridging the gap between demand prediction and inventory decision-making to enhance overall efficiency. Phatangare proposed a machine learning based food inventory management system, leveraging linear regression, random forest, and LSTM networks [101] to optimize inventory levels through demand forecasting.

The primary advantage of hybrid models is their synergy, which combines the strengths of different techniques

to achieve superior performance. For instance, the LSTM-PSO model integrates the forecasting accuracy of LSTM with the optimization capability of PSO. This integration reduces fulfillment time by 25% and improves both model accuracy and robustness [58]. Another key benefit is their adaptability to complex scenarios. However, these advantages come at the cost of structural complexity and high computational demands, a primary disadvantage evident in the increased training times required for AE-Clustering hybrids.

D. RQ4: What Challenges does AI Face in Inventory Management, and What Directions can be Explored in Future Research?

The integration of artificial intelligence into inventory management also faces challenges spanning data dependency, model architecture, and operational viability.

First, the performance of AI models is critically constrained by data dependency. Most algorithms presuppose the availability of large, high-quality datasets and are highly sensitive to common data imperfections such as noise, outliers, and incompleteness [80]. A more profound limitation is their frequent inability to adapt to the complex data landscapes characteristic of real-world inventory systems: the heterogeneous, imbalanced, and non-stationary data associated with scarce, high-value components or sudden market disruptions [24][29]. Second, significant challenges are inherent to the architecture and functionality of current AI models. The inherent 'black box' nature of DL models impedes their adoption in high-stakes environments where decision transparency and interpretability are paramount [75]. Furthermore, many models exhibit narrow functional scopes. For instance, a DRL agent optimized for policy control may fail to manage volatile demand without an integrated forecasting component [60]. Finally, operational costs present a barrier to widespread adoption. For example, baseline models such as A2C [27] and DDPG [84] can require millions of simulation steps to achieve convergence.

To overcome these challenges, future research may focus on several key directions:

- A primary avenue is the development of data-efficient and robust learning paradigms. This includes leveraging frontier technologies like the Internet of Things (IoT) and Computer Vision to capture high-fidelity, real-time data, thus mitigating issues of scarcity and quality. Furthermore, the application of Generative AI and LLMs holds immense potential for creating high-fidelity simulation environments and synthetic training data. Such approaches can augment sparse datasets, balance class distributions, and simulate black swan events, thereby enhancing model resilience and generalization in dynamic conditions.
- Another critical research frontier is the pursuit of explainable, integrated, and automated modeling frameworks. Incorporating explainable AI techniques is crucial for demystifying model predictions, allowing managers to understand the rationale behind AI-driven decisions and fostering greater trust.
- Finally, to tackle the prohibitive operational costs, future research must move towards more efficient and

lightweight models. A key direction is to develop algorithms that learn faster from less data, such as advancing offline reinforcement learning to leverage existing historical records instead of relying on extensive live simulations.

VI. CONCLUSION

This systematic review consolidates the current landscape of AI in inventory management by analyzing 87 articles published between 2021 and 2025. Our main finding is that AI applications primarily focus on three core areas. The first is demand forecasting, where deep learning is effective at capturing complex patterns. The second is inventory control, where reinforcement learning is increasingly used to handle dynamic and uncertain environments. The third is inventory classification, where explainable AI makes traditional methods more transparent. We also identified a consistent trade-off among different AI approaches. Machine learning is computationally efficient, while deep learning offers high accuracy but requires large amounts of data. Reinforcement learning allows for real-time adaptation but demands significant training resources. These results highlight both the great potential and the practical challenges of using AI for inventory management.

The novelty of this study is its focused and timely analysis of literature published after 2020. Unlike broader reviews, our work provides a detailed map of specific AI techniques to fundamental inventory problems. This mapping clarifies the distinct advantages and trade-offs of each technique. A key contribution of our study is the identification of a clear agenda for future research aimed at overcoming current limitations. By suggesting a focus on data-efficient learning, integrated prediction and decision models, and lightweight algorithms, this study guides future academic research and industry applications.

Despite these contributions, this study has several limitations. Its timeframe may have excluded foundational research published before 2021. In addition, our keyword-based search strategy might have missed relevant studies that used different terminology. These weaknesses indicate that our conclusions offer a comprehensive but not exhaustive overview of the field, which can be further strengthened in future studies.

REFERENCES

- [1] Mugdha, D. Sharma, and D. Jose, "Transforming inventory management through machine learning based demand forecasting for a circular economy," in *2024 International Conference on Communication, Control, and Intelligent Systems (CCIS)*, 2024, pp. 1–6.
- [2] X. Kong, J. Yang, W. Chen, and J. Pan, "Joint multimission selective maintenance and inventory optimization for multicomponent systems considering stochastic dependency," *IEEE Transactions on Reliability*, vol. 73, no. 4, pp. 1967–1981, 2024.
- [3] F. Nurprihatin, Y. T. Prasetyo, R. Chandra, I. T. B. Widiwati, T. E. Lestari, and S. S. Islam, "Strategic inventory control using economic order quantity and abc classification to enhance operational excellence," in *2025 4th International Conference on Computational Modelling, Simulation and Optimization (ICCMO)*, 2025, pp. 40–46.
- [4] V. O. Adebajo-Akinpelu, M. O. Onibonjo, S. L. Gbadamosi, A. O. Femi-Onibonjo, A. S. Yusuff, and T. M. Azeez, "Enhancing inventory and payment management: A review of current technologies and future direction," in *2024 IEEE 5th International Conference on Electro-Computing Technologies for Humanity (NIGERCON)*, 2024, pp. 1–4.

- [5] S. Impram, S. V. Nese, and B. Oral, "Challenges of renewable energy penetration on power system flexibility: A survey," *Energy strategy reviews*, vol. 31, p. 100539, 2020.
- [6] Q. Tan, X. Li, and Y. Liang, "Risks, challenges and strategies of power systems against the background of carbon neutrality," *Clean Energy*, vol. 7, no. 4, pp. 767–782, 2023.
- [7] C.-y. Liu and Y.-f. Sun, "Modeling process integrated quality management system in manufacturing enterprises," in *2009 Second International Conference on Future Information Technology and Management Engineering*, 2009, pp. 77–80.
- [8] S. Ruidas, M. Rahaman Seikh, and P. Kumar Nayak, *Application of particle swarm optimization technique in an interval-valued EPQ model*, 2022, pp. 51–78.
- [9] M. Khaleel, A. Jebrel, and D. M. Shwehdy, "Artificial intelligence in computer science: <https://doi.org/10.5281/zenodo.10937515>," *Int. J. Electr. Eng. and Sustain.*, pp. 01–21, 2024.
- [10] M. K. A. Ismaeil, "The role and impact of artificial intelligence on supply chain management: efficiency, challenges, and strategic implementation," *Journal of Ecumanism*, vol. 3, no. 4, pp. 89–106, 2024.
- [11] M. Pournader, H. Ghaderi, A. Hassanzadegan, and B. Fahimnia, "Artificial intelligence applications in supply chain management," *International Journal of Production Economics*, vol. 241, p. 108250, 2021.
- [12] P. Sharma, A. Gunasekaran, and G. Subramanian, "Enhancing supply chain: exploring and exploiting ai capabilities," *Journal of Computer Information Systems*, pp. 1–15, 2024.
- [13] G. Manoharan, A. Sharma, V. D. Vani, V. H. Raj, R. Jain, and G. Nijhawani, "Predictive analytics for inventory management in e-commerce using machine learning algorithms," in *2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*. IEEE, 2024, pp. 1–5.
- [14] T. Yavuz and O. Kaya, "Deep reinforcement learning algorithms for dynamic pricing and inventory management of perishable products," *Applied Soft Computing*, vol. 163, p. 111864, 2024.
- [15] J. Zhu, S. A. Bazaz, S. Dutta, B. Anuraag, I. Haider, and S. Bandyopadhyay, "Talk to your data: Enhancing business intelligence and inventory management with llm-driven semantic parsing and text-to-sql for database querying," in *2023 4th International Conference on Data Analytics for Business and Industry (ICDABI)*, 2023, pp. 321–325.
- [16] K. Wang, C. Long, D. J. Ong, J. Zhang, and X.-M. Yuan, "Single-site perishable inventory management under uncertainties: A deep reinforcement learning approach," *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, no. 10, pp. 10807–10813, 2023.
- [17] W. Villegas-Ch, A. M. Navarro, and S. Sanchez-Viteri, "Optimization of inventory management through computer vision and machine learning technologies," *Intelligent Systems with Applications*, vol. 24, p. 200438, 2024.
- [18] L. Chen, S. Zhang, N. Wu, Y. Qiao, Z. Zhong, and T. Chen, "Optimization of inventory space in smart factory for integrated periodic production and delivery scheduling," *IEEE Transactions on Computational Social Systems*, vol. 10, no. 6, pp. 3488–3511, 2023.
- [19] P. Verma, "Transforming supply chains through ai: Demand forecasting, inventory management, and dynamic optimization," *Integrated Journal of Science and Technology*, vol. 1, no. 3, 2024.
- [20] P. Gupta and A. Sachan, "Resource planning and inventory management in supply chain," in *Supply Chain Management*. CRC Press, 2024, pp. 58–79.
- [21] Ö. Albayrak Ünal, B. Erkeyman, and B. Usanmaz, "Applications of artificial intelligence in inventory management: A systematic review of the literature," *Archives of computational methods in engineering*, vol. 30, no. 4, pp. 2605–2625, 2023.
- [22] B. J. De Moor, J. Gijsbrechts, and R. N. Boute, "Reward shaping to improve the performance of deep reinforcement learning in perishable inventory management," *European Journal of Operational Research*, vol. 301, no. 2, pp. 535–545, 2022.
- [23] J. N. Gonçalves, P. Cortez, M. S. Carvalho, and N. M. Frazao, "A multivariate approach for multi-step demand forecasting in assembly industries: Empirical evidence from an automotive supply chain," *Decision Support Systems*, vol. 142, p. 113452, 2021.
- [24] Q. Wang, Y. Peng, and Y. Yang, "Solving inventory management problems through deep reinforcement learning," *Journal of Systems Science and Systems Engineering*, vol. 31, no. 6, pp. 677–689, 2022.
- [25] H. Meisheri, N. N. Sultana, M. Baranwal, V. Baniwal, S. Nath, S. Verma, B. Ravindran, and H. Khadilkar, "Scalable multi-product inventory control with lead time constraints using reinforcement learning," *Neural Computing and Applications*, vol. 34, no. 3, pp. 1735–1757, 2022.
- [26] T. Abu Zwaide, C. Pham, and Y. Beauregard, "Optimization of inventory management to prevent drug shortages in the hospital supply chain," *Applied Sciences*, vol. 11, no. 6, p. 2726, 2021.
- [27] M. Selukar, P. Jain, and T. Kumar, "Inventory control of multiple perishable goods using deep reinforcement learning for sustainable environment," *Sustainable Energy Technologies and Assessments*, vol. 52, p. 102038, 2022.
- [28] Y. M. Tang, K. Y. Chau, Y.-y. Lau, and Z. Zheng, "Data-intensive inventory forecasting with artificial intelligence models for cross-border e-commerce service automation," *Applied Sciences*, vol. 13, no. 5, p. 3051, 2023.
- [29] M. A. Jahin, M. S. H. Shovon, M. S. Islam, J. Shin, M. F. Mridha, and Y. Okuyama, "Qamplifynet: pushing the boundaries of supply chain backorder prediction using interpretable hybrid quantum-classical neural network," *Scientific reports*, vol. 13, no. 1, p. 18246, 2023.
- [30] M. Shajalal, A. Boden, and G. Stevens, "Explainable product back-order prediction exploiting cnn: Introducing explainable models in businesses," *Electronic Markets*, vol. 32, no. 4, pp. 2107–2122, 2022.
- [31] J. Xu and L. Bo, "Optimizing supply chain resilience using advanced analytics and computational intelligence techniques," *IEEE Access*, 2024.
- [32] C. Deng and Y. Liu, "A deep learning-based inventory management and demand prediction optimization method for anomaly detection," *Wireless communications and mobile computing*, vol. 2021, no. 1, p. 9969357, 2021.
- [33] M. Hasni, M. Z. Babai, and B. Rostami-Tabar, "A hybrid lstm method for forecasting demands of medical items in humanitarian operations," *International Journal of Production Research*, vol. 62, no. 17, pp. 6046–6063, 2024.
- [34] L. A. C. Ahakonye, A. Zainudin, M. J. A. Shanto, J.-M. Lee, D.-S. Kim, and T. Jun, "A multi-mlp prediction for inventory management in manufacturing execution system," *Internet of Things*, vol. 26, p. 101156, 2024.
- [35] C.-Y. Kao and H.-E. Chueh, "Deep learning based purchase forecasting for food producer-retailer team merchandising," *Scientific Programming*, vol. 2022, no. 1, p. 2857850, 2022.
- [36] A. Aktepe, E. Yanik, and S. Ersöz, "Demand forecasting application with regression and artificial intelligence methods in a construction machinery company," *Journal of Intelligent Manufacturing*, vol. 32, no. 6, pp. 1587–1604, 2021.
- [37] Y. Liang, Y. Hu, D. Luo, Q. Zhu, Q. Chen, and C. Wang, "Distributed dynamic pricing strategy based on deep reinforcement learning approach in a presale mechanism," *Sustainability*, vol. 15, no. 13, p. 10480, 2023.
- [38] D. Li, F. Gu, X. Li, R. Du, D. Chen, and A. Madden, "Dynamic sales prediction with auto-learning and elastic-adjustment mechanism for inventory optimization," *Information Systems*, vol. 119, p. 102259, 2023.
- [39] S. K. Jauhar, S. Harinath, V. Krishnaswamy, and S. K. Paul, "Explainable artificial intelligence to improve the resilience of perishable product supply chains by leveraging customer characteristics," *Annals of Operations Research*, pp. 1–40, 2024.
- [40] T. Sathish, D. SaiKumar, S. Patil, R. Saravanan, J. Giri, and A. A. Aly, "Exponential smoothing method against the gradient boosting machine learning algorithm-based model for materials forecasting to minimize inventory," *AIP Advances*, vol. 14, no. 6, 2024.
- [41] K. Lutoslawski, M. Hernes, J. Radomska, M. Hajdas, E. Walaszczyk, and A. Kozina, "Food demand prediction using the nonlinear autoregressive exogenous neural network," *IEEE Access*, vol. 9, pp. 146 123–146 136, 2021.

- [42] M. Kim, J. Lee, C. Lee, and J. Jeong, "Framework of 2d kde and lstm-based forecasting for cost-effective inventory management in smart manufacturing," *Applied sciences*, vol. 12, no. 5, p. 2380, 2022.
- [43] S. Abualurouq, A. Alzubi, and K. Iyiola, "Inventory prediction using a modified multi-dimensional collaborative wrapped bi-directional long short-term memory model," *Applied Sciences*, vol. 14, no. 13, p. 5817, 2024.
- [44] Y. Yang, M. Wang, J. Wang, P. Li, and M. Zhou, "Multi-agent deep reinforcement learning for integrated demand forecasting and inventory optimization in sensor-enabled retail supply chains," *Sensors (Basel, Switzerland)*, vol. 25, no. 8, p. 2428, 2025.
- [45] R. Liu and V. Vakharia, "Optimizing supply chain management through bo-cnn-lstm for demand forecasting and inventory management," *Journal of Organizational and End User Computing (JOEUC)*, vol. 36, no. 1, pp. 1–25, 2024.
- [46] H. Cui, H. Guo, J. Wang, and Y. Wang, "Point and interval forecasting for wine prices: an approach based on artificial intelligence," *International Journal of Contemporary Hospitality Management*, vol. 36, no. 8, pp. 2752–2773, 2024.
- [47] S. K. Panda and S. N. Mohanty, "Time series forecasting and modeling of food demand supply chain based on regressors analysis," *Ieee Access*, vol. 11, pp. 42 679–42 700, 2023.
- [48] W. A. Zogaan, N. Ajabnoor, and A. A. Salamai, "Leveraging deep learning for risk prediction and resilience in supply chains: insights from critical industries," *Journal of Big Data*, vol. 12, no. 1, p. 94, 2025.
- [49] A. Manos, D. E. Filippidou, N. Pavlidis, G. Karanasios, G. Vachtanidis, I. Mallidis, O. Tsolakakis, and G. Ayfantopoulou, "Dynamic demand forecasting with ai: Maximizing supply chain value," in *2024 International Conference on Engineering and Emerging Technologies (ICEET)*, 2024, pp. 1–4.
- [50] M. Seyedan, F. Mafakheri, and C. Wang, "Order-up-to-level inventory optimization model using time-series demand forecasting with ensemble deep learning," *Supply Chain Analytics*, vol. 3, p. 100024, 2023.
- [51] T. Jin, "Attention-based temporal convolutional networks and reinforcement learning for supply chain delay prediction and inventory optimization," in *2024 International Conference on Image Processing, Computer Vision and Machine Learning (ICICML)*. IEEE, 2024, pp. 1527–1531.
- [52] Y. Zhang, L. He, and J. Zheng, "A deep reinforcement learning-based dynamic replenishment approach for multi-echelon inventory considering cost optimization," *Electronics*, vol. 14, no. 1, p. 66, 2024.
- [53] D. Preil and M. Krapp, "Artificial intelligence-based inventory management: a monte carlo tree search approach," *Annals of Operations Research*, vol. 308, no. 1, pp. 415–439, 2022.
- [54] B. Yang, X. Xu, Y. Gong, and Y. Rekik, "Data-driven optimization models for inventory and financing decisions in online retailing platforms," *Annals of Operations Research*, vol. 339, no. 1, pp. 741–764, 2024.
- [55] T. Temizöz, C. Imdahl, R. Dijkman, D. Lamghari-Idrissi, and W. van Jaarsveld, "Deep controlled learning for inventory control," *European Journal of Operational Research*, vol. 324, no. 1, pp. 104–117, 2025.
- [56] D. S. Kurian, V. M. Pillai, A. Raut, and J. Gautham, "Deep reinforcement learning-based ordering mechanism for performance optimization in multi-echelon supply chains," *Applied Stochastic Models in Business and Industry*, vol. 40, no. 5, pp. 1433–1454, 2024.
- [57] A. Rohilla, T. Kundu, R. Kapoor, and J.-B. Sheu, "Enhancing retail inventory replenishment amid product life cycle shifts: A system dynamics approach," *IEEE Transactions on Engineering Management*, 2025.
- [58] J. Xu and L. Bo, "Enhancing supply chain efficiency resilience using predictive analytics and computational intelligence techniques," *IEEE Access*, 2024.
- [59] H. J. Wahedi, M. Heltoft, G. J. Christophersen, T. Severinsen, S. Saha, and I. E. Nielsen, "Forecasting and inventory planning: An empirical investigation of classical and machine learning approaches for svanehøj's future software consolidation," *Applied Sciences*, vol. 13, no. 15, p. 8581, 2023.
- [60] T. Demizu, Y. Fukazawa, and H. Morita, "Inventory management of new products in retailers using model-based deep reinforcement learning," *Expert Systems with Applications*, vol. 229, p. 120256, 2023.
- [61] Y. Guan, Y. Huang, and H. Qin, "Inventory management optimization of green supply chain using ipso-bpnn algorithm under the artificial intelligence," *Wireless Communications and Mobile Computing*, vol. 2022, no. 1, p. 8428964, 2022.
- [62] R. Singh and V. K. Mishra, "Machine learning based fuzzy inventory model for imperfect deteriorating products with demand forecast and partial backlogging under green investment technology," *Journal of the Operational Research Society*, vol. 75, no. 7, pp. 1223–1238, 2024.
- [63] X. Liu, M. Hu, Y. Peng, and Y. Yang, "Multi-agent deep reinforcement learning for multi-echelon inventory management," *Production and Operations Management*, vol. 34, no. 7, pp. 1836–1856, 2025.
- [64] D. Y. Mo, Y. P. Tsang, Y. Wang, and W. Xu, "Online reinforcement learning-based inventory control for intelligent e-fulfilment dealing with nonstationary demand," *Enterprise Information Systems*, vol. 18, no. 2, p. 2284427, 2024.
- [65] J. W. Chong, W. Kim, and J. Hong, "Optimization of apparel supply chain using deep reinforcement learning," *IEEE Access*, vol. 10, pp. 100 367–100 375, 2022.
- [66] F. Stranieri, F. Stella, and C. Kouki, "Performance of deep reinforcement learning algorithms in two-echelon inventory control systems," *International Journal of Production Research*, vol. 62, no. 17, pp. 6211–6226, 2024.
- [67] L. Galli, T. Levato, F. Schoen, and L. Tigli, "Prescriptive analytics for inventory management in health care," *Journal of the Operational Research Society*, vol. 72, no. 10, pp. 2211–2224, 2021.
- [68] H. J. Zietsman and J. H. van Vuuren, "A generic decision support framework for inventory procurement planning in distribution centres," *Computers & Industrial Engineering*, vol. 177, p. 109057, 2023.
- [69] C. Xie and C. Xie, "Inventory control strategy based on neural network and fuzzy algorithm in intelligent warehousing system," *Discover Artificial Intelligence*, vol. 5, no. 1, p. 159, 2025.
- [70] R. N. Boute, J. Gijsbrechts, W. Van Jaarsveld, and N. Vanvuchelen, "Deep reinforcement learning for inventory control: A roadmap," *European journal of operational research*, vol. 298, no. 2, pp. 401–412, 2022.
- [71] D. García-Barrios, "A machine learning based method for managing multiple impulse purchase products: an inventory management approach," *Journal of Engineering Science and Technology Review*, 2021.
- [72] S. Keskin and A. Taskin, "A novel autoencoder-integrated clustering methodology for inventory classification: A real case study for white goods industry," *Sustainability (2071-1050)*, vol. 16, no. 21, 2024.
- [73] K. S. K. Maathavan and S. Venkatraman, "A secure encrypted classified electronic healthcare data for public cloud environment," *Intelligent Automation & Soft Computing*, vol. 32, no. 2, 2022.
- [74] R. Alabdan, H. K. Alkahtani, K. M. Othman, R. Alrooba, S. Algarni, A. A. Alharbi, and K. Shankar, "Advanced imaging technologies with ensemble learning for consumer products identification and classification," *IEEE Transactions on Consumer Electronics*, vol. 70, no. 4, pp. 7174–7182, 2024.
- [75] A. A. Qaffas, M.-A. Ben HajKacem, C.-E. Ben Ncir, and O. Nasraoui, "An explainable artificial intelligence approach for multi-criteria abc item classification," *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 18, no. 2, pp. 848–866, 2023.
- [76] P. H. M. Piratelo, R. N. de Azeredo, E. M. Yamao, J. F. Bianchi Filho, G. Maidl, F. S. M. Lisboa, L. P. de Jesus, R. d. A. Penteado Neto, L. d. S. Coelho, and G. V. Leandro, "Blending colored and depth cnn pipelines in an ensemble learning classification approach for warehouse application using synthetic and real data," *Machines*, vol. 10, no. 1, p. 28, 2021.
- [77] H. Kaabi, "Comparative analysis of multicriteria inventory classification models for abc analysis," *International Journal of Information Technology & Decision Making*, vol. 21, no. 05, pp. 1617–1646, 2022.
- [78] M. Mao, A. Lee, and M. Hong, "Efficient fabric classification and object detection using yolov10," *Electronics (2079-9292)*, vol. 13, no. 19, 2024.
- [79] S. Zhang, X. Qin, S. Hu, Q. Zhang, B. Dong, and J. Zhao, "Importance degree evaluation of spare parts based on clustering algorithm and back-propagation neural network," *Mathematical Problems in Engineering*, vol. 2020, no. 1, p. 6161825, 2020.

- [80] A. A. Qaffas, M. A. B. Hajkacem, C.-E. B. Ncir, and O. Nasraoui, "Interpretable multi-criteria abc analysis based on semi-supervised clustering and explainable artificial intelligence," *IEEE Access*, vol. 11, pp. 43 778–43 792, 2023.
- [81] K. L. Yung, G. T. S. Ho, Y. M. Tang, and W. H. Ip, "Inventory classification system in space mission component replenishment using multi-attribute fuzzy abc classification," *Industrial Management & Data Systems*, vol. 121, no. 3, pp. 637–656, 2021.
- [82] W. Shen and Y. Qin, "Lcnet-vit-fg: a product recognition method based on the fusion of self-supervised pretrained cnn and transformer," *Journal of Electronic Imaging*, vol. 34, no. 3, pp. 033 026–033 026, 2025.
- [83] K. Yang, Y. Wang, S. Fan, and A. Mosleh, "Multi-criteria spare parts classification using the deep convolutional neural network method," *Applied sciences*, vol. 11, no. 15, p. 7088, 2021.
- [84] Y. Khanorkar and P. Kane, "Selective inventory classification using abc classification, multi-criteria decision making techniques, and machine learning techniques," *Materials Today: Proceedings*, vol. 72, pp. 1270–1274, 2023.
- [85] J. Svoboda and S. Minner, "Tailoring inventory classification to industry applications: the benefits of understandable machine learning," *International Journal of Production Research*, vol. 60, no. 1, pp. 388–401, 2022.
- [86] J. Khan, A. Ishizaka, and M. Z. Babai, "Enhancing multi-criteria inventory classification: Resolving boundary issues with vikor-fuzzy sorting," *International Journal of Production Economics*, vol. 281, p. 109526, 2025.
- [87] R. Chompu-inwai and T. Thaiupathump, "Applying genetic algorithm in abc analysis for jewelry raw material inventory management," in *2023 2nd International Conference on Computer Technologies (ICCTech)*, 2023, pp. 23–28.
- [88] G. C. Medina, S. E. Cabello, Y. S. Garcia, G. Quispe Santivañez, and E. Castañeda, "Inventory management model applying cyclic counting by abc-ahp classification in a laboratory equipment distribution company," in *2022 8th International Conference on Information Management (ICIM)*, 2022, pp. 151–154.
- [89] I. Jackson, M. Jesus Saenz, and D. Ivanov, "From natural language to simulations: applying ai to automate simulation modelling of logistics systems," *International Journal of Production Research*, vol. 62, no. 4, pp. 1434–1457, 2024.
- [90] B. Yoon, H. Kim, G. Youn, and J. Rhee, "3d position estimation of objects for inventory management automation using drones," *Applied Sciences*, vol. 13, no. 19, p. 10830, 2023.
- [91] S.-C. Wu, W.-Y. Chiu, and C.-F. Wu, "Deep reinforcement learning for task assignment and shelf reallocation in smart warehouses," *IEEE Access*, vol. 12, pp. 58 915–58 926, 2024.
- [92] S. Arun, S. A. Wagle, P. Nambiar, P. Panalkar, P. Ekka, V. Kumar, H. Dhiman, and A. Roy, "Optimizing micro cold storage for detecting stale food and fruits," *Science and Technology for Energy Transition*, vol. 80, p. 43, 2025.
- [93] Z. Hu, S. Liu, F. Yang, X. Geng, X. Huo, and J. Liu, "Research on multi-objective optimization model of power storage materials based on nsga-ii algorithm," *International Journal of Computational Intelligence Systems*, vol. 17, no. 1, p. 76, 2024.
- [94] N. Thoummala, Y. Kang, and D. Min, "A deep learning-based approach to a newsvendor problem considering uncertainty and time-varying costs," *Optimization Letters*, vol. 18, no. 9, pp. 1963–1974, 2024.
- [95] I. Kaynov, M. Van Knippenberg, V. Menkovski, A. Van Breemen, and W. Van Jaarsveld, "Deep reinforcement learning for one-warehouse multi-retailer inventory management," *International journal of production economics*, vol. 267, p. 109088, 2024.
- [96] S. K. Sardar, B. Sarkar, and B. Kim, "Integrating machine learning, radio frequency identification, and consigning policy for reducing unreliability in smart supply chain management," *Processes*, vol. 9, no. 2, p. 247, 2021.
- [97] X. Zhu, A. Ninh, H. Zhao, and Z. Liu, "Demand forecasting with supply-chain information and machine learning: Evidence in the pharmaceutical industry," *Production and Operations Management*, vol. 30, no. 9, pp. 3231–3252, 2021.
- [98] N. Mohamadi, S. T. A. Niaki, M. Taher, and A. Shavandi, "An application of deep reinforcement learning and vendor-managed inventory in perishable supply chain management," *Engineering Applications of Artificial Intelligence*, vol. 127, p. 107403, 2024.
- [99] A. Adedugba and D. Inegbedion, "Inventory control optimisation: the dynamics of deterministic request model of pharmaceutical appropriation and storage," *International Journal of Operational Research*, vol. 54, no. 1, pp. 33–50, 2025.
- [100] Z. Wang, W. Wang, T. Liu, J. Chang, and J. Shi, "Iot-driven dynamic replenishment of fresh produce in the presence of seasonal variations: A deep reinforcement learning approach using reward shaping," *Omega*, vol. 134, p. 103299, 2025.
- [101] S. Phatangare, L. Sharma, A. Mate, O. Jaiswal, and D. Pardeshi, "Revolutionizing food ordering: An ml-driven system for predictive sales and inventory optimization," in *2025 International Conference on Computing Technologies (ICOCT)*. IEEE, 2025, pp. 1–6.

APPENDIX

As shown in Table V, the acronyms and full names of various AI methods are presented.

TABLE V. TABLE OF AI ALGORITHM ACRONYMS

Acronym	Complete name
AHK-ELM	Attention-based Hybrid Kernel Extreme Learning Machine
ANN	Artificial Neural Network
BiLSTM	Bi-directional Long Short-Term Memory
BNN	Bayesian Neural Network
DL	Deep Learning
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
DRLOM	Deep Reinforcement Learning-based Ordering Mechanism
DT	Decision Tree
DTL	Decision Tree Classifier
ES	Exponential Smoothing
GA	Genetic Algorithm
GB	Gradient Boosting
GBDT	Gradient Boosting Decision Trees
IMOHHO	Improved Multi-Objective Harris Hawk Optimization
LGB	Light Gradient Boosting Machine
LSTM	Long Short-Term Memory
MAML	Model-Agnostic Meta-Learning
MARL	Multi-Agent Reinforcement Learning
MCTS	Monte Carlo Tree Search
ML	Machine Learning
MLR	Multiple Linear Regression
MLR	Natural Language Processing
MNB	Multinomial Naive Bayes
MNLR	Multinomial Logistic Regression
NARXNN	Nonlinear Autoregressive Exogenous Neural Network
PSO	Particle Swarm Optimization
RF	Random Forest
SAC	Soft Actor-Critic
SHAP	Shapley Additive Explanations
SVM/R	Support Vector Machine/Regression