INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN SOCIAL SCIENCE (IJRISS)
ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue I January 2026

Evolution of Inventory Control Models: A Narrative Review

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DOI: https://doi.org/10.47772/IJRISS.2026.10100326

Received: 20 January 2026; Accepted: 26 January 2026; Published: 05 February 2026

ABSTRACT

This paper examined the evolution of inventory control models from traditional models which were largely mathematically based to contemporary digital models. Theoretically founded on the Diffusion of Innovation (DOI) theory, the review comprehensively synthesised recent scholarly works of literature to identify patterns and trends as well as analysing the future trajectory of inventory control models. Findings revealed that evolution from deterministic models such as Economic Order Quantity (EOQ) and (s,S) policies, to a more integrated approach of Material Requirements Planning (MRP), Just-in-Time (JIT) and Enterprise Resource Planning (ERP) and the contemporary era of digital technologies which includes the Internet of Things (IoT), Artificial Intelligence (AI), cloud computing, and blockchain technology, have transformed inventory management into a strategic and data-driven function with real-time visibility and more predictive analytics, and seamless supply chain integration. In addition, adoption of these new technologies was accompanied by long-term benefits including agility, cost optimization in the long run, and customer responsiveness. This review concludes that embracing digital inventory models is imperative for sustainable competitiveness in increasingly complex global supply chains.

Keywords: Artificial intelligence, Digital transformation, Inventory control models, Supply chain management.

INTRODUCTION

Historically, inventory control practices have been an integral part of human endeavours, at least in some primitive form. From the ancient times when it started to gather and stockpile resources of the planet, to the present age, inventory control has been an integral part of human system (Nya & Abouaissa, 2022). Moreover, the past 100 years have seen inventory control at the centre of key discussions in industrial engineering and operations research (Jackson et al., 2020). Inventory and supply chain management continues to play a pivotal role in economic and industrial efficiency, as it manages the activities around the supply chain and also regulates the movement of goods, services, and information. Today's competitive business environment has invariably made effective inventory control system a an essential ingredient for organizational's success (Sharma, 2022). The evolution of inventory management has transitioned from primitive barter systems and manual stock counts to advanced digital models driven by artificial intelligence and machine learning. The evolution primarily involves the integration and advancement of mathematical inventory models, transitioning from rudimentary and frequently empirical approaches to sophisticated, algorithmic, and technology-driven models (Rossit et al., 2022). This transition has enhanced operational accuracy and transformed how firms manage inventory, predict demand, control expenses, and fulfil consumer expectations in real time.

Historically, inventory systems were founded on fundamental mathematical principles and manual supervision. These methods depended significantly on human discretion and manual record-keeping. Common methodologies encompassed periodic review systems, wherein inventory was assessed at regular intervals, and the economic order quantity (EOQ) model, which sought to minimise overall inventory expenses by equilibrating ordering and holding costs (Abdolazimi et al., 2021). Although useful during their day, these models possessed intrinsic limitations in flexibility and precision. They are rigid in adjusting to demand in market volatility, and interruption within the supply chain (Sharma, 2020). Moreover, human error and lagging data updates frequently resulted in reduced efficiency characterised by ageing stocks, over stocking, unexpected stockouts and elevated operational expenses. Notwithstanding their obvious constraints, these conventional methods established the essential framework for contemporary digital inventory systems.

The emergence of computers in the late 20th century heralded a new era in inventory management. The capacity to rapidly store and handle substantial data quantities facilitated the deployment of more intricate mathematical models (Zhou et al., 2023). Linear programming, probabilistic models, and stochastic analysis begin to augment or supplant previous deterministic models. This period also saw the incorporation of inventory management into Enterprise Resource Planning (ERP) systems, enabling organisations to optimise operations and make datainformed choices across several departments. At this juncture, mathematics assumed an increasingly crucial role not just in inventory assessment but also in modelling, forecasting, and optimisation. The degree of automation remained comparatively low, and inventory models frequently place substantial reliance on historical data, and their predictive ability was essentially low (Murthi et al., 2022).

The digital revolution, driven by progress in software engineering, data science, and telecommunications, signified the subsequent significant transformation in the development of inventory systems (Rossit et al., 2022). Digital inventory management systems utilise real-time data collecting, cloud computing, Internet of Things (IoT), and artificial intelligence to establish responsive, adaptive, and intelligent inventory networks. These systems monitor inventory levels in real time across many locations and employ predictive analytics and machine learning algorithms to accurately forecast future demand (Zhou et al., 2023). Methods including time series analysis, neural networks, and Bayesian inference enable systems to adapt dynamically to market trends, seasonal fluctuations, and unforeseen disruptions such as global pandemics or supply chain failures. However, the shift from conventional to digital inventory systems also presents several issues and challenges. Challenges including data security, system integration, substantial initial expenses, and the requirement for proficient individuals may impede adoption particularly in a globalised economy where agility and accuracy are essential (Nya & Abouaissa, 2022).

Objective

The aim of this study is to examine the evolution of inventory control models from traditional models to contemporary digital models across different periods in a narrative review. The study does not aim to carry out an overview all the wide spectrum of literature related to inventory control model. In this regard this study mentions scientific papers selectively in order to identify patterns and trends, characterize the current status and guide future trajectory and research.

THEORETICAL FRAMEWORK

The adoption of new technologies has been examined for over three decades, with one of the most prominent theories articulated by Rogers in his work, Diffusion of Innovation Theory (DOI) (Rogers, 2003). The theory was formulated by Everett Rogers in 1962 as a model that can be used to understand how a social system or group of people adopts new ideas, solutions, technologies, products, or behaviours across a period of time. The theory highlights five stages of adoption process - knowledge, persuasion, decision, implementation, and confirmation. Furthermore, He posited that the adoption rate of an innovation is contingent upon five perceived attributes: relative advantage, compatibility, complexity, trialability, and observability. The theory highlights the processes through which innovations are generated, communicated, and adopted, within individuals and organisational settings. (Rogers, 2003). The theory has been widely supported in studies that involves technology adoption across several sectors, such as healthcare, agriculture, and information systems, due to its explanatory power in understanding diffusion patterns (Marques, 2011; Yu, 2022; Greenacre et al., 2012). However, the theory has also been criticised across different front including the argument that the theory oversimplifies the process of adoption largely because it focuses on individual responses to the adoption process without taking good cognizance of other underlying factors such as cultural, organisational and environmental factors (Nelson & Winter, 1977; Kapoor et al 2011; Wisdom et al, 2014). This criticism gave rise to further works that extended the framework of the model which now incorporates organisational and environmental factors – Technology - Organization - Environment (TOE) framework (Baker, 2011; Nguyen et al., 2022; Chittipaka et al., 2023). Despite these criticisms, DOI remains a foundational basis for analysing technological evolution.

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

This study utilises Diffusion of Innovation Theory DOI to examine the historical evolution of inventory control models, transitioning from early analytical models such as Economic Order Quantity (EOQ) and (s,S) policies to integrated systems like Material Resource Planning (MRP) and Enterprise resource Planning (ERP), culminating in modern digital solutions including Radio Frequency Identification (RFID), Internet of Things (IoT), and Artificial Intelligence (AI) driven inventory models. This research utilises Diffusion of Innovation Theory (DOI) to analyse how innovation attributes has influenced the speed and pattern with which inventory control models have evolved over several periods, providing insights into the transition and adoption pattern.

Review of Related Literature

Inventory control balances service levels with ordering, holding, and shortage costs. Early days scholars established analytical models (EOQ, newsvendor, and dynamic (s, S) models), while subsequent decades layered information technologies and organizational practices (MRP, JIT, ERP, WMS) and, lately, digital sensing and analytics (RFID, IoT, AI/ML). This review synthesizes that trajectory as a periodic narrative, highlighting the dominant models and the technological context that made each viable.

Pre-1950s: Manual Control and Periodic Review

Conventional inventory systems provide the fundamental methods for managing commodities, materials, and stock levels before the extensive adoption of digital technologies. These systems were predominantly manual, dependent on human discretion, and underpinned by fundamental mathematical techniques to regulate inventory levels (Nerkar, 2021). Their emergence signified a crucial stage in supply chain history, aimed at ensuring sufficient inventory to satisfy demand while reducing surplus and waste. Despite their simplistic structure and frequent lack of response, ancient inventory methods established the foundation for contemporary inventory management models (Sukendar, 2022). Earlier traditional methods fundamentally relied on physical ledgers, paper records, and periodic inventory assessments. Storekeepers, warehouse managers, and procurement officers utilised handwritten diaries and spreadsheets to monitor incoming and exiting inventory. These records were frequently updated daily or weekly, contingent upon the volume and nature of business operations (Panigrahi et al, 2024). Although these approaches provided fundamental control and organisation, they were prone to human mistake, theft, misplacement, and inefficiencies stemming from delays in data updating and reporting.

Inventory control has maintained a significant position as a critical subject in operations research. The historical development of the mathematical theory of inventory and production can be attributed to Edgeworth (1888), who formulated a variation of the news-vendor model to represent cash flow in banking. Nonetheless, the inaugural formal model created to assist managers in ascertaining the appropriate amount and timing of inventory replenishment originates from Ford W. Harris's square-root lot-size formula balancing ordering/setup and holding costs. (Panigrahi et al, 2024). The economic order quantity (EOQ) model is simplistic; nonetheless, it remains the most essential and popular. Due to its algebraic formulation, it is commonly referred to as the "square-root formula." The classical EOQ model imposes stringent assumptions, including the prohibition of backlogs and a replenishment lead time of zero. Notwithstanding its simplicity, the equation adeptly delineates the essential relationship in inventory management, specifically the trade-off between replenishment and holding costs. This fact clearly highlights why several scholars continue to utilise the EOQ model as a basic model, augmenting it with various expansions and superstructures (Jackson *et al*., 2020; Panigrahi et al, 2024).

1950s–1970s: Mathematical Formalization

The work progressed from EOQ-based models to those that integrate uncertainty and dynamics (Arrow et al., 1951). Models where the demand flow is a random variable with a defined probability distribution. This pioneer study was succeeded by the further works on inventory theory by (Arrow et al., 1958; Scarf, 1960). These efforts led to the development of (R, s, S) and (s, S) policies, which are the most renowned in inventory control theory (Alfares & Afzal, 2021). The (R, s, S) policy has been thoroughly examined, and its optimality, based on the premise of independent and stationary demand along with deterministic replenishment lead time, was established by Karlin (1960) for single-product inventory control systems. In stochastic single-product inventory control models, it has been established that the (s, S) policy is optimal under various scenarios, which was demonstrated by various scholars as revealed in the optimality for a scenario including fixed ordering and setup cost (Joshi & Gupta, 2021). Nevertheless, as highlighted by Menkar & SSChavan (2023), this evidence does not apply when the replenishment lead time is non-zero.

These shortcomings clearly reveal the primary limitation of analytic models in the sense that they provide a series of assumptions and considerations that often do not align with actual inventory management issues and do not ensure an ideal solution if these assumptions are breached. Considering that inventory control issues occur across diverse industries, and each business-related problem is characterised by unique elements and complexities, it would be shortsighted to assume that a uniform set of assumptions is universally applicable to all inventory control systems. In addition to this inflexibility, researchers Duan and Liao (2013) acknowledge that real-world inventory control issues are analytically unsolvable due to their complexity and stochastic nature (Jackson *et al*., 2020). The limits of analytic methodologies have led to the emergence of new fields in inventory control research. Despite the ongoing development of classical analytic models, which remain significant in inventory theory, a vast and varied array of non-analytic models are still been employed, particularly in complex business-related issues.

Notwithstanding its constraints, inventory control models within this period were pivotal in the initial stages of corporate operations and still utilised in certain small enterprises and emerging areas owing to their affordability and ease of use. However, due to the escalating intricacy of global trade, consumer demand trends, and supply chain logistics, these systems have predominantly been supplanted or enhanced by digital alternatives. Nevertheless, understanding these inventory systems is essential, as numerous ideas and models continue to support the algorithms and frameworks employed in contemporary digital inventory management systems.

1990s – Early 2010s: MRP and JIT, ERP-Enabled Integration, E-Commerce, RFID, and Multi-Channel Complexity

The advent of computer-aided inventory systems signified a crucial transformation in inventory management, connecting conventional manual and mathematical techniques with contemporary digital technologies. As enterprises expanded and supply chain complexities increased, the deficiencies of manual inventory management became increasingly evident. The integration of computers into company operations during the mid-to-late 20th century transformed inventory management by facilitating expedited, precise, and data-informed decision making (De-la-Cruz-Márquez et al, 2021). This transformation was not solely technological; it was fundamentally anchored in the mathematical and logistical foundations that informed inventory optimisation. This era saw the advent of affordable computing enabled Material Requirements Planning (MRP) to explode the master schedule through bills of materials into time-phased net requirements, replacing static reorder rules for dependent-demand items. Joseph Orlicky (1975) codified MRP as “the new way of life,” formalizing lot-sizing, lead-time offsetting, and exception control; this later evolved into MRP II, integrating capacity and financial planning. Initially, computer-aided inventory systems were predominantly independent applications intended to automate fundamental inventory functions, including stock level monitoring, reorder point determination, and invoice creation. These systems employed computer languages such as Common Business-Oriented Language (COBOL) and Formula Translation (FORTRAN) to process inventory data more efficiently than human techniques (Lagoda & Klumpp, 2024). Fundamental inventory management models, including Economic Order Quantity (EOQ), reorder point computations, and safety stock equations, have been digitised, therefore minimising human error and markedly accelerating calculations. Organisations can now execute intricate calculations in seconds with computers, a process that once required hours or days.

The emergence of Enterprise Resource Planning (ERP) systems in the 1990s significantly advanced the adoption of computer-aided inventory systems. ERP platforms amalgamated inventory management with essential company operations including procurement, finance, and sales, establishing a cohesive data environment. These systems provided functionalities such as real-time reporting, inventory visibility throughout the supply chain, automated order generation, and performance dashboards. The integration enhanced operational efficiency and facilitated cross-functional cooperation, enabling firms to be more responsive and customer-oriented (Mandl, 2023). These improvements reduced inventory discrepancies, enhanced warehouse efficiency, and facilitated just-in-time (JIT) inventory methods, aimed at minimising waste and increasing responsiveness (Dubey & Kumar, 2024). By integrating classical inventory theory with digital technologies, enterprises transitioned from reactive to proactive inventory practices. This fundamental transformation paved the way for the subsequent incorporation of artificial intelligence, machine learning, and

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

cloud computing, which currently characterise the most sophisticated inventory systems of the digital era (Lin et al, 2023).

Furthermore, barcode scanning and RFID (Radio Frequency Identification) technologies emerged as crucial elements of computer-aided systems, improving data precision and facilitating real-time tracking of products. RFID matured as a complement to barcodes, providing non-line-of-sight identification and higher read speeds. Ali et al (2024) conclude that despite cost and interoperability challenges, RFID significantly enhances inventory accuracy, shrinkage control, and traceability particularly in retail, healthcare, and asset management thereby foreshadowing real-time inventory visibility. As online retail surged, firms faced multi-node, multi-channel allocation problems, deciding where to stock, from where to fulfil, and how to handle returns. Research on omni-channel logistics shows how distribution architectures (store-fulfil, DC-fulfil, click-and-collect) complicate inventory positioning and last-mile trade-offs, pushing beyond single-echelon models (Hübner et al., 2016; Maitra et al., 2023). These complex challenges required solution which beyond what existing models and system can support.

Mid-2010s–2020s: Contemporary Digital Models - IoT, AI/ML, and Real-Time Control

This era saw the introduction of various digital, sophisticated and more intelligent models using advanced technologies such artificial intelligence (AI), machine learning (ML), cloud computing, and the Internet of Things (IoT) to establish highly responsive, adaptive, and predictive inventory management system (Praveen et al, 2024). The transition signifies a shift from static data processing and rule-based models to intelligent systems that can learn, adapt, and make real-time judgements. This transition has transformed inventory management from a mere operational requirement into a strategic business function, simultaneously redefining the structure of supply chains in the digital era. In addition, these platforms facilitated the uninterrupted exchange of information among diverse business groups, providing centralised oversight of procurement, sales, finance, and logistics (Devi et al, 2023, Maiorova & Balashova, 2023). In contrast to conventional computer-aided systems that mostly automated operations, digital solutions revolutionised inventory management into a real-time, data driven process propelled by advancements in hardware (accelerated processors, sensors, and mobile devices), software (data analytics, cloud applications), and connectivity (internet, wireless communication).

Central to digital inventory models is the capability to retrieve, store, and analyse extensive quantities of data. Cloud computing is essential in this context, providing scalable storage solutions and facilitating remote access to inventory data across several locations (Bose et al, 2022). Cloud computing has changed the landscape of inventory management coupled with the existence of faster internet speeds which enables expanded reach. Thus, inventory management has benefited from the introduction of an integrated cloud computing technology with IoT based platforms. (Tan et al, 2024). Cloud-based inventory management systems enable organisations to oversee inventory levels, track shipments, collaborate with suppliers, and manage client orders in real time (Chebet & Mbandu, 2024). Cloud platforms thus enhance interdepartmental and partner cooperation, resulting in improved supply chain coordination and diminished lead times.

A major element in this progression is the Internet of Things (IoT). Internet of Things (IoT) devices such as intelligent sensors, RFID tags, and Global Positioning System (GPS) trackers gather real-time data regarding inventory location, movement, temperature, and condition. With universal connectivity and cheap sensors, IoT architectures now stream location, condition, and handling events, thereby supporting in-transit inventory visibility, dynamic ETAs, and automated exception management (Carpitella & Izquierdo, 2025). This detailed degree of information enables enterprises to exert stringent control over perishable items, oversee product integrity during transportation, and foresee problems before they intensify (Mittal, 2024). Temperature-sensitive products, such as pharmaceuticals and food, can be continuously monitored throughout the supply chain to ensure adherence to quality standards and minimise losses from deterioration. The system is designed in such a way that it creates a digital platform that serves as a representation of physical inventory flows using integrated solutions that connects sensors, wireless networks, and cloud-based analytics solutions. Previous studies revealed the integration of IoT solutions into inventory tracking systems marks a paradigm shift from reactive to proactive supply chain management (Praveen et al, 2024; Lin et al, 2023). Research indicates that organizations implementing IoT-based tracking solutions reduce transit times by an average of 14.2% and decrease inventory shrinkage by 11.7% compared to traditional methods (Rao, 2025).

Artificial intelligence (AI) and machine learning signify more advancement in the progression of inventory models. These technologies integrate intelligence into inventory systems, enabling them to analyse past data, identify patterns, and generate forecasts. AI-powered forecasting instruments can anticipate future demand by analysing seasonality, market patterns, promotional efforts, and external influences such as weather or social media mood (Madamidola et al., 2024). AI algorithms have the capability to learn from new data and modify their predictions over time, hence improving their accuracy. This capacity enables organisations to sustain optimal inventory levels, save carrying costs, and enhance customer satisfaction by mitigating stockouts and overstocking. Recent research shows the capacity of machine learning to facilitate sophisticated inventory categorisation and segmentation techniques, including Activity-Based Classification (ABC) analysis and demand-driven planning (Shokri et al., 2024, Verma, 2024). With the use of machine learning, systems can dynamically categorise products depending on profitability, turnover rate, or service level needs, facilitating customised inventory policies for various product categories. Rani et al (2024) found that predictive maintenance, an application of AI, guarantees the efficient operation of warehouse equipment by forecasting failures and proactively arranging maintenance, thus preventing downtime and delays in inventory flow.

Recent research reveal that digital inventory systems are progressively integrating Robotic Process Automation (RPA) and autonomous mobile robots (AMRs) within warehouses (Sharma & Guleria, 2021; Punukollu et al., 2022; Mungla, 2019). These technologies automate monotonous processes including picking, sorting, packaging, and delivering items, thus enhancing efficiency, precision, and labour productivity. Autonomous Mobile Robots (AMRs) cruise warehouse floors utilising sensors and algorithms to adjusting to real-time environmental changes (Shamsuzzoha & Pelkonen, 2025). When integrated with sophisticated inventory management, these systems facilitate rapid fulfilment and are essential for sectors experiencing substantial order quantities, such as e-commerce and retail. A study by Information Services Group (ISG), a global technology research firm, revealed that Robotics Process Automation (RPA) facilitated a 43% decrease in resources for order-to-cash procedures, encompassing billing, credit, collections, and pricing (Mungla, 2019) Owing to cognitive augmentation, RPA is progressively being integrated into the supply chain to emulate human employees' actions: acquiring, reproducing, and processing data, engaging with consumers, and making decisions while learning from previous experiences (Waduge et al., 2024).

Blockchain technology is an emerging instrument that improves transparency and traceability in digital inventory systems. Blockchain technology is a revolutionary advancement that facilitates decentralised and secure information exchange across supply chain portfolio managers (Choi, 2021). Blockchain facilitates secure and verifiable tracking of products from origin to destination by establishing a decentralised and tamper-proof ledger of inventory transactions. This is especially crucial in sectors necessitating regulatory compliance and certification, including pharmaceuticals, luxury goods, and food supply chains. Once a record is inscribed on the blockchain, it cannot be modified without the consensus of a majority of stakeholders, hence ensuring security from a business operations standpoint (Bogucharskov et al., 2018). Smart contracts developed on blockchain platforms can automate payment and inventory reconciliation operations according to predetermined circumstances, thereby minimising manual intervention and enhancing efficiency (Li, 2023). This self-focused trigger mechanism facilitates inventory replenishment locations to minimise errors within the inventory system. In addition, effective execution of blockchain diminishes inventory holding costs (Kaushik, 2025).

METHODOLOGY

Having discussed the theories and the assumptions thereof, it is necessary to carefully determine the methodology to be adopted. The study adopted a narrative literature review design to synthesize the historical progression of inventory control models from traditional manual systems to contemporary digital solutions. A narrative review is appropriate because the objective is to describe, interpret, and critically analyse the evolution of concepts and practices over time rather than to statistically aggregate findings as in a systematic review or meta-analysis. The literature search focused on peer-reviewed journals, seminal books, and authoritative industry reports, non-scholarly blogs or opinion pieces without empirical or theoretical grounding were excluded. In conducting the search, the following keywords were combined *"inventory control models"*, *"evolution of inventory management"*, *"EOQ"*, *"Just-in-Time"*, *"Material Resource Planning"*, *"Enterprise Resource Planning"*, *"RFID"*, *"Internet of Things in inventory"*, *"Artificial Intelligence in supply chain"*. As a narrative review, this study does not employ quantitative synthesis or meta-analysis, which may limit generalizability.

However, the approach provides rich contextual insights into the evolution of inventory control models.

Comparative Analysis of Traditional and Digital Models

The transition from traditional to digital inventory management signifies a significant change in how businesses manage stock, optimise operations, and address market demands. Conventional inventory systems, based on manual procedures and fundamental mathematical concepts, formerly constituted the foundation of retail, manufacturing, and distribution activities. They predominantly depended on paper documentation, ledger books, and human supervision to monitor inventory levels, compute order quantities, and administer replenishment cycles. These systems employed static mathematical models, including the Economic Order Quantity (EOQ), Reorder Point (ROP), and Safety Stock equations. Although useful and economical for small-scale activities, previous methods were intrinsically constrained regarding speed, precision, and adaptability. Errors stemming from manual data entry, delayed updates, and interdepartmental miscommunication were prevalent. Furthermore, conventional systems were reactive, typically resolving inventory discrepancies only after they resulted in operational inefficiencies such as stockouts, overstocking, or supply chain bottlenecks (Modares, et al., 2023; Güngör & Leindecker, 2024).

Conversely, digital inventory models have transformed inventory management through the integration of automation, real-time data processing, predictive analytics, and sophisticated algorithms. These systems utilise software platforms including Enterprise Resource Planning (ERP), Warehouse Management Systems (WMS), and Inventory Management Software (IMS), frequently integrated with cloud computing, the Internet of Things (IoT), and Artificial Intelligence (AI) (Al-Amin et al., 2024). Digital models avoid manual data entry by automating inventory management via technologies such as barcode scanning, RFID tagging, and IoT-enabled sensors. This real-time visibility improves the precision and dependability of inventory data, offering organisations a current perspective on stock levels, item locations, movement trends, and demand variations (Ugbebor et al., 2024; Güngör & Leindecker, 2024). In contrast to conventional systems reliant on static assumptions, digital models are dynamic and adaptable; they can perpetually learn from new data, modify forecasts, and optimise inventory parameters in response to fluctuating market conditions.

According to Singh and Adhikari (2023), a primary distinction between the two models resides in their decision making methodologies. Conventional systems depend on historical analysis and fixed models, rendering them sluggish in responding to unforeseen changes such as demand spikes, supplier disruptions, or economic fluctuations. The decision-making process is frequently compartmentalised, exhibiting minimal integration among departments or supply chain participants. Conversely, digital inventory systems are engineered to be predictive and integrative. They employ sophisticated analytics and machine learning algorithms to predict future demand, discern patterns, and suggest appropriate inventory levels. These insights enable firms to make proactive rather than reactive decisions. Cross-platform integration facilitates uninterrupted communication among procurement, sales, finance, and logistics, leading to enhanced coordination and reduced operational delays.

Scalability is another aspect in which digital models remarkably exceed analogue models. According to Villacis et al., (2024), as enterprises grow geographically and broaden their product lines, conventional systems falter to adapt because of their manual and inflexible nature. On the other hand, digital inventory systems provide modular and scalable solutions that can support expansion without compromising performance. As opined by Ugbebor et al., (2024), cloud-based technologies facilitate centralised oversight of scattered inventory, enabling organisations to administer global operations from a singular interface, with the use of a centralise software. This adaptability of digital systems help customisation to meet industry-specific demands, regulatory obligations, and consumer preferences.

With digital systems, there is enhanced accuracy and dependability in inventory tracking, compared to conventional techniques which substantially relies on human involvement and are prone to errors that may result in expensive differences between documented and actual inventory. These discrepancies adversely influence operational efficiency, customer happiness, and financial reporting. Digital technologies mitigate these risks by automation and real-time updates, with the guarantee that inventory data remains consistently accurate and readily accessible. Technologies such as RFID and IoT offer a detailed perspective of inventory at the unit level, enabling firms to exercise stringent control over stock and enhance traceability across the supply chain. Highlighting this further, extant literature showed that a significant distinction is in the velocity and reactivity of operations when both technologies are examined (Albayrak Ünal et al., 2023; Arnawtee & Zaiter, 2024). Conventional inventory systems function through batch processing and periodic stock assessments, frequently causing delays between data acquisition and decision-making. This delay might impede a company's capacity to react promptly to market opportunities or disruptions. However, digital inventory systems offer immediate data access and instantaneous analytics, facilitating swifter response times. Automated notifications, dashboard representations, and scenario analyses enable managers to detect problems, assess remedies, and execute modifications with remarkable immediacy (Qi et al., 2023). This agility is essential in sectors like e-commerce, where customer demands for rapid delivery and precise order fulfilment are exceedingly high.

The cost-effectiveness of traditional vs digital approaches is another area that is frequently disputed (Filani et al, 2023). Although conventional methods may appear economically advantageous at first due to minimal initial costs, they frequently result in elevated long-term expenditures stemming from labour-intensive procedures, inaccuracies, inefficiencies, and lost opportunities. Digital systems require substantial initial investment in technology and training; however, they produce above par returns over time by optimising processes, decreasing inventory carrying costs, minimising waste, and ensuring overall efficiency. Moreover, the emergence of cloudbased subscription models has rendered digital inventory management attainable for small and medium-sized organisations, thereby democratising access to sophisticated functionalities (Ugbebor et al., 2024; Al-Amin et al., 2024).

The role of human resources also varies between the two models. Conventional systems depend significantly on manual labour for data entry, inventory assessment, and decision-making. This reliance not only escalates labour expenses but also constrains scalability. In digital models, human functions are predominantly strategic and supervisory. Automation manages repetitive operations, allowing staff to concentrate on strategic planning, optimisation, and innovation. This transition requires new competencies, highlighting data literacy, system management, and interdisciplinary collaboration. Furthermore, another key feature of intelligent inventory models is their capacity to facilitate real-time decision-making (Tadayonrad et al., 2023). Dashboards utilising business intelligence tools display inventory indicators, KPIs, and alarms, enabling managers to respond promptly to developing trends and anomalies. For instance, if an abrupt increase in demand for a certain product is identified, the system can activate automatic reordering or commence supplier interaction.

The transition to digital and intelligent inventory models signifies a paradigm shift in inventory management and control for enterprises. This shift is propelled by the convergence of mathematical optimisation, data science, and intelligent technology. These systems transcend mere task automation; they possess the ability to think, learn, and adapt, offering strategic insights that improve decision-making and competitiveness. As organisations adopt digital transformation, intelligent inventory models will be essential for attaining operational excellence, resilience, and long-term sustainability in a rapidly evolving global market. Furthermore, the future of inventory management will be defined by more autonomy, sustainability, and a focus on customer needs as digital technologies advance. Autonomous inventory systems will manage stock and engage with suppliers and logistics providers, establishing a self-regulating supply chain. Artificial Intelligence will boost demand forecasting by integrating real-time market information, whilst the Internet of Things and blockchain technology will improve traceability and sustainability reporting. Sustainability is being prioritised, with intelligent technologies enhancing inventory management to minimise waste, decrease carbon emissions, and promote circular economy efforts.

Although digital and intelligent inventory systems provide significant potential, their implementation presents obstacles. Integrating legacy systems, controlling cybersecurity threats, assuring data veracity, and educating workers in new technologies are essential challenges that organisations must confront. Furthermore, the expense associated with the adoption of modern technologies may be excessive for small and medium-sized firms (SMEs), while the increasing accessibility of Software-as-a-Service (SaaS) models is facilitating broader access to digital tools. Furthermore, digital models pose issues like the necessity for effective cybersecurity, data integrity, system interoperability, and continuous technical assistance. Shifting from a conventional to a digital inventory system requires thorough planning, effective change management, and comprehensive training. Nonetheless, the long-term advantages in enhanced accuracy, visibility, scalability, and responsiveness render this transformation not merely beneficial but imperative in an increasingly complex and competitive market.

CONCLUSION

The story of inventory control model is a story of better models riding on better information. From ledgers to EOQ, from (s,S) to MRP and JIT, from ERP to RFID/IoT and now AI/ML, each era compresses information delays and expands the scope of optimization. Contemporary "digital" models do not discard classical theory; rather, they incorporate it at greater scale and speed, with real-time sensing, predictive analytics, and platform integration turning inventory from a static asset into a dynamically managed flow. For scholars, the open frontier lies in learning-to-control at network scale; for practitioners, in embedding these capabilities into everyday planning and financial stewardship.

The transition from conventional to digital inventory systems signifies a pivotal change in organisational resource management, market demand responsiveness, and supply chain optimisation. Conventional models, based on manual processes and fixed mathematical equations, were essential foundations but lacked the agility, precision, and scalability required in the contemporary business landscape. Conversely, digital and intelligent inventory systems utilise real-time data, automation, and sophisticated analytics to facilitate predictive decision making, seamless integration, and improved operational efficiency. Technologies including IoT, AI, cloud computing, and blockchain have transformed inventory management from a reactive role into a strategic facilitator of growth and competitiveness. While the change to digital systems offers obstacles, the long- term benefits in terms of cost reduction, customer satisfaction, and agility are enormous. As global supply chains become more complex and customer expectations rise, embracing digital inventory models is not just an option, it is a necessity for sustainable business success.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Funding Statement

There was no funding obtained for the research

Authors' Contributions

Adedoyin, Oluseye Omoniyi - Conceptualization, Methodology, Writing, and Data Curation.

Ajibade Ayodeji Temitope - Review & Editing and Supervision

ACKNOWLEDGMENT

Not applicable

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APPENDIX

77. Acronyms	**78. Full Meaning**
79. ABC	80. Activity-Based Classification
81. AI	82. Artificial Intelligence
83. COBOL	84. Common Business-Oriented Language
85. EOQ	86. Economic Order Quantity
87. ERP	88. Enterprise Resource Planning
89. FORTRAN	90. Formula Translation
91. GPS	92. Global Positioning System
93. IMS	94. Inventory Management Software
95. IoT	96. Internet of Things
97. JIT	98. Just in Time
99. ML	100. Machine Learning
101. MRP	102. Material Resource Planning
103. RFID	104. Radio Frequency Identification
105. ROP	106. Re-order Point
107. RPA	108. Robotic Process Automation
109. TOE	110. Technology – Organization - Environment
111. WMS	112. Warehouse Management System