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A REVIEW OF ARTIFICIAL INTELLIGENCE MODELS FOR DEMAND FORECASTING IN HEALTHCARE SUPPLY CHAINS

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ABSTRACT

Healthcare supply chains, especially those handling essential medicines - still struggle with a basic but critical problem: making sure the right medicines are accessible when they're needed. In reality, this comes down to two issues: unreliable demand forecasts and inefficient inventory practices. Traditional statistical methods are widely used, but they tend to fall short when demand shifts due to seasonality, disease outbreaks, or policy changes. More advanced machine learning and deep learning models help capture these patterns better, but they're often not well incorporated with real-world decision-making.

This review looks at a variety of forecasting approaches, including statistical models like SARIMA, machine learning methods such as Random Forest and XGBoost, and deep learning techniques like LSTM. Each approach is examined based on what it does best- whether it's identifying trends, handling nonlinear relationships, or learning long-term demand patterns. Their performance is also discussed using standard evaluation parameters such as MAE, RMSE, and MAPE, which help compare their practical effectiveness.

Beyond forecasting, this paper also speaks about how these predictions can be utilised to guide inventory decisions. This includes basic but essential parameters like safety stock levels and reorder points. Studies that attempt to link forecasting with inventory management are reviewed critically to understand their usefulness in real-world settings. Overall, the review highlights a clear gap: while forecasting models are becoming increasingly advanced, fully integrated solutions that augment prediction with action are still limited. Addressing this gap is essential. Future work should concentrate on building practical, data-driven systems that not only enhance forecasting accuracy but also support better inventory decisions. This can help decrease waste, prevent stockouts, and ultimately improve access to essential medicines while enhancing the resilience of healthcare supply chains.

Keywords: Essential medicines; Demand forecasting; Healthcare supply chain; Machine learning; Deep learning.

INTRODUCTION

Healthcare supply chains are highly sophisticated networks that include varied groups, such as manufacturers, hospitals, regulators, and patients. This makes it hard to plan for demand and coordinate (Kumar, 2023).The pharmaceutical industry has shown exponential growth in recent years, with global revenues reaching extremely high levels, which increases the need for accurate demand forecasting. Managing such large-scale operations requires reliable predictions to avoid shortages or excess stock (Konstantinos P. Fourkiotis, 2024).

Accurate demand forecasting plays a critical role in supply chain performance, as it directly affects planning activities, customer satisfaction, and resource utilization. It is considered a key factor in avoiding stock-outs while minimizing resource wastage, especially in dynamic environments like healthcare systems (Aicha El Filali, 2022)

Healthcare supply chains face several challenges. Demand changes in pharmaceutical supply chains caused by seasonal patterns, consumption behaviour, and unexpected events like pandemics make it difficult to plan resources and make

reliable forecasts (Espinel & Barón, 2025). Additionally, healthcare supply chains often experience demand fluctuations, delays, and resource wastage, which can directly influence patient care and operational efficiency (Dr. Rishi JP, 2025)

In modern healthcare systems, managing large volumes of supply chain data has turned increasingly complex, requiring advanced technologies to improve forecasting accuracy and operational efficiency. Traditional statistical models such as ARIMA and SARIMA have been widely used but are limited in handling nonlinear and complex healthcare data (Jorge Blanco et al., 2026). Studies have shown that, while these models are suitable for time-series forecasting, they may fail with complex and dynamic healthcare datasets (Francois Mbonyinshuti, 2024)

Recent innovations and advancements in artificial intelligence (AI), particularly machine learning and deep learning, have improved forecasting accuracy by capturing complex patterns and integrating diverse variables. Factors influencing healthcare demand include demographic, economic, and health-related components, as described in Andersen's Behavioral Model (Fatih Orhan, 2025).

This review aims to examine AI-based models utilised for demand forecasting in healthcare supply chains and compare their effectiveness.

LITERATURE REVIEW

Increasing complexities and challenges in healthcare systems and pharmaceutical supply chains are being observed, due to which, the need for smarter product demand forecasting and adequate resource planning is paramount. The primary core of this challenge is demand prediction – accuracy is required to ensure that medicines are available whenever needed, while limiting unnecessary wastages and costs. Models like ARIMA and sARIMA have been used conventionally as they exhibit ability to forecast trends and identify seasonal patterns reasonably well (Douaioui et al., 2024; Meher et al., 2021). However, these methods tend to rely on fairly simple assumptions, and tend to struggle during cases of irregular demand or other real-world factor influences. (Douaioui et al., 2024).

This is where machine learning models find their applications. Models such as Random Forest and XGBoost are observed to be more suitable for capturing complex, non-linear relationships in data trends. In many cases, they have exhibited clear superiority over traditional models in terms of accuracy and reliability (Douaioui et al., 2024; Mbonyinshuti et al., 2021; Sattar et al., 2025). These models are particularly useful in the context of healthcare supply chains as they are capable of handling messy, incomplete data which can show high variability, a common issue in real-world settings (Douaioui et al., 2024; Mbonyinshuti et al., 2021; Sattar et al., 2025). On a larger scale, data-driven approaches aid organizations and planners to make better and quicker decisions across the supply chain (Riahi et al., 2021; Kumar et al., 2024).

Deep learning models have helped make further advancements to combat these issues. Models like LSTM (Long Short-Term Memory) have been specifically designed for sequential data, making them more suitable for time series forecasting. They pick up on long-term patterns and subtle demand shifts that simpler models tend to miss. Studies consistently show that LSTM models outperform both statistical and standard machine learning models when dealing with dynamic and unpredictable demand (Mbonyinshuti et al., 2024; Sierra Espinel & Suarez Barón, 2025). This is especially valuable during events like disease outbreaks and sudden demand spikes, where quick model adaptability is critical (Nguyen et al., 2021; Orhan & Kurutkan, 2025).

To reduce dependence on a single method, researches are now exploring hybrid and ensemble techniques. The basic idea is to combine the strength of different models to improve overall performance. For example, pairing SARIMA with machine learning or deep learning models would help capture both linear trends and complex patterns more effectively (Douaioui et al., 2024; Fourkiotis & Tsadiras, 2024). Ensemble methods take it a step further by combining multiple models, which often helps make more stable and reliable predictions in uncertain environments (Kaushik et al., 2020; Nguyen et al., 2021).

Beyond general forecasting, there is increasing interest on how predictions are actually made use of. Artificial intelligence is finding increased applications in the improvisation of inventory management and overall supply chain performance. With better forecasts, systems can adequately anticipate demand changes, reduce stockouts and help prevent overstocking (Kumar et al., 2024; Senapati et al., 2024). When forecasting and optimization techniques are combined, it makes it possible to balance multiple goals at once – cost, service levels and waste reduction (Pathy & Rahimian, 2023; Kaur & Prakash, 2025). This is particularly crucial in pharmaceutical supply chains, where uncertainty and product expiry add extra pressure (Hezam Al-Mishnanah et al., 2024; Boualam & Ibn El Farouk, 2025).

These challenges were more apparent during the COVID-19 pandemic. Traditional models failed under extreme conditions, while AI-based approaches exhibited greater flexibility in handling sudden disruptions and capturing shifting demand patterns (Goh et al., 2021; Vadaga et al., 2025). Newer frameworks are helping address emergency scenarios more directly, improving decisions around medical supply allocation and logistics during crises (Pang et al., 2025).

In spite of these advancements, clear gaps in the research exist. Many studies on model performance are set in controlled environments, which doesn't sufficiently reflect real-world complexity. There is a lack of thorough comparisons across different models under varying conditions of supply and demand. Most importantly, many approaches still treat forecasting and decision-making as separate problems, rather than focusing on integrating them into a single system with wider practical applications (Douaioui et al., 2024; Dixit & Shivhare, 2025; Waghodekar et al., 2025).

Gaps in Literature

Despite significant progress in demand forecasting for healthcare supply chains, several limitations remain. Most studies focus primarily on improving prediction accuracy but do not clearly link forecasts to practical inventory decisions, creating a gap between model performance and real-world application. In addition, statistical, machine learning, and deep learning models are quite often evaluated independently, with limited comparative analysis under consistent conditions.

Another key limitation is the lack of real-world validation. Many models are tested on controlled or clean datasets and do not fully capture demand variability, disruptions, or sudden spikes typical in healthcare systems. Furthermore, very few studies focus specifically on essential medicines, despite their importance being paramount to public healthcare delivery.

Finally, while hybrid and AI-based approaches are emerging, their application remains limited, and fully integrated frameworks that connect forecasting with operational decision-making are still largely underexplored.

METHODOLOGY

4.1 Approach to Research

This study employs a structured literature review approach to understand how demand forecasting is currently being handled in healthcare supply chains, particularly in case of essential medicines. Rather than building new models, the focus here is on analysing and comparing existing research. The goal is to get a clear picture of what methods are being used, where they perform well, and where they fall short.

4.2 Literature Selection

Relevant papers were gathered from well-known academic sources such as ScienceDirect, MDPI, Springer, and ResearchGate. To keep the study current, the focus was mainly on work published between 2020 and 2026, covering recent developments in machine learning and deep learning.

Search terms included combinations of keywords like demand forecasting, healthcare supply chain, machine learning, LSTM, and inventory optimization. Preference was given to peer-reviewed and Scopus-indexed journals to ensure reliability and quality.

4.3 Inclusion and Exclusion Criteria

Not every paper was relevant, so a clear filtering process was used.

Included studies:

Focus on healthcare or pharmaceutical supply chains. Use statistical, machine learning, or deep learning models. Provide clear methodology and performance evaluation

Excluded studies:

Unrelated to demand forecasting. Focused on non-healthcare domains without strong relevance. Lacked measurable results or proper evaluation

4.4 Data Extraction

From each selected study, key details were carefully noted. This included the type of model used (such as ARIMA, Random Forest, XGBoost, or LSTM), the application area, dataset characteristics, evaluation metrics (like MAE, RMSE, MAPE), and the main findings or limitations. This step helped build a consistent base for comparison across different studies.

4.5 Comparative Analysis Framework

To make the comparison meaningful, all studies were evaluated using a common set of criteria. This included prediction accuracy, ability to handle non-linear patterns, performance under changing demand conditions, data requirements, and practical usability in healthcare settings. Looking at each model through the same lens made it easier to identify real differences in performance.

4.6 Synthesis of Findings

After analyzing the studies individually, the results were brought together to identify broader patterns. This made it possible to compare statistical, machine learning, and deep learning approaches more clearly, and to understand where each one fits best. Emerging trends, such as hybrid models and AI-driven decision systems, also became more visible at this stage.

4.7 Identification of Research Gaps

The reviewed studies were further analyzed to identify common limitations and research gaps, which are mentioned in detail in Chapter 2.

RESULTS AND DISCUSSION

The analysis of the selected research papers highlights a significant evolution in healthcare demand forecasting, transitioning from traditional statistical models to advanced artificial intelligence (AI) and deep learning (DL) frameworks. The findings indicate that forecasting accuracy is influenced not only by the choice of algorithm but also by the quality of input data, feature engineering techniques, and the specific forecasting context. Collectively, these factors determine the effectiveness, scalability, and real-world applicability of AI-driven solutions in healthcare supply chains.

1. Comparative Performance of Predictive Models

Across the reviewed studies, deep learning models particularly Long Short-Term Memory (LSTM) consistently demonstrated superior predictive performance compared to traditional statistical approaches such as ARIMA. LSTM models were observed to accurately capture nonlinear relationships and temporal dependencies in healthcare demand data, exhibiting significantly lower prediction errors. For example, LSTM models achieved an accuracy of 93% with RMSE values around 2.043, whereas ARIMA models showed comparatively higher error values (RMSE ≈ 8.926), highlighting the challenges it faces with handling complex demand patterns (Mbonyinshuti et al., 2024). Similar results were seen in case of pharmaceutical demand forecasts, where LSTM exhibited lower RMSE and MAE values across varied drug categories (Sierra Espinel et al., 2025). Additionally, LSTM architectures with multi-layer optimizations showed significantly enhanced model performance, achieving a SMAPE value as low as 0.026 compared to 0.12 for ARIMA (El Filali et al., 2023).

Machine learning models, like XGBoost and Random Forest were also observed to exhibit strong predictive capabilities, when provided with structured healthcare datasets.

XGBoost achieved low error values (MAE ≈ 0.157; RMSE ≈ 0.533), demonstrating robustness in handling non-stationary demand patterns (Sattar et al., 2025). Random Forest models provided reliable performance with 88% training accuracy and 76% testing accuracy, outperforming traditional regression models and simple neural networks (Mbonyinshuti et al., 2022). Additionally, Gradient Boosting and Logistic Regression achieved high recall values (~0.90) and F1-scores (~0.87–0.88), making them suitable for healthcare utilization prediction (Orhan & Kurutkan, 2025).

Hybrid and ensemble approach consistently produced the most robust and accurate results by integrating multiple modeling techniques. A hybrid LSTM–GRU model achieved an accuracy of 95.8%, outperforming Gradient Boosting and ARIMA models in hospital logistics forecasting (Dixit & Shivhare, 2025). Similarly, the ICSL framework, which combines signal decomposition with deep learning, improved prediction accuracy by 29.37% over standard LSTM models (Pang et al., 2025). Ensemble models integrating ARIMA, multilayer perceptron (MLP), and LSTM further enhanced predictive stability and reduced variance across datasets (Kaushik et al., 2020). These findings collectively suggest that hybridization and ensemble learning are highly effective for addressing the complexity and variability of healthcare demand.

Model Type	Model	Key Performance	Application	Citation
Statistical	ARIMA	RMSE ≈ 8.926; Accuracy ≈ 85%	Medicine demand	(Mbonyinshuti et al., 2024)
Statistical	SARIMA	MAE = 1.18 (improved baseline)	Blood supply chain	(Silva Filho et al.)
Machine Learning	Random Forest	88% train; 76% test accuracy	Essential medicines	(Mbonyinshuti et al., 2022)
Machine Learning	XGBoost	MAE ≈ 0.157; RMSE ≈ 0.533	Demand forecasting	(Sattar et al.)
Machine Learning	Gradient Boosting	Recall ≈ 0.90; F1 ≈ 0.87	Healthcare utilization	(Orhan & Kurutkan)
Deep Learning	LSTM	RMSE ≈ 2.043; R^2 ≈ 0.912	Medicine demand	(Mbonyinshuti et al., 2024)
Deep Learning	Optimized LSTM	SMAPE ≈ 0.026	Pharma demand	(El Filali et al.)
Deep Learning	LSTM Autoencoder	Recall ≈ 0.9959; F-score ≈ 0.9698	Anomaly detection	(Nguyen et al.)
Hybrid	LSTM–GRU	Accuracy ≈ 95.8%	Hospital logistics	(Dixit & Shivhare)
Hybrid	ICSL Framework	+29.37% accuracy improvement	Emergency supply	(Pang et al.)
Ensemble	ARIMA + MLP + LSTM	Best overall performance	Expenditure forecasting	(Kaushik et al.)
Optimization + AI	GA + LSTM	Cost ↓ 22.5%; Efficiency ↑ 18%	Supply chain	(Rishi et al.)
Reinforcement Learning	MDP Model	Improved service level	Inventory management	(Kaur& Prakash)
ML (Feature-based)	Lag-based ML	Lag-1 ≈ 75% predictive power	Drug shortages	(Pall et al.)

2. Key Drivers: Data Quality and Feature Engineering

A crucial observation from the reviewed literature is that the quality of the data, along with the feature engineering utilised, often play a more decisive role in improving forecasting performance than model complexity alone. Traditional statistical models, which rely on historical demand data, showed limited ability to adapt in cases of sudden fluctuations. Conversely, AI-based models consolidated diverse datasets, including epidemiological factors, demographic features, seasonal patterns and policy-related variables, which significantly improve prediction accuracy and robustness (Rishi et al., 2025; Kaur & Prakash, 2025).

Feature engineering methods were found to help improve model effectiveness. Lag-based features, in particular, Lag-1 variables, accounted for nearly 75% of predictive power in drug shortage forecasts, elucidating the importance of recent demand patterns (Pall et al., 2023). Additional methods, including rolling averages, seasonal decomposition, noise reduction techniques using Iterative Variational Mode Decomposition (IVMD) have been shown to improve signal quality and mitigate forecasting errors (Pang et al., 2025). These findings highlight a clear shift toward data-centric forecasts, where the amalgamation of multi-source data and advanced preprocessing methods is necessary for optimizing model performance.

3. Forecasting Context and Horizon-Specific Performance

The reviewed studies reveal that the effectiveness of forecasting models is extremely dependent on the prediction horizon and application context. Deep learning models exhibit high effectiveness, particularly in case of short-term forecasts, like daily or monthly predictions for emergency medicines and critical care resources, due to their ability to efficiently capture demand patterns that show rapid fluctuations and non-linear trends. Machine learning models, like Random Forest and XGBoost, show a balance between accuracy and interpretability, rendering them suitable for medium term forecasts, like that of hospital inventory planning tasks.

Conversely, statistical models, like ARIMA and SARIMA maintain relevance for long-term forecasting scenarios, incorporating procurement and policy planning, where stability and trend analytics are prioritised over responsiveness to abrupt fluctuations. This variation suggests that there is no single model that is universally optimal, and elucidates the need for context-driven or hybrid forecasting networks that would address multiple time horizons within the healthcare supply chains.

4. Impact on Operations and Real-World Implications

The usage and integration of AI based forecasting models has demonstrated significant improvements in the performance of the healthcare supply chain, beyond just predictive accuracy. Cost reductions of upto 22.5% and an approximate improvement in delivery efficiency by 18% through use of optimized supply chain strategies were reported in studies (Rishi et al.,2025). Predictive analytics-based inventory management systems reduce stockouts by around 27.5% and overstocking by 21.4%, resulting in improved resource utilization and reduced wastage.

Advanced techniques, such as those which employ Markov Decision Process-based models improved inventory control under fluctuating demand conditions, particularly in case of epidemic scenarios (Kaur and Prakash, 2025). Furthermore, high recall values (0.9959) and F-scores (0.9698) were achieved by anomaly detection models using LSTM Autoencoders, enabling early prediction of irregular demand patters and potential supply chain disruptions (Nguyen et al., 2021). These observations demonstrate that AI-driven forecasts enhance predictive accuracy, and as a bonus, improve operational efficiency, resilience and decision-making in healthcare systems.

5. Limitations and Future Directions

In spite of the significant advancements, numerous challenges remain in the adoption and implementation of AI-based forecasting models. A major issue is the reliance on statistical evaluation parameters such as RMSE, MAE, and MAPE, which do not adequately capture real-world healthcare scenarios like stockouts, delayed therapies, and resource wastage. A relatively lower number of studies incorporated operational performance metrics, showing a gap between model evaluation and its practical relevance.

Additionally, deep learning models, even if they exhibit high accuracy, require considerable computational resources, large datasets, and technically skilled experts, which would limit their application in resource-constrained healthcare settings. Conversely, machine learning models, like Random Forest and

XGBoost, offer an increased practical balance between accuracy, reliability and scalability. An additional issue in case of advanced AI models is the lack of interpretability, which reduces trust and adoption among healthcare professionals and associates.

Further research should concentrate on the development and validation of hybrid, multi-horizon forecasting frameworks that incorporate diverse data sources, including real-time and epidemiological data. The usage of simple and easily explainable AI techniques is crucial to enhance transparency and trust in model predictions. In addition, multi-centre validation studies are required to ensure the generalizability and scalability of forecasting frameworks across varied healthcare settings.

6.CONCLUSION

The evidence gathered and analysed in this review elucidates that while AI models, particularly deep learning and hybrid models, have significantly improves predictive accuracy in healthcare demand forecasts, the field remains challenged by deeper structural constraints. Model performance shows heavy dependence on the quality of data, feature engineering, and contextual inputs rather than just algorithmic sophistication, yet, a vast number of studies continue to prioritize model comparison over data design. More importantly, the widespread dependence on statistical error metrics like RMSE and MAE fails to reflect real-world healthcare scenarios, including but not limited to stockouts, delayed treatments, and resource allocation failures. Despite exhibiting high accuracy, complex models, like LSTM and hybrid frameworks, face significant constraints to actual implementation due to high computational requirements, reduced interpretability, and reliance on continuous, high-quality data streams, rendering them less feasible for many healthcare systems. This results in a mismatch between theoretical performance and practical applicability, where simpler models would be more deployable but less suitable to capture volatile demand situations.

Moving forward, the field must change from accuracy-centric benchmarks towards the development of data-centric, interpretable and operationally aligned forecasting systems that augment real time and epidemiological data, utilise healthcare relevant evaluation criteria, and are validated across diverse, real-world settings to ensure scalability and clinical relevance.

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