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AI-Driven Optimization for Vendor-Managed Inventory in Dynamic Supply Chains

Erumusele Francis Onotole [1], Tunde Ogunyankinnu [2], Akintunde Akinyele Osunkanmibi [3], Yetunde Adeoye [4*], Chioma Emmanuela Ukatu [5], Oluwasegun Ayodeji Ajayi [6]

[1] Duquesne University, 600 Forbes Avenue, Pittsburgh, PA, 15282, USA
[2] University of Surrey, Guildford, UK
[3] Sheffield Hallam University, Howard Street, Sheffield, S1 1WB, UK
[4, 6] Ladoke Akintola University of Technology, Ogbomosho, Nigeria
[5] University of East Anglia, Norwich, UK

* Corresponding Author: **Yetunde Adeoye**

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Abstract
AI-Driven Optimization for Vendor-Managed Inventory in Dynamic Supply Chains explores the transformative impact of artificial intelligence (AI) in streamlining and enhancing the Vendor-Managed Inventory (VMI) process. VMI is a collaborative supply chain model where vendors are responsible for managing and replenishing inventory at the customer's location. However, traditional VMI systems face significant challenges, such as inaccurate demand forecasting, stockouts, overstocking, and manual monitoring, which often hinder supply chain efficiency and lead to increased costs. AI-driven optimization leverages advanced data analytics, machine learning (ML), and predictive algorithms to address these challenges and optimize inventory management. By utilizing AI, businesses can improve demand forecasting, enabling more accurate predictions of inventory requirements based on historical data, real-time inputs, and market trends. Machine learning models can adapt to changing demand patterns, reducing forecasting errors and ensuring optimal stock levels. Furthermore, AI-powered predictive analytics can trigger automatic replenishment decisions, aligning inventory with demand in real-time, leading to a more responsive supply chain. The integration of AI in VMI not only enhances inventory accuracy but also improves efficiency by automating processes, reducing manual interventions, and optimizing decision-making. This results in significant cost savings, reduced waste, and improved service levels for both vendors and customers. Moreover, AI facilitates stronger vendor-customer collaboration through transparent, data-driven communication and shared insights. While AI-driven VMI optimization offers considerable benefits, challenges remain, such as data integration, initial investment costs, and system adaptability in dynamic environments. Nevertheless, AI's potential to revolutionize supply chain operations and move towards autonomous, sustainable systems makes it a critical tool in modern VMI management. This explores these opportunities, challenges, and the future potential of AI in dynamic supply chains.

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Keywords: AI-driven optimization, Vendor-managed inventory, Dynamic supply chains

1. Introduction

Vendor-Managed Inventory (VMI) is a supply chain management strategy in which the vendor, or supplier, is responsible for managing and replenishing the inventory of the customer (Beheshti *et al*., 2020). In a VMI model, the supplier has direct access to the customer's inventory levels and demand data, allowing them to take proactive steps to ensure that inventory is maintained at optimal levels. This approach shifts the responsibility for inventory control from the customer to the supplier, aiming to streamline the ordering process, reduce stockouts, and improve overall efficiency in the supply chain.

VMI offers several advantages, including reduced inventory carrying costs for customers, improved order fulfillment rates, and the ability to align production with actual demand (Omar *et al*., 2020).

Since the vendor has more visibility into the customer's inventory needs and is directly responsible for stock replenishment, it can help optimize inventory management by ensuring that goods are delivered just in time and in the right quantities. In turn, this reduces the need for customers to engage in regular stocktaking and order placement, allowing them to focus on other core operations.

Supply chains today are characterized by increasing complexity and dynamism. Modern supply chains are global, interconnected, and subject to frequent disruptions, ranging from fluctuating demand and supply imbalances to unexpected market shifts, geopolitical factors, and natural disasters (Lund *et al*., 2020; Pinkwart *et al*., 2022). These dynamic conditions make inventory management more challenging, as businesses must continuously adjust to changing demand patterns while ensuring that inventory levels are optimized. In this volatile environment, managing inventory effectively becomes increasingly difficult, as traditional approaches based on static models or historical trends often fail to account for real-time fluctuations and uncertainties. As a result, organizations need a more adaptive, responsive, and efficient approach to supply chain management, one that can handle the constant change inherent in modern markets (Srinivasan *et al*., 2021; Richey *et al*., 2022). This is where Vendor-Managed Inventory (VMI) can play a critical role, as it allows vendors to directly manage inventory levels and replenish stock based on real-time data, helping mitigate some of the challenges posed by supply chain dynamics.

Effective inventory management in a dynamic supply chain requires the ability to balance demand and supply, minimize stockouts, reduce excess inventory, and ensure timely product delivery all while maintaining cost-efficiency (Kaul and Khurana, 2022; Singh, 2022). However, fluctuating demand, uncertainty in lead times, and the risks associated with overstocking or understocking pose significant challenges. Traditional inventory management systems, while effective in stable conditions, often struggle to adapt to these uncertainties and rapid changes, resulting in inefficiencies and potential disruptions. Another key challenge lies in forecasting demand accurately. In a dynamic supply chain, demand patterns can shift rapidly due to external factors such as seasonality, economic trends, or unexpected events (Davis *et al*, 2021). In such environments, organizations need to rely on advanced methods that can dynamically adjust to new data and provide real-time insights into inventory needs. This is where the combination of Vendor-Managed Inventory and Artificial Intelligence (AI) can bring substantial benefits, as AI-driven tools can better predict demand patterns, automate inventory control, and provide vendors with the tools to optimize stock levels more effectively (Ivanov *et al*., 2021; Noor *et al*., 2022).

Artificial Intelligence (AI) has become a transformative force in supply chain management. AI-driven tools, such as machine learning algorithms, predictive analytics, and real-time data processing systems, can provide organizations with the ability to analyze large volumes of data and generate actionable insights (Volikatla *et al*., 2022). In the context of inventory management, AI models can analyze historical sales data, market trends, and external factors to forecast future demand with a higher degree of accuracy than traditional methods. AI also enables real-time decision-making by continuously processing incoming data and adjusting inventory levels, order quantities, and delivery schedules based on current conditions (Javaid *et al*., 2022). This dynamic and data-driven approach to inventory management enhances the overall responsiveness of the supply chain, improving efficiency and reducing costs.

AI has significant potential to enhance Vendor-Managed Inventory systems. By integrating AI technologies into VMI models, suppliers can improve their decision-making capabilities, providing more accurate and timely inventory replenishment solutions. AI can process real-time data from various sources such as point-of-sale systems, inventory management platforms, and external data like market trends or weather patterns to predict customer demand and ensure that the right amount of inventory is available at the right time (Kalusivalingam *et al*., 2020; Mohammed and Mandal, 2022). Predictive analytics can forecast demand more accurately, reducing the risk of overstocking or understocking. Moreover, AI-powered automation tools can help vendors streamline their inventory management processes, allowing them to manage larger and more complex supply chains with greater ease and efficiency.

Additionally, AI can enhance communication and collaboration between suppliers and customers in VMI systems (Fang and Chen, 2022). By enabling better data-sharing and transparency, AI can ensure that both parties are aligned on inventory needs and can work together to proactively manage stock levels, reducing the risk of disruptions in the supply chain. Ultimately, the integration of AI in VMI models represents a step toward more adaptive, responsive, and efficient supply chain management in a world marked by constant change and uncertainty. Vendor-Managed Inventory (VMI) offers significant benefits for businesses seeking to optimize their inventory management processes. By entrusting vendors with the responsibility of managing inventory, organizations can reduce carrying costs and improve stock replenishment accuracy. However, the dynamic nature of modern supply chains, with its inherent challenges, requires more adaptive solutions to meet changing demand and unpredictable supply conditions. The integration of Artificial Intelligence (AI) into VMI systems has the potential to address many of these challenges by improving demand forecasting, inventory optimization, and real-time decision-making (Abosuliman and Almagrabi, 2021; Kao and Chueh, 2022). As AI-driven tools continue to evolve, their role in supply chain management will only grow, helping businesses enhance the efficiency and responsiveness of their VMI systems and, ultimately, their entire supply chain.

2. Methodology

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology was applied to systematically review the literature on AI-driven optimization for Vendor-Managed Inventory (VMI) in dynamic supply chains. A comprehensive search was conducted across multiple academic databases such as Google Scholar, Scopus, IEEE Xplore, SpringerLink, and Web of Science using keywords like *"AI in supply chain," "Vendor-Managed Inventory," "AI optimization," "machine learning in VMI," "predictive analytics,"* and *"dynamic supply chain."* Inclusion criteria were established to focus on peer-reviewed articles published in English that discussed AI technologies applied to VMI, with an emphasis on inventory management, forecasting, and the challenges of dynamic supply chains. Studies unrelated to AI or VMI in dynamic contexts were excluded.

The search results were first screened by reviewing titles and abstracts to identify potentially relevant studies. Articles that did not align with the focus on AI-driven optimization in VMI were excluded. The full text of the remaining articles was then assessed to determine eligibility, focusing on studies that explored AI-based methods for optimizing inventory management, replenishment, and demand forecasting in VMI systems.

Data was extracted from the selected studies, including information on the type of AI technique used (e.g., machine learning models, predictive analytics), the outcomes related to inventory management improvements, and any challenges or limitations discussed. The studies were analyzed both qualitatively and quantitatively, synthesizing key themes related to the use of AI in VMI optimization. This included an assessment of how AI technologies such as machine learning, predictive analytics, and reinforcement learning contributed to overcoming challenges like stockouts, overstocking, and demand forecasting errors in dynamic supply chain settings.

The findings revealed several AI-driven techniques that significantly improved VMI performance, particularly in demand forecasting accuracy, real-time inventory optimization, and vendor-retailer collaboration. However, common challenges were identified, such as data integration issues, high initial costs of AI implementation, and the need for AI systems to adapt to rapidly changing supply chain conditions.

The review concluded that AI-driven optimization holds great potential for transforming VMI processes in dynamic supply chains, improving inventory accuracy, efficiency, and collaboration between vendors and customers. It also highlighted areas for future research, particularly in integrating AI with emerging technologies like IoT and blockchain and addressing the scalability of AI models in supply chains. A PRISMA flow diagram was included to illustrate the article selection process, showing the number of studies identified, screened, assessed for eligibility, and included in the final synthesis.

2.1 Key components of vendor-managed inventory

Vendor-Managed Inventory (VMI) is a supply chain strategy that shifts the responsibility for inventory management from the customer to the vendor (Zhao, 2019). In a traditional inventory model, the customer is responsible for monitoring stock levels, placing orders, and ensuring that inventory is replenished as needed. However, under VMI, the vendor assumes responsibility for tracking the inventory levels at the customer's location, forecasting demand, and determining when and how much stock to supply. This model encourages closer collaboration between vendors and customers, as the supplier must have access to real-time data about the customer's inventory levels, sales trends, and demand fluctuations. The VMI process begins with the vendor gaining visibility into the customer's inventory management system through shared data. The supplier uses this information to analyze current stock levels, predict future demand, and schedule regular replenishment (Boone *et al.*, 2019). In most cases, the vendor sets reorder points and timing, ensuring that inventory is delivered just in time to meet demand. This collaborative approach ensures that inventory is optimized, reducing the risk of stockouts or excess inventory, and improving overall supply chain efficiency.

A key aspect of VMI is the exchange of information between the vendor and the customer. The vendor requires access to real-time data, such as point-of-sale (POS) data, inventory levels, and historical demand patterns, to effectively forecast future demand and replenish stock accordingly (Feizabadi, 2022; Hübner *et al.*, 2022). For VMI to work effectively, both parties must implement systems that enable seamless data integration. This may involve sharing data through Electronic Data Interchange (EDI), cloud-based platforms, or other real-time communication tools. Data integration is crucial for improving the accuracy of demand forecasting and inventory management. By ensuring that both parties have access to consistent, up-to-date information, VMI helps streamline the replenishment process and allows the vendor to respond more quickly to changes in demand. Furthermore, information sharing fosters a more transparent relationship, building trust and collaboration between the customer and vendor. This reduces the need for constant communication and decision-making and helps optimize inventory management with minimal intervention.

One of the primary benefits of VMI is the reduction of stockouts and overstocking as shown in figure 2. Traditional inventory management systems are often reactive, meaning that customers may place orders when they notice that inventory is running low, leading to potential stockouts if lead times are long or supply chain disruptions occur. In contrast, VMI enables the vendor to monitor inventory levels and adjust stock replenishment proactively based on real-time demand data (Weraikat *et al.*, 2019). This reduces the likelihood of stockouts and helps ensure that inventory is available when customers need it, without overstocking, which can lead to high carrying costs.

By leveraging demand data and predictive analytics, VMI also helps prevent overstocking, which can tie up working capital and increase storage costs (Govindasamy *et al.*, 2022). The vendor, with better insight into the customer's demand, can make more accurate replenishment decisions, ensuring that inventory levels are aligned with actual consumption. This leads to better inventory turnover rates, cost savings, and improved customer satisfaction.

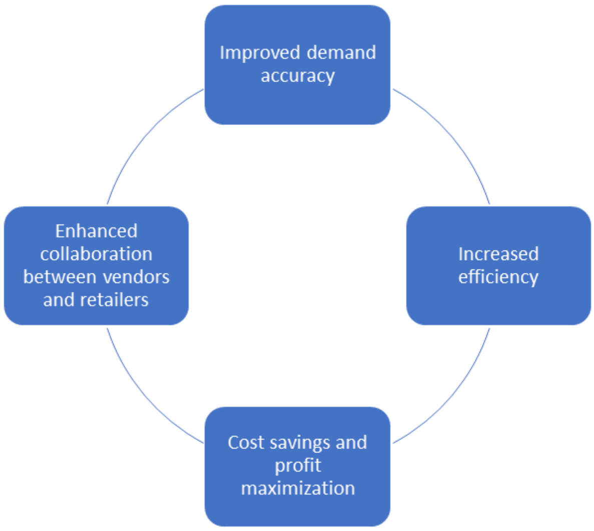

Fig 1: Benefits of AI-driven VMI optimization

VMI strengthens the relationship between the vendor and the customer by fostering collaboration and trust. When vendors assume responsibility for inventory management, customers can focus on other core activities, such as sales and customer service, while relying on their suppliers to manage stock levels efficiently. This collaborative approach creates a partnership between the vendor and the customer, with both parties sharing the goal of optimizing inventory levels and ensuring smooth operations. The transparency inherent in VMI systems encourages open communication and data sharing, which helps to build trust (Omar *et al*., 2020). As the vendor gains a deeper understanding of the customer's operations and demand patterns, they can offer more tailored solutions and improvements. In turn, customers are more likely to view the vendor as a strategic partner rather than just a supplier, leading to stronger, long-term business relationships. These improved relationships can also lead to better terms, discounts, and more favorable service agreements.

One of the most significant challenges in traditional Vendor-Managed Inventory systems is forecasting errors. Demand forecasting is inherently uncertain, and even slight inaccuracies can lead to significant disruptions in the supply chain. If the vendor overestimates demand, it may result in excess inventory and unnecessary storage costs. On the other hand, underestimating demand may cause stockouts and missed sales opportunities. In the context of VMI, where the vendor assumes responsibility for inventory levels, these forecasting errors can have a direct impact on the customer's ability to meet demand, leading to dissatisfaction or lost revenue (Panigrahi *et al*., 2022). The accuracy of demand forecasts is influenced by numerous factors, including seasonality, economic conditions, and unforeseen events. Without robust predictive models and real-time data, vendors may struggle to predict demand accurately, resulting in missed opportunities or inefficiencies. As the VMI model relies heavily on accurate forecasting, addressing forecasting errors through advanced forecasting tools and technologies becomes a critical challenge.

In many industries, demand patterns can be volatile and unpredictable, making it difficult to forecast accurately. Fluctuating demand due to external factors such as changes in consumer behavior, economic conditions, or unexpected disruptions like natural disasters or pandemics—compounds the challenges of VMI. Traditional inventory management methods may struggle to adapt to these sudden shifts, but the dynamic nature of demand is even more problematic in VMI systems, where the vendor must react quickly to ensure inventory levels remain balanced (Binos *et al*., 2021; Niaz, 2022). Inconsistent demand patterns can create significant risks for both vendors and customers. For vendors, fluctuating demand can lead to either understocking or overstocking, both of which undermine the value of VMI. Similarly, for customers, erratic demand can disrupt operations and lead to issues such as delayed deliveries, stockouts, or the need for emergency shipments, which can be costly. Managing demand volatility requires flexible, adaptive systems that can incorporate real-time data and adjust forecasts accordingly, a capability that traditional VMI models may not always possess.

Despite the benefits of VMI, many organizations still rely on manual inventory monitoring processes, which can lead to errors, inefficiencies, and delays. In traditional VMI systems, inventory levels are often tracked manually by vendors based on periodic reports or customer communications. This approach can lead to delays in replenishment, as inventory levels may not always be updated in real-time. Furthermore, manual monitoring increases the risk of human error, which can result in incorrect stock counts or missed opportunities for restocking (Herlin *et al*., 2021). To overcome this challenge, companies need to invest in automated systems and tools that allow for real-time inventory monitoring and replenishment. These systems should be integrated with AI-driven forecasting models and data-sharing platforms, which can provide continuous visibility into inventory levels and demand patterns. Automation not only reduces human error but also enhances the efficiency and accuracy of the VMI process, enabling vendors to respond quickly to changing inventory needs.

Vendor-Managed Inventory (VMI) is an effective strategy that shifts inventory responsibility from the customer to the vendor, fostering collaboration and streamlining the replenishment process. By ensuring that inventory levels are monitored and replenished proactively, VMI helps reduce stockouts, prevent overstocking, and strengthen vendor-customer relationships. However, challenges such as forecasting errors, inconsistent demand patterns, and manual inventory monitoring remain barriers to achieving optimal performance in VMI systems (Raba *et al*., 2022). To address these challenges, businesses must invest in advanced forecasting tools, automation technologies, and real-time data-sharing platforms. With these improvements, VMI can enhance inventory management, improve supply chain efficiency, and lead to stronger partnerships between vendors and customers.

2.2 The role of AI in VMI optimization

Vendor-Managed Inventory (VMI) is a supply chain strategy where the supplier is responsible for managing the inventory of their products at the customer's location, ensuring that stock levels are maintained efficiently (Daniella and Anthony, 2021; Makepiboon and Krichanchai, 2022). The rise of artificial intelligence (AI) has significantly transformed VMI systems, enabling enhanced data analysis, predictive modeling, and real-time inventory control. AI applications such as predictive demand forecasting, machine learning (ML), and optimization algorithms have optimized inventory replenishment and improved the overall efficiency of VMI systems. This explores the role of AI in VMI optimization, focusing on data analytics and predictive modeling, machine learning, and optimization algorithms.

One of the most impactful ways AI enhances VMI is through predictive demand forecasting. In traditional inventory management, forecasting is often based on historical data, which can be prone to errors when external variables, such as seasonal demand fluctuations or supply chain disruptions, are not accounted for. AI, however, can analyze massive datasets that go beyond historical trends, incorporating real-time data from various sources like market trends, consumer behavior, weather patterns, and promotional activities. AI algorithms, particularly machine learning techniques, can process these data points to generate more accurate demand forecasts (Kilimci *et al*., 2019). By leveraging predictive models, suppliers in VMI systems can more accurately anticipate when a customer will need a replenishment of stock. For example, AI can identify periods of increased demand (e.g., holiday seasons or sales events) and adjust replenishment schedules accordingly, reducing the risk of stockouts or overstocking. Predictive demand forecasting thus helps ensure that the right amount of inventory is available at the right time, improving service levels and reducing excess inventory.

The integration of real-time data analysis further enhances predictive forecasting. In traditional systems, inventory levels are usually updated on a periodic basis, often leading to outdated information that can cause delays in decision-making. However, with AI, VMI systems can constantly monitor inventory levels in real-time, factoring in external factors such as sales data, delivery statuses, and changes in demand (Yerpude and Singhal, 2020). By analyzing this real-time data, AI can dynamically adjust forecasts and stock levels, ensuring that the VMI system is always aligned with the current market conditions. This enables suppliers to act swiftly and make inventory adjustments when necessary, thereby maintaining a smoother flow of goods and optimizing the replenishment process. For example, a retailer might experience an unexpected surge in demand for a particular product, and AI would immediately update the forecast, triggering a faster response from the supplier to prevent stockouts.

Machine learning, a subset of AI, plays a crucial role in enhancing VMI systems by learning from historical data. ML algorithms can analyze years of past sales data to identify patterns, trends, and factors that influence demand. These models continually learn from new data, improving their predictions over time. By incorporating such insights, ML models can predict demand more accurately, helping suppliers optimize inventory replenishment schedules. The more data the system processes, the better it becomes at recognizing subtler demand drivers, such as changing consumer preferences or supply chain disruptions. This capability reduces reliance on simplistic historical averages and allows for more granular, precise forecasting in VMI systems (Ranganathan *et al*., 2022).

Another key strength of machine learning in VMI systems is its ability to identify demand patterns and anomalies. Traditional forecasting methods might struggle to detect subtle changes in demand or unexpected disruptions in the supply chain (Ambrogio *et al*., 2022). In contrast, ML algorithms can quickly recognize patterns in the data, even those that are not immediately obvious to human analysts. Furthermore, ML can identify outlier events, such as an unexpected surge in demand, and adjust inventory replenishment strategies accordingly. This enhances the flexibility of VMI systems, enabling them to respond to rapid shifts in demand while ensuring that suppliers can efficiently manage inventory.

Optimization algorithms are another powerful tool for enhancing VMI systems. These algorithms use AI to adjust stock levels dynamically based on predicted demand, available supply, and delivery lead times. Instead of simply maintaining a static inventory threshold, AI-driven systems continuously calculate the optimal stock levels based on a range of factors, such as expected future demand, seasonal fluctuations, and supplier capabilities. Conversely, when demand drops, AI can reduce stock levels to avoid overstocking and excess inventory (Long *et al*., 2022). This level of optimization ensures that the VMI system operates at peak efficiency, maintaining the right balance between supply and demand without incurring unnecessary costs from excess inventory.

The ability to balance supply with demand in real-time is a key benefit of AI-powered optimization algorithms in VMI systems. AI systems continuously evaluate supply and demand in real time, adjusting inventory replenishment orders as needed (Modgil *et al*., 2022). Moreover, AI-driven optimization can account for external variables such as transportation delays or supplier constraints, adjusting replenishment schedules and stock levels accordingly. This real-time flexibility allows VMI systems to remain agile and responsive, ensuring that inventory is always available when needed, without disrupting production schedules or customer satisfaction.

2.3 AI Techniques for VMI Optimization

Vendor-Managed Inventory (VMI) is a supply chain model where the supplier manages the inventory levels at the customer's location. VMI systems help optimize inventory levels and ensure that the customer always has the right stock on hand. However, as the supply chain environment becomes increasingly complex, AI techniques are emerging as powerful tools for enhancing the efficiency and performance of VMI systems as shown in figure 2. By utilizing various AI models such as machine learning (ML), natural language processing (NLP), computer vision, and predictive analytics, VMI can be optimized to address demand fluctuations, improve stock monitoring, and streamline decision-making processes (Nagaiah, 2022; Asthana *et al*., 2022). This explores the AI techniques used in VMI optimization, including machine learning models, NLP, computer vision, and predictive analytics.

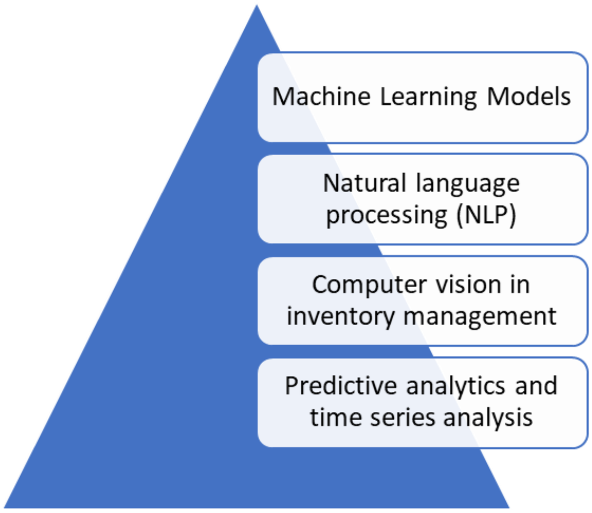

Fig 2: AI techniques for VMI optimization

Machine learning (ML) plays a significant role in improving VMI optimization by utilizing supervised and unsupervised learning techniques. Supervised learning models are trained on historical data with known outcomes to predict future demand and inventory requirements. For example, by training on historical sales data, a supervised learning algorithm can forecast future demand for a product, helping suppliers better align their stock levels with anticipated customer needs. On the other hand, unsupervised learning involves clustering and pattern recognition without pre-labeled outcomes. In the context of VMI, unsupervised learning can be used to segment products into categories based on demand patterns or identify anomalies in supply chains, such as unexpected demand spikes or product shortages (Sankaran *et al*., 2019). Both supervised and unsupervised learning allow for the more efficient and responsive management of inventory, helping vendors adjust their strategies and replenish stock levels according to real-time demand shifts.

Reinforcement learning (RL) is a type of machine learning that trains models through trial and error, rewarding models for actions that lead to favorable outcomes and penalizing them for undesirable results. In VMI optimization, RL can help optimize inventory replenishment decisions by continuously adjusting inventory levels and reorder points based on ongoing performance (Buyko, 2022). By simulating various supply chain scenarios, RL models can determine the best strategies for ordering stock, minimizing stockouts and excess inventory while maximizing customer satisfaction. This ability to adapt and learn over time makes RL particularly useful for dynamic and uncertain supply chains, where demand and supply conditions can change rapidly.

Natural Language Processing (NLP) is a branch of AI focused on enabling machines to understand and interpret human language. One important application of NLP in VMI optimization is its ability to process unstructured data, such as emails, product reviews, and customer feedback. In traditional inventory management systems, much of this data remains untapped. However, NLP techniques allow businesses to analyze text data to gain valuable insights about customer preferences, potential supply chain issues, and product quality concerns (Aldunate *et al*., 2022). Such insights can inform VMI decision-making by allowing suppliers to adjust inventory levels proactively or prioritize specific products that are experiencing increased demand or quality concerns.

NLP can also enhance demand prediction by extracting trends and sentiment from social media, customer service conversations, and online reviews. By analyzing customer sentiments and discussions surrounding products, NLP algorithms can detect early signals of shifts in consumer demand. This additional layer of demand forecasting can improve the accuracy of inventory predictions, especially in industries where trends change rapidly, such as fashion or consumer electronics. By incorporating NLP-driven insights into demand forecasting, businesses can better anticipate demand surges and adjust inventory levels accordingly, reducing the risk of stockouts or excess inventory.

Computer vision is an AI technique that enables machines to interpret and understand visual information from the world, such as images and video. In VMI optimization, computer vision can be applied to monitor inventory levels by utilizing image recognition technologies (Bulgakova and Vertakova, 2021). For instance, cameras and sensors installed in warehouses or retail environments can capture images of stock and analyze these images to determine current inventory levels. AI-powered image recognition can identify the presence or absence of products on shelves, track product movements, and even monitor the condition of items (e.g., detecting damaged products). This continuous monitoring improves the accuracy of inventory counts and ensures that stock levels are always aligned with real-time demand. Additionally, automated image recognition can reduce the need for manual stock counts, which are time-consuming and prone to human error.

Computer vision also plays a crucial role in warehouse automation, which is an integral component of VMI optimization. By using computer vision to guide robotic systems, warehouses can automate tasks such as picking, sorting, and packing. These robots use real-time visual data to navigate the warehouse, identify products, and transport goods to the correct locations for shipment or replenishment. The integration of computer vision in warehouse automation not only improves efficiency but also enhances the speed and accuracy of inventory management, ensuring that products are consistently replenished on time and without errors (Dash *et al*., 2019; Gregory *et al*., 2021).

Predictive analytics is an essential AI technique for optimizing VMI systems, as it enables businesses to forecast future trends and consumption patterns. By analyzing historical data and trends, predictive analytics algorithms can provide valuable insights into how demand will evolve in the future (Seyedan and Mafakheri, 2020). This can help suppliers optimize stock levels, ensuring that inventory is aligned with predicted demand fluctuations. Predictive analytics also incorporates time series analysis, which helps identify temporal patterns in demand, such as daily, weekly, or seasonal cycles. By understanding these patterns, VMI systems can proactively adjust replenishment schedules and stock levels, preventing stockouts or overstocking

Time series analysis helps businesses better understand seasonality and demand spikes, which are crucial factors in VMI systems. By examining past consumption data over specific time intervals, AI can predict when demand will peak (e.g., during holidays or special promotions) and adjust inventory replenishment strategies accordingly. Recognizing seasonal trends allows suppliers to better plan for changes in demand, ensuring that the right amount of stock is available to meet customer needs without causing supply chain disruptions.

2.4 Benefits of AI-Driven VMI optimization

Vendor-Managed Inventory (VMI) has long been a cornerstone of efficient supply chain management, allowing vendors to directly manage inventory levels for their customers. Integrating Artificial Intelligence (AI) into VMI systems offers numerous advantages, including improved demand forecasting accuracy, increased efficiency in inventory management, substantial cost savings, and enhanced collaboration between vendors and retailers (Shiau, 2020; Lahjouji *et al*., 2021). By leveraging AI's advanced capabilities, businesses can optimize their VMI systems, leading to smoother operations, higher customer satisfaction, and more profitable partnerships as shown in figure 3.

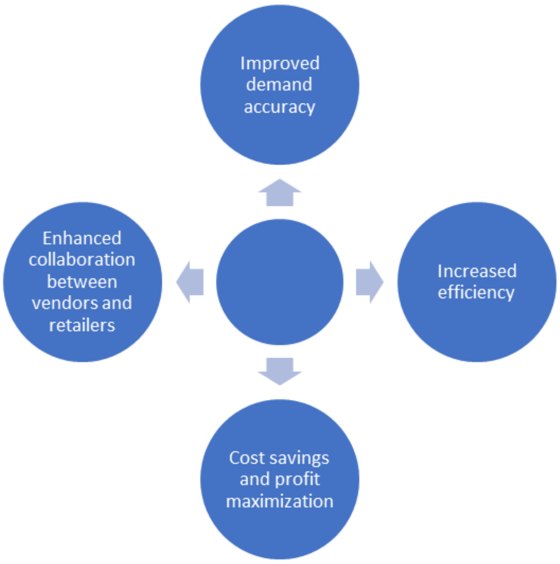

Fig 3: Benefits of AI-driven VMI optimization

One of the primary benefits of incorporating AI into VMI is the enhanced accuracy of demand forecasting. Traditional forecasting methods often rely on historical sales data and simple models, which can be inaccurate in dynamic, fast-changing market environments. AI-driven models, however, utilize machine learning algorithms to analyze vast amounts of data and identify complex patterns in demand that human-driven models may overlook. These algorithms learn from historical data, seasonality, trends, external factors (such as weather, economic conditions, and social media), and real-time customer inputs, improving the accuracy of demand predictions. By implementing AI models, vendors can make more informed decisions about inventory replenishment, ensuring that the right products are available at the right time (Zdravković *et al.*, 2022). This enhanced forecasting accuracy reduces the risk of both stockouts and overstocks, which are detrimental to supply chain efficiency and customer satisfaction. With better demand predictions, AI can optimize inventory levels, ensuring that businesses only hold necessary stock, which improves the overall supply chain performance.

The most immediate benefit of better demand forecasting is the minimization of stockouts and overstocks, two of the most common challenges in inventory management. Stockouts can result in lost sales, damaged customer relationships, and a negative impact on brand reputation, while overstocks can lead to increased carrying costs and reduced inventory turnover. By leveraging AI to predict demand more accurately, vendors can ensure that they replenish stock just in time, reducing both stockouts and overstocks (Avlijas *et al.*, 2021). This precision enables a more efficient supply chain, where products are always available when needed, but excess inventory is avoided, optimizing inventory costs and overall efficiency. AI enhances the efficiency of VMI systems by enabling real-time inventory management. Traditional inventory management systems typically rely on periodic updates to monitor stock levels, but AI-powered systems can continuously track inventory in real-time, making adjustments based on fluctuations in demand. Using sensors, RFID technology, and integrated data systems, AI can provide up-to-the-minute visibility into stock levels, enabling vendors to respond rapidly to changes in demand and automatically adjust replenishment schedules. This real-time monitoring minimizes the time lag between inventory consumption and replenishment, allowing vendors to adjust deliveries and manage stock proactively rather than reactively. Real-time data-driven decisions help prevent delays in product availability, ensuring that customers always receive their orders on time, thus enhancing the overall supply chain efficiency (Vieira *et al.*, 2019).

Another critical area where AI optimizes VMI systems is through the automation of replenishment decisions. Traditionally, inventory replenishment decisions were based on static reorder points and manual inputs, leading to inefficiencies and human errors (Custodio and Machado, 2020). AI systems, on the other hand, can automate the entire replenishment process by integrating with inventory data and predictive algorithms. The AI models continuously analyze sales trends, seasonality, and market conditions, making data-driven decisions about when and how much inventory to order. This automation significantly reduces the time and effort required for inventory management, allowing vendors to focus on more strategic activities. By optimizing replenishment schedules and inventory flow, businesses can streamline operations, reduce human intervention, and improve the responsiveness of the entire supply chain.

One of the most significant benefits of AI-driven VMI optimization is the reduction of inventory carrying costs. Carrying costs include expenses associated with storing, handling, and insuring inventory. Overstocks lead to higher carrying costs because excess inventory must be stored, often for extended periods, taking up valuable warehouse space and tying up capital (Tien *et al.*, 2019). AI models, by providing more accurate demand forecasts and optimizing replenishment cycles, ensure that businesses carry only the inventory needed to meet demand, thus minimizing excess stock. Additionally, AI can optimize order sizes and frequencies, reducing the amount of unsold inventory that accumulates in warehouses. This lowers the need for warehousing space, reduces the risk of obsolescence (especially in industries like fashion and technology), and ultimately improves cash flow by freeing up capital that would otherwise be tied up in unsold stock.

AI-driven VMI systems not only reduce costs but also improve service levels, leading to higher customer satisfaction. By maintaining optimal inventory levels, AI ensures that products are always available when customers need them, which enhances delivery reliability and order fulfillment rates. As stockouts are minimized and product availability is increased, customers are more likely to have a positive experience with the retailer or supplier. Increased customer satisfaction often translates into repeat business, greater customer loyalty, and an improved reputation in the market. Satisfied customers are more likely to make additional purchases, recommend the business to others, and contribute to long-term revenue growth (Hamzah and Shamsudin, 2020). Consequently, businesses that utilize AI-driven VMI systems can not only optimize their operational costs but also maximize profitability by offering superior service levels.

AI-powered VMI systems foster better collaboration between vendors and retailers by streamlining communication and facilitating the exchange of data in real-time. Traditional methods of inventory management often involve multiple steps of communication between the customer and the vendor, which can lead to delays, misunderstandings, and inefficiencies. However, with AI, inventory updates, sales forecasts, and replenishment schedules can be shared instantly, ensuring that both parties have the most up-to-date information. By enhancing the visibility of inventory levels, sales trends, and demand forecasts, AI ensures that vendors and customers are aligned in their inventory management goals (Kathiriya *et al.*, 2022). This reduces the need for manual communication and decreases the chances of errors, resulting in a more effective and efficient supply chain.

AI-driven VMI models also enable more transparent data sharing between vendors and retailers. Since both parties have access to real-time inventory and demand data, they can make more informed decisions and adjust strategies quickly. This transparency reduces the risk of miscommunication, promotes trust, and fosters a collaborative approach to inventory management. By sharing critical information, such as demand forecasts and inventory levels, both vendors and retailers can better anticipate changes in the market and make proactive adjustments to their operations (Wen *et al.*, 2019; Sharma *et al.*, 2021). This mutual transparency enhances the vendor-retailer relationship and creates a more agile, responsive supply chain.

2.5 Challenges and Limitations

While AI-driven Vendor-Managed Inventory (VMI) systems present significant opportunities for enhancing supply chain management, their implementation and ongoing operation come with various challenges and limitations (Poursoltan *et al*., 2021). These include data quality and integration issues, high initial investments, interpretability and trust concerns, and the ability to adapt to dynamic supply chain changes. Addressing these challenges is essential for optimizing the benefits of AI in VMI systems.

A fundamental challenge in implementing AI-driven VMI optimization lies in the integration of diverse data sources. In modern supply chains, data is often fragmented across multiple platforms, including Enterprise Resource Planning (ERP) systems, customer relationship management (CRM) systems, and third-party logistics providers. These systems may store data in different formats, making it difficult to consolidate and use effectively. AI models rely on large volumes of high-quality, consistent data to make accurate predictions and decisions. The challenge, therefore, is not only obtaining data from multiple sources but also ensuring that this data is synchronized and aligned in a way that the AI model can use effectively (Zhang *et al*., 2021). To address this, organizations must invest in robust data integration frameworks that ensure real-time synchronization between disparate systems. This requires developing interoperable data pipelines, incorporating standardized data formats, and ensuring that data flows seamlessly between vendors, retailers, and other partners. Failure to adequately address these issues can result in inconsistent or incomplete data, which negatively impacts the performance of AI models (Slota *et al*., 2020).

AI models are only as good as the data they are trained on. The quality of the data used in AI-driven VMI systems is crucial for ensuring the accuracy of demand forecasting and inventory optimization. However, maintaining accurate, clean data is a continual challenge. Data can become outdated, contain errors, or reflect biases that influence the AI models. To overcome these issues, businesses need to implement comprehensive data validation and cleaning processes. This can involve the use of automated tools to detect anomalies and inconsistencies, as well as manual audits to ensure that data is accurate and up-to-date. Organizations must also invest in data governance practices to ensure that data quality is maintained across the entire supply chain (Sambasivan *et al*., 2021).

The adoption of AI-driven VMI optimization can require significant financial investments. Building the infrastructure necessary to support AI systems such as cloud computing, high-performance servers, and specialized AI software can be costly. Additionally, businesses need to invest in skilled personnel to manage and implement AI solutions, which can include data scientists, machine learning engineers, and supply chain analysts. For small and medium-sized enterprises (SMEs), these initial costs can be a significant barrier to adopting AI-driven technologies. While the long-term benefits of AI-driven VMI optimization, such as improved efficiency and cost reductions, may offset the initial investment, the upfront financial burden can be prohibitive (Sheffi, 2020). To mitigate this challenge, businesses may need to explore alternative funding models, such as partnerships or subscription-based AI services, which provide access to AI tools without the need for large upfront investments.

Another challenge businesses face when implementing AI-driven VMI systems is the integration with existing legacy systems. Many organizations still rely on traditional, on-premises systems that may not be compatible with modern AI technologies. Integrating AI solutions with these older systems often requires complex customization and data migration efforts, which can delay implementation and increase costs. Additionally, legacy systems may lack the necessary data-sharing capabilities or real-time data access, which is essential for AI models to function effectively (Gill t al., 2019). To address this, businesses may need to modernize their existing systems or adopt middleware solutions that allow AI tools to interface with legacy infrastructure. This can be a time-consuming and resource-intensive process but is necessary for enabling the smooth integration of AI-driven VMI systems.

AI models, particularly machine learning and deep learning models, are often described as "black boxes" because they can make decisions based on complex, non-linear patterns that are difficult for humans to interpret. This lack of transparency is a significant concern in the context of VMI systems, where decisions about inventory replenishment can have direct financial and operational consequences. Vendors and customers must trust AI models to make accurate, unbiased decisions, but this trust is hard to establish when the decision-making process is not easily understood (Ashoori and Weisz, 2019). Ensuring that AI systems are interpretable is critical for building confidence among stakeholders. If the reasons behind AI-driven decisions are unclear, vendors and customers may hesitate to fully rely on these systems, limiting their effectiveness. Efforts to make AI models more interpretable, such as using explainable AI (XAI) techniques, can help address these concerns and promote greater trust in AI-driven VMI systems.

Along with interpretability, ensuring transparency and accountability in AI decision-making is crucial. If AI systems are responsible for making inventory management decisions, stakeholders need assurance that the system's actions are aligned with business goals and ethical standards. Transparency in AI models can help identify any biases or flaws in the system, while accountability measures can ensure that vendors or customers can challenge or audit AI-driven decisions. Building trust in AI requires ongoing efforts to improve the explainability of the models and maintain accountability for their outcomes. Transparency not only helps ensure that AI systems are functioning correctly but also fosters collaboration between vendors and customers, as both parties need to feel confident in the system's decisions to optimize inventory management (Felzmann e al., 2020).

One of the significant limitations of AI-driven VMI systems is their ability to adapt to rapid, unexpected changes in supply chain dynamics. Market volatility, such as sudden demand spikes or drops, and supply chain disruptions, like transportation delays or shortages of critical raw materials, can throw off AI models' predictions (Subhash, 2022). While AI systems are designed to make data-driven decisions based on historical patterns, these models may struggle to adjust in real time to unforeseen events that fall outside of these patterns. To improve adaptability, AI systems need to be trained on a broad range of scenarios, including rare and extreme events. Additionally, businesses should incorporate real-time data feeds and monitoring tools to ensure that AI models can quickly adapt to disruptions. However, while AI can help identify trends and anomalies in demand patterns, there will always be some level of unpredictability that may challenge AI-driven VMI systems.

The need for AI systems to adapt quickly to changing conditions is paramount in a dynamic supply chain environment. This requires the development of real-time learning capabilities, where AI models can adjust to new data and optimize inventory decisions continuously. However, real-time adaptation requires substantial computing power and data integration capabilities. Businesses must ensure that their AI infrastructure is capable of processing and analyzing large volumes of data in real time, which can be costly and complex to implement (Machireddy *et al*., 2021). Additionally, continuous adaptation may require AI models to integrate external data sources, such as market trends, customer sentiment analysis, or global economic indicators, to ensure that they reflect current conditions. Balancing the need for real-time adaptability with the computational demands of AI models is an ongoing challenge for organizations aiming to optimize VMI systems.

2.6 Future Outlook

The field of Vendor-Managed Inventory (VMI) has been significantly impacted by advancements in artificial intelligence (AI), offering new solutions for optimizing inventory levels, streamlining supply chains, and improving overall efficiency. As AI technologies continue to evolve, VMI systems are poised for transformative improvements (Goldsby *et al*., 2019). This explores the future outlook for AI in VMI, particularly focusing on the evolution of AI technologies, the move towards autonomous supply chains, and the sustainability considerations in AI-optimized VMI systems.

The ongoing development of advanced AI technologies such as generative AI promises to revolutionize VMI practices. Generative AI, which refers to AI systems capable of creating new content based on learned patterns, can have a profound impact on demand forecasting, inventory replenishment, and supply chain optimization (Oosthuizen *et al*., 2021). In the future, generative AI could simulate entire supply chain scenarios, generate optimal strategies for inventory management, and even forecast future market demands with unprecedented accuracy. This ability to simulate various outcomes would allow businesses to prepare for a wider range of supply chain challenges and uncertainties. These insights could allow suppliers to proactively address issues before they impact customers, leading to better VMI decision-making and reduced operational risk. Furthermore, as generative AI becomes more advanced, it may allow systems to automatically create and execute replenishment strategies, significantly reducing human intervention in the VMI process (Bozic, 2021; Abbasi and Varga, 2022).

The future of VMI will see an increasing integration of the Internet of Things (IoT), AI, and big data to create more connected and intelligent supply chains. IoT devices, such as sensors and RFID tags, will continue to generate vast amounts of real-time data related to inventory, product conditions, and movement (Mashayekhy *et al*., 2022). AI algorithms will analyze this data to identify trends, forecast demand, and optimize inventory replenishment schedules. Moreover, AI's ability to process big data will enhance decision-making, enabling more granular and accurate predictions regarding inventory levels and customer demand. The system would then process this data in conjunction with historical sales trends, seasonal patterns, and external factors (such as market trends or weather conditions) to recommend the ideal inventory replenishment schedules (Campbell *et al*., 2020; Lalou *et al*., 2022). This integration will not only improve VMI accuracy but also create more resilient and adaptive supply chains capable of responding to sudden shifts in demand or supply disruptions.

As VMI systems continue to evolve, automation will play an increasingly central role. AI-driven automation will allow for more efficient inventory management by reducing manual intervention and human errors. Automated systems will be able to handle routine tasks, such as stock counting, order placement, and demand forecasting, with greater speed and accuracy than human operators (Apolonio and Norona, 2021). By continuously adjusting inventory levels and replenishment schedules based on real-time data, automated VMI systems will ensure that stock levels are always aligned with actual demand, reducing excess inventory and stockouts. Additionally, AI-enabled robots and drones are already being used in warehouses for tasks such as picking, sorting, and transporting goods. These robots, powered by AI and computer vision, will become even more advanced in the future, improving warehouse efficiency and facilitating seamless VMI processes. Automation will help reduce costs, improve supply chain reliability, and enable faster responses to changes in customer demand (Attaran, 2020).

The ultimate goal is the development of fully integrated AI and VMI systems that can operate autonomously across the entire supply chain (Shcherbakov and Silkina, 2021). In such systems, AI would not only optimize inventory management but also control logistics, procurement, and production processes. These systems would communicate seamlessly with suppliers, distributors, and retailers, enabling the automatic and real-time adjustment of inventory levels based on demand fluctuations. The AI would continuously learn and adapt to supply chain dynamics, leading to a self-optimizing supply chain that requires minimal human oversight. By integrating AI into every aspect of the supply chain, VMI systems could achieve near-perfect alignment between supply and demand, dramatically improving operational efficiency and customer satisfaction (Yu *et al*., 2020). The result would be a more agile and resilient supply chain capable of responding to disruptions in real time and maintaining optimal inventory levels across all touchpoints.

One of the most important benefits of AI-optimized VMI systems is their potential to reduce waste and excess inventory. Excess stock ties up capital, increases storage costs, and contributes to environmental waste, especially in industries with perishable goods. AI-driven VMI systems can predict demand with higher precision, reducing the need for overstocking and ensuring that products are replenished only when necessary (Takami *et al*., 2021). This level of demand accuracy minimizes waste, reduces unnecessary resource usage, and contributes to more sustainable inventory management practices. By reducing excess inventory, businesses can also lower their environmental impact. For instance, fewer products need to be manufactured and transported, leading to reductions in carbon emissions and energy consumption associated with production and logistics. AI can also help optimize the use of resources in VMI systems, ensuring that inventory is managed in a way that minimizes environmental and operational costs. Through real-time monitoring and data analysis, AI can help identify inefficiencies in the supply chain, such as underutilized storage spaces or inefficient transportation routes. By optimizing these resources, AI can contribute to a more sustainable supply chain that minimizes environmental impact while maintaining operational effectiveness. Furthermore, as AI systems become more adept at forecasting demand and managing inventory levels, businesses will be better equipped to adopt sustainable practices like circular supply chains, where products are reused or recycled. (Chauhan *et al*., 2022; Guan *et al*., 2022) AI could support such practices by predicting the lifespan of products and facilitating the return of goods for reuse, helping reduce waste and supporting the circular economy.

3. Conclusion

AI-driven Vendor-Managed Inventory (VMI) systems have significantly impacted supply chain management by improving demand forecasting, inventory optimization, and enhancing collaboration between vendors and retailers. By leveraging machine learning algorithms and big data analytics, AI models provide more accurate demand predictions, reduce stockouts and overstocks, and streamline the replenishment process. These advancements not only enhance the efficiency of inventory management but also contribute to cost savings and improved customer satisfaction. As AI continues to evolve, its ability to optimize VMI systems promises to address many of the inherent challenges faced by traditional inventory management approaches.

The potential for AI-driven VMI to revolutionize supply chains is immense. With the ability to integrate real-time data, AI can ensure that inventory levels are consistently optimized in response to dynamic changes in demand and market conditions. This results in more agile and responsive supply chains, capable of adapting to unforeseen disruptions or market shifts. Furthermore, AI's capacity to automate decision-making processes reduces human error, accelerates decision-making, and enhances the scalability of supply chain operations. By integrating AI into VMI systems, businesses can achieve more efficient and sustainable inventory management, ultimately improving their competitive advantage in the marketplace.

Looking to the future, AI optimization in dynamic supply chains holds great promise. As the technology advances, AI's ability to handle increasingly complex supply chain variables will continue to improve. The growing integration of AI with other emerging technologies, such as the Internet of Things (IoT) and blockchain, will further enhance its effectiveness in real-time monitoring and data sharing. However, the continued success of AI-driven VMI will depend on overcoming challenges related to data integration, trust, and adaptability. As these barriers are addressed, AI will undoubtedly play a central role in the transformation of modern supply chains, making them more efficient, resilient, and customer-centric.

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