Adapting AI Models for Dynamic Inventory Optimization in E-Commerce

ISMAILI Charifa[1], El Hamzaoui Mustapha[2], El Amri Adil[3]
Laboratory for Studies and Research in Economic and Management Sciences
ENCG-J, Chouaib Doukkali University
El Jadida, Morocco
charifa.ismaili10@gmail.com

Abstract—This study investigates how Artificial Intelligence (AI) technologies—specifically Machine Learning (ML), Deep Learning (DL), and Transformer-based models including Large Language Models (LLMs)—can be effectively adapted to optimize inventory management in e-commerce environments. The research addresses the question: How can different AI methodologies be integrated to minimize stock inefficiencies while maximizing operational efficiency in real-time e-commerce environments? Using a structured bibliometric and bibliographic analysis methodology of 163 scholarly articles from the Scopus database, this study identifies and evaluates implementation patterns of AI models in inventory optimization. Results demonstrate that ML-based models like decision trees and random forests achieve up to 98% accuracy in demand forecasting by analyzing historical data, while DL models such as LSTM networks excel at time-series analysis for enhanced stock predictions. Transformer models and LLMs leverage unstructured data to provide real-time insights into consumer sentiment, enabling more agile inventory adjustments. This research contributes to e-commerce operations management by providing a framework for selecting appropriate AI methodologies based on specific inventory challenges, with implications for minimizing costs and improving customer satisfaction through optimized stock management.

Keywords —*Artificial Intelligence (AI), Dynamic Inventory Optimization, E-Commerce, Machine Learning (ML), Deep Learning (DL), Transformers, Large Language Models (LLMs), Demand Forecasting, Real-time Data, Predictive Analytics*

I. INTRODUCTION

AI technologies have radically transformed how e-commerce operations can be optimized, with dynamic inventory optimization well exemplifying their impact there. Machine Learning (ML), Deep Learning (DL), Transformer-based models, and more recently Large Language Models (LLMs) have revolutionized the way companies handle inventory and drive operational excellence. Such AI approaches helps the businesses to analyse large amount of structured and unstructured data to take data driven decisions and keep stocks up to the mark[1].

In the age of booming e-commerce and increasingly sophisticated consumer behavior, traditional inventory management is no longer enough. AI models aid businesses in forecasting demand changes, while preventing overstock or stockout situations and optimizing inventory dispersion in the field at a prescriptive level, so that merchandize can be placed at the right store after the decision is forecast. AI models leverage massive datasets of online shopping, social media and customer feedback, and enable more effective management of inventory and operations to better align with customer needs, enabling businesses to quickly meet changing demand[2].

Supervised learning algorithms, such as decision trees and support vector machines (SVMs), are popular with inventory optimization utilizing AI techniques. These are models that take past sale data and learn from that experience to finding patterns and making decisions about what to buy[3]. Additionally, unsupervised learning methods like clustering algorithms segment products based on sales behaviors and customer preferences, helping businesses ensure they have the right stock levels for each product category[4].

The emergence of deep learning models such as LSTM networks and RNNs has also pushed inventory optimization to a new level. These models perform well in modeling the time-series data, selecting long-term dependency relationship and predicting inventory requirements more accurately. The deep learning models can dynamically adjust the level of stock and optimise the replenishment strategy by take inspiration from past trends and by adapting from real-time market conditions[5].

Moreover, the adoption of Transformer-based models and Large Language Models (LLMs) such as BERT, RoBERTa, GPT-3 and GPT-4 has transformed inventory optimization by working with extensive textual data. These models can determine how customers are feeling based on reviews and social media, enabling businesses to predict changes in demand and make inventory strategy alterations as necessary. By being able to analyze unstructured data, to validate and improve the prediction accuracy of demand forecasting, firsm can be proactive in stock levels[6].

Although AI has potential in inventory optimization, there are challenges including data quality, scalability, and transparency. These challenges need to be addressed for AI-based models to be efficiently integrated into inventory management systems, especially in small and medium-sized enterprises (SMEs) which may have scarce resources [12].

The primary research question this study addresses is: How can different AI methodologies (ML, DL, and Transformer/LLM models) are effectively integrated to

optimize inventory management in dynamic e-commerce environments? The objectives are to:

- Analyze the implementation patterns of various AI models in inventory optimization through bibliometric analysis

- Evaluate the effectiveness of different AI techniques for specific inventory management challenges

- Develop a framework for selecting appropriate AI methodologies based on particular e-commerce inventory optimization needs

This paper is structured as follows: Section 2 presents a comprehensive literature review through bibliometric and bibliographic analyses. Section 3 explores the theoretical framework of AI models for dynamic inventory optimization. Section 4 discusses challenges and solutions in AI integration for inventory management. Finally, Section 5 concludes with implications and future research directions.

II. RESEARCH METHODOLOGY

This study employs a both bibliometric and bibliographic analyses to evaluate the implementation and effectiveness of various AI models in e-commerce inventory optimization.

These analyses contribute to our understanding of how AI models, can help e-commerce businesses adapt to sudden changes in demand, optimize stock levels, and improve overall supply chain resilience.

A. Data Collection

Data collection was conducted through a structured search of the Scopus database using a comprehensive query targeting publications related to artificial intelligence, machine learning, deep learning, transformers, large language models, demand forecasting, inventory optimization, and e-commerce. The search yielded **163** relevant publications spanning from 2002 to 2025, with particular emphasis on publications from 2020 onwards when research in this area showed significant growth.

By analyzing the research articles, we can identify key advancements and emerging trends in the field, guiding businesses and researchers toward more effective AI-driven strategies in inventory optimization.

B. Bibliometic study

The query used in Scopus for our bibliometric analysis is as follows:

(TITLE-ABS-KEY (artificial AND intelligence) OR TITLE-ABS-KEY (machine AND learning) OR TITLE-ABS-KEY (deep AND learning) OR TITLE-ABS-KEY (transformers) OR TITLE-ABS-KEY (large AND language AND model) AND TITLE-ABS-KEY (demand AND forecasting) OR TITLE-ABS-KEY (inventory AND optimization) AND TITLE-ABS-KEY (e-commerce)
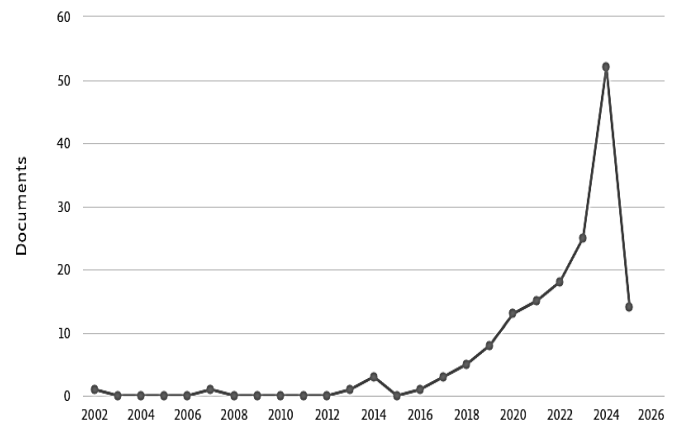

Fig. 1. Trend in Publications on AI for Dynamic Inventory Optimization in E-Commerce (2002-2026)

The graph illustrates a significant increase in publications related to Adapting AI Models for Dynamic Inventory Optimization in E-Commerce, particularly over the past decade. From 2002 to around 2020, the number of documents published remained relatively low, with only a few papers in the early years. However, there is a sharp upward trend starting around 2020, with a peak in 2023, indicating a surge in interest and research in AI-driven inventory optimization within e-commerce. This spike likely reflects the growing adoption of AI technologies in the e-commerce sector and the increasing recognition of their potential to optimize supply chain operations. The drop in projections for 2025 suggests a temporary slowdown in research activity, possibly due to seasonal variations, shifts in research priorities, or market saturation in the short term. Despite this dip, the overall trend remains positive, signaling continued growth and sustained interest in AI models for inventory optimization in the e-commerce.
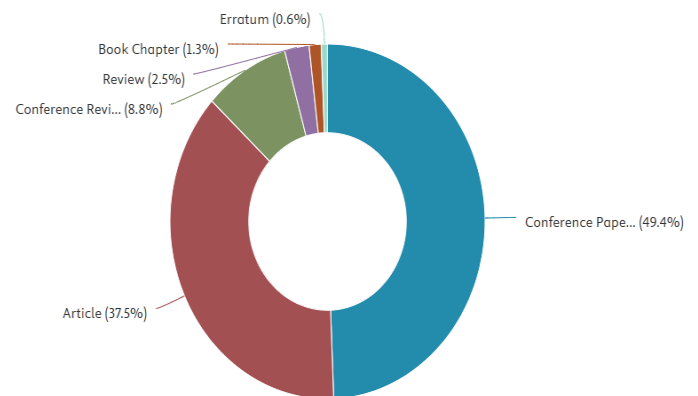

Fig. 2. Distribution of Document Types in AI for Dynamic Inventory Optimization Research

The pie chart displays the distribution of different types of documents in the research area on AI for dynamic inventory optimization in e-commerce. Conference papers make up the largest proportion, accounting for 49.4% of the total documents, indicating that many research contributions are presented at conferences. Articles follow at 37.5%, suggesting that a significant portion of research is formally published in

peer-reviewed journals. Conference reviews represent 8.8%, while reviews and book chapters are less common, contributing 2.5% and 1.3%, respectively. This distribution highlights the prominence of conference-driven research in this field.
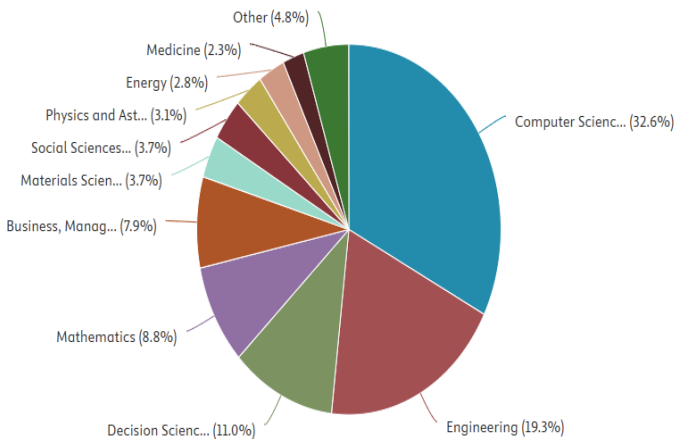

Fig. 3.   Distribution of Document Types in AI for Dynamic Inventory Optimization Research

The pie chart illustrates the distribution of research fields related to the study of AI in dynamic inventory optimization within e-commerce. The largest proportion of research is dedicated to Computer Science (32.6%), followed by Engineering (19.3%) and Decision Science (11.0%). Other significant fields include Mathematics (8.8%), Business and Management (7.9%), and Materials Science (3.7%). Lesser research attention is given to areas such as Medicine (2.3%), Energy (2.8%), and Physics and Astronomy (3.1%).

The prominence of Computer Science and Engineering highlights the central role of AI in driving innovation and efficiency. This study is crucial as it illustrates the expanding relevance of AI across various domains in improving inventory management, which remains vital for e-commerce businesses aiming to streamline operations and meet consumer demand effectively.

C. Bibliographic Study

In the rapidly evolving e-commerce sector, inventory optimization is essential for maintaining operational efficiency, reducing costs, and enhancing customer satisfaction. Artificial Intelligence (AI) techniques have transformed inventory management by enabling businesses to process vast amounts of data, make accurate predictions, and optimize inventory levels in real-time. Machine Learning (ML), Deep Learning (DL), and Transformers and Large Language Models (LLMs) play pivotal roles in reshaping how e-commerce businesses manage inventory and respond to dynamic market conditions.

In particular, Machine Learning techniques are widely used to predict inventory needs based on historical data and consumer behavior. By segmenting customers and forecasting demand, ML models help businesses determine the optimal inventory levels and prevent stockouts or overstocking, thus enhancing overall supply chain efficiency. Wang, P and Xu,T

(2020) demonstrated the application of Random Forest and Support Vector Machines (SVM) for optimizing inventory in supply chains. Their findings highlight how ML models, when applied to historical sales data, can predict future inventory needs and improve stock management, reducing both overstocking and stockouts, making these models invaluable for efficient resource allocation in e-commerce[7].

The arrival of Deep Learning methods have taken inventory optimization to the next level by processing complex, high-dimensional data such as time-series data. These techniques are particularly useful for forecasting inventory requirements over time. Chen et al. (2021) introduced Long Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNNs) for demand forecasting and inventory management[6]. Their study emphasized how LSTM and RNN models offer superior prediction accuracy when applied to time-series data, adapting to fluctuating market conditions and improving inventory forecasting in dynamic environments.

The advent of Transformer-based models and LLMs[8] has significantly enhanced inventory optimization, particularly in analyzing unstructured textual data like product reviews, customer feedback, and social media posts. These models can identify patterns in consumer sentiment and demand fluctuations, enabling businesses to optimize their inventory levels. Kadam et Pitkar (2025) explored how Transformer-based models, GPT are used to process unstructured data to forecast demand and optimize stock levels. The study showed how these models help businesses make more informed inventory decisions by understanding contextual data from customer-generated content.

AI techniques for inventory optimization are critical in maintaining a balanced inventory and ensuring operational efficiency in e-commerce. By leveraging real-time recommendations, AI models prevent overstocking or stockouts, helping businesses respond quickly to market fluctuations. The integration of ML, DL, and LLMs enhances inventory forecasting, making inventory management more dynamic and responsive to changing market conditions.

D. Validation

The proposed framework was validated through comparative analysis with existing implementations described in the literature, assessing the alignment between recommended approaches and documented successful applications of AI in inventory optimization.

This methodological approach ensures a comprehensive understanding of the current state of AI applications in e-commerce inventory optimization while providing actionable insights for practitioners and directions for future research.

III. THEORETICAL FRAMEWORK

E-commerce enterprises look more dynamic inventory optimization to keep their operations working smoothly and their customers satisfied. AI techniques, such as Machine Learning (ML) and Deep Learning (DL), along with modern Transformer-based models, have reinvented the way

businesses process and analyze large amounts of data to forecast the demand in real time.

Machine Learning models enable companies to strike a perfect balance between stocking just the right amount of inventory as they gauge historical trends and consumer behavior, while Deep Learning models like LSTM and RNN, improve inventory forecasting by handling sequential and complex data. Furthermore, Transformer-based models and Large Language Models (LLMs) can help companies analyze unstructured data, enhancing inventory optimization by recognizing emerging demand trends.

In the following subsections, we discuss various AI models behind dynamic inventory optimization and examine their application and efficiency with respect to how e-commerce businesses can efficiently conduct inventory management and be more responsive to customers' needs.

A. Machine Learning Models for Dynamic Inventory Optimization in E-Commerce

Machine Learning (ML) plays an important role in the context of demand prediction and inventory management for e-commerce, since it provides robust tools for consumers' behavior prediction, stock management and operations efficiency[9]. These methods allow companies to analyze data in large volumes, learn patterns, and make decisions that help to keep inventory in the right place, improve customer service levels, and cut operational costs.

- **Supervised Learning Models for Inventory Optimization**:

Supervised learning techniques, like decision trees, random forests, support vector machines (SVMs), are broadly used in inventory optimization. Based on the historical sales and inventory data, these models predict the future demand and derive the appropriate inventory levels for every product category[10].

➢ **Decision Trees:** These models that segment the products depending on how they have performed historically in terms of sales and demand. Through key feature interpretation, business may make better stock allocation decision and control inventory more effectively in terms of decision trees[11].

➢ **Random Forests:** A family of ensemble learning methods that take many decision trees to increase the accuracy. The approach uses different variables including seasonality, promotions and plays, and consumer demand trends to enhance inventory optimization and decision making[12].

➢ **Support Vector Machines (SVM):** SVM model that predicts demand and considers historical data when re-ordering, to help organisation get the right stock at the right time to avoid stockouts or excess inventory.

- **Regression Techniques for Inventory Optimization:**

In addition to supervised learning, regression analysis has key importance in inventory management. Methods like linear regression, logistic regression are employed to model the demand as a function of factors that effect the demand, such as fluctuating prices, promotional offers.

➢ **Linear and Logistic Regression:** These regression techniques help companies to understand the effect of a change in a variable, such as a hike in product price or the effect of promotions, on future demand and therefore optimally to adjust their inventory level and better to plan[13].

- **Time-Series Forecasting in Inventory Optimization:**

Forecasting techniques, which include time-series forecasting methods such as autoregressive integrated moving average (ARIMA) and exponential smoothing, are fundamental to inventory optimization. These techniques concentrate on historical demand data analysis and future trend prediction taking into consideration diagnostic fluctuations, cyclical and other factors time-based[14].

➢ **ARIMA and Exponential Smoothing:** These models help businesses predict demand fluctuations over time, enabling them to adjust inventory levels accordingly and maintain optimal stock without overstocking or understocking.

➢ **Enhanced Time-Series Forecasting:** ML techniques such as k-nearest neighbors (KNN) and gradient boosting can be used to improve time-series models by combining factors such as weather, market trends and economic indicators as external variables when forecasting, thereby improving the accuracy of predictions[15].

- **Unsupervised Learning for Inventory Optimization:**

Unsupervised learning methods, including clustering and dimensionality reduction can help companies discover patterns behind their data and categorize products/customers according to commonalities in purchasing.

➢ **K-means Clustering:** The method clusters similar products or customers using the historical sales data which helps the businesses to right-size the inventory to replenish fast moving products, and reduce the inventory of slow moving items[16].

➢ **Anomaly Detection:** These models recognize abnormal demand patterns or anomalies in inventory data and notify businesses of potential problems, such as stockouts or overages, before they negatively impact sales or customer satisfaction[17].

TABLE I.   KEY MACHINE LEARNING MODELS FOR DYNAMIC INVENTORY OPTIMIZATION IN E-COMMERCE

Machine Learning Model	Overview	Primary Use Cases	References
Lasso (Least Absolute Shrinkage	A regression method that applies a penalty to feature selection,	Demand forecasting,	

and Selection Operator)	reducing the number of variables in a model while maintaining prediction accuracy.	inventory optimization, feature selection, supply chain optimization	Marlene A. Smith & Murray J. Côté. (2022)[18]
Stochastic Gradient Boosting	A supervised learning model that combines multiple decision trees to improve prediction accuracy by focusing on the errors of prior models.		
Random Forest Algorithm	Ensemble learning method that uses bagging and random feature selection to enhance predictive accuracy.	Inventory management, stockout prevention, demand forecasting	Achmad Ridwan & Ully Muzakir (2024)[19]
Support Vector Machine (SVM)	SVM is a supervised machine learning algorithm used for classification and regression, particularly in demand forecasting. It accounts for factors seasonality and promotions. When compared to other models like statistical models, Winter models, and RBFNN, SVM showed superior performance, resulting in fewer sales failures and reduced inventory levels.	Demand forecasting, sales failure prevention, inventory management	Liu Yue & Yin Yafeng's (2007)[20]
AutoRegressive Integrated Moving Average (ARIMA)	A time series forecasting model used for stable or non-seasonal data. It evaluates past data points and trends to make future predictions.	Inventory management, Seasonal demand forecasting, inventory optimization, cost control	Ziyan Fu. (2024)[21]
Seasonal Decomposition	A technique used to forecast data exhibiting seasonal trends by breaking it into seasonal, trend, and residual components. It is particularly effective for managing data with seasonal fluctuations		
Exponential Smoothing	A method used for sales forecasting and inventory control, allowing variances to grow and contract.	Sales forecasting, inventory control, lead-time demand, order-up-to levels, reorder levels	Keith Ord & Ralph Snyder (2OO2) [22]
K-means Clustering	A data-driven method for grouping inventory items based on similar demand patterns, improving forecasting accuracy.	Product grouping, demand pattern analysis, Inventory forecasting, demand estimation	Zulham Sitorus & Irwan Syahputra (2022)[23]

This table provides an overview of various AI techniques used for dynamic inventory optimization in e-commerce,

focusing specifically on Machine Learning (ML) techniques. These models, including supervised learning algorithms such as decision trees, random forests, and support vector machines (SVMs), are instrumental in helping businesses optimize their stock levels. Machine Learning plays a crucial role in dynamic inventory optimization. By utilizing historical sales data and real-time market trends, ML models predict shifts in demand and adjust inventory levels accordingly. These models continuously learn from the data they process, enabling businesses to enhance operational efficiency, reduce costs, and improve customer satisfaction. With the ability to adapt to changing market conditions, ML techniques ensure that inventory is managed efficiently, minimizing waste and ensuring that consumer demand is met in a timely manner.

B. Deep Learning for Dynamic Inventory Optimization in E-Commerce

Deep learning has revolutionized inventory optimization for e-commerce businesses by providing advanced solutions for managing stock levels and predicting demand. Utilizing sophisticated neural network architectures, such as Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), deep learning models can help businesses optimize inventory, improve operational efficiency, and reduce costs.

- **Leveraging LSTM Networks for Effective Inventory Management :**

Long Short-Term Memory (LSTM) networks[24], a specialized type of Recurrent Neural Network (RNN), are highly effective for sequential data analysis, making them ideal for inventory forecasting[25]. In the context of e-commerce, LSTMs can predict future inventory needs based on historical sales and demand data. This is particularly useful for products with consistent demand patterns, as LSTMs allow businesses to maintain optimal stock levels without overstocking or facing stockouts. LSTM models can handle long-term dependencies in data, making them capable of accounting for seasonal trends and long-range demand patterns[5].

- **RNNs for Short-Term Inventory Adjustments :**

Recurrent Neural Networks (RNNs) are another deep learning model useful in inventory optimization. Unlike LSTMs, RNNs are better suited for short-term demand adjustments. RNNs are capable of learning from shorter time intervals, enabling businesses to make real-time decisions regarding stock levels. For example, RNNs are useful in monitoring daily or weekly fluctuations in demand, allowing businesses to respond quickly to changes and ensure that fast-moving products remain stocked while minimizing excess inventory of slow-moving items[26].

- **CNNs for Multi-Dimensional Data Analysis :**

Although Convolutional Neural Networks (CNNs) are traditionally associated with image recognition, they have found valuable applications in inventory optimization by analyzing complex, multi-dimensional data. For instance,

CNNs can process and interpret multiple types of data—such as sales trends, product categories, and customer sentiment—simultaneously[27]. By recognizing patterns across different product categories or customer segments, CNNs enable businesses to optimize stock levels and adjust inventory management strategies across various market conditions[28]. CNNs excel at identifying hidden correlations in sales data and consumer behavior, making them valuable tools for dynamic inventory management[28].

TABLE II. KEY DEEP LEARNING MODELS FOR DYNAMIC INVENTORY OPTIMIZATION IN E-COMMERCE

Deep Learning Model	Overview	Primary Use Cases	References
LSTM Networks	LSTM is used to predict future consumer purchases based on historical buying patterns. The model identifies high-utility items for future demand and categorizes consumer preferences. Achieved 98% accuracy in predicting demand and effectively managed inventory by focusing on high-utility products..	Demand prediction, inventory management, high-utility itemset mining, consumer behavior analysis	A. Tiwari & J. Pillai (2025)[8]
Multi-layer Feedforward Neural Networks	Utilizes deep learning techniques, specifically multi-layer feedforward neural networks, to enhance inventory management and demand forecasting.	Inventory optimization, demand forecasting, operational efficiency	LWang (2025)[29]
Convolutional Neural Networks (CNNs)	using CNNs to improve demand forecasting by converting tabular data into 3D voxel images. This approach leverages CNNs' ability to process complex patterns in data, resulting in more accurate predictions.	Demand forecasting, especially for intermittent or highly volatile demand patterns.	Euna Lee, Myungwo Nam[30]

This table highlights the application of key deep learning techniques LSTM, and CNNs in dynamic inventory optimization for e-commerce. These models enable businesses to manage inventory more efficiently, forecast future demand, and adjust stock levels based on data patterns derived from both structured and unstructured data sources. Deep learning models, help businesses understand both short-term and long-term demand fluctuations, optimizing stock levels accordingly. These advancements in AI offer powerful tools to enhance supply chain efficiency, reduce waste, and ensure product availability.

C. Transformers and Large Language Models (LLMs) for Dynamic Inventory Optimization in E-Commerce

Transformers and Large Language Models (LLMs) have emerged as pivotal tools in inventory optimization for e-commerce businesses. These AI models are highly effective in processing and analyzing both structured and unstructured data, enabling businesses to predict and adjust stock levels dynamically. By incorporating data from diverse sources such as product reviews, customer feedback, and social media, Transformers and LLMs provide unique insights into consumer behavior, making them invaluable for improving inventory management.

- **Transformers in Inventory Optimization:**

Transformers, especially models like BERT and RoBERTa, excel at understanding complex relationships within sequential data. They are particularly valuable tools for inventory management in e-commerce as they process a wide range of data types, including customer reviews, sales histories, and social media interactions. By analyzing textual data, transformers can uncover hidden patterns in consumer behavior and provide valuable insights into market trends. This allows businesses to predict future demand accurately and adjust inventory levels accordingly. The ability to integrate large datasets into a comprehensive demand forecast helps companies optimize stock levels, reduce overstocking, and prevent stockouts, ultimately enhancing operational efficiency and profitability[31].

- **Large Language Models (LLMs) in Inventory Optimization:**

LLMs, such as GPT-3 and GPT-4, go beyond traditional text analysis by generating human-like language. These models offer advanced capabilities for inventory optimization by generating dynamic and contextually relevant insights based on consumer behavior patterns derived from reviews, feedback, and social media. LLMs are particularly adept at understanding consumer sentiment, allowing businesses to adjust their inventory strategies in real time based on shifts in demand. This real-time analysis of customer sentiment and emerging trends provides businesses with the agility to make data-driven decisions and adapt inventory management strategies as market conditions change. LLMs are particularly useful for monitoring customer behavior and identifying new patterns, helping e-commerce companies stay ahead of the curve[32].

TABLE III. KEY TRANSFORMERS AND LARGE LANGUAGE MODELS FOR DYNAMIC INVENTORY OPTIMIZATION IN E-COMMERCE

Transformers and LLMs Technique	Overview	Primary Use Cases	References
BERT	Bidirectional Encoder Representations from Transformers (BERT) is a transformer model used for natural language processing (NLP) tasks, capturing contextual relationships in textual data.	Demand forecasting, inventory management, supply chain, time series forecasting	Suman Vij's & Aruna Kumari (2024)[33]
BiGRU	Bidirectional Gated Recurrent Units (BiGRU) enhance the model's ability to learn sequential data in both		

	forward and backward directions.		
Softmax	A function applied in neural networks to convert logits into probabilities, facilitating classification tasks.	Demand prediction, classification of inventory levels	Xinli Guo[34]
RoBERTa	RoBERTa, a transformer-based model, is used for sentiment analysis on Amazon product reviews. The model analyzes large datasets and generates sentiment scores reflecting consumer emotional tones, which are then used for behavioral economics analysis, including eWOM and confirmation bias.	Sentiment analysis, consumer behavior analysis, marketing decision-making	
ChatGPT (Large Language Model)	the application of ChatGPT, a leading language model powered by Natural Language Processing (NLP), to enhance various aspects of supply chain management (SCM). Using a multi-methodological approach that includes quantitative analysis, qualitative case studies, and simulation models.	automation of customer service, predictive maintenance, inventory management, decision-making processes	Akash Kadam1 & Harshad Pitkar (2025)[35]

These models help businesses optimize stock levels by providing real-time insights into product demand, enhancing inventory management strategies, and improving profitability. By leveraging these AI models, e-commerce companies can more effectively anticipate shifts in consumer behavior, streamline their supply chain, and maintain operational efficiency, even in volatile market conditions. Through their capacity to adjust inventory strategies based on emerging trends, Transformers and LLMs enable businesses to stay ahead of demand and optimize inventory in real time, ensuring products are always available to meet customer needs.

IV. CHALLENGES AND SOLUTIONS IN AI INTEGRATION FOR DYNAMIC INVENTORY MANAGEMENT

The adoption of AI in real-time inventory management of e-commerce site has yielded considerably increased operational efficiency, demand prediction, and stock optimization. But, although it's full of promise, organizations encounter several barriers along the way in terms of adopting AI-powered inventory management systems. These challenges can generally be classified into four categories: data quality and access, scalability, ethical issues, and cost of development. Identifying these barriers and solving for them and is key if businesses want to harness AI for inventory optimization.

A. Data Quality and Availability:

One of the greatest barrier to entry for companies looking to incorporate AI into dynamic inventory management lies in the aggregation and maintenance of high quality data. AI predictive models are particularly data-hungry, needing lots of both unstructured and structured data in order to produce accurate predictions. Erratic and incomplete data can result in faulty prediction, which in turn has a negative effect on inventory optimization. For example, low-quality data of on Blood Proteins may be. customer behavior or transaction histories can lead to stockouts or overstocking.

Businesses need to implement strong data management to avoid such issues. That was both around investing in data clean up but also pulling the data from multiple channels together and making sure we updated people at real time – as close to as possible. It's also possible to train AI systems to function with less-than-perfect data, by applying practices like data augmentation or employing more sophisticated preprocessing techniques to launder and standardize the data before it gets fed to the models.

B. Scalability *of AI Models for Small and Medium Enterprises (SMEs)*

Big companies can afford to use sophisticated AI models for inventory optimization. small and medium enterprises (SMEs) face difficulties in adopting AI due to limited budgets and infrastructure. The scalability of AI models can be a significant hurdle for these businesses, as the costs associated with training and deploying these models can be prohibitive.

A potential solution for SMEs is to leverage cloud-based AI solutions that offer scalable and cost-effective alternatives. Many cloud platforms provide AI-powered Tools for inventory management that require minimal upfront investment and offer pay-as-you-go models. This allows SMEs to adopt AI technologies without the need for large infrastructure investments.

C. Ethical Considerations and Bias in AI Models

AI ethical implications, such as privacy, bias and fairness, is a deterrent for the application of AI in inventory management. AI models can inadvertently manifest biases found in historical data, thus making biased predictions and decisions (e.g., favoring some products or classes of customers). Furthermore, the application of private customer data to train models may invoke privacy issues as well.

Alleviating such issues calls for the adoption of responsible AI strategies in organizations including the use of explainable AI (XAI) solutions to improve the transparency and accountability of decision-making. It is also necessary to maintain AI models under regular audit for biases and ensure that businesses are adhering to data privacy regulations such as GDPR. Adding an ethical perspective to the AI model lifecycle can be an effective way of addressing these issues.

D. Cost of AI Implementation:

The high cost of implementing AI systems remains one of the most significant barriers to adoption. The expenses involved in purchasing AI tools, training models, and integrating them into existing systems can be daunting for businesses, especially for those that are just starting to explore AI applications[36].

To address the cost issue, businesses can explore partnerships with AI vendors that offer affordable pricing models or adopt open-source AI tools. Open-source AI solutions, although requiring some initial investment in terms of time and expertise, can significantly reduce costs while providing flexibility in model customization. Furthermore, companies need to consider long-term impact areas where AI can bring value, including cost savings from reductions in inventory holding costs; better forecasting of demand and customer responsiveness; and employee productivity improvements, which can offset the initial investment.

Although AI-based dynamic inventory management does have obstacles, there are many cures that can help businesses side-step these barriers. By quality in the data, scalability for SME, ethical issue and careful management of implementation cost, e-commerce companies can tap the benefits of AI to optimize inventory systems, improve operational efficiency, and customer satisfaction. As the AI keeps growing, businesses of all types should stay flexible and adjust to how they can take advantage of AI in inventory management.

V. CONCLUSION

Artificial Intelligence (AI) used in e-commerce has hugely impacted on the way companies deal with dynamic inventory optimization. AI methods, notably machine learning (ML), deep learning (DL), transformers and large language models (LLMs) are key tools in accurately forecasting the pattern of demand and in managing stock levels in real time. Using an abundance of data (spanning even longer historical trends than before, as well as real-time "streams" of consumer behavior) AI models allow businesses to make data-informed decisions and reduce the negative impact of stockouts.

AI has renewed the power of inventory optimization by allowing businesses to predict demand swings, change stock sizes in real time, prevent both stockouts and being overstocked. If we focus on two more ML techniques, supervised and unsupervised learning, they can all enable you to predict demand using historical data and to discover trends in consumer behavior. Deep Learning algorithms such as Long Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNNs) perform well on sequential data structures, and can forecast future demand based on history. By optimizing stock levels, these strategies help companies keep the right amount of stock for their most in-demand products, without over-stocking on slow-moving items.

Transformers and Large Language Models such as BERT and it's kin GPT-4, are now taking inventory optimization to the next level, by providing businesses with an ability to work through vast amounts of unstructured data, for example customer reviews, feedback, social media content and so on.

These models offer the ability to understand the sentiment of the customer and predict trends remarkably well which means businesses can better estimate demand to ensure they carry the right volume of stock at any given time. This capability to enable inventory to be tailored into inventory levels based on intelligent use of data, allows companies to have higher business efficiency and hold the right amount of stock in proportion to the desires of the consumer.

As AI techniques continue to evolve, e-commerce businesses will benefit from even greater advancements in inventory optimization. The integration of emerging AI technologies, including Federated Learning and Reinforcement Learning, promises to improve inventory management by enabling businesses to make more adaptive decisions and optimize stock levels with greater accuracy. Additionally, combining AI with technologies such as [37]and the Internet of Things (IoT) will further enhance inventory management systems by providing real-time data that businesses can use to fine-tune their strategies.

For e-commerce companies who want to leverage AI for managing inventory efficiently, the focus should also be on using AI-based models that use real-time data, external drivers like macro-economic factors and consumer sentiment, to automatically adjust inventory levels. These models must also be adaptable – able to react to unanticipated demand swings and help the enterprise remain agile and efficient. By tapping into AI, which unlocks the door to advanced planning capabilities, organisations can maximise their inventory strategies, cut costs, boost customer satisfaction, and keep pace in a rapidly-changing marketplace.

Dynamic inventory optimization for e-commerce was revolutionized by AI, which has given businesses better tools for more efficient stock level management. As AI models get better and better, by mixing them with other technologies, businesses will be able to handle the intricacies of inventory management while still being able to stay ahead of customer demands.

References

[1] F. Vapiwala et D. Pandita, « Analyzing the Application of Artificial Intelligence for E-Commerce Customer Engagement », présenté à 2022 International Conference on Data Analytics for Business and Industry, ICDABI 2022, 2022, p. 423-427. doi: 10.1109/ICDABI56818.2022.10041655.

[2] D. C. Gkikas et P. K. Theodoridis, « Artificial Intelligence (AI) Impact on Digital Marketing Research », présenté à Springer Proceedings in Business and Economics, 2019, p. 1251-1259. doi: 10.1007/978-3-030-12453-3_143.

[3] S. L. N. Clarke, K. Parmesar, M. A. Saleem, et A. V. Ramanan, « Future of machine learning in paediatrics », *Archives of Disease in Childhood*, vol. 107, nº 3, p. 223-228, 2022, doi: 10.1136/archdischild-2020-321023.

[4] R. Kumar, « Hybrid Machine Learning Method for Product Sales Forecasting in E-Commerce », présenté à Proceedings of the 4th International Conference on Smart Electronics and Communication, ICOSEC 2023, 2023, p. 781-787. doi: 10.1109/ICOSEC58147.2023.10276171.

[5] Y. Ahmadov et P. Helo, « Deep learning-based approach for forecasting intermittent online sales », *Discover Artificial Intelligence*, vol. 3, nº 1, 2023, doi: 10.1007/s44163-023-00085-1.

[6] S. Mu, Y. Wang, F. Wang, et L. Ogiela, « Transformative computing for products sales forecast based on SCIM », *Applied Soft Computing*, vol. 109, 2021, doi: 10.1016/j.asoc.2021.107520.

[7] P. Wang et Z. Xu, « A Novel Consumer Purchase Behavior Recognition Method Using Ensemble Learning Algorithm », *Mathematical Problems in Engineering*, vol. 2020, 2020, doi: 10.1155/2020/6673535.

[8] « (PDF) Leveraging LSTM for precision inventory management by future demand forecasting », ResearchGate. Consulté le: 20 avril 2025. [En ligne]. Disponible sur: https://www.researchgate.net/publication/389637476_Leveraging_LSTM_for_precision_inventory_management_by_future_demand_forecasting

[9] Y. Rao et L. Jia, « E-commerce fruit sales prediction based on machine learning », *International Agricultural Engineering Journal*, vol. 28, nᵒ 4, p. 366-372, 2019.

[10] K. D. Chaudhuri et B. Alkan, « A hybrid extreme learning machine model with harris hawks optimisation algorithm: an optimised model for product demand forecasting applications », *Applied Intelligence*, vol. 52, nᵒ 10, p. 11489-11505, 2022, doi: 10.1007/s10489-022-03251-7.

[11] R. Tugay et S. G. Öğüdücü, « Demand prediction using machine learning methods and stacked generalization », présenté à DATA 2017 - Proceedings of the 6th International Conference on Data Science, Technology and Applications, 2017, p. 216-222. doi: 10.5220/0006431602160222.

[12] K. Danach, A. Rammal, I. Moukadem, H. Harb, et A. Nasser, « Advanced Optimization in E-Commerce Logistics: Combining Matheuristics With Random Forests for Hub Location Efficiency », *IEEE Access*, vol. 13, p. 55915-55926, 2025, doi: 10.1109/ACCESS.2025.3550560.

[13] T. Antamis *et al.*, « AI-supported Forecasting of Intermodal Freight Transportation Delivery Time », présenté à ITMS 2021 - 2021 62nd International Scientific Conference on Information Technology and Management Science of Riga Technical University, Proceedings, 2021. doi: 10.1109/ITMS52826.2021.9615330.

[14] I. K. A. Hamdan, W. Aziguli, D. Zhang, et E. Sumarliah, « Machine learning in supply chain: prediction of real-time e-order arrivals using ANFIS », *International Journal of System Assurance Engineering and Management*, vol. 14, p. 549-568, 2023, doi: 10.1007/s13198-022-01851-7.

[15] B. Han et P. Li, « Apparel livestreaming sales forecasting models based on machine learning algorithms », *Journal of Silk*, vol. 61, nᵒ 7, p. 109-117, 2024, doi: 10.3969/j.issn.1001-7003.2024.07.012.

[16] A. Jha, P. Sharma, R. Upmanyu, Y. Sharma, et K. Tiwari, « Machine Learning-Based Optimization of E-Commerce Advertising Campaigns », présenté à International Conference on Agents and Artificial Intelligence, 2024, p. 531-541. doi: 10.5220/0012456700003636.

[17] C. Zhang, H. Zhang, T. Pu, et J. Pan, « Supply Chain Demand Forecasting Based on Data Mining Algorithm and Seq2Seq », *International Journal of Control, Automation and Systems*, vol. 23, nᵒ 1, p. 89-104, 2025, doi: 10.1007/s12555-024-0141-8.

[18] « PavoneGiulia2021.pdf ». Consulté le: 12 juin 2023. [En ligne]. Disponible sur: https://publications.ut-capitole.fr/id/eprint/44932/1/PavoneGiulia2021.pdf

[19] A. Ridwan, U. Muzakir, et S. Nurhidayati, « Optimizing E-commerce Inventory to prevent Stock Outs using the Random Forest Algorithm Approach », *International Journal Software Engineering and Computer Science (IJSECS)*, vol. 4, nᵒ 1, Art. nᵒ 1, avr. 2024, doi: 10.35870/ijsecs.v4i1.2326.

[20] L. Yue, Y. Yafeng, G. Junjun, et T. Chongli, *Demand Forecasting by Using Support Vector Machine*. 2007, p. 276. doi: 10.1109/ICNC.2007.324.

[21] Z. Fu, « Optimizing Retail Inventory Management Through Time Series Analysis », *Transactions on Economics, Business and Management Research*, vol. 10, p. 42-48, oct. 2024, doi: 10.62051/dy4kaf37.

[22] « Forecasting for Inventory Control With Exponential Smoothing | Request PDF », ResearchGate. Consulté le: 20 avril 2025. [En ligne]. Disponible sur:

https://www.researchgate.net/publication/4960215_Forecasting_for_Inventory_Control_With_Exponential_Smoothing

[23] Z. Sitorus, I. Syahputra, C. Indra Angkat, et D. Sartika, « Implementation of K-Means Clustering for Inventory Projection », *International Journal of Science, Technology & Management*, vol. 5, nᵒ 3, p. 673-678, mai 2024, doi: 10.46729/ijstm.v5i3.856.

[24] K. Chen, « An Online Retail Prediction Model Based on AGA-LSTM Neural Network », présenté à Proceedings - 2020 2nd International Conference on Machine Learning, Big Data and Business Intelligence, MLBDBI 2020, 2020, p. 145-149. doi: 10.1109/MLBDBI51377.2020.00032.

[25] J. Singh, N. A. Shelke, K. Upreti, F. B. J. Saiyad, P. Divakaran, et K. S. Madhukar, « Deep Learning Advancements in E-commerce Supply Chain Management in Forecasting and Optimization Strategies », présenté à 2024 IEEE 4th International Conference on Sustainable Energy and Future Electric Transportation, SEFET 2024, 2024. doi: 10.1109/SEFET61574.2024.10718068.

[26] A. A. Salamai, A. A. Ageeli, et E.-S. M. El-Kenawy, « Forecasting e-commerce adoption based on bidirectional recurrent neural networks », *Computers, Materials and Continua*, vol. 70, nᵒ 3, p. 5091-5106, 2022, doi: 10.32604/cmc.2022.021268.

[27] S. Bir et V. Dhir, « SCNN-UNet: A Novel Deep Learning Approach for Pulmonary Embolism Detection in COVID-19 Patients Using Super Pixel Segmentation », *Journal of Intelligent Systems and Internet of Things*, vol. 16, nᵒ 2, p. 187-201, 2025, doi: 10.54216/JISIoT.160214.

[28] J. Xiang, N. Zhang, R. Pan, et W. Gao, « Fabric Image Retrieval System Using Hierarchical Search Based on Deep Convolutional Neural Network », *IEEE Access*, vol. 7, p. 35405-35417, 2019, doi: 10.1109/ACCESS.2019.2898906.

[29] L. Wang, « Application of Deep Learning Based Inventory Optimization and Intelligent Demand Prediction in E-commerce », in *2024 International Conference on Power, Electrical Engineering, Electronics and Control (PEEEC)*, août 2024, p. 1150-1153. doi: 10.1109/PEEEC63877.2024.00212.

[30] E. Lee, M. Nam, et H. Lee, « Tab2vox: CNN-Based Multivariate Multilevel Demand Forecasting Framework by Tabular-To-Voxel Image Conversion », *Sustainability*, vol. 14, nᵒ 18, p. 11745, sept. 2022, doi: 10.3390/su141811745.

[31] F. Shareef, R. Ajith, P. Kaushal, et K. Sengupta, « RetailGPT: A Fine-Tuned LLM Architecture for Customer Experience and Sales Optimization », présenté à 2nd International Conference on Self Sustainable Artificial Intelligence Systems, ICSSAS 2024 - Proceedings, 2024, p. 1390-1394. doi: 10.1109/ICSSAS64001.2024.10760685.

[32] T. Nie *et al.*, « Joint estimation and prediction of city-wide delivery demand: A large language model empowered graph-based learning approach », *Transportation Research Part E: Logistics and Transportation Review*, vol. 197, 2025, doi: 10.1016/j.tre.2025.104075.

[33] S. Vij, A. Kumari, N. Akram, N. R. Kumar, D. Indoria, et H. Dubal, « Optimizing supply chain management through BERT-BiGRU softmax for demand forecasting and inventory management », 2025, p. 606-611. doi: 10.1201/9781003559115-98.

[34] « (PDF) Sentimental analysis based on RoBERTa for Amazon review: an empirical study on decision making », ResearchGate. Consulté le: 21 avril 2025. [En ligne]. Disponible sur: https://www.researchgate.net/publication/381854335_Sentimental_analysis_based_on_RoBERTa_for_Amazon_review_an_empirical_study_on_decision_making

[35] A. Kadam et H. Pitkar, « Optimizing Supply Chain Management with ChatGPT: An Analytical and Empirical Multi-Methodological Study », mars 2025, doi: 10.32996/jcsts.2025.7.1.25.

[36] T. Ménissier, « Les quatre éthiques de l'intelligence artificielle », *Revue d'anthropologie des connaissances*, vol. 17, nᵒ 2, Art. nᵒ 2, juin 2023, doi: 10.4000/rac.29961.

[37] G. T. S. Ho, Y. M. Tang, H. Y. Lam, et V. Tang, « A Blockchain-based Decision Support System for E-commerce Order Prediction », présenté à 5th International Conference on Artificial Intelligence in Information and Communication, ICAIIC 2023, 2023, p. 41-45. doi: 10.1109/ICAIIC57133.2023.10067036.