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Machine Learning Approaches for Pharmaceutical Demand Forecasting: A Bibliometric and Systematic Review of Methods and Research Trends

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ABSTRACT

Pharmaceutical demand forecasting plays a critical role in ensuring drug availability, reducing waste, and improving supply chain efficiency in healthcare systems. In recent years, machine learning (ML) techniques have emerged as promising tools for addressing the complex and nonlinear characteristics of pharmaceutical demand. This study presents a systematic and bibliometric review of machine learning approaches applied to pharmaceutical demand forecasting. A structured literature search was conducted in the Scopus database using Boolean query strategies to identify relevant studies published over the past decade. The retrieved publications were screened according to predefined inclusion and exclusion criteria. Bibliometric analysis was performed using VOSviewer to map research trends, collaboration networks, and keyword co-occurrence patterns. The analysis reveals a rapidly growing body of research in this field, with algorithms such as long short-term memory networks, random forest, artificial neural networks, extreme gradient boosting, and linear regression widely employed for pharmaceutical demand prediction. Compared with traditional statistical models, these machine learning techniques demonstrate superior capability in capturing nonlinear patterns, seasonality, and complex demand dynamics. The bibliometric results highlight several emerging research themes, including machine learning–driven supply chain management, sustainable pharmaceutical logistics, and hybrid forecasting models. In addition, the integration of advanced technologies such as block chain and enterprise resource planning systems is increasingly explored to improve transparency, data reliability, and forecasting performance. Overall, this review provides a comprehensive synthesis of current methodologies and research trends in pharmaceutical demand forecasting. The findings offer valuable insights for researchers and practitioners seeking to develop more accurate, scalable, and interpretable forecasting models for pharmaceutical supply chain management.

1. INTRODUCTION

In the healthcare sector, ensuring the availability of pharmaceutical stock is a critical concern that requires both cost-efficiency and sustainability in procurement and usage [1]. A significant challenge in this domain is demand uncertainty, which complicates inventory management and requires consideration of various risk factors when estimating future requirements [2]. Consequently, demand forecasting has become an essential tool in healthcare logistics and supply chain operations [3]. Forecasting methodologies are increasingly prominent across industries, particularly in pharmaceutical supply chains, where mathematical models are used to predict inventory trends [4]. These models often incorporate variables such as the number of healthcare facilities, patient counts, and daily consumption fluctuations to mitigate demand uncertainty [5]. Forecasting is now recognized as a strategic tool in sales and operations planning, enabling adjustments to production capacity, strategic positioning, and budgeting. It also enhances operational efficiency and mitigates external risks by providing insights into future demand patterns [6].

Despite its widespread application, forecasting in the pharmaceutical industry presents unique challenges due to the sector's sensitivity to fluctuations in political, social, and economic conditions. Accurate forecasting is crucial for effective planning and resource allocation, especially in pharmaceutical supply chains, where misalignment between supply and demand can have severe consequences. These consequences include disruptions in patient care, inefficiencies in drug distribution, and potential public health risks [7, 8]. Currently, many healthcare institutions rely on rudimentary forecasting methods, such as extrapolating annual demand from average monthly usage. Although simple, this approach often yields inaccurate projections, resulting in two primary issues: overstocking and stockouts. Overstocking leads to drug expiration and waste, while stockouts prevent patients from accessing necessary medications [9]. Both scenarios incur material losses, such as disposal costs and emergency procurement, as well as non-material consequences, including compromised patient safety and diminished trust in healthcare systems [10].

Given the financial and operational risks associated with ineffective drug demand planning, there is a pressing need for more accurate and responsive forecasting models. Recent advancements in artificial intelligence (AI) and ML have introduced sophisticated techniques that address the limitations of traditional statistical models. These techniques include linear regression (LR), decision trees, support vector machines (SVMs), random forests (RFs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks [11, 12]. Time series forecasting remains a foundational approach to demand prediction, relying on historical data collected at regular intervals to estimate future trends [7]. However, the complexity of pharmaceutical demand, characterized by nonlinear patterns, seasonal variations, and external disruptions, necessitates more robust models. ML techniques, particularly those capable of handling large datasets and capturing intricate temporal dynamics, offer promising alternatives.

Recent literature highlights emerging trends in AI and ML within the pharmaceutical sector. Notable contributions include a 2025 review of current and future trends in AI and LR for pharmaceutical supply security [13], a bibliometric overview of computer-aided drug design [14], a review of topic models, and a bibliometric analysis in healthcare applications using AI [15], Additionally, studies have examined bibliometric analysis of healthcare supply chain opportunities and challenges [16], a social network analyses in AI-enabled drug discovery and development [17], and a LR and bibliometric reviews of green and sustainable logistics [18].

This review critically examines the application of LR to pharmaceutical demand forecasting by integrating bibliometric analysis with an evaluation of the employed forecasting methods, a combination rarely addressed in the existing literature. Despite the growing use of LR algorithms such as LR, LSTM, AI, and RFs, current studies often lack methodological integration that connects algorithmic performance with broader research trends and thematic evolution. This gap limits the ability to identify systemic strengths, weaknesses, and opportunities for innovation in forecasting accuracy, responsiveness, and scalability. By mapping scholarly contributions and comparing data sources and algorithmic approaches, this review seeks to uncover these deficiencies and propose future research directions to advance healthcare supply chain management through more robust, data-driven strategies that mitigate demand uncertainty and optimize pharmaceutical logistics.

2. BIBLIOMETRIC APPROACH

This bibliometric review used the Scopus database for its comprehensive coverage and global recognition, with data extracted on August 4, 2025. Bibliometric mapping was conducted using VOSviewer to analyze research patterns and trends. From an initial 705 records retrieved from Scopus, the data were screened and refined to 150 relevant publications, of which 30 closely aligned with prevailing research trends. Overall, the study contributes to existing knowledge by integrating methodological insights with bibliometric trend analysis.

The Boolean search logic for the topic "LR Pharmaceutical Demand Forecasting" is structured as follows: ("LR" OR "artificial intelligence" OR "deep learning" OR "neural network" OR "predictive model" OR "data mining") AND ("pharmaceutical demand forecasting" OR "drug demand prediction" OR "medicine demand forecasting" OR "medication supply prediction" OR "pharmaceutical supply chain" OR "drug sales forecasting"). This structure incorporates synonyms and wildcards to ensure comprehensive retrieval of relevant studies while maintaining a focus on LR techniques and pharmaceutical demand forecasting. Adjustments may be made as needed to meet the specific database syntax requirements.

Inclusion criteria encompass studies that utilize LR or AI methods to predict or forecast pharmaceutical demand, leveraging historical data on sales, consumption, or distribution of medicines. Eligible works include empirical research, simulations, case studies, or systematic reviews published in reputable journals, conference proceedings, or technical reports, preferably within the last ten years and written in English or Indonesian. Exclusion criteria eliminate studies that do not involve AI-based forecasting, focus on non-pharmaceutical sectors, discuss supply chain theory without prediction modeling, or are opinion or editorial pieces lacking empirical analysis. Articles without full-text availability are also excluded.

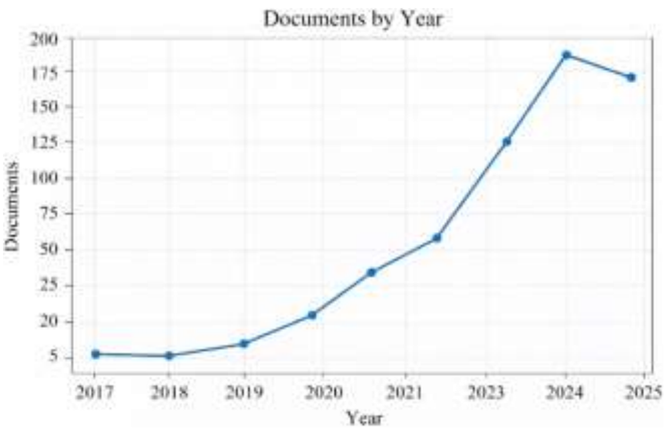

Figure 1. Documents by publication year in Scopus

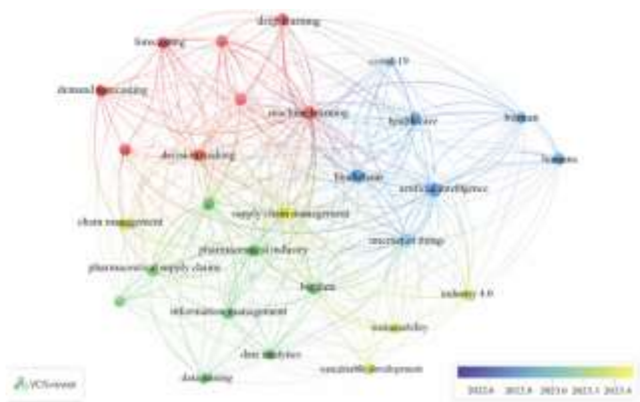

Figure 2. The network visualization in VOSviewer

Figure 1 illustrates a significant upward trend in scholarly interest over the past decade. Starting from just six documents in 2017, the number of research articles steadily increased, peaking at 202 in 2024. This surge reflects the growing importance of LR in pharmaceutical forecasting, likely driven by global healthcare challenges and the demand for more accurate predictive tools in supply chain management. Notably, although 2024 marked the highest publication count, a slight decrease to 183 documents in 2025 may reflect incomplete indexing for the current year or a natural stabilization in research output. The consistent growth from 2020 onward suggests that the topic has transitioned from emerging to mainstream, attracting interest from a range of interdisciplinary fields. This trend highlights future research opportunities, particularly in refining ML models and integrating real-world pharmaceutical data to develop more robust forecasting solutions.

Figure 2 presents a clear bibliometric map of author keywords, highlighting thematic clusters and patterns of keyword co-occurrence. Using VOSviewer, the visualization displays keywords as nodes, with node size indicating frequency and color representing distinct thematic clusters. Dominant keywords such as "LR," "deep learning," "demand forecasting," "supply chain management," and "artificial intelligence" serve as central nodes in the network, underscoring their pivotal role in pharmaceutical demand forecasting research.

The connections (edges) between nodes reveal strong interrelationships among keywords, indicating the interdisciplinary nature of the research. For instance, the close linkage between "LR" and "supply chain management" reflects the integration of predictive analytics into logistics and inventory planning. Similarly, the clustering of "deep learning," "artificial intelligence," and "forecasting" suggests a growing focus on advanced computational models in pharmaceutical applications. This visualization not only maps the intellectual structure of the discipline but also helps identify emerging research directions and potential gaps for further exploration.

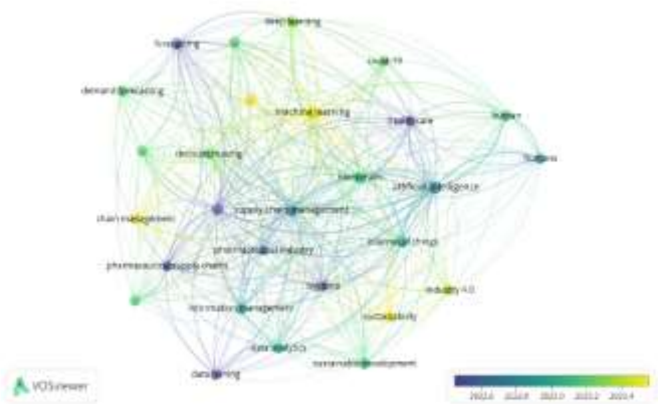

Figure 3. The overlay visualization VOSviewer

The trending keyword in 2023 and beyond is ML, as depicted in Figure 3. ML has become an integral component of pharmaceutical demand forecasting. Its implementation is crucial for the pharmaceutical supply chain, which faces complexities such as fluctuating demand, inventory management challenges, and regulatory compliance requirements. These challenges require sophisticated solutions to enhance accuracy and efficiency [19, 20]. One prominent aspect of using ML in pharmaceutical demand forecasting is its ability to synthesize and analyze vast amounts of historical sales data, seasonal trends, socio-economic factors, and health data. This comprehensive, data-driven approach enables dynamic forecasting models that adapt to changing circumstances, thereby optimizing inventory levels and enhancing distribution strategies [20]. For instance, algorithms such as time-series analysis, regression models, and neural networks have been shown to significantly improve demand-prediction accuracy while minimizing stockouts and waste [21].

The integration of predictive analytics powered by ML also improves resource utilization and medication adherence. By implementing advanced systems such as ERP platforms integrated with ML, pharmaceutical companies can enhance operational efficiency and ensure the timely availability of drugs, ultimately leading to better patient outcomes [22]. As noted by researchers, the collaboration between traditional forecasting methods and ML can yield superior results, especially in environments characterized by high variability and uncertainty [23]. Additionally, the application of advanced ML models such as LSTM networks and SARIMA (Seasonal Autoregressive Integrated Moving Average) is gaining traction for their ability to capture the complexities of seasonal demand fluctuations [24]. These models not only provide resilience against unpredictable demand but also improve decision-making processes in inventory control and production scheduling [25]. Another critical area of exploration within ML applications in pharmaceutical demand forecasting is the emphasis on transparency and accountability, which can be achieved through integrated systems such as blockchain. Implementing blockchain technology alongside ML can ensure the integrity of data used for forecasting while enabling real-time monitoring, which is critical for maintaining regulatory compliance and operational efficiency, as noted by Rahman [26]. Thus, the dual approach leveraging both ML and blockchain represents a forward-thinking strategy to address longstanding challenges in pharmaceutical supply chains.

ML dominates pharmaceutical demand forecasting because it addresses the sector's inherent complexities, including volatile demand, stringent regulations, and inventory challenges, through adaptive, data-driven solutions. Its ability to integrate diverse datasets, ranging from historical sales to socio-economic and health indicators, creates dynamic models that outperform traditional static methods. This approach is closely linked with predictive analytics, ERP integration, and blockchain technology, forming a holistic ecosystem that enhances transparency, operational efficiency, and regulatory compliance. Methodologically, ML introduces advanced algorithms such as LSTM and SARIMA, which allow for nuanced handling of seasonality and uncertainty. Practically, it drives smarter inventory control, minimizes waste, and ensures timely drug availability. Collectively, these innovations signal a paradigm shift toward resilient, technology-driven supply chains in healthcare.

The second keyword for 2023 and beyond is supply chain management, as depicted in Figure 3. Pharmaceutical supply chains are inherently complex, influenced by factors such as regulatory requirements, demand variability, and logistical challenges [19]. The effective application of predictive analytics through ML algorithms offers transformative potential for demand forecasting, risk mitigation, and inventory optimization. For instance, Adekola and Dada present a conceptual framework in which predictive analytics plays a pivotal role in enhancing decision-making and operational efficiency within these supply chains [19]. Similarly, Nguyen and Nghiem emphasize the proactive identification of potential disruptions through ML-based risk prediction, underscoring its indispensable role in minimizing financial losses and ensuring seamless operations [27]. Accurate demand forecasting is essential for the sustainability of pharmaceutical supply chains. Yani and Aamer's [28] study demonstrates that precise demand forecasting, powered by ML techniques, directly impacts the design and effectiveness of supply chain strategies. By leveraging ML algorithms, pharmaceutical companies can better align their production capacities with actual demand, thereby reducing both overstock and stockout situations. Additionally, Rahman's exploration of the synergy between blockchain technology and ML reveals how this integration enhances the integrity of supply chain transactions, further bolstering efficiency and transparency [26].

As the pharmaceutical sector approaches 2025, the critical role of ML in demand forecasting is underscored by case studies from leading pharmaceutical firms. According to Guo, these companies have increasingly adopted AI-driven solutions that have significantly optimized logistics and operational processes [29]. This result is echoed by Rizaldy et al. [30], who detail a comparative analysis highlighting the importance of forecasting accuracy in minimizing logistics costs and streamlining resource allocation. Furthermore, advances in AI empower pharmaceutical companies to proactively adapt to market changes, as discussed by Mottaghi-Dastjerdi and Soltany-Rezaee-Rad [31], who explore the role of AI and ML in optimizing inventory management and distribution. Following the pandemic, there has been a heightened focus on increasing supply chain resilience, leading to a reevaluation of traditional practices [32]. Stochastic optimization and model implementations offer strategic advantages for addressing operational uncertainties in the pharmaceutical sector, as noted by Badejo and Ierapetritou [33].

Supply chain management is central to pharmaceutical operations because it underpins the sector's ability to navigate regulatory constraints, demand volatility, and logistical complexities. It is closely intertwined with themes such as predictive analytics and LR. These themes are deeply interconnected: ML-driven forecasting enhances inventory optimization, risk prediction, and disruption management, while blockchain integration ensures transparency and data integrity across transactions. Methodologically, this convergence introduces advanced models, such as stochastic optimization and AI-enabled visibility tools, that strengthen resilience and adaptability in uncertain environments. Practically, these innovations enable proactive decision-making, reduce logistics costs, and align production with real-time demand, ultimately fostering a more agile and sustainable pharmaceutical supply chain in the post-pandemic era.

The third trending keyword in 2023 and beyond is sustainability, as depicted in Figure 3. In the context of pharmaceutical demand forecasting, sustainability has become a key theme, particularly as the industry faces numerous challenges stemming from rising demand, resource constraints, and ethical concerns about supply chain practices. The integration of LR (ML) techniques into pharmaceutical demand forecasting is expected to enhance operational efficiency and promote sustainable supply chain practices, ensuring that medicines are available to patients while minimizing waste and costs. Firstly, the necessity for sustainability in pharmaceutical demand forecasting underscores the critical role of accurate predictions in managing drug supplies. As highlighted by Angula and Dongo [34], effective pharmaceutical quantification plays a key role in reducing costs and optimizing inventory management. This requirement is crucial in healthcare systems, where drug shortages can have severe consequences. The integration of AI and ML is pivotal in enhancing forecasting accuracy, thereby supporting sustainability by improving resource management and minimizing waste [34].

Moreover, Adeleke and Samuel [19] emphasized the importance of AI-driven predictive analytics for optimizing supply chains. Their proposed framework signals a shift toward resilient supply chain systems that can respond to fluctuating demand while leveraging real-time data analytics to minimise their environmental footprint. The adoption of such technological advancements aligns with sustainability principles, enabling companies to maintain product availability without incurring excessive waste or financial costs [19]. Bilal et al. [35] highlighted the challenges faced by pharmaceutical supply chains, particularly in regions such as Ethiopia, where responsible forecasting is crucial for sustainable supply chain management. Their findings present a compelling argument for integrating innovative technologies and ethical responsibilities throughout the supply chain. Such approaches can contribute to a more integrated and sustainable framework for demand forecasting, emphasizing the importance of transparency and collaboration among stakeholders [35].

Furthermore, challenges such as fluctuating demand and stringent regulatory requirements necessitate the adoption of sophisticated forecasting models. Kakade and Vitalkar [36] discussed strategies to enhance inventory management practices by improving forecasting accuracy, enabling stakeholders to make well-informed decisions that not only bolster patient safety but also optimize supply chain efficiency. The integration of regulatory compliance within forecasting practices is crucial for ensuring sustainability while upholding ethical standards in public health [36]. LR methods, exemplified by Wagaw and Demisse [37] and Fourkiotis and Tsadiras [11], provide powerful tools for refining demand forecasts by analyzing complex datasets to uncover underlying patterns and trends. These insights support proactive management of drug inventories, which is essential to minimizing waste, a key aspect of sustainability in the pharmaceutical industry. By leveraging advanced algorithms, pharmaceutical companies can more accurately anticipate demand shocks and adjust inventory levels accordingly, thereby mitigating potential shortages or overstocking [37].

Sustainability is a central focus in pharmaceutical demand forecasting because it addresses the industry's pressing need to balance resource efficiency, ethical responsibility, and patient safety amid rising demand and regulatory constraints. This theme is closely interrelated with LR and supply chain management, as advanced ML-powered forecasting models enable precise inventory control, reducing waste and ensuring timely drug availability. Meanwhile, sustainable supply chain practices minimize environmental impact and operational costs. Methodologically, sustainability drives the adoption of AI-driven predictive analytics, real-time data integration, and compliance-focused frameworks that optimize resource allocation and enhance system resilience. Practically, these innovations foster transparent, collaborative systems that mitigate shortages, prevent overstocking, and uphold ethical standards, ultimately creating a more responsible and adaptive pharmaceutical ecosystem aligned with global sustainability goals.

3. FORECASTING METHODS EMPLOYED

Figure 4 illustrates the Forecasting Methods Employed in Pharmaceutical Demand Forecasting through LR. The reviewed literature reveals a broad spectrum of forecasting techniques applied to pharmaceutical drug demand, ranging from conventional statistical models to advanced LR algorithms. Among the most frequently employed methods are RF, LSTM, Artificial Neural Network (ANN), XGBoost, and LR. RF is widely acknowledged for its robustness in handling high-dimensional, nonlinear data; studies by Nabizadeh et al. [38], Mbonyinshuti et al. [9], and Haoudi et al. [39] confirm its efficacy. LSTM, a deep learning model designed explicitly for time series forecasting, has consistently demonstrated superior performance over traditional models, such as ARIMA, in capturing temporal dependencies, as noted by Mbonyinshuti et al. [12]. ANNs, used in various configurations, have proven effective for modelling complex relationships in data [40, 41], while XGBoost, a gradient boosting framework, has demonstrated high predictive accuracy in studies by Fourkiotis and Tsadiras [11].

The selection of forecasting methods is primarily influenced by the nature of the dataset and the complexity of demand patterns. Simpler models, such as LR, are often applied to datasets with linear trends; however, they are generally outperformed by more sophisticated models when dealing with dynamic, seasonal, or nonlinear data. LR models were particularly favored for their adaptability and precision in handling variability and uncertainty in pharmaceutical demand forecasting. This methodological diversity highlights the importance of tailoring forecasting techniques to specific data characteristics and operational requirements to achieve the most accurate predictive outcomes.

Figure 4. The forecasting methods employed

3.1 The long short-term memory

LSTM networks are particularly advantageous for modelling complex temporal patterns due to their ability to learn nonlinear relationships and dynamically adapt to factors such as market trends, seasonal fluctuations, and economic indicators [28, 42]. For instance, traditional statistical methods often fail to capture the intricate dynamics of pharmaceutical demand. Comparative studies consistently demonstrate that LSTM networks outperform traditional models, such as ARIMA, particularly when external variables are incorporated into the forecasting process, resulting in greater accuracy [34].

The utility of LSTM models is further enhanced when combined with external variables. Chen [42] highlighted that incorporating variables such as promotional activities, market conditions, and broader economic indicators significantly improves the accuracy and robustness of LSTM models. This integration reflects the growing recognition within the pharmaceutical industry of the need to use comprehensive datasets to improve demand predictions [19, 34]. Practical applications further underscore LSTM's relevance in pharmaceutical demand forecasting. Yani and Aamer [28] noted that adopting LR techniques, particularly LSTM, has led to substantial improvements in forecast precision, thereby helping mitigate common disruptions in pharmaceutical supply chains. These findings align with broader research emphasizing the transformative potential of AI and LR in the health and pharmaceutical sectors, suggesting that improved demand forecasting can enhance the availability of medicines and patient outcomes [11, 34]. Additionally, LSTM's versatility extends beyond basic demand forecasting; it can be tailored to optimize performance across different types of pharmaceutical products by adapting its architecture and training parameters to the unique characteristics of each segment [43]. This adaptability makes LSTM a practical and strategic tool in pharmaceutical logistics and the optimization of patient care.

A pivotal finding from the discussion is that LSTM networks not only outperform traditional statistical models such as ARIMA in pharmaceutical demand forecasting but also demonstrate transformative capabilities when integrated with external variables, such as promotional activities and economic indicators. This synergy enables LSTM models to dynamically adapt to complex, nonlinear market dynamics, significantly enhancing forecast accuracy and resilience against supply chain disruptions. Their architectural adaptability to different pharmaceutical product types further underscores their strategic value, solidifying LTSM as a cornerstone technology in the evolution of data-driven healthcare logistics and patient care optimization.

3.2 Artificial neural networks

ANN has gained increasing recognition for its effectiveness in pharmaceutical demand forecasting. The integration of AI and ML, including ANNs, into forecasting systems holds significant potential to enhance accuracy, optimize inventory levels, and improve overall supply chain efficiency in the pharmaceutical sector. Rathipriya et al. indicate that various neural network models, including Radial Basis Function (RBF), Generalized Regression Neural Network (GRNN), and Probabilistic Neural Network (PNN), are commonly applied for time-series pharmaceutical data forecasting [10]. These models capture nonlinear relationships in the data, enabling more precise demand predictions than traditional statistical methods. Furthermore, the study emphasizes the advantages of deep learning approaches, an evolution of ANN, which can improve forecasting accuracy by uncovering complex data patterns that simpler models often overlook.

In a broader context, Angula and Dongo's systematic review further emphasizes the transformative role of AI and ML in enhancing medication demand forecasting in public pharmaceutical systems. Their research suggests that incorporating ANN into forecasting models can improve cost efficiency, accessibility, and inventory management [34]. This work highlights the impact of AI on public health outcomes by enabling more efficient resource allocation and reducing waste. This finding suggests that incorporating ANN into demand forecasting frameworks can significantly alleviate management challenges faced by healthcare systems. Yani and

Aamer emphasize the ongoing need for advanced ML techniques in the pharmaceutical supply chain. Their research indicates that deploying LR algorithms, particularly ANN, can help mitigate supply chain disruptions [28]. Although forecasting challenges persist in this industry—including unpredictable demand fluctuations, a structured application of ANNs has the potential to offer adaptable solutions that enhance supply chain resilience.

Moreover, the conceptual framework proposed by Adeleke and Samuel underscores the importance of AI-driven predictive analytics for optimizing pharmaceutical supply chains [19]. Their findings demonstrate that integrating LR techniques, including ANN methodologies, into supply chain management strategies enhances decision-making and operational efficiency. This ongoing evolution of supply chain practices, amid stringent regulations and logistical constraints, illustrates the adaptability and efficacy of ANN in this context. Additionally, Fourkiotis and Tsadiras explore the application of LR and statistical forecasting methods for pharmaceutical sales predictions, underscoring the range of methodologies, including ANN, that can improve accuracy [11]. They posit that combining traditional statistical methods with advanced neural network techniques enables businesses to address market demands better. The literature indicates a growing consensus that a transformational wave is emerging through the use of AI and ANN in pharmaceutical demand forecasting. As supply chain management becomes increasingly complex due to external factors, the need for robust forecasting methods becomes paramount. This sentiment is supported by recent studies advocating for the adoption of ANN as a standard practice in future pharmaceutical demand forecasting [44-46].

A profound insight from the discussion is that ANN, particularly advanced variants such as RBF, GRNN, and PNN, are not merely enhancing pharmaceutical demand forecasting—they are redefining it by enabling systems to learn and adapt to complex, nonlinear patterns that traditional models often overlook. This evolution is especially critical in public health contexts, where accurate forecasting directly influences the accessibility, cost efficiency, and inventory management of medical services. The convergence of ANN with deep learning and predictive analytics frameworks empowers healthcare systems to anticipate disruptions, optimize supply chains, and make data-driven decisions within regulatory and logistical constraints. Consequently, ANN is emerging not just as a forecasting tool but as a strategic asset that transforms pharmaceutical operations and improves patient outcomes.

3.3 Extreme gradient boosting

Extreme Gradient Boosting (XGBoost) has emerged as a robust LR technique, particularly effective for demand forecasting within the pharmaceutical industry. The growing complexity of pharmaceutical supply chains, driven by factors such as regulatory compliance, demand variability, and logistics, necessitates accurate predictive analytics, where techniques like XGBoost can deliver substantial benefits. XGBoost is particularly well-suited for forecasting with limited datasets, making it advantageous for pharmaceutical companies that may lack extensive historical data. For instance, Abdurohman and Putrada [46] highlighted XGBoost's effectiveness even with short datasets, generally requiring less data than other deep learning methods, such as LSTM. This feature aligns well with the pharmaceutical domain, where data may often be sporadic due to the nature of drug production and market demands. Additionally, the model's inherent capacity to handle various data types, including categorical and continuous variables, enhances its adaptability across diverse forecasting scenarios [19].

Moreover, the pharmaceutical industry is experiencing unprecedented fluctuations in demand, as noted by Adeleke and Samuel [19]. Advanced AI-driven frameworks, such as those based on XGBoost, can improve decision-making and risk management, enabling pharmaceutical companies to adapt more rapidly to supply chain disruptions. Various studies have highlighted XGBoost's strong performance in scenarios characterized by uncertainty, thereby reinforcing its relevance for pharmaceutical demand forecasting, as reported by Mishra et al. [47]. Recent research has revealed that integrating XGBoost within broader supply chain management theories can significantly streamline operations. For instance, Mishra *et al*. conducted comparative analyses that established XGBoost as a leading algorithm for demand forecasting under uncertainty, outperforming several traditional methods. Furthermore, Pan [48] demonstrated that improvements in forecasting capabilities can directly improve inventory management and reduce costs, critical outcomes for pharmaceutical companies navigating volatile markets.

Given its significant advantages, it is critical to understand the specific contexts in which XGBoost excels. The combination of XGBoost with other models (such as SSA-XGBoost) has demonstrated improvements in forecasting accuracy by capturing complex patterns embedded in historical demand data [49]. These hybrid approaches provide pharmaceutical companies with deeper insights into demand trends, enabling them to optimize inventory levels more effectively and enhance service delivery. Angula and Dongo's [34] systematic review underscores the transformative potential of AI and LR for medication supply forecasting in public pharmaceutical systems, a subsector that stands to benefit significantly from improved demand predictability. As a central component of such AI methodologies, XGBoost plays a crucial role in enhancing efficiency and resource allocation across public and private pharmacy networks.

A particularly compelling finding from this analysis is the recognition of XGBoost as a highly effective forecasting tool, particularly in the pharmaceutical industry. This effectiveness stems from its ability to deliver accurate predictions even with limited and heterogeneous datasets, a common challenge in pharmaceutical supply chains. Unlike deep learning models that typically require extensive datasets, XGBoost thrives in data-constrained environments, making it especially valuable for forecasting in emerging markets or niche drug categories. Its flexibility in handling both categorical and continuous variables, along with its robustness in the face of uncertain and volatile demand conditions, positions XGBoost not only as a technical solution but also as a strategic enabler of agile decision-making. When integrated into hybrid models and broader supply chain frameworks, XGBoost empowers pharmaceutical companies to optimize inventory, reduce operational costs, and enhance service delivery, marking a significant shift toward intelligent, data-driven operations in healthcare logistics.

3.4 Linear regression

LR is a fundamental statistical technique for demand forecasting, particularly within the pharmaceutical industry.

Its simplicity, interpretability, and computational efficiency make it a widely adopted method for predicting demand based on historical data. The foundational principle of LR is to model the relationship between independent variables and a dependent variable, using the least-squares method to minimize discrepancies between observed and predicted values [50]. In the pharmaceutical sector, LR effectively addresses challenges, such as optimizing inventory levels and anticipating market fluctuations. Studies demonstrate that incorporating key variables, such as pricing, promotional efforts, and seasonal trends, into LR models can significantly improve forecasting accuracy [51]. For instance, research has shown that accurate demand forecasting directly affects logistics costs and resource planning in the pharmaceutical supply chain, underscoring the importance of robust predictive models [28].

The practical application of LR in pharmaceutical demand forecasting is supported by empirical evidence. Research indicates that LR can accurately predict sales performance by analyzing historical data, achieving high accuracy rates up to 98.505% in some instances [52]. Moreover, the method's transparency and ease of explanation make it appealing to stakeholders who require clear insights into demand drivers [53]. By using LR, companies can improve their demand predictions and align production and supply chain strategies accordingly [54]. While LR offers substantial advantages, it is essential to acknowledge its limitations, particularly those related to the assumptions of linearity and error independence. Advances in LR, such as integrating momentum-based gradient descent, have been proposed to accelerate convergence and improve forecasting performance [55]. Furthermore, comparisons with more complex LR methods suggest that LR can outperform these models in specific scenarios, especially when the underlying relationships in the data are approximately linear [56].

A key insight from this discussion is that, despite its simplicity, LR remains a powerful and highly interpretable tool for pharmaceutical demand forecasting, especially when the data relationships are linear. Its ability to incorporate key variables, such as pricing, promotions, and seasonality, allows actionable insights that directly influence inventory optimization and cost management. Notably, empirical evidence indicates that LR can achieve remarkably high accuracy up to 98.505% in specific pharmaceutical contexts, challenging the assumption that only complex LR models can deliver high-performance forecasting. Moreover, enhancements such as momentum-based gradient descent further enhance its effectiveness, suggesting that LR, when applied thoughtfully, can compete with more advanced techniques while maintaining transparency and building stakeholder trust in decision-making processes.

3.5 The random forest

RF method has become a key LR technique for pharmaceutical demand forecasting, providing innovative solutions to the industry's complex challenges, including fluctuating demand, regulatory constraints, and the need for precision in inventory management. This discussion synthesizes recent findings and applications of RF in this domain, highlighting its strengths and emerging trends. As a powerful ensemble learning technique, RF improves forecasting accuracy by combining the predictions of multiple decision trees. Research by Yani and Aamer [28] emphasized that accurate demand forecasting in the pharmaceutical supply chain significantly enhances recovery planning and resilience, asserting that RF is one of the leading LR algorithms for this purpose [28]. Additionally, empirical analysis by Taparia et al. [51] indicated that RF outperformed other regression algorithms in retail contexts, achieving the lowest mean absolute percentage error (MAPE) of 8%, which is crucial in demand forecasting. This capability is increasingly recognized in the pharmaceutical sector, as RF can adapt to the nonlinear relationships characterizing demand patterns, which is especially valuable.

Moreover, RF's adaptability is particularly suited for pharmaceutical supply chains, which are often influenced by external factors such as public health crises and seasonal variation trends. Adeleke and Samuel [19] elaborated on this adaptability, advocating for the integration of AI-driven analytics, specifically RF, into pharmaceutical supply chain management to optimize operational efficiency. This perspective aligns with a systematic review by Angula and Dongo [34], who identified RF as a prevalent model for predicting medication quantity demand in public health systems, highlighting its relevance for ensuring reliable supply in complex healthcare environments. The predictive power of RF is further enhanced by incorporating other ML techniques into hybrid models. For instance, Wang et al. [57] proposed a hybrid model integrating RF with LSTM networks, which significantly improves forecasting accuracy for utility demand. Furthermore, combining RF with neural networks has shown promise in effectively handling time-series data, a common challenge in pharmaceutical demand forecasting [58]. Research confirmed that RF models have delivered superior results, particularly in high-stakes situations such as pandemics or the management of critical medications during shortages [30]. The urgency of efficient demand forecasting in healthcare settings, especially hospitals, is underscored by Tufa et al. [59], who noted that pooled demand management strategies are essential for optimizing inventory control and reducing waste, particularly for essential medications, for which availability is crucial to public health [59].

A key takeaway from this discussion is that RF has emerged as a cornerstone in pharmaceutical demand forecasting due to its exceptional ability to model complex, nonlinear relationships and adapt to volatile market conditions. Its ensemble structure, which aggregates multiple decision trees, not only enhances predictive accuracy but also mitigates the risk of overfitting, making it particularly effective in volatile healthcare environments, such as those experienced during pandemics or drug shortages. Moreover, RF's flexibility is further enhanced when integrated with hybrid models, such as those incorporating neural networks or LSTM, enabling the precise handling of time-series data and external variables. This adaptability makes RF an invaluable tool for optimizing inventory, minimizing waste, and ensuring the timely availability of critical medications, thereby positioning it as a key enabler of data-driven healthcare logistics and policy planning.

3.6 Comparison of previous research based on machine learning algorithms and data sources

Table 1 presents a comparison of previous research using LR algorithms and various data sources. The integration of LR and forecasting techniques into pharmaceutical demand prediction has led to transformative advancements across healthcare and supply chain management. Studies by Nabizadeh et al. [38] and Fourkiotis and Tsadiras [11], for example, demonstrate how predictive models can accurately forecast hospital demands and sales trends. These models not only help reduce waste and prevent shortages but also enable more responsive and agile strategies to cope with fluctuating demand. Notably, the growing use of hybrid approaches that combine statistical methods with LR offers an ideal balance of accuracy and interpretability, key factors for decision-makers in the healthcare sector. The benefits of predictive analytics extend beyond demand forecasting to areas such as environmental and operational efficiency. Kermet-Said et al. [40] applied neural networks to wastewater treatment, demonstrating how AI can optimize pharmaceutical plant operations while ensuring regulatory compliance. Similarly, Li et al. [60] introduced a decomposition-ensemble methodology to forecast emergency medicine demand, which proves invaluable during health crises. These studies illustrate the versatility of LR, not only in predicting demand but also in supporting sustainability and enhancing emergency preparedness.

On the supply chain front, research by Emmanuel et al. [61] and Siddiqui et al. [62] highlights the transformative potential of LR in logistics, particularly during disease outbreaks. By integrating epidemiological data and hybrid models, these approaches enable dynamic, adaptable supply chains that respond to changing real-world conditions. Emmanuel et al.'s [61] systematic review further emphasizes the growing role of AI in building resilient pharmaceutical networks that can withstand disruptions and ensure uninterrupted care. Finally, the landscape of predictive analytics in healthcare continues to evolve rapidly. Surveys by Chen et al. [63] and Badawy et al. [64] illustrate the potential of deep learning in handling long time-series data and complex healthcare scenarios. These technologies are not just tools; they are becoming strategic assets. From traditional medicine forecasting in Indonesia to optimizing insulin distribution, the studies collectively suggest a future in which data-driven insights guide every aspect of pharmaceutical planning, leading to a more efficient, equitable, and intelligent healthcare system.

Table 1. Comparison of previous research based on LR algorithms and data sources

Ref.	Method	Important Findings
[65]	Golden Eagle Optimization and Extreme Gradient Boosting (EGEO-XGBoost)	The study found that the EGEO-XGBoost model significantly improved drug sales prediction accuracy, achieving 0.90 accuracy.
[38]	LR Algorithms	ML can effectively predict hospital pharmaceutical necessities.
[40]	Neural Network	NN accurately predicts the removal of solids and COD in pharmaceutical wastewater.
[11]	ML & Statistical Forecasting	Combined methods improve the accuracy of pharmaceutical sales predictions.
[66]	Short Time-Series Framework	Proposed framework for predicting drug consumption using short time series.
[67]	Single Exponential Smoothing	Effective for forecasting traditional medicine production.
[60]	Decomposition-Ensemble Methodology	A novel method improves forecasting of emergency medicine reserve demand.
[68]	RF	RF model predicts drug demand based on epidemiological factors.
[39]	ML Algorithms	ML enables optimal insulin distribution by predicting demand.
[61]	ML	ML enhances drug supply chain management during outbreaks.
[69]	Case Study	Planning improves pharmaceutical inventory management in hospitals.
[70]	Inventory Forecasting	Forecasting supports state-wide pharmaceutical inventory planning.
[71]	Structural Equation Modeling	Inventory management impacts hospital pharmacy supply chain performance.
[63]	Deep Learning Survey	DL is effective for long sequence time-series forecasting.
[41]	Deep Learning & Classification	DL models accurately predict drug demand.
[64]	ML & DL Survey	Predictive analytics in healthcare benefit from ML/DL techniques.
[62]	Hybrid Forecasting Model	Hybrid models enhance the accuracy of pharmaceutical demand forecasting.
[28]	ML Approach	ML enhances demand forecasting accuracy in pharmaceutical supply chains.
[72]	Data Analytics Review	Highlighting opportunities and challenges in pharmaceutical supply chain analytics.
[73]	ML with Supply Chain Information	ML with supply chain data improves pharmaceutical demand forecasting.

Note: LR = linear regression; ML = machine learning; RF = random forest; DL = deep learning; NN = neural network; COD = Chemical Oxygen Demand.

4. ADVANTAGES AND DISADVANTAGES

In recent years, LR methodologies have become increasingly prevalent in pharmaceutical demand forecasting due to their ability to handle complex, nonlinear relationships in data. Among the various algorithms available, LR, RF, LSTM, ANN, and XGBoost (Extreme Gradient Boosting) have garnered significant attention for their respective strength and weaknesses in this domain, specifically for the period from 2022 to 2025. LR remains a popular choice due to its simplicity and interpretability. It serves as a good baseline modeling technique, particularly when the relationship between independent and dependent variables is linear. LR is also computationally efficient and requires less training data compared to more complex models [51, 53]. However, its primary disadvantage lies in its inability to capture nonlinear relationships, which can lead to substantial forecasting errors, particularly in contexts such as pharmaceutical demand forecasting, where factors such as seasonality and market trends introduce nonlinear patterns [74].

RF is a powerful ensemble learning method that offers significant advantages in terms of robustness and accuracy [30]. RF excels in managing a large number of variables without variable deletion, making it suitable for complex datasets common in pharmaceutical demand forecasting [10, 28]. Nevertheless, a key disadvantage of RF is that it becomes less interpretable as model complexity increases, which can be a significant drawback for stakeholders who need actionable insights [75]. LSTM networks, a type of recurrent neural network, have demonstrated superior performance over traditional methods in time series forecasting, owing to their ability to retain long-term dependencies in sequential data [76]. This characteristic is particularly valuable in pharmaceutical demand forecasting, where historical demand plays a crucial role in predicting future demand. Furthermore, LSTM can incorporate exogenous variables, further improving forecast accuracy [77]. On the downside, LSTM networks require large amounts of training data and are computationally intensive, limiting their feasibility in certain applications [78]. Moreover, tuning LSTM models can be time-consuming and requires considerable expertise to understand their complex architectures.

ANNs are well-regarded for their capacity to model nonlinear relationships and extract insights from large datasets [79]. They have been instrumental in pharmaceutical demand forecasting, allowing companies to identify patterns in sales data and other relevant variables. However, like LSTMs, ANNs face challenges related to interpretability and require substantial training data to avoid overfitting [75, 80]. Their training can also be resource-intensive, which may deter smaller organizations from fully leveraging ANN models. XGBoost, renowned for its speed and performance, has been widely adopted due to its ability to efficiently handle large datasets and produce highly accurate predictions [30]. Its ensemble learning approach, which reduces bias and variance through regularization techniques, enables XGBoost to outperform many other LR methods. However, the downside is not without its drawbacks; it is susceptible to overfitting if not properly tuned, and its complex boosting algorithm can make it less transparent [51]. Like RF, XGBoost also requires careful parameter tuning, which can pose a barrier to use for non-expert users as shown in Table 2.

Table 2. The advantages and disadvantages

Ref.	Methods	Advantages	Disadvantages
[75]	ML algorithms (e.g., SVM, RF, ANN) for load forecasting	High accuracy and adaptability to smart grid data	Performance varies across models; requires tuning, and large datasets
[74]	Systematic review of ML/DL in building energy	Comprehensive overview; identifies best practices and gaps	Lacks experimental validation; mostly theoretical
[76]	DL vs traditional ML for advertising demand	DL captures complex patterns; better sustainability insights	DL models are resource-intensive and less interpretable
[78]	Wavelet-enhanced feature selection + DL	Improves multi-step forecasting accuracy; handles noisy data	Complex implementation and computationally demanding
[79]	ANN + (r, q) continuous review model	Minimizing total supply cost by integrating forecasting with inventory control.	Requiring accurate parameter estimation may not generalize well.
[10]	Shallow vs deep neural networks for pharma demand	Deep models outperform shallow ones in capturing time-series trends	Deep models need more data and training time
[30]	Comparative analysis of forecasting methods	Identifying optimal methods for pharma supply chain efficiency	May lack generalizability across different industries
[80]	ANN with backpropagation for bottled water demand	Effective for nonlinear demand patterns; scalable	Sensitive to initial weights; risk of overfitting
[77]	Hybrid LSTM-Neural Prophet model	Combining the strengths of both models is suitable for electric load forecasting.	Complex architecture requires careful tuning.
[53]	Linear regression for SIM card demand	Interpretable, simple, and fast computation	Limited in handling nonlinear trends and seasonality
[51]	ML for retail demand forecasting and price optimization	Enhances retail decision-making; supports dynamic pricing	Data quality and feature engineering are critical
[28]	ML for pharma supply chain forecasting	Improves accuracy and responsiveness in inventory planning	ML models may struggle with sparse or noisy data

Note: ML = machine learning; SVM = support vector machines; RF = random forest; ANN = Artificial Neural Network; DL = deep learning; LSTM = long short-term memory; SIM = subscriber identity module.

In summary, each LR method has distinct advantages and limitations when applied to pharmaceutical demand forecasting. LR offers simplicity and interpretability but struggles with nonlinear complexities; RF is robust against overfitting but sacrifices interpretability; LSTM excels in handling sequential data but requires substantial data and computational resources; ANN is effective at identifying patterns in complex datasets, albeit with similar resource concerns. Ultimately, XGBoost distinguishes itself for its speed and accuracy, although it necessitates careful tuning and may lack transparency.

5. CONCLUSION

This systematic review and bibliometric analysis highlight the growing role of ML in pharmaceutical demand forecasting, particularly in addressing the challenges related to demand variability, inventory optimization, and supply chain resilience. The study reveals that advanced ML models such as LSTM, RF, ANN, and XGBoost offer superior performance compared to traditional statistical methods, such as linear regression, especially in capturing complex, nonlinear demand patterns. Bibliometric mapping further illustrates the thematic evolution of research, with keywords such as "LR," "supply chain management," and "sustainability" emerging as dominant trends in the field. The integration of ML with technologies such as blockchain and ERP systems signals a transformative shift toward data-driven, intelligent pharmaceutical logistics that not only improve operational efficiency but also enhance patient outcomes.

This review contributes to the existing body of knowledge by bridging methodological insights with bibliometric trends, offering a comprehensive understanding of how ML techniques are applied and evaluated in pharmaceutical demand forecasting. It also identifies key gaps in current research, such as the need for hybrid models, the integration of real-world data, and the need for more interpretable complex algorithms. The findings underscore the strategic value of ML in healthcare planning and policy, suggesting that future research should focus on developing scalable, transparent, and context-aware forecasting frameworks. By combining bibliometric analysis with a thorough evaluation of forecasting methods, this study offers a roadmap for researchers and practitioners seeking to advance pharmaceutical supply chain management through innovative, AI-powered solutions.

While this review provides valuable insights into the application of LR in pharmaceutical demand forecasting, several limitations warrant attention. The bibliometric approach, although effective in mapping research trends, is inherently constrained by its reliance on indexed databases, which may exclude relevant gray literature or non-English studies, potentially introducing bias. Furthermore, most of the reviewed studies suffer from data scarcity and lack real-world validation, limiting the generalizability of the proposed models. Complex algorithms such as LSTM and XGBoost, though powerful, often lack interpretability, posing challenges for regulatory compliance and stakeholder trust. Future research should prioritize developing explainable ML frameworks, leveraging synthetic or federated data to address privacy and availability issues, and integrating predictive models with real-time supply chain systems to enable dynamic decision-making under uncertainty.

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