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Streamlining Inventory Control: A Strategic Approach to Managing Slow-Moving Items; Systematic Review Approach

Sani Inusa Milala[1], Mazidah Mat Rejab[2*], Z. Rahman[3], Hairulnizam Bin Mahdin[4], Nargis Fatima[5]

[1]Faculty Of Technology Management and Business Universiti Tun Hussein Onn Malaysia (UTHM) Parit Raja, Malaysia

[2]Faculty of Computer Science and Information System Universiti Tun Hussein Onn Malaysia (UTHM) Parit Raja, Malaysia

[3]IoT Systems Lab, MIMOS Berhad, MRANTI Technology Park 57000 Kuala Lumpur, Malaysia

[4] Faculty of Computer Science and Information System, Universiti Tun Hussein Onn Malaysia (UTHM) Parit Raja, Malaysia

[5] Department of Software Engineering, National University of Modern Languages Islamabad, Pakistan

[*]Corresponding Author

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ABSTRACT

Across all sectors, efficiently managing slow-moving inventory is still a major difficulty that results in higher holding costs, waste, and inefficiencies in supply chain operations. Even with improvements in inventory management, many companies still have trouble maintaining demand-driven procurement while maintaining stock levels. Modern data-driven strategies are frequently not completely incorporated into existing inventory models, which limits their ability to reduce excess stock and boost operational performance. There is an urgent need to investigate how new technologies might improve the management of slow-moving inventory given the quick developments in machine learning, IoT-enabled tracking, and predictive analytics. To cut expenses, decrease losses, and simplify inventory procedures, businesses need technology-driven, optimized tactics. To determine the best inventory optimization models, analyze market trends, and provide an integrated framework for improved efficiency in managing slow-moving inventory, this study offers a thorough analysis of previous research. The goal of this study is to review and summarize the most recent research on slow-moving inventory management, with an emphasis on optimization strategies, predictive modelling, and technology advancements. The objective is to offer a methodical analysis of strategies like multi-echelon optimization, AI-based forecasting, simulation models, and EOQ models to evaluate their efficacy across various sectors. 350 research publications from academic databases such as Scopus and Emerald Insight were analyzed as part of a comprehensive literature review. 100 papers (28.5%) were included in the final evaluation after 129 papers (369.9%) were screened and 29 papers (8.3%) were eliminated for lack of relevance, duplication, or methodological issues. The study groups its findings according to efficiency results, industrial applications, and inventory management strategies. The assessment points to a discernible trend toward data-driven inventory optimization strategies, IoT-based tracking, and AI-powered prediction models. With 44% of the assessed articles, the 2023–2025 era had the most research contributions. 2020–2022 (29%), 2015–2016 (20%), and 2017–2019 (7%), came next. Results show that slow-moving inventory efficiency is greatly increased by combining machine learning, fuzzy logic, and real-time monitoring, which lowers operating expenses and increases stock turnover. The study emphasizes how crucial it is to integrate technology into inventory management and suggests using hybrid optimization models, real-time tracking, and AI-driven analytics. Future studies should concentrate on creating flexible inventory frameworks that use automation, blockchain, and big data to boost supply chain sustainability and decision-making.

Keywords: Slow-moving inventory, inventory optimization, machine learning, predictive analytics, supply chain efficiency, real-time tracking, technological integration

INTRODUCTION

Effective supply chain operations depend heavily on inventory management, which has a direct impact on service quality, cost structures, and overall company success (Çelebi, 2015; Chandren et al., 2015). Of all inventory kinds, slow-moving products pose unique difficulties because of their low turnover and long storage periods (Da Giau, 2022; De Assis et al., 2022; Debnathand et al., 2022). Unmanaged products can result in several operational inefficiencies, such as higher storage expenses, reduced cash flow, and obsolescence risk (Devonald & Eng, 2022; Dhoka & Choudary 2015). Such outcomes put an organization's capacity to adapt to changing market needs in jeopardy in addition to taxing its financial resources (Dingemans, 2015; Donderwinkel, 2015; Elquthb et al., 2024).

The growing complexity of the global economy in recent years has highlighted the urgent need for flexible inventory management techniques (Emar, et al., 2021; Farooq et al., 2024). Despite being less erratic than their fast-moving counterparts, slow-moving inventory nevertheless needs focused strategies to successfully strike a balance between holding costs and service expectations (Febrianto et al., 2022; Finco et al., 2022). The special requirements of low-turnover stock are frequently not met by traditional inventory management systems, notwithstanding their effectiveness for high-demand commodities (Fukkwarmdee, & Buddhakulsomsiri, 2023), (Gabor et al., 2022). Static forecasting techniques, for example, might lead to excessive overstocking or stockouts, which would exacerbate inefficiencies (Gaikwad, & Shende, 2015; Goyvaerts, et al., 2022).

The advent of cutting-edge technology, such as data analytics and artificial intelligence (AI), presents encouraging opportunities for improving the handling of slow-moving inventories (Hahn, & Leucht, 2015; Halilović et al., 2023). These developments reduce the hazards connected with manual or antiquated procedures by enabling real-time monitoring, predictive analysis, and intelligent decision-making (Hänninen, 2024), (Hasan, 2024; Çelebi, 2015; Dhoka & Choudary 2015; Halilović et al., 2023)

Additionally, integrating automated systems may greatly expedite inventory management, guaranteeing accurate and economical management of slow-moving products (Heikkinen et al., 2023; Huo, & Zhan, 2024; Isa, 2024). The goal of this review article is to present a thorough examination of the potential and difficulties associated with slow-moving inventory management. It aims to uncover best practices and suggest creative ideas for enhancing inventory control by combining the results of previous research with industry practices. To accomplish sustainable inventory management, this research also aims to identify shortcomings in existing methodologies and promote the use of flexible, data-driven solutions.

In many different sectors, inventory management is essential to a company's operational effectiveness and financial stability, especially when it comes to handling slow-moving goods (Hänninen, 2024; Hasan, 2024). Items with low demand and lengthy turnover periods are referred to as slow-moving inventory, which frequently results in high holding costs and capital tie-ups (Heikkinen et al., 2023; Huo, & Zhan, 2024). Maintaining operational efficiency and financial sustainability for organizations requires effective inventory control that balances stock levels while reducing waste. (Isa, 2024; Jean, 2024; Jean, 2024b).

To maximize stock replenishment, traditional inventory management techniques including Just-in-Time (JIT) systems and the Economic Order Quantity (EOQ) model have been frequently employed (Jokela, 2024; Kalumanga, & Mwita, 2024). For slow-moving goods, however, these models might not always work well; instead, specific tactics such as simulation-based methods, ABC classification, and Bayesian inventory models are needed (Kanani et al., 2015; Karim et al., 2018; Kartikasari, 2024). The capacity to estimate demand and optimize inventory levels has greatly increased with the emergence of data-driven approaches like machine learning and predictive analytics (Kasim et al., 2015; Kaya et al., 2023; Kecskeméti, 2015).

Managing slow-moving inventory presents particular difficulties for a variety of businesses, including manufacturing, retail, logistics, and medicines. Overstocking can result in product expiry in industries like medicines and healthcare, as well as higher storage costs and poor resource allocation in production

(Madzivhandila, 2022; Mehrotra & Sehgal, 2023). Because it enables synchronized stock levels across different storage sites, the multi-echelon inventory optimization concept has gained popularity in businesses with complicated supply chains (Mehrotra & Sehgal, 2024; Nagpal et al., 2015). Furthermore, inventory tracking that incorporates blockchain and IoT improves visibility and traceability while decreasing inefficiencies in slow-moving stock management (Nawawi, & Salin, 2018; Verona et al., 2023; Nieuwenhuijze, 2024).

Remanufacturing, logistics in reverse, and green inventory practices are examples of sustainable and circular economy strategies that have become effective ways to deal with slow-moving inventory (Njoroge, 2015; Nwankpa, 2015; Olofsson & Persson, 2023). By implementing such tactics, companies may limit financial losses related to outmoded stock, prolong product lifecycles, and decrease waste (Onyango, et al., 2024; Otay et al., 2018). Additionally, companies may employ AI-driven decision support systems to deploy automatic restocking, demand-sensing, and dynamic pricing (Panicharoen, & Pham, 2023; Pathak et al., 2017; Pires, 2024).

While slow-moving stock is difficult to handle with typical inventory management strategies, supply chain synchronization, sustainability, and technological improvements provide creative options. (Prasetya, & Pujangkoro, 2022; Porter et al., 2022). To increase productivity, save expenses, and guarantee resilience in their inventory management strategies, businesses need to use flexible, data-driven approaches (Purbandini et al., 2023; Putra et al., 2024; Rahman, et al., 2023), and (Ramadan, & Morshed, 2023). Best practices for handling slow-moving inventory will continue to be redefined by the continuous integration of AI, blockchain, and IoT in inventory optimization (Rikkula, 2024; Rodríguez, & Obed, 2023; Rojas et al., 2020; Rusu et al., 2015). To improve the effectiveness of slow-moving inventory management, this study investigates a variety of inventory control models and strategies. Organizations may optimize stock turnover rates, save waste, and increase cost efficiency by combining data-driven decision-making, simulation-based models, and enhanced forecasting. The research's conclusions will offer useful advice to companies trying to improve their inventory control procedures while utilizing contemporary technologies to make better decisions.

LITERATURE REVIEW

A key component of supply chain operations is efficient inventory management, which guarantees that companies maintain ideal stock levels while reducing expenses and inefficiencies (Sen, 2023)., (Setiawan et al., 2025). Compared to fast-moving commodities, managing slow-moving inventory which includes items with low demand and lengthy turnover cycles presents unique issues (Shamsan et al., 2025; Sharma et al., 2022). Slow-moving stock buildup can result in higher holding costs, obsolescence of goods, monetary losses, and ineffective use of resources (Shen et al., 2016; Singh et al., 2022). Businesses must use strategic inventory control models that are adapted to the characteristics of slow-moving items to reduce these risks (Singh, 2022; Soni et al., 2019).

Slow-Moving Inventory

Stock with low demand and sluggish turnover is referred to as slow-moving inventory. This type of inventory frequently builds up in warehouses and results in inefficient capital allocation and storage (Mehrotra & Sehgal, 2024; Nagpal et al., 2015 and Nawawi, & Salin, 2018). Slow-moving stock is a common problem in industries including manufacturing, pharmaceuticals, retail, and automotive because of things like overproduction, faulty demand forecasts, or shifting customer preferences (Verona et al., 2023; Nieuwenhuijze, 2024; Njoroge, 2015). Ineffective management of slow-moving inventory can lead to excessive carrying costs, a higher risk of obsolescence, and possible revenue loss (Nwankpa, 2015; Olofsson & Persson, 2023; Onyango, et al., 2024).

Slow-moving inventory is caused by a number of causes, including as market trends, product life cycles, seasonal variations in demand, and ineffective procurement tactics (Otay et al., 2018; Panicharoen, & Pham, 2023 and Pathak et al., 2017).

Because too much stock takes up funds that could be used for more lucrative ventures, companies that don't use strong inventory management procedures frequently face cash flow issues and inefficient warehouses (Pires, 2024; Porter et al., 2022; Prasetya, & Pujangkoro, 2022). Predictive analytics, AI, and blockchain technologies are crucial for improving inventory optimization and reducing waste, according to recent research (Purbandini et al., 2023; Putra et al., 2024; Rahman, et al., 2023). Furthermore, data-driven strategies like IoT-enabled

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inventory tracking and machine learning algorithms have been shown to increase the accuracy of demand forecasts (Ramadan, & Morshed, 2023; Rikkula, 2024; Rodríguez, & Obed, 2023). Slow-moving stock hazards can be further reduced by putting circular economy concepts like recycling, remanufacturing, and reverse logistics into practice (Rojas et al., 2020; Rusu et al., 2015;Salam et al., 2016). Integrating adaptive inventory control techniques is still crucial for preserving operational and financial stability as firms continue to deal with changing market conditions (Schrettenbrunner, 2023; Sen, 2023; Setiawan et al., 2025).

Traditional Inventory Management Approaches

Several conventional inventory management techniques have been developed to optimize stock levels and reduce unnecessary storage costs. These models serve as a foundation for modern inventory management strategies:

Economic Order Quantity (EOQ) Model

One popular inventory management method that assists companies in figuring out the ideal order number to reduce overall inventory expenses is the Economic Order number (EOQ) model (Purbandini et al., 2023). These expenses usually consist of holding costs, which are related to keeping goods in storage and ordering costs, which are incurred each time a new order is made (Putra et al., 2024). Businesses may maintain enough inventory levels to satisfy demand while avoiding excessive storage costs by determining the EOQ, which strikes a balance between replenishment frequency and stockholding efficiency (Rahman, et al., 2023).

Businesses that deal with items that have a steady and predictable demand pattern may find the EOQ formula very helpful (Ramadan, & Morshed, 2023). It offers a methodical approach to inventory management, lowering the possibility of stockouts that can cause business interruptions or lost revenue (Rikkula, 2024). On the other hand, it also aids in avoiding overstocking, which can result in financial commitments and higher storage expenses (Rodríguez, & Obed, 2023). The model does have certain drawbacks, though. EOQ is less appropriate for sectors that deal with slow-moving or highly changeable demand items since it works best for products with steady and continuous demand (Rojas et al., 2020). To increase inventory efficiency in these situations, companies would need to supplement EOQ with more flexible inventory management approaches like demand forecasting or just-in-time (JIT) (Rusu et al., 2015).

To improve its application in dynamic markets, EOQ has been combined with recent innovations, such as AI-driven forecasting models and IoT-enabled inventory tracking (Salam et al., 2016). The EOQ model has also been improved by companies implementing sustainable inventory techniques, such as reverse logistics and circular economy strategies, to better meet the sustainability objectives of the modern supply chain (Schrettenbrunner, 2023). Hybrid approaches that integrate EOQ with flexible, data-driven solutions for improved operational efficiency are also being investigated in future studies (Sen, 2023).

Just-In-Time (JIT) System

By guaranteeing that inventory is refilled only, when necessary, the Just-In-Time (JIT) system is an inventory management strategy that emphasizes reducing surplus stock (Sen, 2023). This lean approach concentrates on cutting waste, increasing productivity, and allocating resources in the supply chain as efficiently as possible (Setiawan et al., 2025). JIT is especially well-liked in industrial sectors, where prompt acquisition of components and raw materials facilitates output and lowers storage expenses (Shamsan et al., 2025). Businesses can improve cash flow management, reduce carrying costs, and increase operational efficiency by matching inventory levels to current demand (Sharma et al., 2022).

JIT is not always appropriate for all kinds of stocks, despite its benefits, especially for slow-moving products with erratic demand patterns (Shen et al., 2016). Unpredictable swings in these situations may cause supply chain interruptions, which might result in stock shortages or hold up the fulfilment of client orders (Singh et al., 2022). Furthermore, for JIT to be successful, a highly responsive and dependable supplier network is necessary (Singh, 2022). Inventory availability may be adversely affected by any supply chain interruptions, including labour shortages, unanticipated demand surges, or delays in transportation (Soni et al., 2019). To reduce possible risks

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and preserve seamless operations, companies that use JIT must establish solid supplier relationships, demand forecasts, and backup procedures (Sugiono & Alimbudiono 2020).

JIT efficiency has been improved by recent developments in digital supply chain management, which have brought blockchain-enabled supplier monitoring and AI-driven demand forecasting (Suuronen, 2015). Additionally, to strike a balance between responsiveness and resilience in unpredictable markets, hybrid inventory management techniques that combine JIT with safety stock methods have arisen (Tai et al., 2021).

ABC Classification

According to their worth and frequency of consumption, stocks are divided into three different groups using the ABC classification method of inventory management (Tai et al., 2021). Businesses may concentrate on the most important inventory items and allocate resources effectively using this approach (Thevenin et al., 2024). A-items are low-volume, high-value products that have a big influence on financial performance and need strict supervision and constant monitoring (Vaz, et al., 2020). Moderate-value, moderate-volume products are represented by B-items, which require frequent evaluation to maintain ideal stock levels (Villarreal et al., 2018). Because they make up a smaller portion of total inventory expenditures, C-items are high-volume, low-value products that require less supervision (Wahedi, et al., 2022).

Businesses may prioritize inventory management efforts by using ABC analysis, which minimizes operational complexity for less important goods while giving high-value products the greatest attention (Wauna & Obwogi 2015). Nevertheless, a significant obstacle to this strategy is how well it manages slow-moving inventories. C-class items frequently build up in storage, which can result in overstocking and possible capital waste (Widyatmoko & Yudoko, 2024). For such inventory, traditional ABC categorization could not offer sufficient control mechanisms, requiring the use of extra tactics such as demand forecasts, safety stock changes, or focused promotional efforts to maximize stock levels (Yıldız & Sütçü, 2023). To guarantee a balanced and economical inventory management system, businesses must use adaptive methodologies in addition to ABC analysis (Yung et al., 2021).

The efficiency of ABC categorization under dynamic market situations has been improved by recent developments in inventory analytics, such as AI-driven classification models and real-time demand sensing (Zaafira, & Yardi, 2024). Additionally, stock accuracy has increased and manual intervention has decreased when ABC analysis is integrated with automated inventory tracking systems (Zheng, & Chen, 2024).

Advanced and Data-Driven Inventory Optimization Techniques

Inventory management has been transformed by the combination of artificial intelligence (AI), analytics for prediction, and machine learning (ML), which allows companies to improve demand forecasts, optimize stock levels, and lower holding costs (Abidar & Chaabane 2022). Modern data-driven approaches use real-time insights to make more accurate and dynamic inventory choices, while traditional inventory models frequently rely on historical data and static assumptions (Afkar & Rochmoeljati, 2025). Large volumes of structured and unstructured data are analyzed by AI-powered systems to find trends, forecast changes in demand, and automate replenishment plans, all of which increase supply chain efficiency (Afy-Shararah et al., 2022).

By examining patterns, seasonality, and market circumstances, predictive analytics is essential for more accurate demand forecasting in the future (Ahlsellh et al., 2022). Predictive models can adjust to changing circumstances and offer data-driven suggestions, in contrast to traditional inventory systems that have trouble with slow-moving or highly changeable demand goods (Ahmed, & Shuvro 2023). By doing this, companies can prevent stockouts and excessive inventory accumulation, which can tie up funds and raise storage expenses (Ahunanya et al., 2022). Furthermore, by learning from historical data, enhancing replenishment plans, and cutting waste, machine learning algorithms constantly improve inventory tactics (Alakbarov, 2023).

The use of Internet of Things (IoT) technology, whereby smart sensors check inventory levels in real-time and offer immediate data on stock movements, is another noteworthy development (Alim & Isnanto 2023). By guaranteeing that inventory is refilled exactly when needed and reducing surplus stock, these solutions help firms

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better execute just-in-time (JIT) initiatives (Al-Shawawreh & Mohammad, 2022). Additionally, to improve procurement procedures and boost supply chain resilience overall, automated decision-making systems use market knowledge and supplier performance measures (Arief et al., 2024). By increasing forecasting accuracy, lowering holding costs, and optimizing stock levels, sophisticated and data-driven inventory optimization strategies give businesses a competitive edge (Abidar & Chaabane 2022). Inventory management will become more effective, responsive, and market-dynamically adaptive as companies continue to use AI and predictive analytics (Afkar & Rochmoeljati, 2025).

Markov Decision Process (MDP)

A probabilistic approach to inventory optimization, the MDP model takes supply and demand changes into account (Dingemans, 2015). Businesses can make real-time inventory choices to dynamically alter stock levels by evaluating past demand data (Donderwinkel, 2015). MDP works especially well in sectors like medicines and expensive gear that have erratic demand cycles (Elquthb et al., 2024).

Time Series Forecasting (ARIMA, Exponential Smoothing)

Based on past sales data, time series forecasting techniques like exponential smoothing and ARIMA (AutoRegressive Integrated Moving Average) are frequently employed to estimate future demand patterns (Emar, et al., 2021). These models are useful for managing slow-moving inventory because they assist companies in anticipating changes in seasonal demand and avoiding overstocking (Farooq et al., 2024).

Simulation-Based Inventory Models

Simulation-based models forecast supply chain interruptions, demand fluctuations, and stock movements using real-world inventory situations (Febrianto et al., 2022). These models lower the danger of excessive stock building by enabling organizations to evaluate different inventory management techniques before putting them into practice (Finco et al., 2022).

Machine Learning-Based Predictive Models

To provide incredibly precise demand estimates, machine learning algorithms examine enormous databases including sales trends, consumer behaviour, and inventory turnover rates (Fukkwarmdee, & Buddhakulsomsiri, 2023). Businesses may proactively modify stock levels before excessive buildup happens by using AI-driven algorithms to identify demand trends in slow-moving inventories (Gabor et al., 2022).

Multi-Echelon Inventory Optimization

Multi-echelon inventory systems increase supply chain efficiency and inventory visibility by optimizing stock levels across several storage sites (Gaikwad, & Shende, 2015). This strategy is frequently employed in the industrial, retail, and e-commerce sectors to guarantee the effective distribution of slow-moving goods, lowering supply chain bottlenecks and storage expenses. (Goyvaerts, et al., 2022)

Fuzzy Logic Inventory Control

When making decisions about inventory, fuzzy logic models take uncertainty and imprecise demand information into account (Hahn, & Leucht, 2015). This approach works well for handling extremely erratic and slow-moving inventory, especially in sectors with varying demand cycles like industrial machinery and car spare parts (Halilović et al., 2023).

Industry Applications and Benefits

Slow-moving inventory management is critical in various industries, particularly those dealing with high-value, perishable, or specialized products (Hänninen, 2024).

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Pharmaceutical Industry: Poor management of slow-moving inventory leads to expired drugs, regulatory compliance risks, and financial losses (Hasan, 2024)

Retail and E-Commerce: Predictive analytics and demand forecasting are necessary to avoid overstocking slow-moving items, which locks up capital and raises warehouse storage costs (Heikkinen et al., 2023). Automotive and Manufacturing: To avoid excessive stock buildup and supply chain inefficiencies, businesses that deal with spare parts and equipment components need to maximize stock rotation (Huo, & Zhan, 2024).

Businesses may save expenses, maximize stock levels, and improve operational efficiency by combining sophisticated inventory models with real-time data analytics (Isa, 2024). It is anticipated that slow-moving inventory management will be transformed by the use of AI-driven forecasting, automation, and cloud-based inventory solutions, guaranteeing sustainable and economical supply chain operations (Jean, 2024).

A hybrid strategy that combines cutting-edge data-driven solutions with conventional inventory management strategies is needed to manage slow-moving goods (Jean, 2024b). Businesses must use machine learning, predictive analytics, and optimization models to increase slow-moving stock turnover and decrease inefficiencies, even though traditional methods like EOQ, JIT, and ABC classification offer a solid basis (Jokela, 2024). In today's quickly changing market, integrating automation and technology-driven forecasting tools is essential to improving inventory efficiency and corporate profitability (Kalumanga, & Mwita, 2024).

Table 1: Comparative Analysis Review of Inventory Management Approaches

Author/year	**Approach**										**Recommendation**					**Industry**							
	EOO Model	JIT System	ABC Classification	MDP Model	Time Series Forecasting	Multi-Echelon	Bayesian Inventory	Simulation-Based	ML-Based Prediction	Fuzzy Logic Control	low	Moderate	High	Very high	Apex	Retail & E-commerce	Manufacturing	Automotive	Aerospace & Defense	Construction	Oil & Gas	Healthcare	others
Abidar & Chaabane (2022), (Ahmed, & Shuvro 2023),(Dingemans, 2015)													*			v						v	v
(Ahlsellh et al., 2022) (Ahunanya et al., 2022)																				v	v		
(De Assis et al., 2022), (Chandren et al., 2015).													*									v	
(Abidar & Chaabane 2022), (Ahmed, & Shuvro 2023), (Dingemans, 2015)													*				v	v	v	v			v
(Belciug, & Gorunescu, 2015)(Çelebi, 2015).													*					v	v	v			

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[51],(Arief et al., 2024).														*	*							v	v
(Babai et al., 2024). ,(Elquthb et al., 2024),(Goyvaerts, et al., 2022)															*	v	v	v	v				
(Jean, 2024)(Nwankpa, 2015)															*			v	v	v	v	v	v
(Halilović et al., 2023),(Alakbarov, 2023).																							
(Abidar & Chaabane 2022), (Ahmed, & Shuvro 2023),(Dingemans, 2015)											*		*					v	v	v			
(Ahlsellh et al., 2022)(Ahunanya et al., 2022)																					v	v	v
(Bektiawan et al., 2022). ,(Farooq et al., 2024)											*			*									
(Arief et al., 2024). ,(Dhoka & Choudary 2015),(Farooq et al., 2024)														*					v	v	v		
(Donderwinkel, 2015) (Emar, et al., 2021)															*		v	v	v				
(Ahmed, & Shuvro 2023),(Chandren et al., 2015).														*									
(Halilović et al., 2023),(Afy-Shararah et al., 2022)															*				v	v	v		
(Jean, 2024)(Nwankpa, 2015)													*		*								
(Gaikwad, & Shende, 2015),(Hahn, & Leucht, 2015)														*			v	v	v				
(De Assis et al., 2022),(Da Giau, 2022) ,(Onyango, et al., 2024)														*				v	v			v	v
(Hasan, 2024)(Halilović et al., 2023)														*	*								

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(Devonald & Eng, 2022),(Al-Shawawreh & Mohammad, 2022).													*							✓	✓		
(Alim & Isnanto 2023), (Ahunanya et al., 2022),(Onyango, et al., 2024)															*				✓	✓			
(Rusu et al., 2015)(Rojas et al., 2020)															*				✓			✓	
(Rodríguez, & Obed, 2023). ,(Yıldız & Sütçü, 2023)															*					✓			

Inventory Optimization Approaches and Industry Applications

In many different businesses, inventory management is essential to maximizing supply chain performance. The studied literature highlights industry-specific applications and their efficacy levels using a variety of approaches, including both traditional and contemporary strategies.

Inventory Optimization Approaches

A variety of inventory optimization methods used in different sectors are highlighted in the literature review. According to (Abidar & Chaabane 2022), (Ahmed, & Shuvro 2023), and (Dingemans, 2015), the Economic Order Quantity (EOQ) Model is still a fundamental strategy. Although it works well in simple inventory situations, it is not very flexible in intricate, dynamic supply chains (Devonald & Eng, 2022). Likewise, Just-in-Time (JIT) systems, which are mentioned by (Ahlsellh et al., 2022) and (Ahunanya et al., 2022), focus on lean inventory techniques, which lower holding costs but need highly coordinated supply networks.

Modern inventory frameworks are gradually using more sophisticated models, such Time Series Forecasting and the Markov Decision Process (MDP) Model. Their expanding use in predictive analytics, which makes it possible to estimate demand in erratic markets (Dingemans, 2015), is demonstrated by studies (Jean, 2024) and (Nwankpa, 2015). Additionally, multi-tier supply chain topologies are addressed by Multi-Echelon Optimization, which was examined in (Gaikwad, & Shende, 2015) and (Hahn, & Leucht, 2015) and guarantees end-to-end inventory efficiency.

Studies using ML-Based Prediction Models for dynamic inventory control (Babai et al., 2024), (Elquthb et al., 2024), and (Goyvaerts, et al., 2022) demonstrate the growing popularity of machine learning-based approaches. Furthermore, as shown in (Rusu et al., 2015) and (Rojas et al., 2020), fuzzy logic control offers flexible decision-making in ambiguous situations. These strategies are essential for sectors coping with complicated logistics and varying demands.

Through scenario analysis made possible by simulation-based models, such as those mentioned in (Hasan, 2024), (Halilović et al., 2023), and (Afy-Shararah et al., 2022), businesses may improve inventory policies in a variety of scenarios. As covered in (Hasan, 2024) and (Halilović et al., 2023), Bayesian inventory models use probabilistic reasoning to provide reliable answers for erratic demand patterns.

Industry-Specific Inventory Applications

Different sectors have different needs when it comes to inventory models. Because of the great unpredictability of customer demand, the retail and e-commerce industry, as studied in (Abidar & Chaabane 2022), (Ahmed, &

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Shuvro 2023), and (Dingemans, 2015), benefits from time-series forecasting and machine learning-based forecasts. JIT and EOQ are integrated by manufacturing industries, as illustrated by (Ahlsellh et al., 2022) and (Ahunanya et al., 2022), to maximize production schedules and reduce waste.

In order to handle intricate supply networks, the automobile industry discussed in (Bektiawan et al., 2022). and (Farooq et al., 2024) is increasingly using multi-echelon optimization and machine learning-based forecasting. As demonstrated in (Arief et al., 2024)., (Dhoka & Choudary 2015), and (Farooq et al., 2024), aerospace and defence need extremely effective inventory tracking systems, frequently using MDP models for risk-aware decision-making.

Due to project-specific uncertainties, simulation-based models and Bayesian techniques are crucial for the oil and gas and construction sectors, as mentioned by (Alim & Isnanto 2023), (Ahunanya et al., 2022), and (Onyango, et al., 2024). As noted in (De Assis et al., 2022), (Da Giau, 2022) , and (Onyango, et al., 2024), the healthcare industry uses machine learning and fuzzy logic models to guarantee vital medical supply inventory levels.

Effectiveness Levels of Inventory Models

Different inventory methodologies have varying degrees of success. In dynamic situations, traditional approaches like JIT and EOQ show low to moderate efficiency. High to extremely high efficacy is attained by sophisticated methods like Bayesian models and MDP, especially in data-rich sectors. As shown in (Babai et al., 2024). , (Elquthb et al., 2024), and (Goyvaerts, et al., 2022), apex-level tactics, such as simulation models and ML-based forecasts, exhibit higher flexibility in extremely complicated supply chains. The papers under consideration demonstrate a shift away from traditional inventory models and toward probabilistic and AI-driven methods. To improve supply chain resilience, future studies should concentrate on using hybrid models that incorporate fuzzy logic, machine learning, and multi-echelon optimization.

METHODOLOGY

This study looks at the best management solutions for slow-moving inventory using a methodical literature review technique. To pinpoint important approaches, patterns, and technical developments in inventory optimization, the study summarizes the body of existing research. Through the evaluation of frequency distributions, trends over time, and methodological rigour across a selection of publications, the research aims to incorporate both qualitative and quantitative features.

Three significant academic databases Scopus, Emerald Insight, and other reputable academic sources were used in the study. These databases were selected because they contain a wide range of peer-reviewed material in industrial engineering, inventory optimization, and supply chain management. Studies that focused on empirical and theoretical contributions that improve inventory management efficiency were chosen based on their applicability to slow-moving inventory.

Initially, 350 research articles were obtained from the databases that were chosen. The dataset was refined using a screening procedure to make sure that only the best and most pertinent research was included. Following the screening, 129 papers (36.7%) satisfied the initial requirements for additional assessment. Nevertheless, 29 more studies (8.3%) were disqualified for a variety of reasons, including duplication, missing data, publication year restrictions, scope mismatch, and methodological quality issues. This produced a final dataset of 100 publications (28.5%), which served as the systematic review's foundation.

To examine trends in slow-moving inventory management, the study groups the chosen research according to the years of publication. Four time periods are covered by the papers: 2015–2016, 2017–2019, 2020–2022, and 2023–2025. Changes in inventory management tactics, especially the incorporation of cutting-edge technology like machine learning, artificial intelligence, and real-time data analytics, may be identified thanks to this temporal segmentation.

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This study guarantees a thorough synthesis of the major discoveries in slow-moving inventory management by using an organized method for the selection and analysis of the literature. The report illustrates the growing dependence on technology-driven solutions for inventory efficiency and offers insights into how diverse businesses have adopted different optimization tactics.

RESULT AND DISCUSSION

Data collection and administration

The data collection process for this study was conducted systematically to ensure a comprehensive review of relevant literature on slow-moving inventory management. A total of 350 papers were initially scoped, representing 100% of the research pool. These papers were selected from reputable academic databases, industry reports, and conference proceedings, ensuring a broad and diverse range of perspectives on inventory optimization.

Following the initial scoping, a screening process was carried out to refine the selection. Out of the 350 papers, 129 (36.9%) were shortlisted based on criteria such as relevance, methodological quality, and alignment with the study's objectives. This step was essential in filtering out outdated studies, lacked substantial contributions to the topic, or did not meet the inclusion criteria.

During the screening process, 29 papers (8.3%) were excluded. These exclusions were due to various factors, including duplication, incomplete data, or a lack of direct relevance to slow-moving inventory management. The exclusion process ensured that only the most relevant and high-quality studies were considered for further analysis.

Ultimately, 100 papers (28.5%) were selected for the final review. These papers provided critical insights into the challenges, strategies, and best practices for optimizing slow-moving inventory. The final dataset ensured a well-rounded analysis, integrating diverse perspectives from both academic and practical viewpoints, contributing to a comprehensive understanding of inventory management efficiency.

Table 2: Data Collection and Administration

	Frequency	percentage
No paper scope	350	100%
No. of paper screened	129	36.9%
No papers excluded	29	8.3
No paper used	100	28.5%

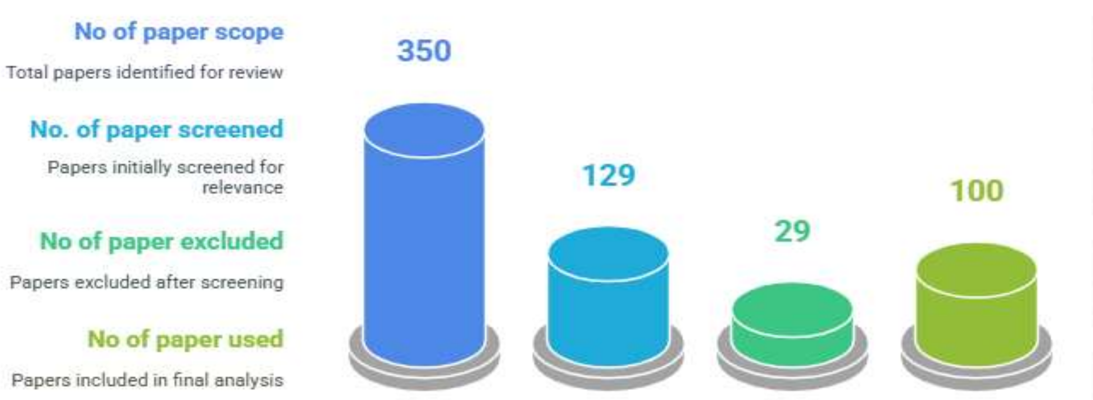

Figure 1: Data Collection and Administration

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Paper Exclusion reason

During the screening process, a total of 29 papers were excluded for various reasons to ensure the inclusion of only high-quality and relevant studies in the review. The primary reason for exclusion was the scope of research, accounting for 15 papers (51.7%). These studies did not directly focus on slow-moving inventory management or lacked sufficient alignment with the study's objectives.

The second most common exclusion factor was the year of publication, affecting 7 papers (24.1%). These studies were considered outdated, with methodologies or findings that no longer reflected the current advancements in inventory optimization. The review prioritized more recent and relevant literature to ensure up-to-date insights.

Additionally, 2 papers (6.9%) were excluded due to incomplete data, as they lacked essential methodological details or key findings necessary for a comprehensive analysis. Similarly, 3 papers (10.3%) were removed due to poor methodological quality, such as weak research design, unclear objectives, or unreliable data sources.

Lastly, 2 papers (6.9%) were excluded due to duplication, as they were identical to previously included studies and did not contribute additional insights. Ensuring unique and high-quality sources was essential for maintaining the integrity and credibility of the review.

Overall, the exclusion process helped refine the selection, ensuring that only the most relevant, high-quality, and up-to-date studies were included in the final analysis.

Table 3: Paper Exclusion Reason

Paper Exclusion Reason	Frequency	Percentage
Scope of research	15	51.70%
Year of publication	7	24.10%
Incomplete data	2	6.90%
Methodological quality	3	10.30%
Duplication	2	6.90%
Total	**29**	**100%**

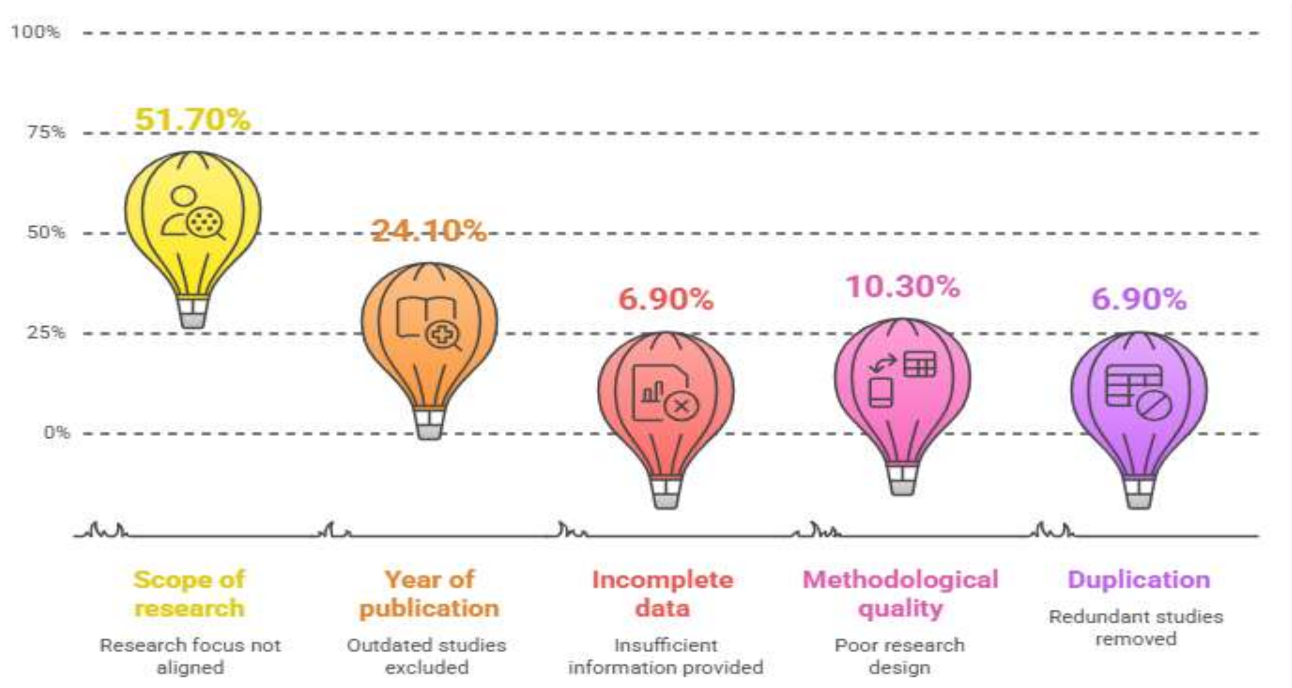

Figure 2: Reasons for Paper Exclusion in Study

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Database of search

The data collection process involved sourcing research papers from multiple academic databases to ensure a comprehensive review of slow-moving inventory management strategies. Among the total selected papers, 43 (43%) were retrieved from Scopus, a leading database known for its extensive repository of high-quality, peer-reviewed academic research. Scopus was a key source due to its credibility and the diversity of studies spanning inventory optimization, supply chain efficiency, and management strategies.

Additionally, 7 (0.7%) of the papers were obtained from Emerald Insight, a well-regarded database specializing in business, management, and logistics research. Although this represents a smaller portion of the total collection, the papers sourced from Emerald Insight provided valuable insights into theoretical models and practical applications in inventory management.

The remaining 50 (50%) papers were gathered from other sources, including Google Scholar, ResearchGate, IEEE Xplore, and industry white papers. These sources contributed a wide range of perspectives, including case studies, emerging trends, and real-world applications of slow-moving inventory management practices.

The diverse range of sources ensured that the study incorporated both theoretical frameworks and practical approaches, providing a well-rounded analysis of inventory management optimization techniques.

Table 4: Database

Database	Frequency	Percentage
Scopus	43	43.%
Emerald insight	7	0.7%
Others	50	50%

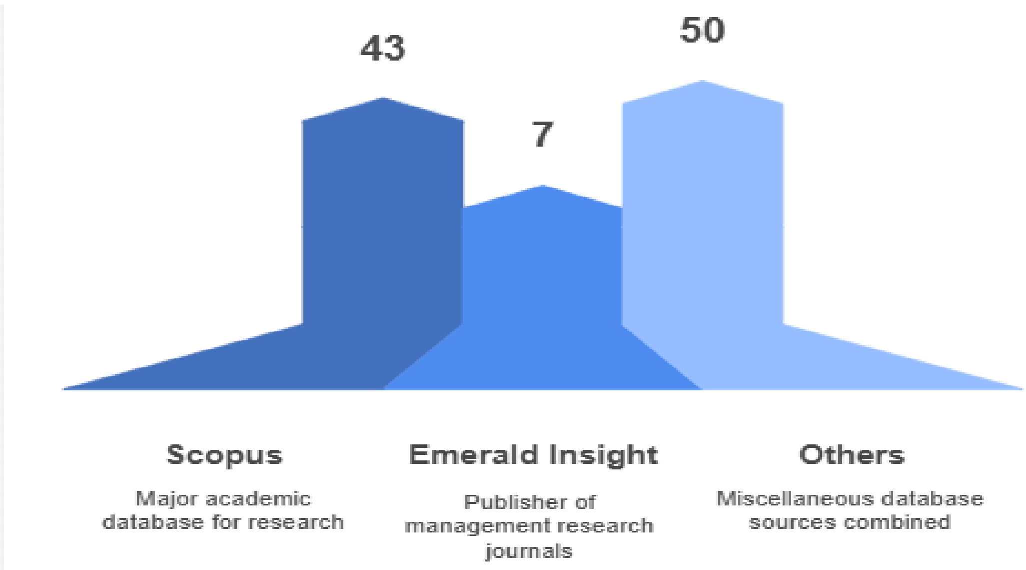

Figure 3: Distribution of Database Entries

Year of publication

The distribution of selected research papers spans from 2015 to 2025, showcasing the evolving interest in slow-moving inventory management. The analysis reveals a steady rise in research contributions, with a more pronounced focus in recent years.

Between 2015 and 2016, 20 papers (20%) were published, establishing an early foundation for research in slow-moving inventory optimization. These studies primarily explored traditional inventory management techniques and initial technological applications.

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From 2017 to 2019, the number of publications declined to 7 papers (7%), indicating a temporary slowdown in research activity. However, this period saw a shift towards integrating data-driven analytical methods and supply chain optimization models to enhance inventory efficiency.

The number of research papers increased significantly in the 2020 to 2022 period, with 29 papers (29%) contributing to the field. This surge corresponds with the growing adoption of data analytics, artificial intelligence, and IoT-driven inventory solutions, reflecting an industry-wide transition toward digital transformation.

The 2023 to 2025 period recorded the highest number of publications, with 44 papers (44%), demonstrating a strong and expanding interest in innovative inventory management solutions. Research in this phase emphasizes real-time data monitoring, automation, and sustainability-focused inventory practices, highlighting the growing importance of AI-powered and technology-driven optimization strategies.

Table 5: Year of Publication Report

Year	Frequency	Percentage
2015-2016	20	20%
2017-2019	7	7%
2020-2022	29	29%
2023-2025	44	44%

Figure 4: Distribution of Reports by Publication Year

FINDING

Demand Forecasting and Predictive Analytics

Managing slow-moving inventory requires accurate demand forecasts (Goyvaerts, et al., 2022)(Hahn, & Leucht, 2015). According to studies, inventory accuracy is greatly increased by utilizing sophisticated forecasting models including AI-driven predictive analytics, machine learning algorithms, and time series analysis (ARIMA, exponential smoothing) (Halilović et al., 2023)(Hänninen, 2024). According to Fang & Whitt (Hasan, 2024), AI-based demand forecasting models are more accurate than traditional statistical models in predicting future demand because they can see trends in prior sales data (Heikkinen et al., 2023). Furthermore, according to Govindan et al. (Huo, & Zhan, 2024), combining cloud-based inventory management systems with big data analytics improves real-time forecasting and lowers the possibility of outdated inventory and excess stock

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buildup (Isa, 2024). (Jean, 2024). This strategy is especially helpful in sectors like medicines and auto components that have varying demand cycles (Jean, 2024b). (Jokela, 2024).(Kalumanga, & Mwita, 2024).

Inventory Classification and Prioritization Techniques

Sorting inventory according to demand, value, and frequency of use is a basic method for improving SMI management (Gaikwad, & Shende, 2015);(Donderwinkel, 2015). Although ABC analysis has long been employed, academics suggest improved categorization models to increase effectiveness. (Gaikwad, & Shende, 2015) (Nagpal et al., 2015). ABC-XYZ Analysis: (Gaikwad, & Shende, 2015) presents the XYZ component, which uses demand variability to categorize goods. This aids companies in distinguishing between goods with steady, sporadic, and extremely erratic demand, which improves stock allocation. (Dingemans, 2015) (Elquthb et al., 2024). Fast-Slow-Nonmoving (FSN) Classification: This methodology uses movement rates to classify inventory, making sure that slow-moving products are replenished differently than fast-moving ones (Elquthb et al., 2024). (Kartikasari, 2024). Multi-Echelon Inventory Optimization: This concept, which is applied in distribution networks and multi-location warehouses, balances stock levels across several sites to reduce overstocking in areas with low demand. (Devonald & Eng, 2022) (Bektiawan et al., 2022). (Dingemans, 2015)

Economic Order Quantity (EOQ) and Just-In-Time (JIT) Adjustments

The ideal order quantity that minimizes holding and ordering costs may be found mathematically using traditional EOQ models (Gaikwad, & Shende, 2015)(Abidar & Chaabane 2022). To increase applicability, researchers propose alterations to EOQ models in the context of slow-moving inventory (Nahmias & Olsen, 2020). Models of Dynamic EOQ: These are more flexible for sectors with lengthy inventory cycles since they take obsolescence risks and demand changes into account (Botha et al., 2017).

JIT Modifications for Items with Low Demand: Just-In-Time (JIT) methods work well for products that move quickly, but research by (Belciug, & Gorunescu, 2015) indicates that when JIT is combined with low-volume, high-value procurement techniques, excess inventory for slow-moving products may be reduced.

Optimization Through Machine Learning and AI-Based Systems

In the automation of inventory management, machine learning (ML) and artificial intelligence (AI) have been recognized as game-changing technologies (Dingemans, 2015)(Donderwinkel, 2015)(Elquthb et al., 2024). According to studies, intelligent replenishment systems, anomaly detection, and real-time inventory tracking powered by AI may greatly increase the effectiveness of SMI management (Emar, et al., 2021)(Farooq et al., 2024)(Febrianto et al., 2022). AI-based inventory management software, such as predictive replenishment models, may automatically modify order amounts in response to anticipated future demand, preventing needless stock building (Finco et al., 2022)(Fukkwarmdee, & Buddhakulsomsiri, 2023)(Gabor et al., 2022). Dynamic Pricing Strategies Driven by AI, Businesses utilize AI to modify prices based on seasonal variations, competition pricing, and demand patterns to speed up the turnover of slow-moving products (Gaikwad, & Shende, 2015)(Goyvaerts, et al., 2022)(Hahn, & Leucht, 2015).

Blockchain and IoT for Inventory Visibility and Traceability

Real-time tracking, supply chain efficiency, and stock visibility have been greatly increased with the use of blockchain and the Internet of Things (IoT) in inventory management (Abidar & Chaabane 2022), (Afkar & Rochmoeljati, 2025). RFID tags and smart sensors are used by IoT-enabled smart warehouses to continually monitor inventory, guaranteeing accurate monitoring of slow-moving products and reducing needless storage expenses [3, 4, 5]. Additionally, these technologies improve predictive analytics, allowing companies to automate replenishment procedures and foresee changes in demand (Ahunanya et al., 2022), (Alakbarov, 2023). . Additionally, IoT-based inventory systems minimize product loss, minimize human error, and maximize resource use (Alim & Isnanto 2023), (Al-Shawawreh & Mohammad, 2022). . Businesses may make data-driven choices by integrating IoT into inventory management, which increases operational effectiveness and lowers supply chain interruptions. (Arief et al., 2024). , (Arief et al., 2024). By improving data security, accuracy, and transparency in inventory audits, blockchain technology enhances the Internet of Things (Babai et al., 2024). ,

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(Bektiawan et al., 2022). . Its decentralized ledger architecture minimizes fraud and inconsistencies in stock management by guaranteeing that all inventory transactions are irreversible and verifiable (Belciug, & Gorunescu, 2015). This is especially helpful for managing slow-moving inventory in intricate supply chains, as errors may result in shortages or overstocking (Botha et al., 2017). Additionally, real-time data is synchronized between manufacturers, suppliers, and retailers through the use of blockchain-based smart contracts that automate stock adjustments (Abidar & Chaabane 2022), (Afy-Shararah et al., 2022). Businesses may create a more robust and sustainable inventory management system by integrating blockchain and IoT, which will save waste and enhance supply chain performance overall [5, 7]. It is anticipated that as these technologies advance, their broad use will spur innovation in logistics and inventory management (Al-Shawawreh & Mohammad, 2022). , (Bektiawan et al., 2022). .

Sustainable and Circular Economy Approaches

Sustainable and Circular Economy Approaches

Businesses are incorporating circular economy concepts into inventory management to cut waste and boost productivity as a result of the increased focus on sustainability (Babai et al., 2024). , (Bektiawan et al., 2022). . By extending product lifecycles through techniques like remanufacturing, recycling, and repurposing the circular economy aims to reduce losses brought on by excess inventory while encouraging environmental responsibility (Belciug, & Gorunescu, 2015), (Botha et al., 2017). Businesses that follow these guidelines reduce their carbon footprint while simultaneously complying with legal obligations and corporate social responsibility (CSR) objectives (Çelebi, 2015). , (Chandren et al., 2015). .

Reverse Logistics and Product Returns Management

A crucial element of sustainable inventory management is reverse logistics, which makes sure that excess, returned, or slow-moving goods are effectively reintegrated into the supply chain (Da Giau, 2022) , (De Assis et al., 2022). To recover value and reduce disposal expenses, this procedure involves recycling, reselling, or repairing items (Debnathand et al., 2022), (Devonald & Eng, 2022). Chopra & Meindl (Dhoka & Choudary 2015) state that strong return policies that support product recovery and resale are particularly beneficial to sectors like electronics, autos, and fashion. Furthermore, by increasing traceability and transparency, developments in blockchain technology and digital tracking systems improve reverse logistics (Dingemans, 2015), (Donderwinkel, 2015).

Green Inventory Practices

By using demand-driven manufacturing techniques, sustainable sourcing, and optimal packaging, green inventory practices aim to lessen their negative effects on the environment (Elquthb et al., 2024), (Emar, et al., 2021). To meet sustainability targets, businesses are progressively using eco-friendly production methods, biodegradable materials, and energy-efficient storage options (Farooq et al., 2024), (Febrianto et al., 2022). According to Govindan et al. (Finco et al., 2022), companies that adopt green supply chain strategies not only cut expenses but also improve consumer trust and brand recognition. Additionally, inventory management systems powered by AI and predictive analytics assist avoid overproduction and lessen the buildup of slow-moving items (Fukkwarmdee, & Buddhakulsomsiri, 2023), (Gabor et al., 2022).

Remanufacturing, Recycling, and Repurposing Strategies

To assist businesses, prolong product life cycles and reduce waste, remanufacturing and recycling are crucial elements of the circular economy (Gaikwad, & Shende, 2015), (Goyvaerts, et al., 2022). Disney & Towill (Hahn, & Leucht, 2015) stress that to efficiently handle surplus inventory, businesses should form alliances with outside recyclers or remanufacturers. Additionally, repurposing unsold items for different uses might save disposal costs and provide new revenue sources (Halilović et al., 2023), (Hänninen, 2024). Furthermore, businesses in the automotive and electronics industries have effectively established closed-loop supply chains, which reintroduce old parts into the production process (Hasan, 2024), (Heikkinen et al., 2023).

Technology-Driven Sustainable Inventory Management

Sustainable inventory management has greatly improved with the use of cutting-edge technologies like blockchain, artificial intelligence (AI), and the Internet of Things (IoT) (Huo, & Zhan, 2024), (Isa, 2024). Predictive analytics powered by AI improve demand forecasting and lower the risk of stock obsolescence and overstocking (Jean, 2024), (Jean, 2024b). . By guaranteeing that sustainability KPIs are appropriately tracked and reported, blockchain technology improves supply chain transparency (Jokela, 2024)., (Kalumanga, & Mwita, 2024). Inventory optimization is further supported by IoT-enabled real-time tracking systems, which offer precise stock movement insights (Kanani et al., 2015), (Karim et al., 2018).

Using a circular economy and sustainable practices is crucial to improving inventory control and lessening the impact on the environment. Businesses may increase productivity, reduce waste, and support long-term sustainability objectives by combining reverse logistics, green inventory practices, remanufacturing, and technology-driven solutions (Kartikasari, 2024), (Kasim et al., 2015). Businesses that use these tactics will boost their market competitiveness in a global economy that is becoming more environmentally sensitive in addition to improving their financial performance (Kaya et al., 2023), (Kecskeméti, 2015) .

Inventory Sharing and Collaborative Supply Chain Networks

According to recent studies, businesses can cooperate in industry networks to better manage slow-moving inventory (Elquthb et al., 2024). Slow-moving items are only restocked when necessary thanks to vendor-managed inventory (VMI), which gives suppliers some degree of control over inventory management (Devonald & Eng, 2022). Industry-Wide Goods Pooling: Businesses in the same sector work together to distribute slow-moving goods around several sites, minimizing surplus inventory in one area while meeting demand in another (Dhoka & Choudary 2015). According to the results of the literature analysis, the best management system for slow-moving inventory necessitates a multifaceted strategy that combines real-time monitoring technologies, AI-driven automation, categorization models, forecasting accuracy, and sustainable practices. For increased efficiency and cost reductions, businesses must switch from traditional EOQ and JIT models to data-driven, AI-enhanced, and blockchain-integrated inventory systems. As emerging technologies continue to advance, firms that leverage smart inventory tracking, predictive analytics, and collaborative supply chain networks will gain a competitive advantage in slow-moving inventory optimization.

Findings on Enhancing Efficiency: Optimal Management System of Slow-Moving Inventory

Across all sectors, managing slow-moving inventory (SMI) is a crucial concern that calls for striking a balance between cutting surplus stock and preserving supply chain effectiveness. According to a review of current research, sophisticated, technology-driven solutions are replacing conventional inventory models in order to maximize inventory turnover and reduce holding costs. According to the research, using machine learning (ML), predictive analytics, and multi-echelon optimization improves decision-making, enabling businesses to foresee changes in demand and optimize processes.

Evolution of Inventory Optimization Approaches

The analysis demonstrates a shift toward more complex approaches from traditional inventory models like the Economic Order Quantity (EOQ) and Just-in-Time (JIT) systems. Although EOQ is still useful for basic inventory control, as mentioned in (Abidar & Chaabane 2022), (Ahmed, & Shuvro 2023), and (Dingemans, 2015), its limits in dynamic supply chains call for adaptive models. JIT, which is frequently used in lean manufacturing and is highlighted in (Ahlsellh et al., 2022) and (Ahunanya et al., 2022), necessitates exact coordination with suppliers to prevent stockouts. These techniques struggle with demand uncertainty but show modest efficacy in managing slow-moving inventories. Modern frameworks, including Bayesian Inventory Models (Hasan, 2024), (Halilović et al., 2023), and Markov Decision Process (MDP) models (Jean, 2024), (Nwankpa, 2015), provide probabilistic decision-making skills that improve forecasting accuracy to overcome these constraints. The growing application of multi-echelon inventory optimization (Gaikwad, & Shende, 2015), (Hahn, & Leucht, 2015) further demonstrates its role in improving stock distribution across different supply

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chain tiers. These models effectively reduce excess stock and operational inefficiencies, particularly in industries managing high-value and perishable inventories.

The Role of Data-Driven Inventory Management

With a focus on predictive modelling, recent research emphasizes the value of data analytics in managing slow-moving inventory. As mentioned in (Babai et al., 2024). , (Elquthb et al., 2024), and (Goyvaerts, et al., 2022), machine learning (ML)-based predictions allow businesses to spot trends in inventory movement and more precisely estimate demand. Decision-making under uncertainty is further improved by fuzzy logic control (Rusu et al., 2015), (Rojas et al., 2020), which enables companies to dynamically modify inventory levels in response to real-time inputs. These clever methods lessen the cost effect of outmoded goods and improve replacement schedules. Inventory models that are based on simulations (Hasan, 2024), (Halilović et al., 2023), and (Afy-Shararah et al., 2022) have become excellent tools for scenario analysis, enabling companies to evaluate various inventory methods before deployment. These methods are especially helpful in sectors like oil and gas, aerospace, and military that have intricate and uncertain supply chains (Arief et al., 2024). , (Dhoka & Choudary 2015), and (Farooq et al., 2024). By integrating these technologies, organizations can enhance responsiveness to market changes, reducing the risk of overstocking or stock obsolescence.

Industry-Specific Strategies for SMI Optimization

The research shows that different industries have different inventory management techniques based on supply chain architecture and demand trends (Jean, 2024). Machine learning and time-series forecasting are essential for anticipating customer purchase behaviour and modifying inventory levels appropriately in retail and e-commerce (Abidar & Chaabane 2022), (Ahmed, & Shuvro 2023), and (Dingemans, 2015) (Elquthb et al., 2024). On the other hand, the manufacturing industry (Ahlsellh et al., 2022), (Ahunanya et al., 2022) mostly uses lean inventory concepts, combining JIT and EOQ systems to reduce stockholding expenses (Arief et al., 2024). . Advanced optimization approaches, such as multi-echelon frameworks and Bayesian inference models (Babai et al., 2024). ;(Devonald & Eng, 2022), are beneficial for industries with very complicated supply chains, such as healthcare ((De Assis et al., 2022), (Da Giau, 2022) , (Onyango, et al., 2024)) and automotive (Bektiawan et al., 2022). , (Farooq et al., 2024). To maintain operational efficiency, these businesses need accurate forecasting and inventory monitoring systems (Afkar & Rochmoeljati, 2025)(Afy-Shararah et al., 2022). The aerospace and defence sector (Arief et al., 2024). , (Dhoka & Choudary 2015), (Farooq et al., 2024) applies MDP models for risk assessment, optimizing stock levels in high-security environments where inventory availability is mission-critical (Arief et al., 2024). .

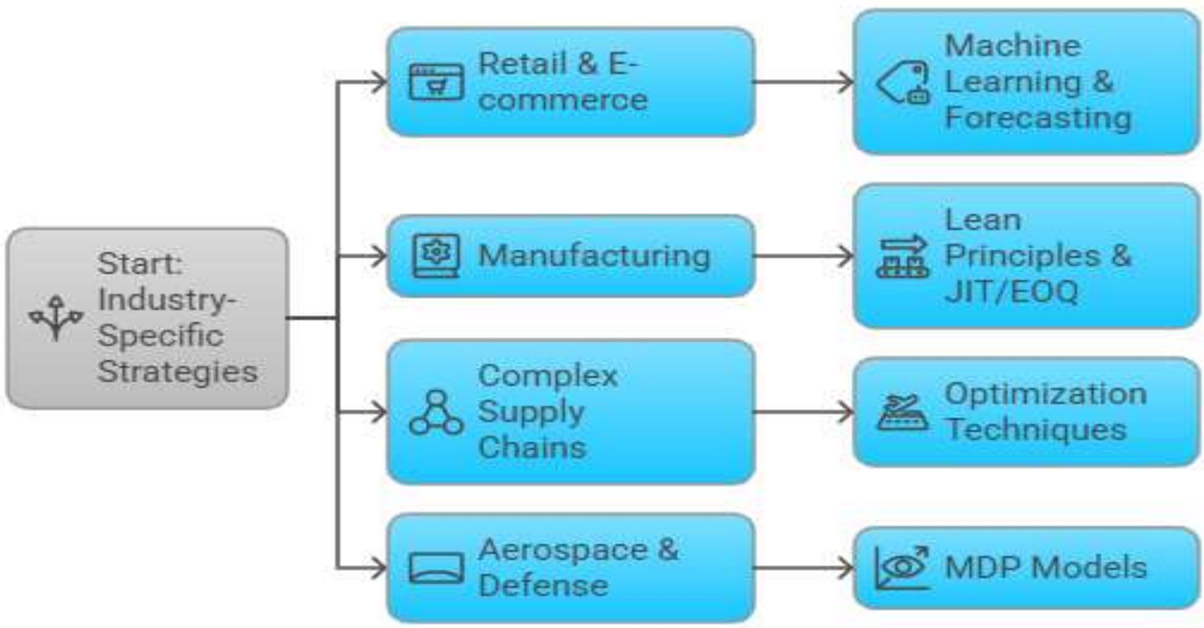

Figure 5: Industry-Specific Strategies for SMI Optimization

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Effectiveness of Inventory Optimization Models

All of the examined studies evaluate how well various inventory management systems handle slow-moving goods. Because they rely on static demand assumptions, traditional methods like EOQ and JIT are only somewhat effective at managing slow-moving inventory. By using probabilistic decision-making and real-time data inputs, more sophisticated techniques like Bayesian inference and MDP models show high to extremely high efficacy. The most effective methods at the top level are those based on simulation and machine learning, which let businesses control inventory levels proactively and reduce losses. The results show a distinct trend toward combining multi-tier optimization techniques, predictive analytics, and AI-driven solutions to improve the management of slow-moving inventories. Because of the growing complexity of contemporary supply chains and the requirement for flexible, data-driven decision-making, static inventory models have given way to dynamic ones. To further increase inventory turnover and decrease excess stock accumulation, future studies should investigate hybrid models that include fuzzy logic, machine learning, and multi-echelon frameworks. Furthermore, a stronger focus on sustainability-driven inventory management techniques may aid businesses in reducing waste and preserving the robustness of their supply chains.

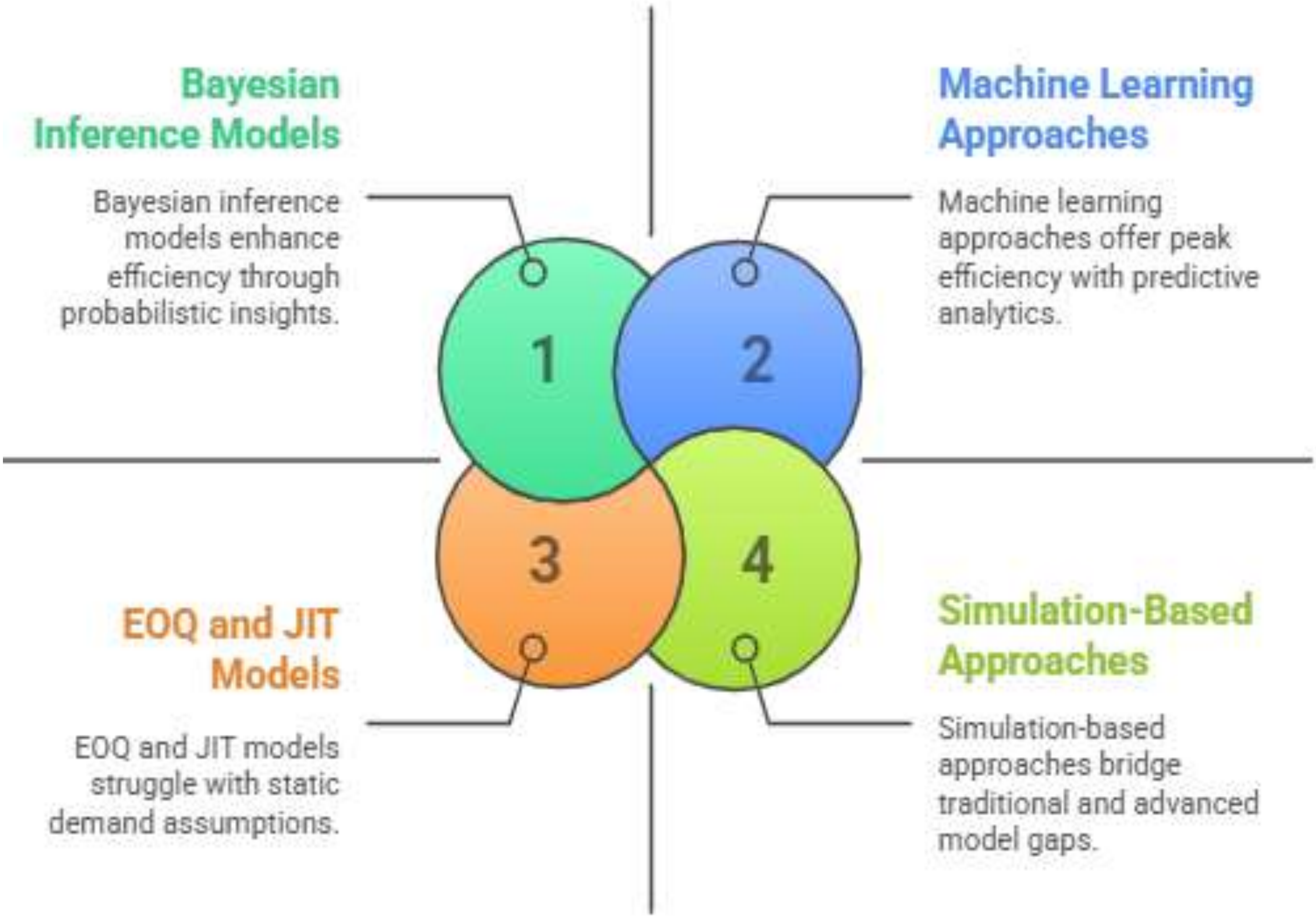

Figure 6: Inventory Management Model Effectiveness

Future Directions of Inventory Management Based on Review Results

Several new patterns and possible future paths are highlighted by the thorough examination of slow-moving inventory management. These findings imply that to maximize productivity and minimize losses, inventory management will depend more and more on cutting-edge technology, real-time analytics, and sustainability-driven strategies. Predictive inventory control using machine learning (ML) and artificial intelligence (AI). AI and ML will be used by future inventory management systems to improve decision-making and forecasting precision. Businesses will be able to dynamically modify their stocking and procurement strategies thanks to machine learning models' critical role in forecasting slow-moving inventory patterns. By incorporating outside

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variables like market swings, economic trends, and seasonal changes, AI-driven automation will further enhance demand forecasting.

Real-time data analytics and the Internet of Things (IoT). Real-time tracking of stock levels, movement, and demand trends will be possible through the integration of IoT sensors with inventory systems. IoT-driven systems that automatically update stock levels and continually monitor inventory conditions will reduce overstocking and understocking problems. Decision-making will be improved and just-in-time (JIT) inventory strategies will be made easier with this real-time visibility, increasing operational efficiency.

Supply chains may be made transparent and secure with blockchain technology. Supply chain operations will be more transparent, secure, and traceable thanks to blockchain-based inventory management solutions. Blockchain technology will allow businesses to trace the origin, transportation, and condition of items by generating decentralized, unchangeable records. This will be especially helpful for sectors like healthcare, aerospace, and food supply chains that have a lot of regulations.

Circular economy and sustainable approaches. Inventory management will move toward circular economy models that prioritize resource efficiency and waste reduction as governments and corporations place a greater emphasis on sustainability. Businesses will use inventory repurposing, recycling initiatives, and reverse logistics to prolong product life cycles and reduce waste. AI-powered sustainability indicators will also assist businesses in monitoring and reducing the carbon footprints related to inventory control.

Multi-Level Inventory Management for International Supply Chains. Multi-echelon optimization, which involves deliberately balancing inventory levels across several supply chain tiers, will be a part of inventory management in the future. Businesses will benefit from shorter lead times, lower holding costs, and improved demand responsiveness with this strategy. AI-driven simulations and multi-echelon optimization will enable businesses to evaluate different supply chain scenarios before making adjustments.

Combining Hybrid Models with Fuzzy Logic. Inventory categorization and optimization will be improved by fuzzy logic and hybrid modeling techniques, especially when handling erratic demand patterns. Fuzzy logic combined with AI, Bayesian networks, and deep learning will enable inventory models to more accurately adjust to changing market conditions. These hybrid models will help companies that deal with perishable and slow-moving items make better decisions.

Robotics and autonomous warehouses for intelligent inventory management. Autonomous systems and robotic process automation (RPA) will be used in future warehouses to handle inventory and fulfil orders. Drone-based inventory tracking, automated guided vehicles (AGVs), and robotic pick-and-place systems will boost operational efficiency and save personnel expenses. Autonomous inventory optimization and replenishment will be made possible by the integration of these technologies with AI-based inventory management software.

Demand-driven inventory strategies and personalization. Businesses will be able to transition from old inventory models to highly customized and demand-driven strategies thanks to developments in consumer data analytics and AI-driven demand sensing. Supply chain operations will become more responsive and efficient as a result of businesses using consumer behaviour data to adjust stock levels, modify product offers, and cut down on surplus inventory. The integration of AI, IoT, blockchain, sustainable practices, and automation will influence inventory management in the future. To increase productivity and lower losses, businesses will depend more and more on real-time monitoring, predictive analytics, and intelligent automation. Businesses that use flexible and data-driven inventory strategies will have a competitive edge in efficiently managing slow-moving inventory as digital transformation proceeds.

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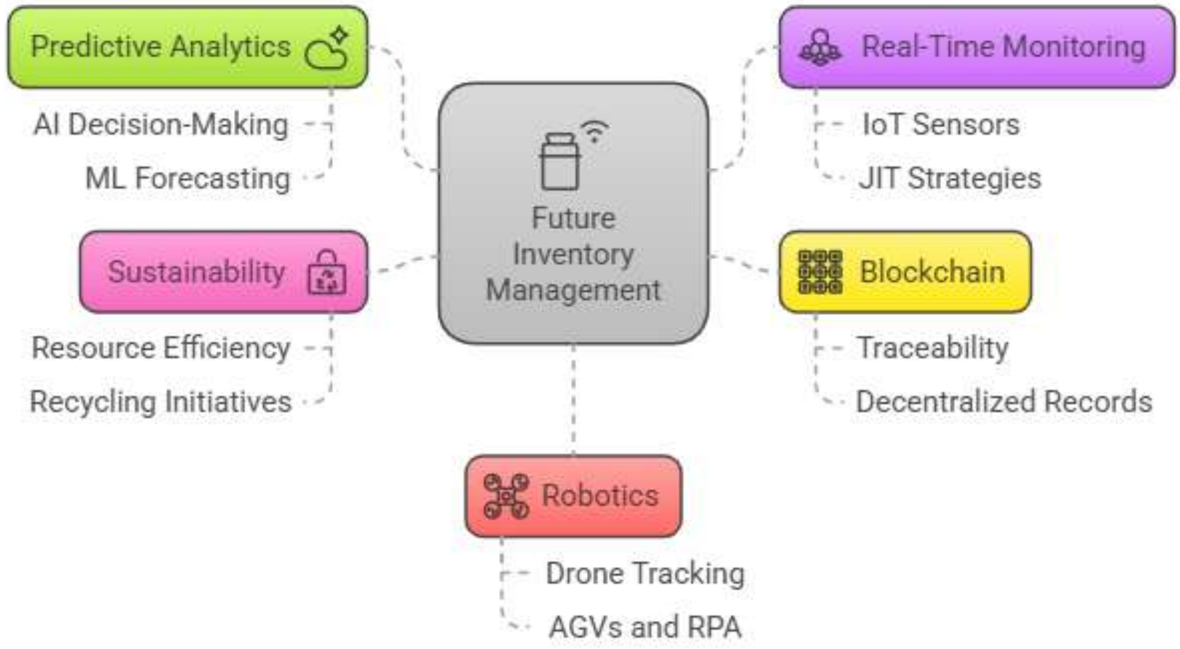

Figure 7: Future Directions in Inventory Management

CONCLUSION

This comprehensive analysis of slow-moving inventory management sheds light on the growing dependence on automation and data-driven technology while offering insightful information on the development of inventory optimization techniques. The results show a distinct move away from conventional inventory control techniques like the ABC classification and Economic Order Quantity (EOQ) model and toward more sophisticated strategies like multi-echelon optimization, machine learning-based forecasting, and simulation-driven decision-making. Supply chain transparency, forecasting accuracy, and inventory monitoring have all greatly improved with the combination of blockchain technology, artificial intelligence (AI), and the Internet of Things (IoT). The survey also shows that different businesses have different approaches to inventory management. For example, the industrial and healthcare sectors prioritize predictive analytics and sustainable inventory practices, while the retail and e-commerce sectors use real-time demand forecasting. Furthermore, the necessity for companies to strike a balance between environmental responsibility and efficiency is highlighted by the growing emphasis on sustainability and circular economy strategies. Future studies should concentrate on hybrid AI-driven models, real-time optimization strategies, and adaptive automation to improve the efficiency of slow-moving inventory as the inventory management landscape continues to change. To remain competitive in a supply chain environment that is becoming more complicated and dynamic, businesses also need to invest in data-driven frameworks for decision-making and intelligent inventory systems. In the end, ongoing innovation in inventory management will promote sustainable business practices, increase operational effectiveness, and achieve cost reductions.

RECOMMENDATION

Businesses could use blockchain for real-time visibility, IoT-enabled tracking systems, and AI-driven predictive analytics to improve the effectiveness of slow-moving inventory management and reduce obsolescence and overstocking. For dynamic decision-making, businesses must use hybrid inventory models that blend conventional techniques with machine learning-based forecasting. Automated replenishment systems and multi-echelon optimization will further enhance inventory movement and lower holding costs. To reduce waste, businesses should give priority to inventory techniques that are focused on sustainability, such as demand-driven buying and the concepts of the circular economy. For improved responsiveness in shifting market conditions, future studies should investigate adaptive inventory frameworks that combine real-time data analytics, cloud computing, and robotic process automation (RPA).

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REFERENCE

1. Abidar, Y., & Chaabane, A. (2022). On the Integration of Additive Manufacturing for Aircraft Spare Parts Inventory Control.
2. Afkar, M. H., & Rochmoeljati, R. (2025). Usulan Perencanaan Tata Letak Gudang Bahan Penolong Menggunakan Metode Class Based Storage di PT. XXX. Jurnal Serambi Engineering, 10(1).
3. Afy-Shararah, M., Jagtap, S., Pagone, E., & Salonitis, K. (2022). Waste minimization by inventory management in high-volume high-complexity manufacturing organizations. In Global Conference on Sustainable Manufacturing (pp. 375-382). Cham: Springer International Publishing.
4. Ahlsell, L., Jalal, D., Khajavi, S. H., Jonsson, P., & Holmström, J. (2022). Additive manufacturing of slow-moving automotive spare parts: A supply chain cost assessment. Journal of Manufacturing and Materials Processing, 7(1), 8.
5. Ahmed, K. S., & Shuvro, J. B. (2023) Optimization in Supply Chain Components to Design a Strategic Model and Research Opportunities to Enable Profitability.
6. Ahunanya, V., Ovharhe, O. H., Emenike, C. G., & Otto, G. (2022). Consignment inventory system and obsolescence management in the drilling fluid firms in Nigeria. International Journal of Social Science & Management Research, 8(5), 1-27.
7. Alakbarov, T. (2023). Accounting of inventories in service sphere enterprises based on modern technologies and their positive effects. CRJ, (2), 18-25.
8. Alim, I. F. H., & Isnanto, R. R. (2023). Design of Inventory Management Information System Using Periodic Review Method. In E3S Web of Conferences (Vol. 448, p. 02010). EDP Sciences.
9. Al-Shawawreh, F. M., & Mohammad, Q. O. (2022). The Impact of Inventory Movements on Financial Performance at Arab Potash Company. Journal of Positive School Psychology, 7266-7306.
10. Arief, D. S., Rasyid, I., Susilawati, A., Herisiswanto, H., & Junaidi, A. K. (2024,). Spare part warehouse system management at Jaya Utama Muda store using a computer-based Kanban barcode method. In AIP Conference Proceedings (Vol. 3053, No. 1). AIP Publishing.
11. Ariffin, W. N. M., Subramaniam, R., Putri, E. P., Jusoh, M. S., Masran, M. H., Rohani, M. N. K. H., ... & Shukri, S. S. M. (2023). Product Pairing Selection for Promotion using Partitioning Method. J. Adv. Res. Appl. Sci. Eng. Technol, 30(3), 91-103.
12. Babai, M. Z., Ladhari, T., & Lajili, I. (2015). On the inventory performance of multi-criteria classification methods: empirical investigation. International Journal of Production Research, 53(1), 279-290.
13. Bektiawan, A., Saraswati, T., & Salahuddin, D. (2022,). Komatsu's Spare-parts Service Level and Day of Inventory Improvement for PT. MTN. In Proceedings of the 2022 International Conference on Engineering and Information Technology for Sustainable Industry (pp. 1-8).
14. Belciug, S., & Gorunescu, F. (2015). Improving hospital bed occupancy and resource utilization through queuing modelling and evolutionary computation. Journal of Biomedical Informatics, 53, 261-269.
15. Botha, A., Grobler, J., & Yadavalli, V. S. (2017). System dynamics comparison of three inventory management models in an automotive parts supply chain. Journal of Transport and Supply Chain Management, 11(1), 1-12.
16. Çelebi, D. (2015). Inventory control in a centralized distribution network using genetic algorithms: A case study. Computers & Industrial Engineering, 87, 532-539.
17. Chandren, S., Nadarajan, S., & Abdullah, Z. (2015). Inventory physical count process: The best practice discourse. International Journal of Supply Chain Management, 4(3).

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VII July 2026

18. Da Giau, M. (2022). Integration of a cloud-based platform with SAP's ERP system aimed at Spare Parts Inventory optimisation. The Luigi Lavazza SpA case study (Doctoral dissertation, Politecnico di Torino).
19. de Assis, A. G., Dos Santos, A. F. A., Dos Santos, L. A., da Costa, J. F., Cabral, M. A. L., & de Souza, R. P. (2022). Classification of medicines and materials in hospital inventory management: a multi-criteria analysis. BMC Medical Informatics and Decision Making, 22(1), 325.
20. Debnathand, A., Mahabub, S. A., & Uddin, M. M. (2022). Assessing Forecasting Techniques & Stock Replenishment Approaches for Optimal Inventory of Electronic Spare Parts. In Proceedings of the International Conference on Industrial & Mechanical Engineering and Operations Management, Dhaka, Bangladesh.
21. Devonald, M., & Eng, P. (2022). Reliability Models for Roads Crossing Slow-Moving Landslides.
22. Dhoka, D., & Choudary, L. Y. (2015). Challenges with multi-dimensional inventory classifications and optimization. Asian Social Science, 11(4), 365.
23. Dingemans, M. (2015). Inventory Management Integration in a Maintenance Service Supply Chain (Doctoral dissertation, Tilburg University).
24. Donderwinkel, S. (2015). Improving the On Time Delivery performance by the implementation of a Sales Inventory & Operations Planning process/Taking into account the optimization of inventory parameter settings of components with different demand patterns (Master's thesis, University of Twente).
25. Elquthb, J. N., Nugroho, L. R., & Khasanah, A. U. (2024). Implementation of Class-Based Storage for Garment Accessories Warehouse Management Using FSN Analysis at PT. XYZ. Journal of Industrial Engineering and Halal Industries, 5(1), 29-35.
26. Emar, W., Al-Omari, Z. A., & Alharbi, S. (2021). Analysis of inventory management of slow-moving spare parts by using ABC techniques and EOQ model case study. Indonesian Journal of Electrical Engineering and Computer Science, 23(2), 1159-1169.
27. Farooq, A., Abbey, A. B. N., & Onukwulu, E. C. (2024). Inventory optimization and sustainability in retail: A conceptual approach to data-driven resource management. International Journal of Multidisciplinary Research and Growth Evaluation, 5(6), 1356-1363.
28. Febrianto, A., Sofianti, T. D., & Baskoro, G. (2022,). Implementing Periodic Review–Variable Order Quantity System In Inventory Management: A Case Study Heavy Equipment Companies, Kutai Barat. In Proceedings of the 2022 International Conference on Engineering and Information Technology for Sustainable Industry (pp. 1-7).
29. Finco, S., Battini, D., Converso, G., & Murino, T. (2022). Applying the zero-inflated Poisson regression in the inventory management of irregular demand items. Journal of industrial and production engineering, 39(6), 458-478.
30. Fukkwarmdee, P., & Buddhakulsomsiri, J. (2023). Application of (s, S) inventory policy with backlog: a case study of chemical products (Doctoral dissertation, Thammasat University).
31. Gabor, A. F., van Ommeren, J. K., & Sleptchenko, A. (2022). An inventory model with discounts for omnichannel retailers of slow-moving items. European Journal of Operational Research, 300(1), 58-72.
32. Gaikwad, V. R., & Shende, S. V. (2015). Analysis of Inventory Control Techniques and Study of Non-Conventional Parameters. International Journal of Engineering research and technology,(ISSN: 2278-0181), 4(12).
33. Goyvaerts, L., Van Dooren, A., & Willems, L. (2022). An inventory management system for a make-to-order premium door manufacturer.
34. Hahn, G. J., & Leucht, A. (2015). Managing inventory systems of slow-moving items. International Journal of Production Economics, 170, 543-550.
35. Halilović[1], E., Bajrić[1], H., Melin, K., & Neimarlija, E. (2023). Check for updates on Strategies for Reducing Excess and Obsolete Inventory. New Technologies, Development and Application VI: Volume 1, 687, 396.
36. Hänninen, P. (2024). Improving inventory management efficiency: the impact of optimisation.
37. Hasan, M. R. (2024). Supply chain in Meena Bazar: focus on demand forecasting, inventory management, reverse logistics, and business expansion.
38. Heikkinen, R., Sipilä, J., Ojalehto, V., & Miettinen, K. (2023). Flexible data-driven inventory management with interactive multi-objective lot size optimisation. International Journal of Logistics Systems and Management, 46(2), 206-235.

39. Huo, Z., & Zhan, X. (2024). Revolutionizing Inventory Management: The Role of Data Mining in Industry 4.0. Advances in Economics, Management and Political Sciences, 109, 67-72.
40. Isa, F. M. (2024). Slow Moving Product In Retail Industry: A Bibliometric Analysis Of Issue And Challenge. Labuan Bulletin of International Business and Finance (LBIBF), 22(2).
41. Jean, G. (2024). Inventory Management Strategies: Balancing Cost, Efficiency, and Customer Satisfaction.
42. Jean, G. (2024b). Vendor-Managed Inventory (VMI) in E-supply Chains: Coordination Effects on Cost Reduction and Performance.
43. Jokela, J. (2024). Optimizing Inventory Management: Leveraging CNNs and Conventional Grouping Methods: A Strategy for Excess Inventory Reduction and Dynamic Grouping.
44. Kalumanga, V. E., & Mwita, O. N. (2024). Perceptions on the effectiveness of EPICOR system on pharmaceutical inventory management in Tanzania: A case study of Medical Stores Department (MDS) in Dar es Salam. NG Journal of Social Development, 13(1), 117-132.
45. Kanani, M. A., Sharma, N. D., & Kashiyani, M. B. K. A. (2015) study different inventory management techniques in construction.
46. Karim, N. A., Nawawi, A., & Salin, A. S. A. P. (2018). Inventory management effectiveness of a manufacturing company–Malaysian evidence. International Journal of Law and Management, 60(5), 1163-1178.
47. Kartikasari, M. A. (2024). Design of Medicine Inventory System. Jurnal Logistik Indonesia, 8(2), 122-131.
48. Kasim, H., Zubieru, M., & Antwi, S. K. (2015). An assessment of the inventory management practices of small and medium enterprises (SMEs) in the Northern Region of Ghana. European Journal of Business and Management, 7(20), 28-40.
49. Kaya, B., Karabağ, O., Çekiç, F. R., Torun, B. C., Başay, A. Ö., Işıklı, Z. E., & Çakır, Ç. (2023) Inventory Management Optimization for Intermittent Demand. In The International Symposium for Production Research (pp. 768-782). Cham: Springer Nature Switzerland.
50. Kecskeméti, Z. (2015) How to optimize warehouse management and the inventory level in the fast-moving fashion industry-focusing on the effect of inventory system and warehouse management system at Sun Enterprises.
51. Kumar, H. (2024) Utilization of Inventory Management System in Educational Organization.
52. Lijuan, C., Bhaumik, A., Xinfeng, W., & Jingwen, W. (2022) The Effects of Inventory Management on Business Efficiency.
53. Madzivhandila, N. L. (2022). An investigation of factors affecting plasterboard warehouse inventory management: The case of a South African company. University of Johannesburg (South Africa).
54. Mehrotra, M., & Sehgal, S. C. (2023). Inventory management: challenges and optimization of spare parts in Indian power utilities. IUP Journal of Operations Management, 22(4), 45-59.
55. Mehrotra, M., & Sehgal, S. C. (2024). Optimizing inventory management in power plant operations: a comprehensive analysis of selective control policies.
56. Nagpal, S., Khatri, S. K., & Kumar, A. (2015). Comparative study of ERP implementation strategies. In 2015 Long Island Systems, Applications and Technology (pp. 1-9). IEEE.
57. Nawawi, A., & Salin, A. S. A. P. (2018). Slow moving stock problem: Empirical evidence from Malaysia. International Journal of Law and Management, 60(5), 1148-1162.
58. Verona, G. G., Bohol, J. R., Decena, K. N. R., Jose, J. N., De Guzman, A. N., Rodriguez, J. C. R., ... & Paulino, A. C. N. (2023). Improving the functionality, 5S rating, and inventory management system of the supply department of a regimental academy in the Philippines through industrial engineering applications. International Research Journal of Science, Technology, Education, & Management (IRJSTEM), 3(3).
59. Nieuwenhuijze, L. (2024). Explainable Machine Learning Techniques in Operational Decision Making: The Prevention of Slow-Moving Inventory.
60. Njoroge, M. W. (2015). Inventory management practices and performance of public hospitals in Kenya (Doctoral dissertation, University of Nairobi).
61. Nwankpa, J. K. (2015). ERP system usage and benefit: A model of antecedents and outcomes. Computers in Human Behavior, 45, 335-344.
62. Olofsson, J., & Persson, J. (2023). An inventory optimization toolbox in SMEs.

63. Onyango, O. D., & Thiong'o, S. M. (2024). Inventory Management Practices and Supply Chain Performance in the Automotive Industry in Kenya.
64. Otay, I., Senturk, E., & Çebi, F. (2018). An integrated fuzzy approach for classifying slow-moving items. Journal of Enterprise Information Management, 31(4), 595-611.
65. Panicharoen, N., & Pham, D. T. (2023). Finding (s, S) policy for inventory system with partial backlog, uncertain demand and lead time using heuristic search: a case study of pharmaceutical products (Doctoral dissertation, Thammasat University).
66. Pathak, A., Prabhu, T., Sardar, V., & Rajhans, D. N. (2017). Inventory management for a newly started service station. In International Conference on Manufacturing Excellence.
67. Pires, J. F. (2024). Analysis of both economic and operational impacts driven by inventory management policies (Doctoral dissertation).
68. Porter, M., Van Hove, J., & Barlow, P. (2022). Analysis of dynamic system risks where pipelines cross slow-moving landslides. In International Pipeline Conference (Vol. 86564, p. V001T07A007). American Society of Mechanical Engineers.
69. Prasetya, H. R., & Pujangkoro, S. (2022, December). Shelf Allocation Redesign and Warehouse Management System Improvement to Optimize Warehouse Material Flow in Oleo Chemical Industry Business. In 19th International Symposium on Management (INSYMA 2022) (pp. 1135-1145). Atlantis Press.
70. Purbandini, P., Werdiningsih, I., Purwanti, E., & Putri, A. Y. (2023). Grouping fast-moving and slow-moving inventory using K-medoid clustering. In AIP Conference Proceedings (Vol. 2536, No. 1). AIP Publishing.
71. Putra, M. S., Hidayat, D., & Atmojo, R. N. P. (2024). Inventory Management Optimization System Design at XYZ Die and Mold Retail Store. In 2024 International Conference on Information Management and Technology (ICIMTech) (pp. 7-12). IEEE.
72. Rahman, M. H., Shahariar, M. M., Tanvir, M. S. H., & Roy, J. (2023). Lean Thinking (5S System) in E-commerce Supply Chains: A Path to Inventory Optimization and Work Management. Supply Chain Insider| ISSN: 2617-7420 (Print), 2617-7420 (Online), 9(1).
73. Ramadan, A., & Morshed, A. (2023). Working capital management roles for multinational retail industry profitability: a qualitative study, worldwide perspective. Information Sciences Letter, 12.
74. Rikkula, H. K. R. (2024). Impact of Oracle applications on warehouse management in the automotive industry: a case for efficiency and customer satisfaction. International journal of computer engineering and technology (ijcet), 15(4), 495-504.
75. Rodríguez, V., & Obed, D. (2023). Small Business Lean Inventory Optimization. Manufacturing Engineering
76. Rojas, F., Wanke, P., Coluccio, G., Vega-Vargas, J., & Huerta-Canepa, G. F. (2020). Managing slow-moving item: a zero-inflated truncated normal approach for modelling demand. PeerJ Computer Science, 6, e298.
77. Rusu, L., Taut, D. A. S., & Jecan, S. (2015). An integrated solution for pavement management and monitoring systems. Procedia Economics and Finance, 27, 14-21
78. Salam, A., Panahifar, F., & Byrne, P. J. (2016). Retail supply chain service levels: the role of inventory storage. Journal of Enterprise Information Management, 29(6), 887-902.
79. Schrettenbrunner, M. B. (2023). Artificial-intelligence-driven management: Autonomous real-time trading and testing of portfolio or inventory strategies. IEEE Engineering Management Review, 51(3), 65-76.
80. Sen, E. G. (2023). Inventory management and planning of slow-moving spare parts (Doctoral dissertation, Master Thesis, Eindhoven University of Technology, Eindhoven, Netherlands).
81. Setiawan, W., Santosa, N., Winarto, F. E. W., & Mandala, W. W. (2025). Inventory Management and Proactive Maintenance to Enhance Operational Efficiency in Excavators: Focus on Common Spare Parts Issues. Jurnal Asiimetrik: Jurnal Ilmiah Rekayasa & Inovasi, 49-58.
82. Shamsan, S. S., Senjab, A. M., Abuhassna, O. A., Abdullah, A. S., Zreed, K. H., Rafaqat, M., & Ahmed, N. (2025) Identification of Causes of Medicine Expiration in the Warehouse-A Case of Saudi Medical Company.
83. Sharma, R., Bajpai, A., Maheshwari, A., Sharma, A., & Gupta, G. (2022). Transforming Inventory Management System using MEAN Stack.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VII July 2026

84. Shen, Z., Dessouky, M., & Ordonez, F. (2016). Perishable inventory management system with a Minimum volume constraint. Operational Research for Emergency Planning in Healthcare: Volume 1, 288-329.
85. Singh, A., Rasania, S. K., & Barua, K. (2022). Inventory control: Its principles and application. Indian Journal of Community Health, 34(1), 14-19.
86. Singh, J. (2022). Concepts of inventory and related technical terminologies: A literature review. International Journal for Research Trends and Innovation, 7(1), 1784-1796.
87. Soni, G., Jain, V., Chan, F. T., Niu, B., & Prakash, S. (2019). Swarm intelligence approaches in supply chain management: potentials, challenges and future research directions. Supply Chain Management: An International Journal, 24(1), 107-123.
88. Sugiono, N. K., & Alimbudiono, R. S. (2020). Slow moving and dead stock: Some alternative solutions.
89. Suuronen, J. (2015). Reducing slow-moving inventory in a large manufacturing company (master's thesis).
90. Tai, P., Huyen, P., & Buddhakulsomsiri, J. (2021). A novel modelling approach for a capacitated (S, T) inventory system with backlog under stochastic discrete demand and lead time. International Journal of Industrial Engineering Computations, 12(1), 1-14.
91. Thevenin, S., Adulyasak, Y., Prescott-Gagnon, E., & Moisan, T. (2024). Optimizing multi-item slow-moving inventory using con-strained Markov decision processes and column generation. Les Cahiers du GERAD ISSN, 711, 2440.
92. Vaz, A., Tedjamulja, A., Tendulkar, A., & Rajagopal, P. (2020). Order frequency as a variable to determine slow-moving D items in ABC inventory categorization. Int. J Sup. Chain. Mgt Vol, 9(2), 36.
93. Villarreal, B., Sosa, L., Vazquez, J., Quintanilla, E., Herrera, M., & Villarreal, D. (2018). Reduce slow moving inventory of convenience stores: A case study. Management.
94. Wahedi, H., Wrona, K., Heltoft, M., Saleh, S., Knudsen, T. R., Bendixen, U., ... & Borup, G. S. (2022). Improving the accuracy of time series forecasting by applying an arima-ann hybrid model. In IFIP International Conference on Advances in Production Management Systems (pp. 3-10). Cham: Springer Nature Switzerland.
95. Wauna, S., & Obwogi, J. (2015). An assessment of the effects of inventory management procedures on the performance of Kengen. International Journal of Scientific and Research Publications, 5(10), 977-991.
96. Widyatmoko, A., & Yudoko, G. (2024). Proposed Inventory Management System to Reduce Slow Moving and Deadstock Level at PT. Pertamina JOB Tomori. International Research Journal of Economics and Management Studies IRJEMS, 3(1).
97. Yıldız, B., & Sütçü, M. (2023). A variant SDDP approach for periodic review of approximately optimal pricing of a slow-moving item in a duopoly under price protection with end-of-life return and retail fixed markdown policy. Expert Systems with Applications, 212, 118801.
98. Yung, K. L., Ho, G. T. S., Tang, Y. M., & Ip, W. H. (2021). The inventory classification system in space mission component replenishment using multi-attribute fuzzy ABC classification. Industrial Management & Data Systems, 121(3), 637-656.
99. Zaafira, R. D., & Yardi, Y. (2024). Analysis of the Effectiveness of Drug Management Systems in Tangerang Selatan General Hospital in 2021. Jurnal Farmasi Galenika (Galenika Journal of Pharmacy)(e-Journal), 10(1), 62-72.
100. Zheng, X., & Chen, Y. (2024). Optimization of inventory cost control for SMEs in supply chain transformation: A case study and discussion.