Forecasting Drug Demand: A Review of Predictive Methods, Limitations, and Future Directions

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Abstract. Accurate forecasting of pharmaceutical demand is critical for healthcare sustainability, yet it faces persistent challenges stemming from data limitations and contextual complexities. This review synthesizes evidence from 12 studies (2018–2023) identified through systematic searches of Scopus, Web of Science, and DOAJ, with a focus on methodological approaches and implementation barriers. Geographically, the analyzed studies originated predominantly from Indonesia and Thailand, utilizing retrospective analyses of hospital, pharmacy, and primary care datasets. Methodologies included statistical models (e.g., ARIMA, SES) for stable demand patterns, machine learning techniques (e.g., LSTM, Random Forest) for epidemic-driven demand surges, and hybrid frameworks integrating both approaches. Both traditional statistical models and machine learning demonstrated promising results in predicting drug demand across healthcare facilities; however, several limitations were identified. Key gaps include the exclusion of multifactorial influences (e.g., socioeconomic factors), inconsistent data quality and scope, limited algorithm comparisons, and challenges in translating model complexity into practical implementation. To address these issues, future research should prioritize the expansion of datasets to encompass diverse geographic and demographic contexts, rigorous evaluation of additional algorithms (e.g., transformer-based models), and the development of user-centered forecasting tools that balance computational complexity with real-world feasibility.

Keywords: Forecasting, Predictive analysis, Drug consumption, Accuracy, Healthcare.

1 Introduction

Accurate forecasting of pharmaceutical demand is crucial for healthcare planning and policy development, as it helps in managing pharmaceutical expenditure and ensuring the sustainability of healthcare services [1], [2]. The pandemic led to widespread shortages of essential medicines, including IV sedatives for mechanical ventilation, cardiovascular drugs, anti-asthma medications, etc. Another study, conducting a systematic

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review, also stated that the availability of essential medicines in Asia is below the World Health Organization (WHO) standard [3]. These shortages were exacerbated by inaccurate predictions, manufacturing disruptions, export bans, and stockpiling by hospitals and patients [4]. Such misalignments between predicted and actual demand result in financial losses due to overproduction or stockouts [5], operational challenges such as increased disposal costs for expired drugs, and the need for emergency procurement during shortages [6].

Traditional models and emerging AI-driven approaches struggle with real-world complexities, including epidemiological shifts [7], socio-economic uncertainties [8], and limited amount of data infrastructures [9], underscoring the urgent need for adaptable solutions. Despite a surge in research exploring forecasting algorithms from classical time-series analyses to advanced machine learning, critical debates remain unresolved. While metrics like RMSE and MAPE dominate performance evaluations, the real-world applicability of AI in low-data environments or its added complexity remains contested [10]. Challenges like dataset bias, reproducibility issues from proprietary software dependencies, and inconsistent cross-study comparisons further hinder progress, leaving a gap between theoretical advancements and practical implementation.

This review addresses these limitations by (1) evaluating the methodological and dataset used in forecasting and (2) contrasting findings with implementation barriers and future perspectives. By advocating standardized reporting and WHO-aligned equitable access strategies, this work bridges technological potential with actionable solutions, paving the way for resilient, equitable healthcare systems.

2 Methods

2.1 Search Strategy

A literature search was conducted to identify studies that addressed forecasting models for predicting drug needs in healthcare facilities. Databases such as Scopus, Web of Science, and the Directory of Open Access Journals (DOAJ) were utilized, employing a search strategy that combined Boolean operators (AND, OR) with targeted terms, including “forecasting,” “drug forecasting,” “drug demand prediction,” “healthcare,” “pharmacy,” “primary health center,” and “hospital.”. The search was restricted to titles, abstracts, and full-text fields to ensure comprehensive coverage of relevant literature.

2.2 Eligibility Criteria

Inclusion criteria encompassed: 1) address forecasting methodologies for predicting medication requirements in healthcare facilities, (2) evaluate forecast accuracy, and (3) published in English from 2014 onward. Exclusion criteria eliminated non-empirical works such as systematic reviews, meta-analyses, letters, and commentaries, as well as articles with restricted access or paywalled content.

2.3 Data Extraction

Following the initial search, twelve articles met the eligibility criteria and were included for comparative analysis. The first author (MQA) independently extracted data pertaining to study characteristics, forecast algorithm and metrics accuracy, themes and key findings related to forecasting methodology, as well as limitations and future directions. To ensure consistency and minimize bias, co-authors (SS, SAK, FS) independently reviewed the extracted data. Discrepancies were resolved through iterative discussions.

2.4 Study Risk of Bias Assesments

The authors conducted bias assessments for the included studies using PROBAST (Prediction model Risk of Bias Assessment Tool), which serves as a framework for evaluating the risk of bias (ROB) and the applicability of prediction models. PROBAST is structured around four key domains: participants, predictors, outcomes, and analysis [11].

3 Results

3.1 Search Results

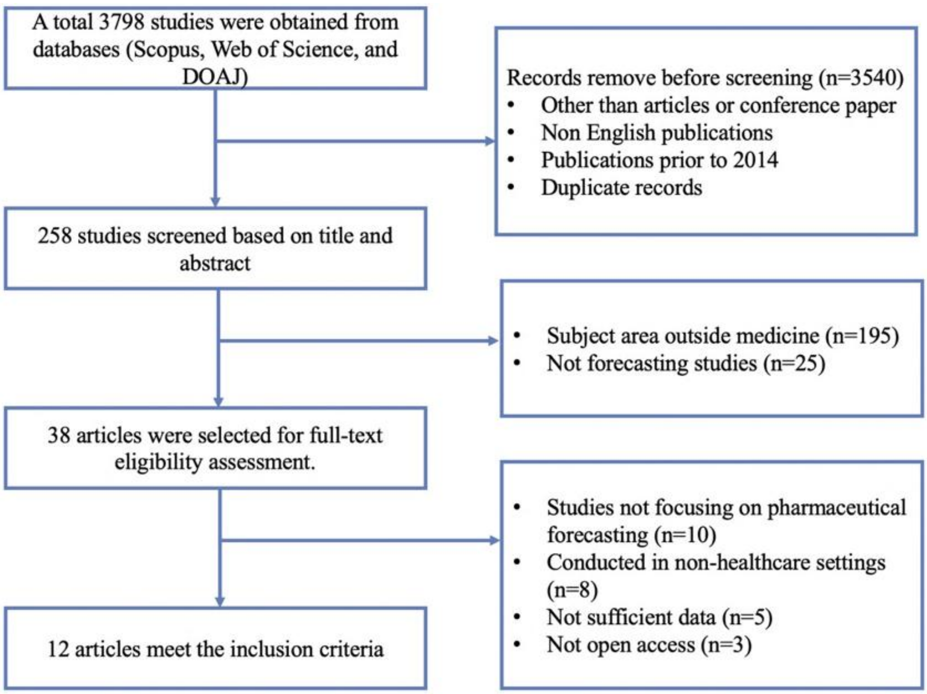

Fig. 1. Articles selection flowchart

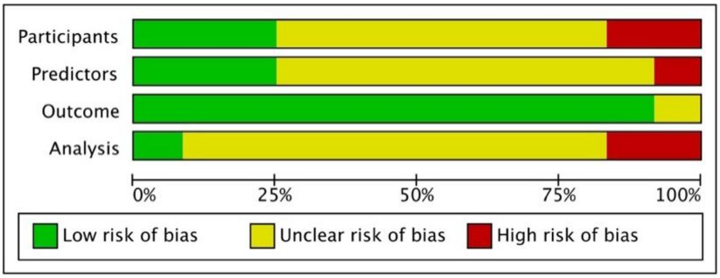

Fig. 2. Risk of bias graph

A total of 3.798 studies were identified through the database search. Following an initial screening of titles and abstracts, 38 articles were selected for full-text eligibility assessment. During the full-text review, studies were systematically excluded based on predefined inclusion and exclusion criteria. Ten articles were excluded for not focusing on drug demand or pharmaceutical forecasting, while eight were omitted due to being conducted in non-healthcare settings (e.g., industrial or logistical contexts unrelated to clinical practice). Five additional studies were excluded for insufficient discussion of forecast accuracy metrics, such as failing to report error measurements (e.g., MAPE, RMSE) or validation methods. Three articles were further removed due to the unavailability of complete text or incomplete data presentation. Ultimately, 12 articles met all the criteria and were deemed relevant to healthcare drug demand forecasting. These articles were retained for comparative analysis in the review, as shown in the flowchart in Fig. 1, while the results of the risk of bias assessment are presented in the risk of bias graph in Fig. 2.

3.2 Characteristics of Included Studies

The descriptive overview of the 12 included studies is summarized in Table 1. Temporally, all investigations were published between 2018 and 2023, reflecting recent advancements in drug demand forecasting research. Geographically, the majority of studies originated from Indonesia [7], [12], [13], [14], [15], [16], followed by Thailand [17], [18], [19], with additional contributions from China [20], Greece [21], and Iran [22]. Methodologically, all studies employed retrospective observational designs, with data collection settings spanning diverse healthcare contexts focused on hospital inventory systems [7], [13], [14], [15], [17], [18], [19], [20], primary healthcare centers [12], [16], and community pharmacies [21], [22]. The temporal scope of datasets varied substantially, ranging from short-term analyses (<1 year) to longitudinal evaluations (>5 years), with most data sourced directly from institutional records (e.g., electronic health records, pharmacy dispensing logs).

Table 1. Characteristics of included studies

Author, year	Country	Setting	Study Designs	Forecast subject	Dataset	Period
(Thaiudomsap and	Thailand	Hospital	Retrospective	Drug demand	Monthly demand for	2014-2019

Sribundit 2022)			observational study		41 drugs from the Samroiyod Hospital	
(Restyana et al. 2021)	Indonesia	PHCs	Retrospective observational study	Drug demand	Secondary data on 5 drugs with the biggest planned demand from 34 public health centers	2017-2019
(Permanasari et al. 2018)	Indonesia	Hospital	Retrospective observational study	Drug demand	Weekly usage of the digestive enzyme medicine Enzyplex at a hospital	January 2015-December 2015
(Yawara et al. 2023)	Thailand	Hospital	Retrospective observational study	Drug demand	29 AV drug usage data from the drug warehouse of the case study hospital, including drug list, unit price, order quantity, monthly discharged amount, order costs, and storage costs	July 2019-September 2021
(Yang 2024)	China	Hospital	Retrospective observational study	1. Outpatient volume 2. Hospital revenue 3. Drug demand	Hospital outpatient volume data, income data, and monthly sales data for 10 different drugs used in the hospital	2000-2011
(Husein et al. 2019)	Indonesia	Hospital	Retrospective observational study	Drug demand	Attributes such as gender, age of patient, ICD code,	2015-2017

					length of stay, and stock-based medical notes from patients	
(Fourkiotis and Tsadiras 2024)	Greece	Pharmacy	Retrospective observational study	Pharmaceutical sales	600,000 pharmaceutical sales records from a single pharmacy. The dataset was categorized into eight groups comprising 57 different products based on the Anatomical Therapeutic Chemical Classification System	2014-2019
(Jahani et al. 2025)	Iran	Pharmacy	Retrospective observational study	Drug demand	Hamedan University of Medical Sciences (HUMS) dataset, which contains 14,860 drug sales from 12 pharmacies	2019-2023.
(Zahra and Putra 2019)	Indonesia	Hospital	Retrospective observational study	Drug demand	Medicine usage data from Indramayu Regional General Hospital (RSUD Indramayu) including data on prescriptions and inpatient needs, with the unit of	3 year periode

					measurement being per item/tablet	
(Dengen et al. 2018)	Indonesia	PHCs	Retrospective observational study	Drug demand	Drug consumption data which consists of 197 samples obtained from the PHCs. The dataset includes 197 types of drugs, which are further categorized into 78 tablets, 22 syrups or infusion solutions, 24 nafza, 22 injections, 42 outers, 9 dentals, and 101 consumables drugs.	January-November 2017
(Laomala et al. 2024)	Thailand	Hospital	Re-trospective observatio-nal study	Drug demand	Three distinct types of time series datasets for drug demand forecasting: nonstatio-nary, inter-mittent, and multi-seaso-nal.	NA
(Emmanuel et al. 2023)	Indonesia	Hospital	Retrospective observational study	Drug demand	Annual drug used and data on 10 major diseases in private hospital	2017-2022

3.3 Drug Demand Forecasting Models

The reviewed studies employed three methodological strategies for drug demand forecasting. Statistical models [12], [15], [17], [18], offering reliable predictions for stable demand patterns, such as routine medication restocking, Machine learning algorithms including LSTM networks [13], [19], random forests [7], and neural network [20] addressed complex scenarios like demand surges during epidemics, and hybrid models combined both approaches to enhance accuracy in volatile settings [16], [21], [22]. To assess performance across these approaches, accuracy evaluation varied by objective: numerical predictions relied on error metrics like MAPE, MSE, and other metrics[12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], whereas classification studies prioritized precision, recall, and Cohen's kappa [7]. The methodological diversity necessitated tailored tools: while statistical analyses often used accessible tools like Excel, Minitab, Matlab or SPSS [12], [14], [15], [18], [20], machine learning workflows required Python's computational libraries (e.g., scikit-learn) to manage large datasets [7], [13], [19], [21]. An overview of the methodological approaches discussed in this section, including their accuracy metrics and implementation tools, is summarized in Table 2.

Table 2. Forecasting algorithm, metrics accuracy, and implementing tools

Author, year	Algorithm	Metrics Accuracy	Software Used
(Thaiudomsap and Sribundit 2022)	1. Single exponential smoothing 2. Croston 3. Syntetos-boylan approximation 4. Teunter, syntetos, and babai	RMSE MAD MASE	NA
(Restyana et al. 2021)	1. Single moving average 2. Single exponential smoothing	MAD MSE	Microsoft Excel
(Permanasari et al. 2018)	1. Long short term memory 2. Autocorrelation function and partial autocorrelation function	RMSE	Python
(Yawara et al. 2023)	1. Linear regression 2. Moving average 3. Exponential smoothing 4. Double exponential smoothing 5. Winters' model	MAD MSE MAPE	Minitab 19 Microsoft Excel
(Yang 2024)	1. Cubic polynomial regression model 2. Gray model 3. Neural network combination models (back propagation, radial basis function, generalized regression neural network) 4. LASSO variable selection model	MSE RMSE	SPSS Excel Matlab
(Husein et al. 2019)	1. Genetic algorithm 2. Genetic algorithm-adaptive neuro fuzzy inference system	RMSE	Matlab
(Fourkiotis and Tsadiras 2024)	1. Traditional forecasting: a. Autoregressive integrated moving average b. Exponential smoothing (single, double, and triple/Holt-Winters) 2. Modern machine learning techniques : a. Facebook prophet b. Long short term memory	MSE MAPE	Python

	c. XGBoost 3. Combination forecasting models		
(Jahani et al. 2025)	1. Classic models: a. Linear regression b. Support vector machines c. Decision trees, d. Fuzzy models e. Basic neural networks 2. Deep learning models: a. Long short term memory b. Gated recurrent unit c. Convolutional neural networks 3. Hybrid models: a. Combination of machine learning and time series techniques (the 5+1 team) 4. K-nearest neighbors and support vector regression	MSE	Python
(Zahra and Putra 2019)	1. Autoregressive integrated moving average 2. Autocorrelation function and partial autocorrelation function 3. Single exponential smoothing and double exponential smoothing	MAPE RMSE	SPSS
(Dengen et al. 2018)	1. Least square model 2. Autoregressive 3. Autoregressive moving average 4. Autoregressive integrated moving average 5. Seasonal autoregressive integrated moving average 6. Exponential smoothing 7. Hybrid and optimization models combining statistical and computational intelligence algorithms	MAD MSE MAPE	NA
(Laomala et al. 2024)	1. Long short term memory 2. Post-prediction adjustment strategies: a. Directional and undirectional double prediction models b. Self-adaptive strategies: • Simple residual adjustment • Recursive residual model • Time adaptive demand forecasting adjustment	RMSE	Python
(Emmanuel et al. 2023)	Random forest algorithm	Accuracy Precision Recall Specificity F-measure Cohen's Kappa	KNMIE software

3.4 Key Findings and Future Research Direction

The reviewed studies exhibit significant methodological diversity, driven by varying algorithmic frameworks and evaluation priorities. While some emphasized models with superior forecast accuracy, minimal error margins, and low bias [7], [12], [13], [14], [15], [16], [17], [20], [21], [22], others highlighted the operational advantages of demand forecasting, such as optimized healthcare resource allocation and cost reduction [13], [18], [19], and factors affecting forecasting results [19], [20], [21], [22]. The integration of epidemiological data was identified as a key enhancer of predictive precision [7]. However, notable limitations include models oversimplifying demand drivers by excluding multifactorial influences [17], limited model used [15], [21] alongside challenges linked to data quality and scope [15], [16], [17], [18], [20], [22]. Conversely, excessive model complexity was cautioned against, with emphasis placed on context-appropriate solutions [20], [22]. All studies stated that future efforts should prioritize comparative analyses of other algorithms, broader datasets [7], [21], [22], and user-centric forecasting tools to translate theoretical innovations into practical healthcare applications [12], [13], [19], [20]. Synthesis of empirical findings is presented in Table 3, while limitations and future research are presented in Table 4.

Table 3. Synthesis of key findings

Author, year	Findings Themes	Key Findings
(Thaiudomsap and Sribundit 2022)	Comparison between forecasting models	1. Teunter, syntetos, and babai: best forecast accuracy, but highest bias 2. Single exponential smoothing: second-best forecast accuracy, but least bias 2. Syntetos-boylan approximation: lower forecast errors than the Croston, but higher bias
(Restyana et al. 2021)	Comparison between forecasting models	1. Single exponential smoothing is more accurate than single moving average based on smaller error measurements 2. Single moving average and single exponential smoothing were determined to have small error measurements overall
(Permanasari et al. 2018)	1. Accuracy of specific model 2. Operational advantages of forecasting	1. Long short term memory is suitable for forecasting time series data on medicine usage, with an RMSE value of 12.733 and closely matched the actual values 2. Predicting medicine usage can help healthcare institutions better manage their medicine resources
(Yawara et al. 2023)	Operational advantages of forecasting	1. The study used five forecasting models to determine the optimal forecasting model for each of the 29 AV drugs, selecting the model with the lowest error 2. To determine the optimal order quantity, reorder point, and safety stock drugs with constant demand used EOQ, while drugs with variable demand used Newsboy model

		3. The proposed drug order planning management model reduced the total annual drug inventory cost by 22.15%
(Yang 2024)	1. Accuracy of specific model 2. Factors affecting forecasting results 3. Comparison between forecasting models	1. A combined neural network for predicting outpatient volume had a 99.3% prediction accuracy for 2011 data 2. GDP, regional population, number of hospitalizations, residential operations, and bed turnover identified by LASSO as the 5 most important factors affecting hospital revenue 3. Combined neural network for predicting drug demand had the highest accuracy and stability compared to individual neural network
(Husein et al. 2019)	Comparison between forecasting models	1. The GA-ANFIS had an RMSE of 0.6598 for predicting drug usage in 2017, which was better than the standard ANFIS 2. The authors suggest that the particle swarm optimization approach may produce even better results than the GA-ANFIS
(Fourkiotis and Tsadiras 2024)	1. Comparison between forecasting models 2. Factors affecting forecasting results	1. Machine learning techniques (XGBoost) outperformed traditional forecasting in predicting pharmaceutical sales 2. Seasonal variations play a significant role in pharmaceutical sales 3. Long short term memory has potential in pharmaceutical sales forecasting, but its performance was hindered by the constraints of a limited dataset
(Jahani et al. 2025)	1. Comparison between forecasting models 2. Factors affecting forecasting results	1. The results showed that the winning model achieved lower MSE rates compared to traditional demand prediction models 2. The winning model utilized a variety of machine learning techniques, including hybrid models combining long short term memory, K-nearest neighbors, and support vector regression, along with feature engineering to improve the accuracy of their drug demand forecasts
(Zahra and Putra 2019)	Comparison between forecasting models	The ARIMA (1,0,0) had the smallest error value of 13% compared to other models and was used to calculate the EOQ for future drug needs
(Dengen et al. 2018)	Accuracy of specific model	The Least Square provided reasonably accurate forecasts of drug consumption, with MAD of 51.20%, MSE of 66.29%, and MAPE of 10% and viable option for forecasting drug availability
(Laomala et al. 2024)	1. Operational advantages of forecasting 2. Factors affecting	1. Long short term memory provided strong baseline predictions for drug demand forecasting across three distinct time series datasets 2. Post-prediction strategies, particularly Directional Double Prediction (DiL) and Time Adaptive Demand Forecasting Adjustment

	forecasting results	(TADFA), significantly improved the accuracy of the LSTM predictions 3. DiL and TADFA reduced the total inventory expenses over 52 and 60 weeks compared to using the Long short term memory alone
(Emmanuel et al. 2023)	1. Accuracy of specific model 2. Factors affecting forecasting results	Random Forest algorithm achieved 90% accuracy in predicting drug demand using a model that considers consumption cycles and therapy group classifications, based on historical data from 10 major diseases in private hospitals

Table 4. Limitations and future directions

Author, year	Limitations	Future Directions
(Thaiudomsap and Sribundit 2022)	Data quality and scope	Analysis of other algorithms
(Restyana et al. 2021)	NA	1. Analysis of other algorithms 2. Development of user-centric forecasting tools
(Permanasari et al. 2018)	NA	1. Analysis of other algorithms 2. Development of user-centric forecasting tools
(Yawara et al. 2023)	Data quality and scope	Analysis of other algorithms
(Yang 2024)	1. Data quality and scope 2. Model complexity	1. Analysis of other algorithms 2. Expand the dataset 3. Development of user-centric forecasting tools
(Husein et al. 2019)	NA	Analysis of other algorithms
(Fourkiotis and Tsadiras 2024)	Limited model used	1. Analysis of other algorithms 2. Expand the dataset
(Jahani et al. 2025)	1. Data quality and scope 2. Model complexity	1. Analysis of other algorithms 2. Expand the dataset
(Zahra and Putra 2019)	1. Limited model used 2. Data quality and scope	Analysis of other algorithms
(Dengen et al. 2018)	Data quality and scope	Analysis of other algorithms
(Laomala et al. 2024)	NA	1. Analysis of other algorithms 2. Development of user-centric forecasting tools
(Emmanuel et al. 2023)	NA	1. Analysis of other algorithms 2. Expand the dataset

4 Discussion

The efficacy of forecasting algorithms in predicting drug demands is contingent upon data integrity and contextual relevance. For instance, Emmanuel et al. demonstrated that integrating epidemiological variables with a Random Forest model improved prediction accuracy by 4.5 % (77.3 % to 81.8 %) [7], a margin critical for avoiding stockouts in malaria-prone regions. This aligns with Stonebraker and Keefer the assertion that contextual data, such as disease prevalence, enhances forecasting precision by bridging statistical outputs with real-world health dynamics [23]. The persistent variability in performance metrics (e.g., MAE vs. RMSE) across studies complicates cross-model comparisons, underscoring the need for standardized evaluation frameworks. Metric selection inherently biases the perceived efficacy of forecasting models, as certain algorithms may excel under specific criteria while faltering in others. For instance, models optimized for mean absolute error (MAE) may underperform when evaluated using root mean squared error (RMSE), creating inconsistencies in benchmarking [24]. Such variability underscores the urgency for transparent and reproducible methods to enhance the credibility and reliability of forecasting studies, ultimately leading to better decision-making [25].

Empirical evidence suggests that algorithmic complexity does not inherently guarantee superior forecasting accuracy. While advanced models (e.g., deep learning) may excel in data-rich environments, their performance often plateaus in scenarios with limited or noisy datasets, where simpler methods (e.g., ARIMA, Exponential Smoothing) can achieve comparable precision. For instance, Restyana et al. (2021) observed minimal accuracy disparities between Single Exponential Smoothing and computationally intensive techniques in drug supply predictions, underscoring that simplicity, when aligned with data characteristics, remains a viable strategy. This phenomenon may stem from overfitting risks in complex models, which prioritize training data patterns over generalizable trends [26]. Consequently, the efficacy of a forecasting approach depends less on algorithmic sophistication and more on its congruence with contextual constraints, such as data granularity, operational infrastructure, and the predictability of demand drivers [27]. Hybrid frameworks that strategically combine interpretable baseline models with context-specific adaptations (e.g., integrating seasonal outbreak data into ARIMA) may thus offer a pragmatic middle ground, balancing robustness and relevance [19].

The identified limitations, particularly the use of narrow datasets and the exclusion of socio-economic variables, underscore the need for methodological improvements. Future research should consider hybrid models that integrate statistical and artificial intelligence techniques to enhance both accuracy and interpretability. These models should incorporate real-time clinical, demographic, and supply chain data and be co-designed with healthcare professionals to ensure practical applicability across diverse settings, such as hospitals and primary healthcare centers. For healthcare institutions, the findings suggest a tiered forecasting approach: employing robust yet interpretable models for routine demand, while utilizing more complex algorithms in high-variability or critical scenarios. At the policy level, addressing systemic challenges such as fragmented health information systems is essential to fully leverage the benefits of forecasting in improving medicine supply planning and healthcare delivery.

5 Conclusion

Forecasting methods hold promise as critical tools for drug demand prediction, requiring approaches that balance precision with feasibility and robust data preparation. Transparent, reproducible strategies, which apply AI for complex scenarios and simpler models for resource-constrained settings, must integrate socio-economic and epidemiological variables. Such alignment with global health imperatives ensures equitable access to medicines.

Abbreviations. DOAJ: Directory of Open Access Journals; ARIMA: Autoregressive Integrated Moving Average; SES: Single Exponential Smoothing; LSTM: Long Short Term Memory; GA: Genetic Algorithm; ANFIS: Adaptive Neuro Fuzzy Inference System; EOQ: Economic Order Quantity; RMSE: Root Mean Square Error; MAD: Mean Absolute Deviation; MASE: Mean Absolute Scaled Error; MSE: Mean Square Error; MAPE: Mean Absolute Percentage Error; GDP: Gross Domestic Product.

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