Archives of Computational Methods in Engineering (2023) 30:2605–2625
https://doi.org/10.1007/s11831-022-09879-5

REVIEW ARTICLE

Applications of Artificial Intelligence in Inventory Management: A Systematic Review of the Literature

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Received: 13 August 2022 / Accepted: 23 December 2022 / Published online: 7 February 2023

Abstract

Today, companies that want to keep up with technological development and globalization must be able to effectively manage their supply chains to achieve high quality, increased efficiency, and low costs. Diversified customer needs, global competitors, and market competition have led companies to pay more attention to inventory management. This article provides a comprehensive and up-to-date review of Artificial Intelligence (AI) applications used in inventory management through a systematic literature review. As a result of this analysis, which focused on research articles in two scientific databases published between 2012 and 2022 for detailed study, 59 articles were identified. Furthermore, the current situation is summarized and possible future aspects of inventory management are identified. The results show that the interest in AI methods has increased in recent years and machine learning algorithms are the most commonly used methods. This study is meticulously and comprehensively conducted so it will probably make significant contributions to the further studies in this field.

keywords Inventory Management · Artificial Intelligence · Machine Learning · Deep Learning · Systematic Literature Review

1 Introduction

As a result of increasing competition, customers today are looking for the products they buy in global markets, at the right time, in the right place, with good quality and at lower prices. Supply chains are complex systems that connect the world. Inventory management is essential for achieving the goals of efficient supply chains, controlling costs, and delivering to customers with minimal delays [1] and goes hand in hand with the supply chain. The word inventory refers to investment in materials and end-products throughout the supply chain for use in production or distribution to the end-customer. Singh and Verma define inventory management as a continuous process of planning, organizing and controlling which minimizes inventory investment while balancing supply and demand [2].

Inventory management is primarily concerned with the planning and controlling an industry's inventory and is an important component of supply chain management. It includes issues such as estimating material requirements at various points in the supply chain, determining necessary material's amount, ordering frequency, and safety stock levels. It also includes inventory visibility, inventory forecasting, inventory management, lead time, inventory shipping costs, inventory forecasting, inventory valuation, forecasting future inventory prices, available physical space, quality management, returns and defective goods, and demand forecasting [2]. It plays a very important role in reducing overall costs and rapid response objectives. Effective inventory management requires the right inventory in the right place at the right time to minimize system costs and meet customer needs.

In inventory management, it is very important to avoid uncertainties, which usually occur in demand forecasts during the lead time. Demand forecasts form the basis of all planning activities as they are the input for many operational decisions [3, 4]. Manufacturing companies

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significantly rely on demand forecasting since it determines production planning. When the demand process is unknown, we generally depend on forecasting expected demand during the lead time. Accurate and reliable demand forecasts are critical as they thoroughly guide supply chain managers' planning, all major operational decisions. Inaccurate estimations mislead service level goals and create additional costs like shortages, lost revenue, or excess inventory. Over demand may lead to inventory depletion, while additional inventory costs may be incurred if demand is below expectations. With sufficient inventory, bottlenecks can be avoided or unnecessarily high inventory costs can be avoided by keeping a correspondingly lower inventory level. Inventory management is used in various domains such as retail [5, 6], logistics [7, 8], supply chain management [9, 10], and availability of multiple sources of supply [11].

Development in artificial intelligence technologies, one of the innovations that technological development has brought with the improving capabilities of computer hardware, allows the inventory management applications turn into an intelligent process. Machine learning (ML) and deep learning (DL) methods, which are sub-branches of AI, play an important role in this sense. Number of studies conducted in recent years shows that the interest in ML and DL techniques is gradually increasing. These methods can quickly analyze large and diverse data sets, and they improve the accuracy of demand forecasting. In addition, combination of inventory management with AI techniques makes it an efficient and flexible process with lower operational costs, supplies faster response times for customers as well as more contextual information. Researchers were allowed to focus on questions aimed at clarifying the true potentials and potential weaknesses of such algorithms, making it easier for them to focus on these techniques.

The aim of this article is to provide a comprehensive overview of the current and future research potential of inventory management through a systematic literature review of articles from 2012 to 2022. Inventory management and related AI techniques are categorized and presented in a way that facilitates orientation for researchers in the field. A bibliometric analysis was used to ensure that studies were investigated and explored in depth with a quantitative analysis.

This study comprehensively explores and investigates AI methods used in inventory management. It also aims to summarize the current applications and points out possible future directions for inventory management. The contributions of this study are as follows:

1 The relevant literature by developing a classification scheme based on previous studies are reviewed.
2 A step-by-step approach to conduct a systematic literature review is provided.
3 By analyzing the status of AI methods, the most commonly used methods in inventory management are identified.
4 Future research directions in the field of inventory management are identified.

The article is organized as follows: After the Sect. 1, information regarding the research methodology is given in Sect. 2. The literature review and related work evaluation strategy are described in Sect. 3. Section 4 contains the practical implications, which explores the research questions in detail. Conclusion and future work directions are given in Sect. 5.

2 Research Methodology

Systematic literature reviews, which are becoming increasingly popular in academic research, are based on a rigorous, robust, well-defined, and reliable methodology for literature search, and they allows the reader to rapidly sample and evaluate the related field [12]. They are used to gain a new and comprehensive understanding of the relevant field and identify other useful areas of research. This approach aims to identify, interpret, evaluate, and categorize all articles related to the identified research question(s). Compared to a literature review, which focuses primarily on the descriptive results of a particular field of knowledge, a systematic literature review provides a more useful and comprehensive overview of research fields [13].

The current study followed a five-step process to better understand the existing literature, identify research questions and keywords, and develop further steps. Figure 1 shows the stages of the systematic literature review used in the study, and Fig. 2 shows the number of articles examined through the review process.

1. *Determination of research questions* Probably the most important and difficult part of the research design is the determination of the research questions. The formulation of a research question leads to the selection of research strategies and methods, i.e. the research is conducted based on the research questions. Formulating a research question plays an important role in the research process as it helps to combat the collection and analysis of unrelated data [14].

Research questions were formulated to accurately determine the purpose considering the scope of the study. Research questions of this study are as follows:

- RQ1. What is the current state of research in inventory management?

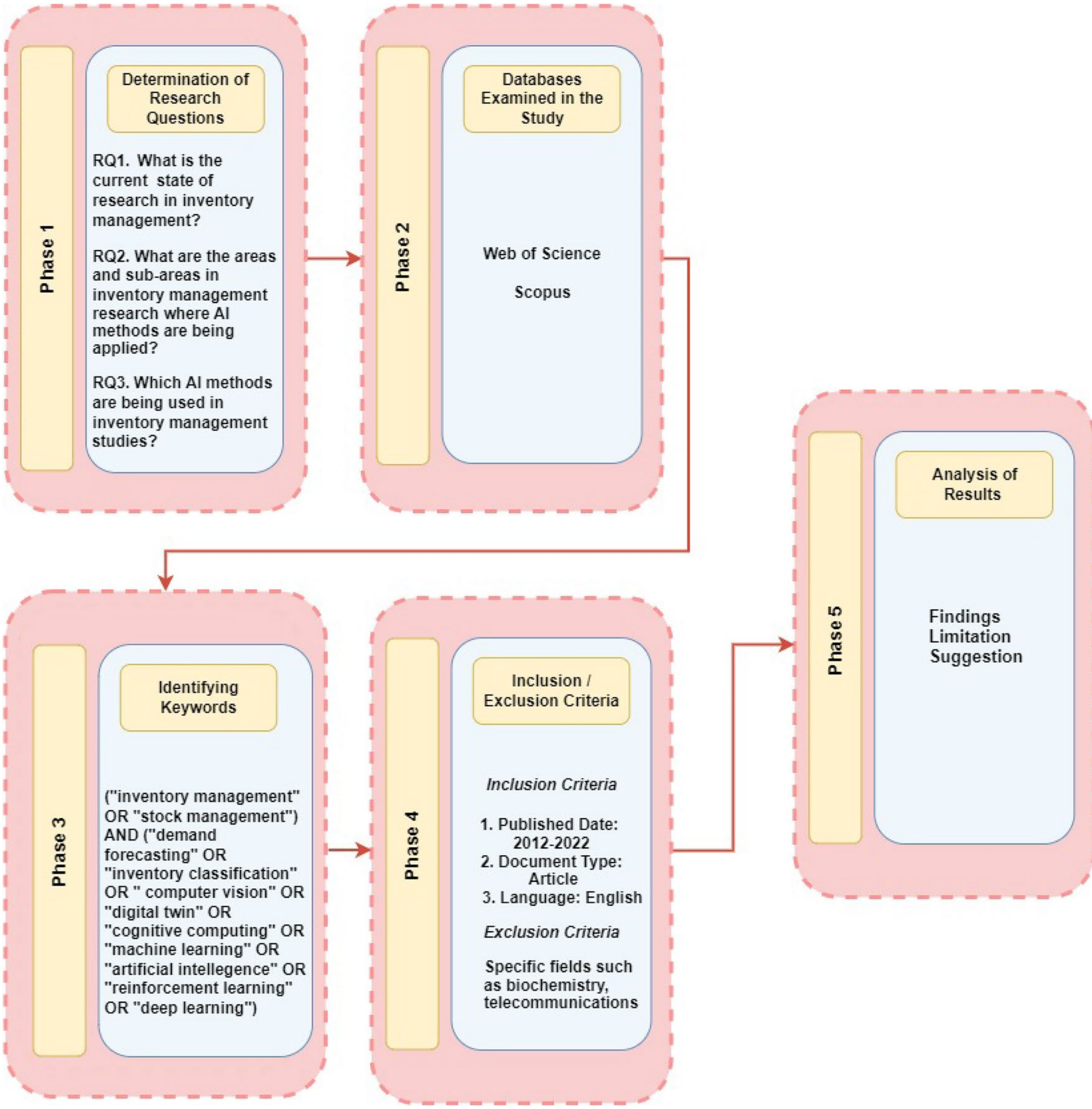
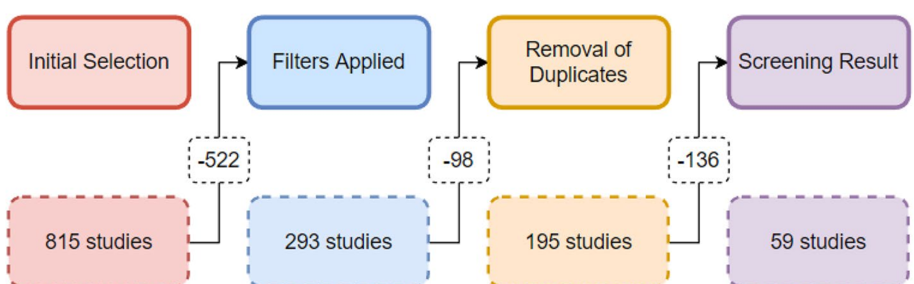


Fig. 1 Stages of systematic literature review

Fig. 2 Number of articles reviewed according to the results of the search



- RQ2. What are the areas and sub-areas in inventory management research where AI methods are being applied?
- RQ3. Which AI methods are being used in inventory management studies?

2. *Databases examined in the study* Web of Science and Scopus, two established academic databases that provide broad access to a wide range of peer-reviewed literature, were utilize to identify the related studies on research topic.

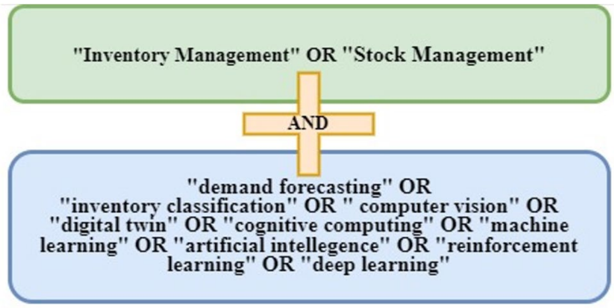


Fig. 3 The identifying keywords used in the study

Table 1 Search results

	Web of science	SCOPUS	Total
Inventory problems	10	9	19
Demand forecast	13	14	27
Inventory classification	10	3	13
Total	33	26	59

3. *Identifying keywords* Web of Science and Scopus search were performed based on title, abstract, and manuscript keywords (TITLE-ABS-KEY) in May 2022. The corresponding literature was searched using the keywords given in Fig. 3.

Here, the "OR" operator is used to combine keywords within the same group while the "AND" operator is used to combine the two main keyword groups. As a result of the initial search, 338 results were obtained in Web of Science and 477 results in Scopus.

4. *Inclusion/Exclusion criteria. Inclusion/Exclusion criteria* Inclusion/exclusion criteria were established to select the most relevant articles. Articles whose language of publication was English in the period from 2012 to 2022 were included in the study. After applying these filters, 175 results were obtained in Web of Science and 186 results in Scopus. Following biochemistry and telecommunications-oriented studies exclusion, 130 articles in Web of Science and 163 articles in Scopus remained in the search list. Research results from the two databases were then merged using Endnote software, removing repetitive publications yielding 195 articles in the list. This process is illustrated in Fig. 2. articles that were insufficient to answer the research questions and not directly related to the topic were excluded. Through the filtering process, the number of articles was reduced to 59 that are included in the study.

Selected studies distribution in terms of three main topics, namely inventory problems, demand forecast and inventory classification, are shown in Table 1. It is clear from this table that majority of the studies have been conducted in the field of demand forecasting.

5. *Analysis of results Findings*, limitations and recommendation were examined in this step that will be presented in Sect. 5 of the study.

2.1 Bibliometric Analysis

Bibliometrics is the census-based field of study to survey published articles, journals, and book editions using mathematical and statistical techniques. Bibliometric analysis, on the other hand, is a research method that examines the characteristics of studies and research in a particular field with a quantitative analysis, i.e. it analyzes certain characteristics of documents/publications such as journal, subject, number of authors, publication information. The bibliometric analysis applied in this study corresponds to the answer to the research question RQ1. In this sense, a quantitative analysis and data visualization of the studies is presented according to the criteria of publication trends, source distribution, distribution by country, most cited articles, and keyword analysis.

2.1.1 Publication Trend

The current study examines 59 AI studies for inventory management and covers the years 2012–2022. Distribution of studies in terms of the publication year is shown in Fig. 4. It is clear from this figure that there has been a rapid growth recently, and about 40% of these studies were published in 2021. The reason for the low number of articles published in 2022 is that the literature review was conducted in May 2022.

2.1.2 Resource Distributions

The distribution of 59 articles among 49 journals are shown in Fig. 5. About 70% of the articles were published as a single study in a particular journal. European Journal of Operational Research, on the other hand, hosts the majority of the publications with 10% followed by Applied Science with 7% and International Journal of Production Economics with 4%. Expert Systems with Application, Computers & Industrial Engineering, and Mathematical Problems in Engineering journals were contributed to publications with 3% each.

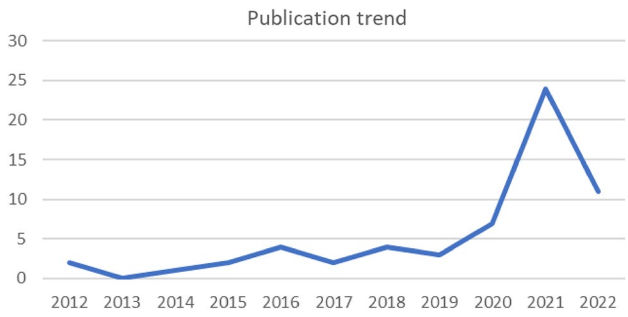


Fig. 4 Publication trends of articles from 2012 to 2022

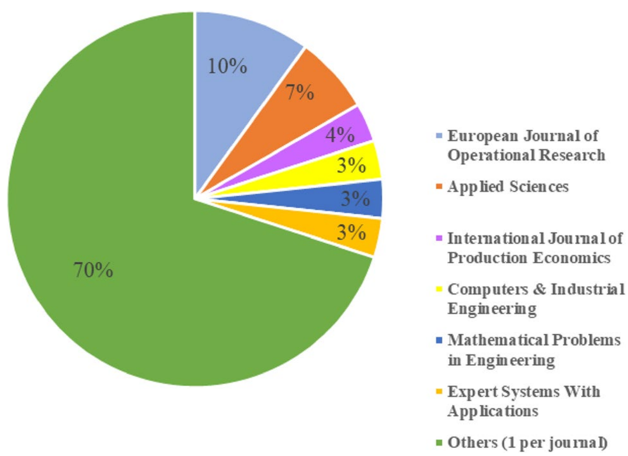


Fig. 5 Resource distributions

2.1.3 Distribution of Articles by Country of Origin

Geographic distribution of countries, defined based on the corresponding authors' institution origin, was also studied. In this sense, there were 21 countries contributed. Top eight countries with a major contribution along with others, combined into a single entry, are given as a bar graph in Fig. 6. It can be concluded, from this figure, that the topic is of global interest. Although there are many China based articles (about 26%), the number of articles from Canada, Belgium, USA and Turkey is also significant.

2.1.4 Most Cited Articles

The most cited five studies along with their application focuses are tabulated in Table 2. Here, Nguyen and Medjaher is the most cited article dealing with the development of a predictive maintenance framework based on sensor measurements [15]. Tabernik and Skocaj studied object detection and recognition [16]. Mohammaditabar et al., Liu et al. and Kartal et al. focused on classification of inventories using different methods [17–19].

2.1.5 Keyword Analysis

Identifying commonly used keywords related to inventory management and artificial intelligence techniques is very important to determine the focus of a study. Therefore, a co-occurrence analysis was performed. With this analysis, 8 different clusters containing the largest number of items were identified utilizing minimum twice co-occurrence threshold. The mapping of 63 qualified keywords out of a total of 603 keywords and their interactions with each other are shown in Fig. 7. Here, each cluster is represented by a different color to indicate that objects in the same cluster have more similarity than objects in a different cluster. Different objects are connected by lines representing the links between them.

The most frequently used keywords in the selected literature are "inventory management" (occurrence = 30, total link strength = 47), "machine learning" (occurrence = 30, total link strength = 37) and "demand forecasting" (occurrence = 25, total link strength = 36). The keywords and their numbers are detailed in Table 3.

3 Review of Literature

This section addresses research questions RQ2 and RQ3. The articles studied were analyzed in detail and discussed under three main headings such as inventory problems, inventory classification, and demand forecasting. Each section is also divided into subsections, and the articles used in the study are presented in the form of a summary table after being examined against the characteristics given in Fig. 8. In addition, studies that did not have similar characteristics in each category were examined in more detail. The list with the full names of the algorithms whose abbreviations are given in the summary table can be found in Appendix. Although this study is limited according to the characteristics given in Fig. 8, important studies on this topic are as follows: Aggarwal provided a comprehensive overview of traditional inventory systems [20]. Giannoccaro et al. used the reinforcement learning algorithm to determine a near-optimal inventory policy [21]. Cachon and Fisher demonstrated the various logistical advantages of sharing inventory management related information with supply chain partners [22]. Partovi and Anandarajan were used artificial neural networks to classify stock keeping units in a pharmaceutical company [23]. Giannoccaro et al. presented a method based on fuzzy set theory and cascade inventory theory to define inventory management policy in the supply chain [24].

3.1 Inventory Problems

This section discusses issues related to general inventory problems associated with optimization, inventory control,

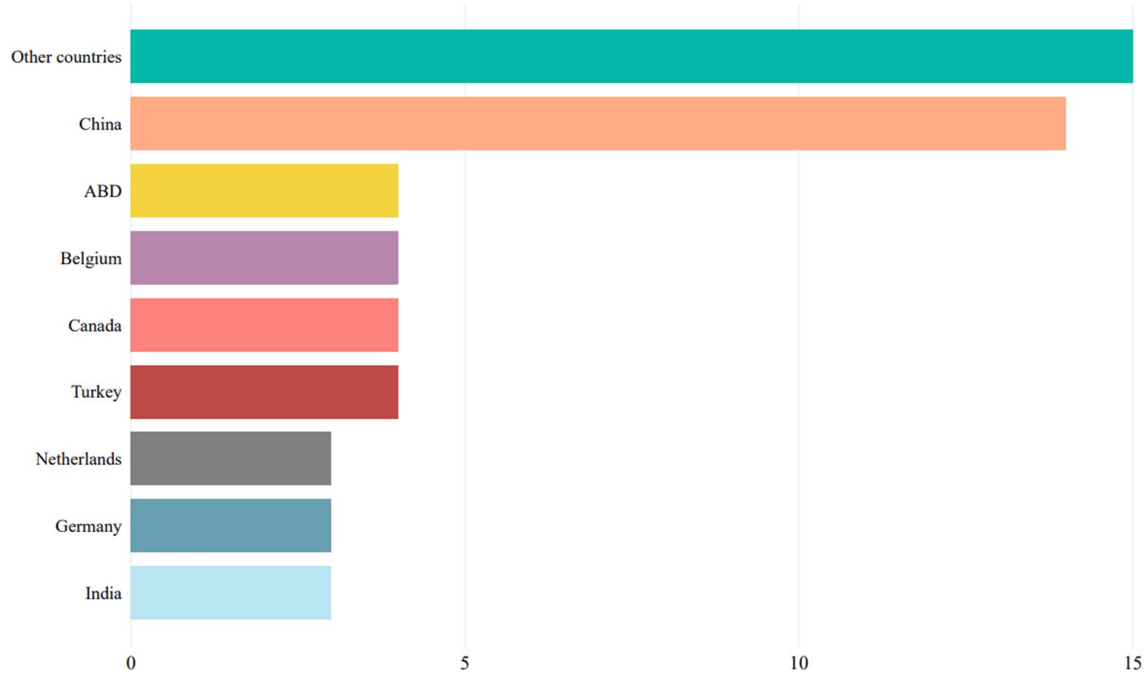


Fig. 6 Distribution of published articles by country of origin

Table 2 Most cited articles

Authors	Year	Citations	Application Focuses
Nguyen and Medjaher	2019	150	Data driven approach
Tabernik and Skocaj	2020	126	Object detection
Mohammaditabar et al.	2012	111	Inventory classification
Liu et al.	2016	102	MCABC inventory classification
Kartal et al.	2016	86	Inventory classification

and policy setting. It is aimed to determine optimal inventory level, minimize operating costs, and maintain that level on a regular basis. In order for production processes to continue without an interruption, requirements must be supplied in a timely manner. Order fulfillment [25], situations where the distribution of demand suddenly changes [26], dynamic inventory management and control [27] and inventory control [28] are studied in the literature.

As a result of the research in the field of inventory management problems, 18 articles were identified, which are presented in Table 4. ML algorithms have been mainly used in this field, and the results have shown that they can be well adapted to this type of problems. Inventory control aims to continuously monitor inventory movements, customer purchasing tendencies, and timing analysis using cumulative sales data. Most articles on inventory control have used reinforcement learning algorithms to track and control inventory movements, solve complex sequential decision problems based on learning using existing data, and enable dynamic learning in a changing environment without the need for a predetermined environment model [29].

The data-driven approach requires manual processing and analysis of data by experts [46]. Inventory problems using ML methods were explored in this subsection. Pirayesh Neghab et al. studied the ordering problem for a single news vendor problem to minimize the expected cost. To solve the model, they proposed a new algorithm called HMMNV based on the integration of neural networks and hidden Markov models, and demonstrated the performance of the algorithm using crude oil demand data. Their model performed 27% better compared to other methods in terms of system cost [30].

The optimization subsection examines how products are procured, managed, used, and product policies are determined. Better results were obtained based on the over-provisioning, ski-rental, and max-min approaches in a problem of replenishing the drug volume to manage a hospital's drug inventory by Zwaida et al. With this study they have proven that DRL is a promising method [33]. Kara and Doğan evaluated inventory management performance under stochastic customer demand and lead time to minimize a retailer's total cost. They observed that short-lived products showed better results under higher variance in demand [32].

One of the widely studied areas in inventory problems is the inventory control. Meisheri et al. suggested a new approach of reinforcement learning to solve practical scenarios with unit weights and quantities, shelf life and capacity,

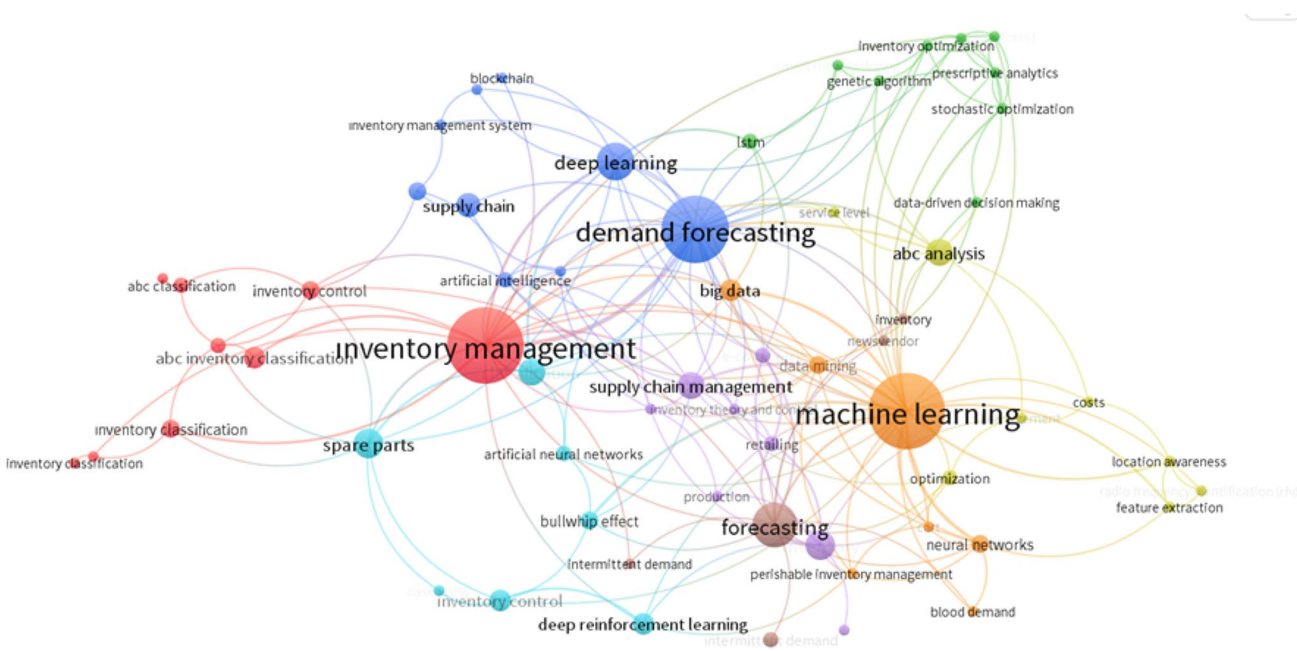


Fig. 7 Keyword co-occurrence map

Table 3 Keywords contained in the eight clusters

Cluster	Keywords	Count
Cluster 1	Inventory management, ABC classification, mixed integer programming, classification, inventory control, inventory classification, inventory, multi-criteria decision making, multi- criteria inventory classification	9
Cluster 2	Inventory optimization, LSTM, genetic algorithms, smart manufacturing, random forest, stochastic optimization, data-driven decision making, prescriptive analytics, XGBoost	9
Cluster 3	Demand forecasting, artificial intelligence, blockchain, deep learning, Internet of Things, supply chain, inventory management system, service level, logistic	9
Cluster 4	ABC analysis, optimization, management, location awareness, feature extraction, radio frequency identification, costs	8
Cluster 5	Supply chain management, production, e-commerce, inventory theory and control, retailing, hidden markov model, operations management, inventory	8
Cluster 6	Spare parts, classification, artificial neural network, deep reinforcement learning, bullwhip effect, inventory control, production	7
Cluster 7	Machine learning, data mining, neural networks, big data, blood demand, perishable inventory management, CART	7
Cluster 8	Forecasting, intermittent demand, inventory, newsvendor, demand, inventory management	6

cross-product constraints, stochastic demand, and multiple products for an inventory control problem of multiple items with different lead times. The proposed solution method using DQN and PPO algorithms were compared, and the results showed that the method is robust and very close to the optimum [39]. De Moor et al. demonstrated that reinforcement learning in perishable inventory management can stabilize the training process and improve DRL performance in inventory control. Results showed that reward shaping had an overall positive effect [35]. Boute et al. used DRL algorithms to facilitate applications in inventory control and aimed to highlight potential research avenues that could expand their scope by improving them [36].

Establishing appropriate inventory policies is very important in order to increase inventory management performance. Decision makers must consider the impact of complex interactions by incorporating both internal and external factors. Priore et al. have developed a dynamic framework for managing inventory in a supply chain. Inductive learning algorithms were used to understand the complex interaction between controllable and uncontrollable factors that affect labor performance. They obtained

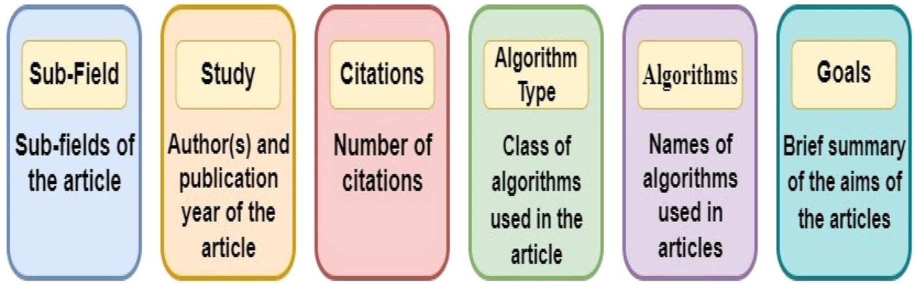


Fig. 8 Features used to analyze the articles used in the study

successful results for the inventory management problem by selecting the best inventory policy for a wholesaler with an average accuracy of 88% [40].

Inventory visibility provides an overview of inventory that allows real time tracking. Demey and Wolff presented an inventory management system called SIMISS to improve the visibility of lost items in the International Space Station, and they used a classical decision tree to show its performance. With this system, they were able to reduce supply costs for long-term missions. [41].

One of the methods used in inventory management is object detection and recognition. Tabernik and Skocaj proposed a Deep Learning based system for traffic sign inventory management using convolutional neural networks. They concluded that the DL based approach has high accuracy and speed for many traffic sign categories with an average error rate of 2–3% [16]. Merrad et al. have proposed a reliable and efficient object detection solution to overcome the inventory management problem of detecting out-of-stocks in warehouses [42].

The digital twin, which connects the physical and virtual worlds [47], can address the challenge of seamless integration between advanced data analytics and IoT [48]. Kegenbekov and Jackson offered a solution to outperform the base stock policy. They also introduced digital supply chain twins for real-world applications [38].

Computer vision enhances human-machine interaction by providing improved visualization of the natural world on a digital platform similar to the human brain [49, 50]. Kalinov et al. found that flight path correction using the CNN approach provided a higher precision score compared to the standard snake-based grid flight trajectory method. They reduced the time of an inventory process without decreasing the percentage of barcode recognition [43].

3.2 Demand Forecasting

This section presents studies on inventory management and demand forecasting. It relates to the processes such as cost-effective inventory management [51], inventory control [52], stock forecasting [53] and sales forecasting [54]. Accurate demand forecasting is considered a necessity for proper inventory management. It supports companies to increase profits, market their products, and improve customer satisfaction [55] by preventing the inventory from being depleted. It improves the developing of an adaptive pricing strategy for better revenue management [56]. Simple moving average, exponential smoothing, Croston method, Sytetos-Boylan approach, etc. are used in demand forecasting as the traditional methods. In recent years, on the other hand, applications of AI methods such as clustering, k-nearest neighbor, neural networks, regression analysis, decision tree, support vector machines, Gaussian processes, regression and long-short term memory, etc. have employed. Unlike traditional demand forecasting methods, Machine Learning does not focus on priori assumptions, but learns from the available data to produce the most accurate result. This, in turn, helps ML-based forecasters increase customer engagement and create more accurate demand forecasts as they expand into new markets or channels [57].

Demand forecasting is mainly concerned with the determining the level of demand for a future period. It is the most studied field as shown in Table 5. Demand forecasting field consists of the sub-fields of customer forecasting, product forecasting, sales forecasting, order forecasting, and information finding/information exchange. Based on the reviews, included 28 demand forecasting articles were analyzed according to their sub-fields.

This section shows that stable predictive performance is achieved by tackling complex problems without requiring long demand histories to properly adjust parameters. The benefits of ML in inventory management are reducing costs, determining the amount of material to procure, estimating material demand, and classifying inventory.

Companies try to predict markets' future trends in order to understand customer demand, and they plan the decisions to be made and the activities to be executed. However, it is very difficult to make an effective forecasting since the customer demand often fluctuates due to various factors. Deng and Liu have shown that their proposed deep inventory management method can effectively predict customer demand trends with a predictive accuracy of more than 80% and reduce overall costs by about 25% [58]. K-nearest neighbor models were used for monthly customer demand by Kack and Freitag. They obtained high average estimation accuracy with short computation times [59].

Table 4 Analysis of studies for inventory problems

Sub-Field	Study	Citations	Algorithm Type	Algorithms	Goals/ Approach
Data-Driven Approach	[15]	150	DL	Long-Short Term Memory (LSTM)	A new dynamic predictive maintenance framework based on sensor measurements is presented.
	[30]	2	DL	Deep Neural Network (DNN)	A new integrated estimation and optimization approach is implemented to solve an inventory problem that considers both observable and unobservable characteristics that affect the randomness of demand.
Optimization	[31]	19	ML AI	Automated Innovization Genetic Algorithm (GA)	The inventory management problem has been applied to an automated innovation framework using genetic programming to achieve higher levels of innovation.
	[32]	83	ML AI	Q-learning and Sarsa algorithms, GA	A reinforcement learning-based approach was used to understand the importance of stock age policy in perishable stock systems.
	[33]	12	ML	Deep Reinforcement Learning (DRL)	An online Deep Reinforced Learning-based solution for the drug refill optimization problem in a hospital is proposed.
Inventory Control	[34]	1	ML	State-Action-Reward-State-Action (SARSA) Algorithm	A reinforcement learning approach was proposed to use knowledge of the structural components of inventory management problems, and the results showed the applicability of the approach.
	[35]	3	ML	Deep-Q-Network (DQN)	A reward design method was used to accelerate training and learning in perishable inventory management.
	[36]	21	ML	DRL	A roadmap for the application of DRL in inventory control was presented, along with a list of issues that need to be addressed for the solution to work.
	[37]	44	ML	DRL	The problems of lost sales, dual-sourcing, and multi-echelon inventory management were evaluated.
	[38]	8	ML Digital Twin	DRL	Demonstrated how inbound and outbound data flows can be synchronized and business continuity supported when end-to-end visibility is provided based on the Proximal Policy Optimization algorithm.
	[39]	5	ML	DQN Proximal Policy Optimization (PPO)	A general framework using RL algorithms is presented, explaining why the general inventory problem cannot be solved using classical optimization techniques.
Inventory Policy	[40]	70	ML	Inductive Learning Algorithm	It provides a dynamic framework for periodically determining the best renewal rule for a given node in the supply chain and the determination of the appropriate inventory policy.
Stock Visibility	[41]	6	ML	Decision Tree (DT)	An inventory management system called SIMISS was offered to increase the visibility of lost items.
Object Recognition	[16]	126	DL	Mask R-CNN	A Deep Learning based system is proposed to detecting and recognizing multiple traffic sign categories.
	[42]	1	ML	Random Sample Consensus (RANSAC), Scale Invariant Feature Transform (SIFT)	A real-time machine learning-based notification system for the inventory shortage problem in warehouses was presented.
	[43]	22	Computer Vision	Convolutional Neural Network (CNN)	Presented a hybrid robotic system based on unmanned aerial vehicles for detecting and scanning of barcodes scanned as landmarks in a real warehouse in low light conditions.
Customer Sentiment Analysis	[44]	–	Computer Vision DL	Mask-R-CNN YOLOv5	An innovative pipeline is proposed that integrates advanced Deep Learning technologies and includes a visual AI-based customer sentiment assessment engine.
Maintenance Planning	[45]	–	ML AI	DRL Simulated Annealing (SA)	A hybrid solution algorithm based on a Double Deep Q-Network for maintenance planning was developed.

Table 5 Analysis of studies for demand forecasting field

Sub-Field	Study	Citations	Algorithm Type	Algorithms	Goals/Approach
Customer Estimate	[58]	1	DL	LSTM	A deep inventory management method is proposed to forecast future customer demand.
	[59]	38	ML	K-Nearest Neighbor (KNN)	The local forecasting performance of K-nearest neighbor models is examined in estimating the monthly customer demand of a manufacturing company.
Product Estimate	[60]	52	ML Statistical Methods	K-means Clustering Algorithm, ARIMA	A forecasting model for retailers based on customer segmentation was developed to improve inventory performance.
	[61]	13	Time Series Models DL	Moving Average, Neural Network (NN), ARIMA	By using different methods to estimate the print volume of Taiwan's leading educational publisher, they were able to increase the accuracy of demand forecasting by 3.7% and reduce capacity planning costs by 8.3%.
	[62]	47	ML DL	CART, KNN, Random Forest (RF), MLP, Artificial Neural Network (ANN)	Decisions about the number of transfusions and blood orders in a hospital network were made using forecasting techniques. Comparing the Multilayer Perceptron (MLP) model with other approaches, it was found that it can produce efficient decisions.
	[63]	20	ML	K-Means Clustering Algorithm, RF, Quantile Regression Forest (QRF)	The proposed machine learning-based approach aims to provide pre-launch forecasts and support inventory management decisions by using historical sales data of existing and new products as well as previously launched products.
	[64]	6	DL	Recurrent Neural Network (RNN)	A forecasting framework is proposed that uses information on non-demand characteristics such as past demand and downstream inventory data to forecast the demand for drugs in a group.
	[65]	5	Statistical Methods ML	Comb-TSB, ClustAvg	After a literature review on demand forecasting methods for time series data, a new demand forecasting tool is proposed based on analysis results and findings.
	[66]	3	DL	CNN, LSTM, Graph Embedding	A deep learning-based demand forecasting strategy for cold chain product demand prediction is presented.
	[67]	20	Statistical Methods ML	GAMLSS	An application of Generalized Additive Models for Position, Scale, and Shape (GAMLSS) has been proposed to build distribution regression models to forecast demand for a large number of perishable products.
	[68]	9	Time Series Models ML	Loess, Extreme Gradient Boosting (XGBoost)	A hybrid model is presented that combines seasonal and trend decomposition, considering inventory and replenishment constraints, to estimate future red blood cell demand.
	[69]	1	Time Series Models AI	Simple Exponential Smoothing, Quadratic Exponential Smoothing, Feature Synthesis, GA	Three time series forecasting methods were selected for demand forecasting according to periodic demand, static demand, and trend demand for sensitive parts based on spare parts, and a genetic algorithm was used to check the performance of the inventory management system.

Table 5 (continued)

Sub-Field	Study	Citations	Algorithm Type	Algorithms	Goals/Approach
	[70]	4	ML	XGBoost	The future need for red blood cells was predicted.
	[71]	4	ML DL	Linear Regression, Nonlinear Regression, ANN, SVR	The number of spare parts for construction machinery that the customer will demand in the future was estimated.
	[72]	8	ML	RF, XGBoost, KNN, DT	Stochastic optimization and ML methods were used to examine the ten most commonly used drugs to minimize the need for emergency supplies and inventory in a hospital ward.
	[73]	1	AI	Multiple Linear Regression, GA, Internet of Things	An IoT-based inventory management system is presented that combines the causal method of multiple linear regressions with genetic algorithms for product demand forecasting of a semiconductor manufacturer.
	[74]	–	ML	Generalized Linear Model, Generalized Additive Model, Multivariate Adaptive Regression Splines, RF, Bayesian Additive Regression Trees	A two-stage hybrid model is proposed to study the demand uncertainty of a food bank.
	[75]	2	ML	RF, Gaussian Process (GP), NN, XGBoost, DT	A new ML method for estimating red blood cell requirements was developed and compared with the results of four widely used ML algorithms.
	[76]	6	ML Statistical Methods	Linear regression, GAMLSS, QuantReg, QRF, ARIMAX	Classification-based model selection is presented as a new approach to demand forecasting for perishable retail products.
Sales Forecast	[77]	35	ML	XGBoost	A three-stage XGBoost-based forecasting model was created to predict the sales characteristics and trend of a commodity data series. The CA -XGBoost model was found to outperform the Autoregressive Integrated Moving Average (ARIMA), XGBoost, C-XGBoost, and A-XGBoost models.
	[78]	2	ML DL	LSTM, Generative Adversarial Networks, XGBoost	A sales forecasting model called M- GNA- XGBoost has been proposed to effectively forecast sales for each product in online stores and implement digital marketing strategies.
	[79]	–	ML	LSTM, Core Density Estimation	A framework has been proposed to reliably predict a company's inventory data.
Order Forecast	[80]	1	ML DL	RF, KNN, NN, Logistic Regression, Balanced Blagging (BB), SVM, XGBoost, LightGBM	ML methods are used to solve the problem of backorders prediction problem and maximizing profit on decisions about outstanding orders. A post-hoc explanatory model was applied to the best performing model by comparing it to other commonly used ML methods.
	[81]	22	ML	RF, Gradient Boosting Machine	Product preorders were estimated using a tree-based predictive model.
	[82]	23	ML		A new ML method called Weighted Majority Newsvendor Shifting is proposed to solve a newsvendor problem in estimating an unknown demand without knowing the type of distribution, variance, and mean.

Table 5 (continued)

Sub-Field	Study	Citations	Algorithm Type	Algorithms	Goals/Approach
Knowledge Discovery, Knowledge Sharing	[83]	4	DL	ANN, TREPAN Algorithm	A knowledge discovery system has been researched and developed with ANN for inventory forecasting.
	[84]	8	Time Series Models ML	Naive, Exponential Smoothing (ETS), ARIMAX, Lasso, MLP, SVR, RF, ARIMA-W ETS-W,	A case study of a U.S. pharmaceutical manufacturer examined the use of downward information to improve short-term demand forecasts.
Optimization	[85]	–	AI	GA Digital Twin	A digital twin integrating smart warehouse and production with a roulette genetic algorithm for demand forecasting in a small textile company was proposed.

One of the most studied topics in the field of demand forecasting is product demand forecasting. There exist 14 studies conducted on this topic. Benhamida et al. have proposed the Comb-TSB hybrid method for intermittent and lumpy demand models. In this method, TSB relies on an automatic separation decomposition between a combination method consisting mainly of statistical models, while the Comb method uses two statistical estimation methods (ARIMA and Theta) and ML-based MLP method. Their cluster-based approach was validated in a case study [65]. In another study, Abbasi et al. used four common predictive machine learning models to make blood transfusion decisions in a hospital network. They concluded that use of a trained neural network model reduced average daily costs by about 29% compared with the current policy [62]. Zhang et al. compared the ARIMA, PSO-ELM, and XGBoost methods with an empirical evaluation based on real data to validate the performance of the cold chain storage demand forecasting scheme. While their proposed method had the best performance, the ARIMA method yielded the worst [66]. Ulrich et al. applied GAMLSS to build distribution regression models to predict the demand for a large number of perishable items. They observed the results of linear regression, log-linear regression, log-log regression, quantile regression, random forests, and quantile regression forest methods as performance criteria for the GAMLSS approach [67]. To forecast demand for eight products in a supermarket in India, Bala segmented customers based on various characteristics through cluster analysis and implemented various forecasting models based on ARIMA and neural network based ARIMA. The given forecasting model ensured to improve inventory performance by increasing the level of service to customers and decreasing the level of inventory [60]. Li et al. suggested an integrated ordering strategy to forecast future red cell demand. They reduced the inventory by 40% and ordering frequency by 60%, resulting in significant cost savings for blood suppliers [68].

Sales forecasting is an analytical technique that seeks to predict and understand consumer demand in businesses and support managerial decision-making. Effective demand forecasting not only supply companies a competitive advantage, but also plays a very important role in the strategic decisions they make to satisfy consumer demands and satisfaction, maintain market share, and manage costs [86]. In this sense, Wang and Yang used an effective sales forecasting model called M-GNA-XGBoost, which provides effective forecasting of sales in a short time to perform digital marketing strategies with machine learning. The root mean and absolute error mean of the error squares of the model were obtained as 11.9 and 8.23, respectively. Based on these results, it was proven that the efficiency of the method was increased [78]. Ji et al. created a C-XGBoost model based on the clustering algorithm according to their three-stage XGBoost model, which also includes sales features. To achieve higher prediction accuracy, an A-XGBoost model was created using

ARIMA for the linear part and an XGBoost model for the nonlinear part. C-XGBoost and A-XGBoost models were weighted to form the final model, CA-XGBoost model [77].

In order forecasting problem, a customer places an order for future production and shipment if a product is out of stock or temporarily unavailable. Product order shortages are very important in inventory management as they affect the entire supply chain. According to Ntakolia et al. found that the best models for the back-order estimation problem were the isotonic regression method and the post-calibrated LGBM model. The explainability analysis of the best model was performed, and the results showed a similar performance depending on the area under the curve (AUC) value 0.95 of the RF, XGB, LGBM, and BB models. This result also introduced a significant contribution to the accurate forecasting of future demand and backorders [80].

Demand forecasting is used in knowledge discovery or knowledge sharing to obtain information between variables. Lee et al. designed an inventory information discovery system to capture and predict information between variables and extract the information learned from a ANN in the form of decision trees and explain the demand forecast result with the TREPAN algorithm [83].

3.3 Inventory Classification

This section presents studies on the classification of inventories. The basis of efficient inventory management is based on accurate inventory classification. It provides benefits such as protecting inventories of critical raw materials and finished products, controlling inventories of semi-finished products, and minimizing inventory costs [23]. This way, companies have a competitive advantage as they can provide the best service to their customers. The traditional ABC method of classifying inventory considers only total amount of annual usage. It ignores other criteria and results in an inaccurate classification. Multi Criteria Decision Making (MCDM) methods incorporating order size, delivery time, inventory costs, suppliers, etc., have been developed as a solution for this. Development of technology has led the companies to more efficient methods of classifying their inventories. The use of DL and ML methods provides promising results for classification by automating complex decision-making processes and processing large amounts of data easily.

For the sect. 3.3, 13 articles were identified and are listed in Table 6. It shows the studies using AI and ML methods. The results show that ML methods classify inventories in more detail and provide efficient strategies [87]. The k-means clustering algorithm, which splits the data into multiple groups with similar characteristics, is widely employed in the articles. DL methods have also been applied in many studies.

Material management is the optimization of inventory through classification of materials to ensure continuity of quality performance and to control the material distribution cycle. In this context, using an earthquake disaster as a case study, Huang et al. divided emergency supplies (medical gauze, leech, bandage, alcohol, saline, and blood pressure monitor) into three main categories such as importance, scarcity, and time to analyze them effectively. Their model provided a prediction accuracy of up to 92.45% compared to other models [88].

Inventory classification is used in many sectors such as healthcare, defense, and automotive production. Various methods were applied to find a better classification model for obtaining, organizing, and analyzing useful information by collecting large amounts of data. Maathavan and Venkatraman implemented various machine learning methods to find a better classification model for electronic health records [91]. The results showed that the KNN method achieved the highest performance in terms of precision, recall, and F1 score. According to the average execution time of the encryption algorithms, KNN still has the best performance. The genetic algorithm was used to estimate the weights of the criteria to perform the ABC inventory classification and MCDM methods were preferred to calculate the weighted score of the inventory items by Kaabi et al. [90]. The results show that the genetic algorithm-based models outperform the existing classification models in terms of total cost and inventory turnover functions. In the model by Aktepe et al. for the classification of inventory items in terms of multiple criteria, the inventory units are first classified according to the decision rules of an expert system and then the k-means clustering algorithm is used to make the second assignment [87]. When expert systems and k-means clustering algorithms are not sufficient for grouping some items, they have developed a fuzzy rule-based method to make the final assignment.

Product management includes all the strategic directions and practices that enable the development, marketing and improvement of products. In this context, García-Barrios et al. studied the problem of sourcing impulse purchase products and showed that this problem can be solved with low-cost groupings based on the clustering process [92]. They have shown that the proposed method can be used to cluster impulse purchase products more effectively.

Spare parts management plays an important role in maintenance planning and logistics activities. Decision makers can determine the optimal strategy for inventory management by overcoming the problems such as explanation and learning ability and criteria selection based on right classification methods. In this manner, Zhang et al. concluded that the order of importance of spare parts is same, and the gravity values are very close when they are compared with the actual gravity values to check the validity of the model [94]. Moreover, they ensured the correct evaluation of the importance of these items by adding new spare parts.

3.4 Methods Used in Studies

Table 7 lists the artificial intelligence methods used in this study and the number of uses.

In the literature, many AI based methods have been used for inventory management. Among these, the random forest method is the most commonly used one with 9 occurrences. The K-Means clustering algorithm, encountered in 8 studies, is the second most widely applied method. XGBoost and ANN, employed 7 times, are the third most preferred methods followed by SVM, GA and RA with 6 times. On the other hand, RNN, CART, and DNN were used once. Note that the total number of artificial intelligence techniques is greater than the number of articles since some articles utilizes more than one method.

4 Practical Implications

This section examines the RQ answers in a more comprehensive and detailed manner.

RQ1: What is the current state of research in inventory management?

The purpose of this question is to obtain a quantitative overview of the current work on this topic. A bibliometric analysis was conducted to answer the question. This analysis provided a detailed data visualization that allowed the perception of key characteristics of the literature. It also defined the publication trends, source distributions, influential authors, regions, and keywords of the articles included in the current study. In addition, the use of network analysis revealed important research and relationships issues.

For publication trends, articles covering the years of 2012–2022 period and containing AI techniques in inventory management were examined. Since 2010–2012, considered the beginning of Deep Learning practical implementations, the number of published articles has increased. The growth was observed especially in 2021. This is because researchers are getting familiar with the potential of these methods in inventory management studies and discovering that employing such methods yield in a performance increase. In addition, the rapid development of artificial intelligence technology has made inventory management processes intelligent. Although there exist many studies on inventory management in the literature, the number of studies dealing with artificial intelligence applications is limited.

Evaluation of the distribution of studies shows that most of the journals are production-related, indicating the active role of inventory management research. It appears that publications from China account for more than a quarter of the 59 examined articles. It can be concluded that AI applications in inventory management are intensively pursued by Chinese authors, they are actively working on this topic, and they are leading the literature by developing new methods.

Keyword analysis is very important for a study. The VOS (visualization of similarities) Viewer software, was preferred to visualize the relationships between the articles. It performs clustering techniques and provides a graphical representation of bibliometric maps using custom labeling algorithms or density metaphors [97]. Based on this map, one can see the most common variables of the inventory management concept and the relationship pattern between these variables. It can be concluded that inventory management, machine learning, and demand forecasting have the most similarities and connections among all items, as they have the largest nodes. It is clear from Fig. 7 that the concept of inventory management is often associated with concepts such as demand forecasting, classification, control, optimization, and artificial intelligence methods (deep learning, machine learning, and reinforcement learning). According to the distribution of keywords, location awareness, smart manufacturing, big data, e-commerce, Internet of Things, and deep reinforcement learning are the current areas of work.

RQ2. What are the areas and sub-areas in inventory management research where AI methods are being applied?

AI methods, which are widely used in many industries and fields, affect almost all areas of inventory management. Considering the relevant literature, studies have been carried out in many areas such as operations management, inventory control, inventory visibility, supply chain management, optimization, knowledge discovery, object recognition, estimation, classification, and etc. The contributions of AI methods to the field and sub-fields of inventory management and their impact on the literature are examined in more detail. As a result of the keyword analysis, it is observed that inventory management is mainly focused on three categories: inventory problems, demand forecasting, and classification. For this reason, this study conducted a comprehensive investigation by dividing these areas into subcategories.

The inventory problem articles are divided into data-driven approach, optimization, inventory control, inventory policy, inventory visibility, and object recognition subsections. These fields are interrelated if meeting service quality requirements, managing product procurement and administration, and minimizing costs are being investigated. The main methods performed in this field are ML and DL. These methods are able to process huge amounts of data quickly to consistently identify patterns and gain insights that may be too complex for the human mind to manage. The genetic algorithm method, on the other hand, is an optimization method and was used along with the reinforcement learning algorithm. The digital twin was also utilized with the reinforcement learning algorithm. A detailed overview of these methods is given in Table 4.

Table 6 Analysis of studies for the inventory classification field

Sub-Field	Study	Citations	Algorithm Type	Algorithms	Goals/ Appoach
Material Management	[88]	2	DL	Back-Propagation Neural Network (BPNN)	A neural network-based medical equipment management model for emergency classification is proposed.
	[89]	1	ML	K-means Clustering Algorithm	A material recognition method was developed for dynamic inventory management of aerospace companies, including versatile and general materials. Inventory classification based on the numerical concept area was performed, which can automatically identify clusters of materials with the net scale function.
Health Services/ Defense Industry/ Automotive Sector	[90]	10	AI MCDM	GA, WS, TOPSIS	A benchmark dataset consisting of 47 items was used to test the model's performance by proposing a hybrid method for inventory classification.
	[91]	–	ML	Support Vector Machine (SVM), MNB, DT, RF, GB, KNN	An efficient encryption technique has been developed to secure user data by classifying electronic health records with machine learning techniques.
	[87]	12	AI ML	Expert Systems, Fuzzy Logic, K-means Clustering Algorithm	A new classification algorithm was developed by integrating the classical ABC classification with various methods in a large defense industry company.
	[19]	79	MCDM, ML	SAW, AHP VIKOR, Naïve Bayes, Bayesian Network, ANN, SVM	In a case study conducted in an automotive company by integrating machine learning algorithms and MCDM methods, the SVM method was found to have the best classification accuracy.
Inventory Control	[17]	105	AI	SA	An inventory control system is proposed that simultaneous classifies inventory and groups items by inventory cost and similarity, with appropriate guidelines established for each product group.
MCABC Problem	[18]	98	ML AI	K-means Clustering Algorithm, SA	Cluster analysis was used to progress at different levels of detail in forming the preference order of the clusters defined for the MCABC problem, and the simulated annealing method was used to search for the optimal classification according to the hierarchy of clusters from top to bottom.
Product Management	[92]	–	ML	K-means Clustering Algorithm,	Products with similar demand, order, or cost characteristics were grouped to find a near-optimal inventory grouping solution for managing multiple impulse purchase SKUs.
Spare Part	[93]	1	DL	CNN	A new approach to the classification of spare parts is presented to perform multi-criteria classification based on a hierarchical structure through image recognition.
	[94]	1	ML DL	K-means Clustering Algorithm, BPNN	The importance of maintenance spare parts was objectively classified and evaluated.
Object Detection	[95]	67	Computer Vision		A new system has been introduced to recognize traffic signs from Google Street View API images and create an inventory of traffic signs.
	[96]	63	Computer Vision	Adaboost, Linear SVM, Nonlinear SVM	The performance of three computer vision algorithms in detecting and classification of traffic signs for US highways is presented and validated.

Table 7 Number of methods used in the study

Methods	Number of Usage	Methods	Number of Usage	Methods	Number of Usage
RF	9	QRF	3	Internet of things	1
K-Means Clustering Algorithm	8	Digital Twin	3	LASSO	1
XGBoost	7	GAMLSS	2	CART	1
ANN	7	MLP	2	Automated innovization	1
SVM	6	BPNN	2	Fuzzy logic	1
GA	6	ETS	2	MNB	1
RA	6	Naïve/Naive Bayes	2	GB	1
KNN	5	Q-Learning	2	Expert systems	1
Time Series Models	5	Sarsa Algorithms	2	QuantReg	1
LSTM	5	DQN	2	PPO	1
CNN	5	DNN	2	GP	1
ARIMA	5	RNN	1	BB	1
DT	4	Graph Embedding	1	Inductive Learning Algorithm	1
DRL	4	Generative Adversarial Networks	1	SIFT algorithm	1
SA	3	Core Density Estimation	1	Yolov5	1

In the field of demand forecasting, the articles reviewed consist of the sub-areas of customer forecasting, product forecasting, sales forecasting, order forecasting, and information exchange. In this sense, demand forecasts play an important role in managing key operations. They aim to meet incoming demand in the shortest possible time and at the lowest possible cost. Here, the methods of ML provide better results as they can handle complex interdependencies among many causal factors affecting the demand [57]. While CNN, LSTM, ANN and RNN were preferred more among DL methods, KNN, QuantReg, QRF, RF, SVM, XGBoost, CART and GAMLSS were preferred from ML methods. The simple exponential smoothing, the quadratic exponential smoothing, the feature synthesis, and Loess methods were widely implemented among all time series methods. Also, ML and DL methods were jointly applied in many studies, while others used them separately. There are many studies that combine ML methods with time series methods. A detailed overview of these methods is presented in Table 5.

In the field of inventory classification, material management consists of sub-fields on a sectoral basis (healthcare, automotive, defense), inventory control, object detection, and product management. While effective use of ML applications can be observed in this area, GA, fuzzy logic, expert systems and simulated annealing from artificial intelligence methods are also adopted. These methods have been implemented along with ML and MCDM algorithms. In addition, SAW, AHP, TOPSIS and VIKOR are commonly preferred MCDM methods. Another topic in inventory classification that was applied with machine learning algorithms is Computer vision. A detailed overview of these methods is given in Table 6.

RQ3. Which AI methods are being used in inventory management studies?

From the review of literature, it is clear that many AI techniques have been applied to inventory management. In this sense, the most common and effective method is the random forest method, which was used in 9 studies. It is a popular machine learning method introduced by Breiman in 2001 and used to develop predictive models [98]. RF, an ensemble learning method, is widely used in many fields such as computer vision, product demand forecasting, scrap feature filtering, and data mining [99] due to its excellent performance and efficient training process. This unified machine learning algorithm creates a group of trees where each tree, combined with a set of tree classifiers, votes a unit for the most popular class, and, the final ranking is obtained by combining such results [100]. Cluster analysis is the second most commonly used method. Cluster analysis, in short clustering, is referred as an unsupervised learning approach since it does not use label information. It provides information about the data by dividing the objects into clusters, ensuring that the objects in one cluster are more related than objects in other clusters [101].

Following cluster analysis, XGBoost and ANN methods were used in 7 studies. Here, XGBoost is another ensemble learning method that has achieved remarkable results in many research areas. It automatically implements multi-threading of CPU to perform parallel computation and optimize the algorithm. This way, the training speed and prediction accuracy of the models significantly improve [102]. ANN, on the other hand, is one of the most popular machine learning methods. It is an information processing technique that is used to obtain patterns, information or connections in large amount of data. It belongs to the class of black-box models, since ANNs do not require knowledge of the physical parameters of the process [103]. ANN-based methods are useful tools in modeling various engineering systems for real-world conditions without having to solve complex mathematical models.

The results revealed that machine learning methods are generally used in demand forecasting and classification, while reinforcement learning algorithms are preferred in inventory problems. In terms of methods' variety, the field of demand forecasting is quite rich, with 39 techniques. This is because some studies include various AI techniques to compare the results obtained from these methods that have a powerful effect, when applied separately or in combination with others. In terms of AI techniques usage, inventory classification is the second widely-used area with 23 algorithms. Here, the most common method is K-means clustering algorithm, while SVM, BPNN and simulated annealing are other frequently implemented methods. Hybrid techniques have also been employed in many studies. For example, Liu et al. classified products based on clustering analysis and then searched for the most appropriate solution with a simulated annealing algorithm [18].

Inventory problems ranked third with 17 techniques, with Q-learning and Sarsa algorithms. For this, single methods were utilized instead of multiple techniques with limited number of studies. This is because AI methods are recently being replaced by ML and DL applications as they mostly yield better and reliable results.

5 Conclusion

Given the developments in ML and DL algorithms, interest in these methods has greatly increased in many fields. Inventory management and artificial intelligence concepts now occupy an important place and are being studied by many researchers parallel to the growing need with the developing technology. In view of the breadth of the field, this study is mainly descriptive and provides an assessment of the potential that AI methods can offer to solve problems in inventory management. This research study has examined the areas in which these methods are used without considering the best AI method. Not only studies employing AI methods in inventory management are examined, but also the latest research trends are highlighted.

The aim of this study is to provide a systematic review of the literature focusing on the recent development and application of AI methods in inventory management. For this purpose, 59 research studies were evaluated based on pre-defined criteria as a result of the examination of 815 articles from two major databases. These articles are divided into three categories such as inventory problems, demand forecasting, and inventory classification. Considering the categories of reviewed articles, answers were obtained to the three research questions of the current situation in inventory management (RQ1), the field and sub-fields used in the study (RQ2), and the AI methods used (RQ3). In this sense, a bibliometric analysis was initially performed to determine the publication trend, source distribution, publications' country of origin, the most cited articles, and the most frequently used keywords. Finally, the techniques employed in the reviewed articles are discussed and current research developments are summarized. A detailed analysis of the research questions is also provided in the sect. 4.

It has been observed that lower accuracy rates, increased wasted labor and time, and higher inventory costs occurred in studies using statistical or time series methods compared to the studies using AI methods. While some other studies employed both methods in their studies and concluded that AI methods offer improvements in predictive accuracy and achieve higher accuracy rates. Demand forecasting errors, on the other hand, result in high inventory, storage, and transportation costs. For this type of problems, AI has been shown to quickly analyze large and diverse data sets, increase the accuracy of demand forecasting, and enable efficient and flexible inventory management with lower inventory and operational costs as well as providing customers with faster response time and more contextual knowledge.

Examining the distribution of keywords, we conclude that location awareness, smart manufacturing, Big Data, e-commerce, Internet of Things, digital twin, and DRL are current areas of work. Among these, reinforcement learning algorithms are becoming increasingly popular in inventory management. Its use enables dynamic learning that accounts problems with higher complexity. There is also a trend towards the Internet of Things and the digital twin. Despite the limited use of digital twin technology in inventory management, it has recently attracted a great interest and is growing rapidly worldwide.

In the field-based analysis, ML methods are typically used in the areas of demand forecasting and classification, while reinforcement learning algorithms are preferred for inventory problems especially in inventory control, optimization and stock visibility. Computer vision, on the other hand, is mainly considered technique in object recognition.

This study is intended to provide researchers and practitioners with a starting point and roadmap for AI techniques in inventory management by highlighting the most popular research topics. It revealed that there is a gap in the application of AI methods in inventory management, and all applications have not been comprehensively discovered yet. It also shows that collaboration among researchers needs to be improved for increased performance. Nonetheless, current study has some limitations. Use of two different databases during the article filtering procedure causes a confusion in keyword, publication period and language selection. Also, including only articles in the study may cause some other valuable sources such as books, conference papers and business reports, and etc. to be overlooked. Therefore, this study may be expanded including additional sources.

Appendix

Full names of the algorithms used in the study.
Table 8

Table 8 Full names of the algorithms used in the study

Acronym	Full Name
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
ARIMAX	Multivariate ARIMA
BPNN	Back-Propagation Neural Network
BB	Balanced Blagging
CART	Classification and Regression Tree
CNN	Convolutional Neural Network
DL	Deep Learning
DNN	Deep Neural Network
DQN	Deep-Q-Network
DRL	Deep Reinforcement Learning
DT	Decision Tree
ETS	Exponential Smoothing
GP	Gaussian Process
GAMLSS	Generalized Additive Models for Position, Scale, and Shape
GA	Genetic Algorithm
GB	Gradient Boosting
KNN	K-Nearest Neighbor
LSTM	Long-Short Term Memory
ML	Machine Learning
MLP	Multilayer Perceptron
MNB	Multinomial Naive Bayes
MCABC	Multi-Criteria ABC Classification
MCDM	Multi Criteria Decision Making
PPO	Proximal Policy Optimization
QuantReg	Quantile Regression
QRF	Quantile Regression Forest
RF	Random Forest
RANSAC	Random Sample Consensus
RNN	Recurrent Neural Network
SAW	Simple Additive Weighting
SIFT	Scale Invariant Feature Transform
SARSA	State–action–reward–state–action
SA	Simulated Annealing
SVM	Support Vector Machine
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
WS	Weighted Sum
XGBoost	Extreme Gradient Boosting

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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