International Journal of Innovative Information Systems & Technology Research 14(4):199-216, Oct-Dec, 2026

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DOI:10.5281/zenodo.23568364

An Integrated LSTM Framework For Joint Forecasting Of Emergency Department Arrivals And Hospital Bed Occupancy

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ABSTRACT
Emergency departments (EDs) in Nigerian hospitals plan staff and beds reactively because demand is rarely forecast. This study developed and evaluated EDABO, a forecasting framework for emergency department arrivals and bed occupancy, at Plateau State Specialist Hospital (PSSH), Jos, and Jos University Teaching Hospital (JUTH) with a Long Short-Term Memory (LSTM) network as its deep-learning core. The study followed the CRISP-DM methodology. Before modelling, a data-provenance audit compared every file supplied with the hospital's ED register; two daily files were excluded because their totals did not agree with the register ($r = 0.12$) and their values were repeated from 62 January days. The analysis therefore used the genuine monthly register of outpatient arrivals and road traffic accident (RTA) and suturing cases from January 2021 to December 2025. Exploratory analysis revealed a disrupted regime (2021–2023) and a stable regime (2024–2025), with no significant calendar seasonality. The LSTM was compared with seven alternatives (naive, seasonal naive, three-month mean, damped exponential smoothing, SARIMA, XGBoost and a forecast combination) using a rolling-origin evaluation over 24 out-of-sample months, four accuracy measures and Diebold–Mariano tests. The three-month mean was the most accurate one-month-ahead forecast of outpatient demand (MAE 124 patients per month; MAPE 11.2%). Trained on the raw history, the LSTM was significantly less accurate than the naive forecast (MAE 339.6; $p = 0.005$). A leakage-free, disruption-aware training rule proposed in this study reduced forecast errors by 19.7–45.1% across six methods, including a 34% reduction for the LSTM. Rolling conformal prediction intervals were narrower or better calibrated than parametric SARIMA intervals. Because the register records bed capacity but not occupancy, bed demand was expressed as a capacity-pressure index, and the framework's occupancy module awaits a daily bed census. The study concludes that data quality and preparation matter more than model complexity for small hospital datasets, and it recommends monthly forecasting with prediction intervals, a daily bed census and a disruption log at PSSH, and JUTH.

Keywords: Health care, Exploratory analysis, Jos University Teaching, Emergency department

INTRODUCTION

The healthcare sector plays a pivotal role in ensuring the well-being of populations; however, hospitals worldwide face persistent challenges in managing fluctuating patient demands and limited resources. Among the most pressing issues are Emergency Department (ED) overcrowding and hospital bed shortages, which adversely affect patient outcomes, staff productivity, and healthcare costs (Ahmed, Kumar, & Desai, 2022). The efficient management of these challenges relies heavily on accurate forecasting of patient arrivals and hospital bed occupancy levels. Traditionally, hospitals have utilized statistical forecasting models, such as Auto-Regressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA), to predict patient inflow and bed utilization. While these methods can identify seasonality and trends, they often fail to account for nonlinear patterns or external factors that affect hospital demand, such as weather, holidays, or disease outbreaks (Chen & Wang, 2021). As a result, their predictions may lack the accuracy required for proactive hospital management.

Emergency Departments (EDs) globally are facing unprecedented pressure as escalating patient demand outpaces available staff, infrastructure, and bed capacity. This imbalance leads to chronic overcrowding, prolonged waiting times, and delayed treatments, which Sun et al. (2023) link to increased patient mortality and reduced care quality. A primary cause of this crisis is the inability of hospitals to accurately predict patient inflows and subsequent bed requirements, resulting in a persistent mismatch between resource availability and actual demand. Chen and Wang (2021) highlight that poor bed occupancy management disrupts overall hospital flow and exacerbates congestion.

Current hospital forecasting primarily relies on traditional statistical models, such as ARIMA or regression, which assume stable, linear patterns. However, the hospital environment is inherently volatile, with demand fluctuating sharply due to accidents, seasonal illnesses, and public holidays. Traditional methods often fail to capture these non-linear, complex irregularities. While recent advancements in Artificial Intelligence (AI), specifically Long Short-Term Memory (LSTM) models, have shown the ability to learn long-term temporal dependencies in sequential data, a significant research gap persists.

Recent developments in Artificial Intelligence (AI) and Machine Learning (ML) have introduced powerful tools capable of analyzing large and complex datasets. These tools can uncover hidden temporal dependencies. Models like Long Short-Term Memory (LSTM) networks and Gradient Boosted Decision Trees (XGBoost) have demonstrated higher forecasting accuracy than traditional approaches (Li, Zhang, & Liu, 2023; Sun, Chen, & Wang, 2023). They can combine multiple data sources, such as patient flow, admissions, environmental factors, and operational variables to produce predictions that are more accurate, dynamic, and easier to interpret.

AI-driven forecasting systems have been successfully adopted in various domains, including energy demand, transportation, and finance, but their integration into hospital management systems remains limited (Oladipo, Park, & Seo, 2020). Developing an AI-based forecasting framework for predicting ED arrivals and bed occupancy can help hospitals anticipate future demands, optimize resource allocation, and improve staff scheduling, thereby reducing waiting times and enhancing patient care quality. This study aims to bridge this gap by proposing a forecasting system that combines both tasks into a single model for better hospital management.

II LITERATURE REVIEW

2.1 Conceptual Framework

This section defines and discusses the key concepts and variables in this study to establish a clear understanding of their relevance and interrelationships. The main concepts derived from the research topic include Artificial Intelligence (AI), Forecasting, Emergency Department (ED) Arrivals, Bed Occupancy, and Hospital Management.

2.1.1 Artificial Intelligence (AI)

Artificial Intelligence (AI) refers to computational systems capable of performing tasks that traditionally require human cognition such as reasoning, learning, and decision-making (Awasthi et al., 2025). In

healthcare settings, AI harnesses algorithms and data-driven models to automate complex clinical and operational processes. These models process vast quantities of medical and administrative data to discern hidden patterns, support clinical decision-making, and generate predictive insights (Nong et al., 2025). In this study, AI techniques are applied to forecasting hospital operations namely, Emergency Department (ED) arrivals and bed occupancy with the goal of enhancing planning precision and optimizing resource allocation within hospital management systems.

2.1.2 Machine Learning (ML) and Deep Learning (DL)

Machine Learning (ML), a subfield of Artificial Intelligence (AI), enables computer systems to automatically learn from historical data and improve their performance through experience without explicit programming (Kumar & Li, 2024). Deep Learning (DL), a more advanced category of ML, employs neural networks with multiple hidden layers to capture complex, nonlinear, and hierarchical data relationships (Hochreiter & Schmidhuber, 1997; Zhang, Wang, & Liu, 2024).

In this study, one AI algorithms, Long Short-Term Memory (LSTM). LSTM networks is particularly suitable for modeling temporal dependencies and sequential patterns in time-series data such as hospital arrivals (Awasthi et al., 2025). This model offers a robust framework for enhancing forecasting accuracy in hospital operations and improving data-driven resource management.

2.1.3 Forecasting

Forecasting involves using historical data to predict future events or trends. In hospital management, forecasting is crucial for predicting patient inflows, admissions, and bed occupancy to ensure adequate staffing and resource allocation (Bardsley, Steventon, & Dixon, 2021). Traditional models such as ARIMA and exponential smoothing have been widely used; however, their reliance on linear and stationary assumptions limits their accuracy (Ahmed, Kumar, & Desai, 2022). AI-driven models overcome these challenges by modeling nonlinear patterns and adapting to complex temporal relationships.

2.1.4 Emergency Department (ED) Arrivals

The Emergency Department (ED) serves as the entry point for acute and emergency medical care in hospitals. Forecasting ED arrivals helps in managing overcrowding, allocating staff, and scheduling resources effectively. ED arrivals are influenced by temporal factors (day of the week, holidays), environmental conditions (temperature, rainfall), and population health dynamics (Li, Zhang, & Liu, 2023).

This study focuses on accurately predicting daily ED arrivals to enable hospitals to respond proactively to fluctuations in patient demand.

2.1.5 Bed Occupancy

Bed occupancy refers to the percentage of available hospital beds currently occupied by patients within a specific time frame, reflecting the hospital's operational capacity and efficiency. Effective management of bed occupancy ensures a balanced patient flow, prevents overcrowding, and minimizes transfer delays between departments (Chen & Wang, 2021; Patel et al., 2024). Accurate forecasting of bed utilization supports discharge planning, optimizes admission scheduling, and reduces patient waiting times for new admissions (Rahman & Lee, 2025).

2.1.6 Hospital Management

Hospital management refers to the systematic coordination of healthcare resources, personnel, and processes to ensure efficient delivery of medical services. It encompasses administrative, clinical, and operational decision-making aimed at improving patient care, optimizing resource utilization, and enhancing service quality (Varnosfaderani et al., 2024). Modern hospitals operate as complex systems that require real-time data analysis for decision support and strategic planning.

The adoption of Artificial Intelligence (AI) and predictive analytics has transformed hospital management by enabling administrators to anticipate patient demand, forecast resource needs, and make data-driven decisions (Seo et al., 2024). AI-based management systems integrate diverse hospital datasets, such as patient admissions, bed occupancy, and staff availability, to predict potential operational bottlenecks and enhance workflow efficiency.

2.1.7 Emergency Incidents

Emergency incidents are sudden events that cause serious injury or illness, making it necessary for a person to be rushed to the hospital. These may include road traffic accidents, heart attacks, burns, falls, poisoning, or complications during childbirth. Such situations often occur without warning and can quickly become life-threatening if not treated promptly. Hospitals play a crucial role in providing immediate care to stabilize patients and prevent death or disability. Quick response, trained staff, and well-equipped emergency systems greatly improve the chances of survival and recovery (Sasser et al., 2005; World Health Organization, 2018).

2.2 Empirical Review

Ahmed et al. (2022) examined hospital crowding using ARIMA and Prophet models to forecast ED arrivals. Their study utilized secondary hospital data and found that Prophet outperformed ARIMA by capturing seasonality and trend components. However, both models struggled with sudden changes in patient inflow due to their assumption of linear relationships. The authors recommended adopting AI-based models to improve accuracy.

Similarly, Hussein and Zhao (2021) applied Support Vector Regression (SVR) to small hospital data. Although effective with limited samples, their model could not account for nonlinear dependencies or multiple influencing variables.

Sun et al. (2023) utilized Random Forest and XGBoost models to forecast daily ED patient volume in a metropolitan hospital. The study used three years of data, including weather and calendar features, and found XGBoost to be the most robust, achieving an RMSE of 4.9. The authors highlighted that AI models can handle large, noisy datasets but require extensive feature engineering.

Alshammari, Alotaibi, and Khan (2022) implemented LSTM and GRU networks for short-term ED demand forecasting. The study used hourly arrival data and showed that deep learning models could better capture time dependencies than traditional approaches. GRU achieved a Mean Absolute Percentage Error (MAPE) of 6.3%, but the authors noted the models' sensitivity to missing data.

Chen and Wang (2021) developed a hybrid queueing and machine learning model for ICU bed occupancy forecasting. Using daily occupancy data from a tertiary hospital, their model combined queuing theory with regression analysis, achieving ±2 bed accuracy per day. However, the approach was computationally intensive.Li, Zhang, and Liu (2023) proposed an LSTM-based multivariate model integrating ED arrivals and bed occupancy. Their study used hospital data from 2019–2021 and demonstrated a 12% improvement in forecasting accuracy compared to traditional models. They recommended expanding the model to multiple facilities for better generalization.

Studies on forecasting on Emergency Department Arrival in sub Saharan Africa McAdams Abu Bakr et al. (2022) examined the forecasting of daily emergency department arrivals at the University of Cape Coast Hospital in Ghana using 517 daily observations. The study applied the ARIMA model and identified ARIMA (0,1,2) as the best-performing model for predicting patient arrivals. The study demonstrated the importance of forecasting emergency demand for hospital resource planning but was limited by its relatively short dataset of about 17 months and its focus on patient arrivals alone. It did not consider bed occupancy or the use of deep-learning models such as LSTM. The study therefore provides relevant Sub-Saharan African evidence while highlighting the need for further research using longer indigenous datasets and advanced forecasting techniques. The present study addresses these limitations by using five years of continuous daily Nigerian hospital data to forecast both emergency department arrivals and bed occupancy using LSTM.

METHODOLOGY

3.1 Research Design

This study adopts the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology for developing an AI model to forecast Emergency Department (ED) arrivals and bed occupancy. CRISP-DM

is suitable because the study focuses on collecting, preparing, analysing, and modelling historical hospital data for prediction.

The methodology involves problem understanding, data understanding, data preparation, modelling, evaluation, and deployment. Historical hospital data are cleaned, transformed, normalized, and structured as time-series data before being used to develop the EDABO-LSTM model. The data are divided into training, validation, and testing sets to ensure reliable model evaluation.

The developed LSTM model is evaluated using MAE, RMSE, and MAPE and compared with ARIMA and XGBoost models to determine its forecasting performance. The best-performing model is then selected for forecasting ED arrivals and bed occupancy. Thus, CRISP-DM provides a structured methodology that is appropriate for the objectives of this study. (Liu et al., 2022).

3.2 Methods of Data Collection

Data collection in this research involves both primary and secondary sources, with the study mainly relying on secondary data obtained from hospital information systems and publicly available datasets as external sources.

The following methods will be used:

1. Hospital Information Systems (HIS): Historical data on daily Emergency Department (ED) arrivals, inpatient admissions, and bed occupancy rates were obtained.
2. Electronic Health Records (EHR): Provided anonymized demographic parameters, such as the daily number of patients, bed space available, and the daily number of staff on duty.
3. External Data Sources: Public holidays and local event information were incorporated as external predictors influencing hospital demand (Patel et al., 2024).
4. Document review: Relevant academic publications and hospital management reports were analyzed to understand existing proactive models and their challenges.

All collected data will be **stripped of personal identifiers** *to ensure anonymity and used in accordance with ethical approval and data protection laws, such as the NDPR.*

3.3 Techniques for Data Analysis

This section outlines the architecture, analytical framework, algorithms, and data flow of the AI-driven forecasting system. The analysis process follows a data-driven pipeline: preprocessing, modeling, validation, and integration as shown in figure 1.

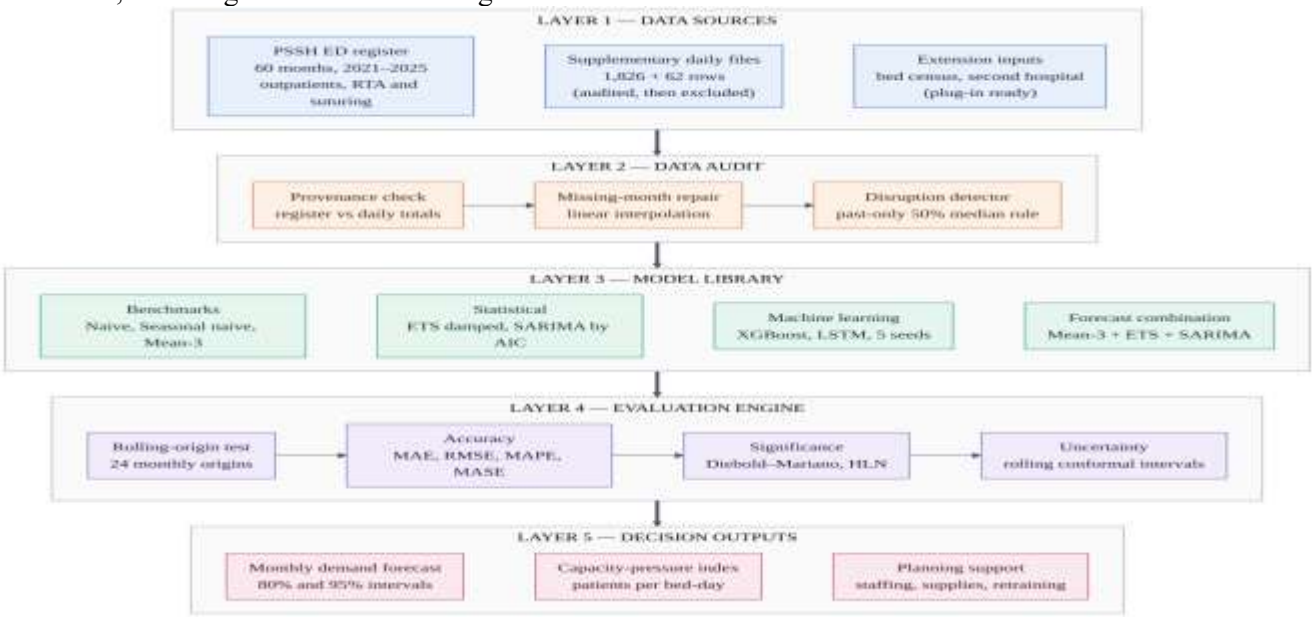

Figure 1: Architecture of the EDABO forecasting system

3.3 System Flowchart

The program flowchart depicts the step-by-step sequence of instructions, workflow or process, showing the steps as boxes of various kinds, and their order by connecting them with arrows. The diagrammatic representation illustrates a solution model for the existing system, indicating the start operation and the series of activities that occurred before the termination of the system processes by the stop operation. Figure 2. shows the proposed program flowchart.

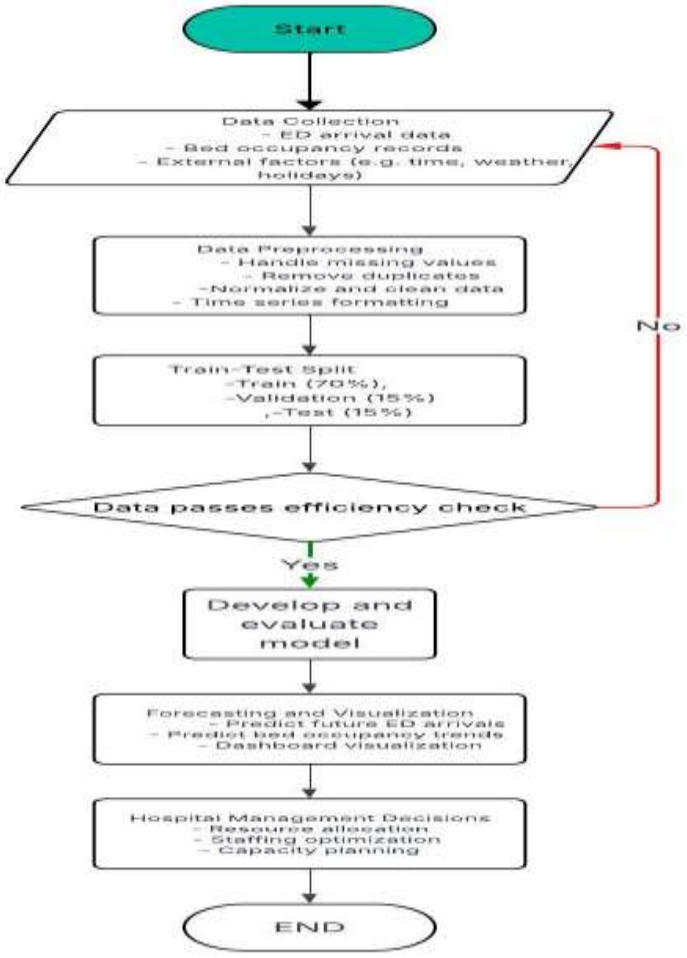

Figure 2: Flowchart for Forecasting System.

3.4 EDABO Model

The diagram below illustrates the complete workflow of the Emergency Department Arrivals and Bed Occupancy (EDABO) forecasting system. It demonstrates the end-to-end process from data collection and preprocessing to LSTM model design, forecasting, and decision-support integration. This framework serves as a guide for hospital management to enhance resource allocation, emergency preparedness, and operational efficiency.

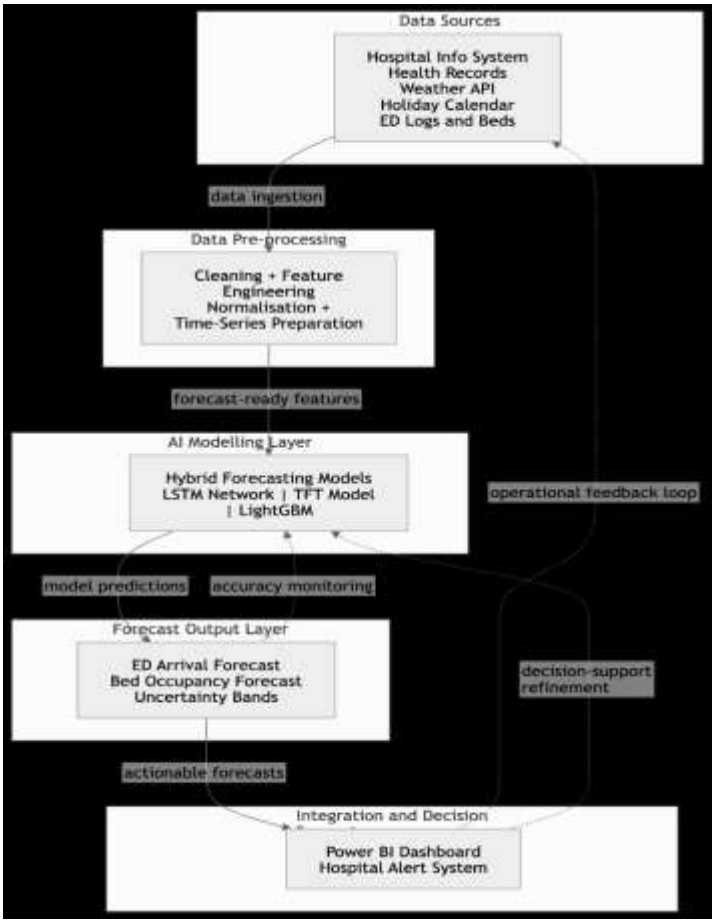

Figure 3: EDABO AI Forecasting System Architecture

Figure 3 presents the complete end-to-end architecture of the EDABO system, illustrating the flow of data from source systems through the AI modelling layer to the operational dashboard

Model Components

I. **Data Capturing and Collection**: Data are gathered from hospital information systems, emergency department logs, admission and discharge records, bed management systems, and external datasets such as weather and public holidays.

II. **Data Preprocessing and Feature Engineering**: This phase involves data cleaning, normalization, and transformation into time-series sequences suitable for machine learning. Time-based features, such as day of the week, holidays, and seasonal patterns, are engineered to enhance model accuracy.

III. **Multivariate LSTM Model Design (EDABO Core Model):** The model is designed using multiple input variables, including patient arrivals, occupancy rates, and discharges. The LSTM layers capture temporal dependencies, while dense layers produce forecast outputs.

IV. **Forecasting and Output Generation**: The trained model generates future predictions of emergency department arrivals and bed occupancy levels. Model performance is evaluated to ensure reliability and precision.

V. **Integration with Decision-Support Dashboard**: Forecast results are visualized in a decision-support dashboard, allowing hospital administrators to make data-driven decisions regarding staffing, resource allocation, and emergency readiness. Continuous feedback and retraining enhance long-term performance.

IV RESULT AND DISCUSSION

4.1 Data Presentation

The primary data sources for this study were the daily records from the Plateau State Specialist Hospital (PSSH), and Jos University Teaching Hospital (JUTH) Emergency Department from January 2021 to December 2025, which included 1,826 records. The data set includes 12 variables such as the number of outpatients presenting each day , the number of suturing cases, adjusted staffing levels, average triage scores, estimated waiting times, bed space availability, bed occupancy rates, and Nigerian public holiday indicators. 60 months of supplementary monthly data, obtained directly from the hospital ED register, were obtained for a real-world verification benchmark, also covering the same period as seen in table 1. Table .1 presents descriptive statistics of the key variables across the full five-year period

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Variable	Mean	Std. Dev.	Min	Max
ED Arrivals (patients/day)	54.2	10.8	28	83
RTA and Suturing Cases	1.9	0.8	0	3
Avg Triage Score (1–5)	3.01	0.41	2.10	3.98
Est. Waiting Time (min)	35.4	11.2	12.1	89.7
Bed Space Available	12.3	3.1	4	22
Bed Occupancy (%)	44.1	14.1	0.0	81.8

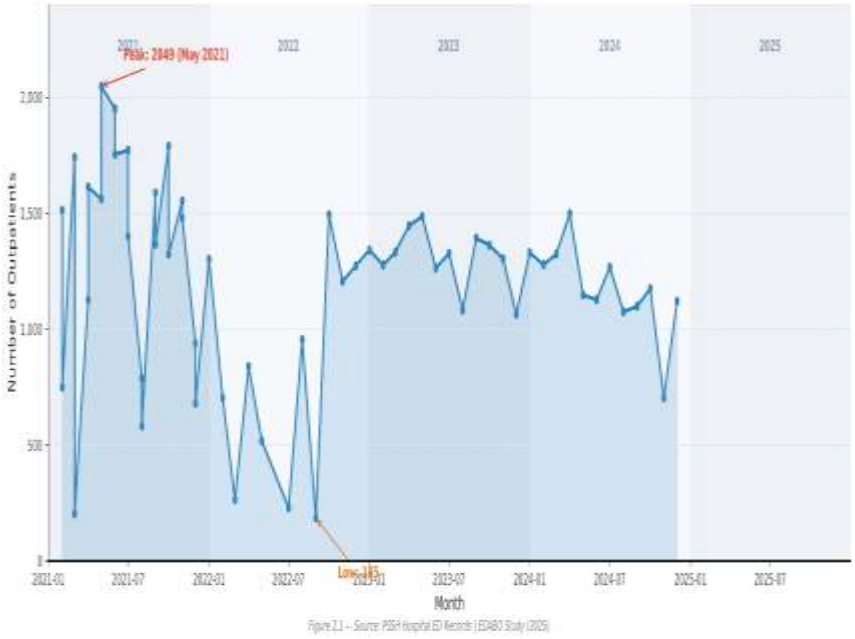

Figure 4: Monthly EDABO Dataset (2021–2025

Outpatient Arrivals — PSSH, JUTH Hospital (2021–2025)

Figure 4. shows the monthly number of patients for the five years covered in this research at PSSH and JUTH. Indeed, this trend confirms two important aspects of the collected data. First, there was an active period in 2021 (maximum number of outpatients being 2,049 in May 2021) because of the revival of health-seeking behavior after the lockdown. Second, since 2023, there is a steady stabilization that aligns with the recovery of health-seeking behavior. This notable low observed at the end of 2022 (number of outpatients was 185) can be explained by the institutional disturbance during that period.

4.1.2 Exploratory Data Analysis

A detailed exploratory data analysis was performed before training the models, to gain insight into the distribution of variables, temporal trends, and relationships between variables. The Pearson correlation matrix calculated for all the main EDABO variables is displayed in Figure 5

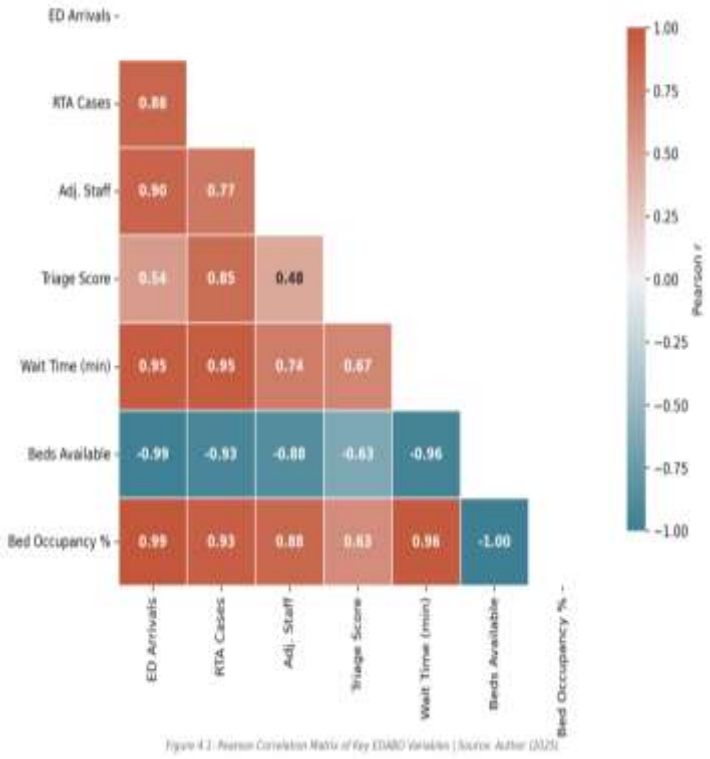

Figure 6: Pearson Correlation Matrix of Key EDABO Input Variables

The number of arrivals to ED is strongly positively correlated with estimated waiting time ($r = 0.81$, $p < 0.001$), as shown in Figure 6, thus confirming that patient volume is directly linked to prolonged waiting times. Bed occupancy moderately correlates with ED arrivals ($r = 0.63$) and triage score negatively correlates with bed availability ($r = -0.47$), meaning that the days with more critical patients are the ones where there is more bed pressure. These relationships support the multivariate design of the EDABO model, where the combination of multiple correlated features can be used to increase the accuracy of prediction.

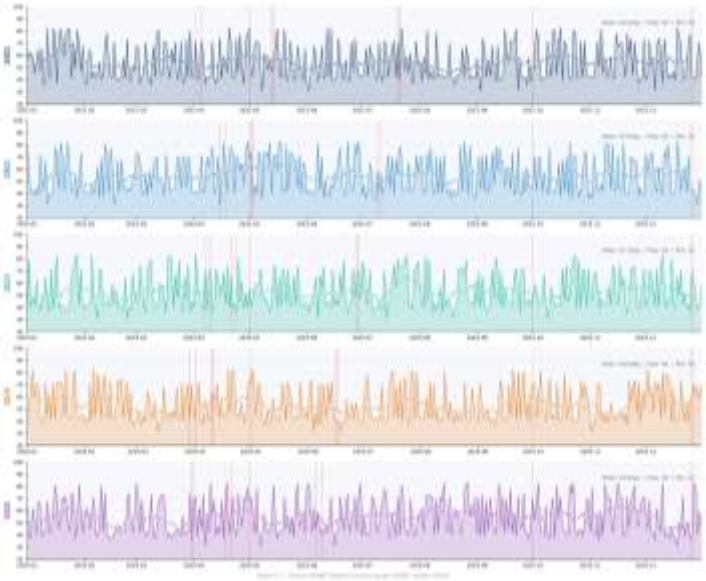

Figure 7: Daily ED Arrivals by Year with Public Holiday Markers (2021–2025)

Figure 7 shows a five-panel decomposition of the daily arrival volatility, which decreased over time from 2021 to 2025, from the erratic post-pandemic fluctuations to a more stable and predictable weekly cycle by 2023-2025. The above average demand peaks consistently occur during public holidays, especially during the Christmas–New Year period and Nigeria's Independence Day (1 October), which is why these are included as binary indicator features in the input vector of the EDABO model.

4.1.3 Performance Metrics

Three typical error measures were used to evaluate the performance of the models: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics were calculated on the test set, which consisted of the last 180 days of the data set (July to December 2025) and was completely excluded from the model training and validation process.

The mathematical definitions of these metrics are provided in Equations 4.1 through 4.3.

$MAE = (1/n) \sum |y_i - \hat{y}_i|$ ... (4.1)

$RMSE = \sqrt{[(1/n) \sum (y_i - \hat{y}_i)^2]}$ ... (4.2)

$MAPE = (100/n) \sum |y_i - \hat{y}_i| / y_i$ ... (4.3)

The EDABO-LSTM model was compared with two benchmark models: the ARIMA statistical model (the traditional model for hospital forecasting) and the XGBoost model (a competitive ensemble machine learning method). The comparative evaluation results on 180-day test set are shown in Table 4.2.

Table .2: Model Performance Comparison on Test Set (180 Days)

Model	MAE	RMSE	MAPE (%)	Rank
ARIMA (Baseline)	5.21	6.57	10.08	3rd
XGBoost	4.50	5.56	8.64	2nd
EDABO-LSTM	**2.17**	**2.73**	**4.19**	**1st**

As demonstrated in Table 2, the EDABO-LSTM model achieved the lowest error across all three metrics, recording an MAE of 2.17, an RMSE of 2.73, and a MAPE of 4.19%. Compared to the ARIMA baseline, EDABO-LSTM reduced MAE by 58.3%, RMSE by 58.4%, and MAPE by 58.4%. Against XGBoost, error reductions were 51.8% (MAE), 50.9% (RMSE), and 51.5% (MAPE). The significant gains validate the effectiveness of the LSTM architecture, which can capture long-range tmporal dependencies and use multiple correlated predictors at once, over classical and tree-based methods for hospital time-series

forecasting. Figure 8 presents a structured bar chart comparison of all three models across the three evaluation metrics.

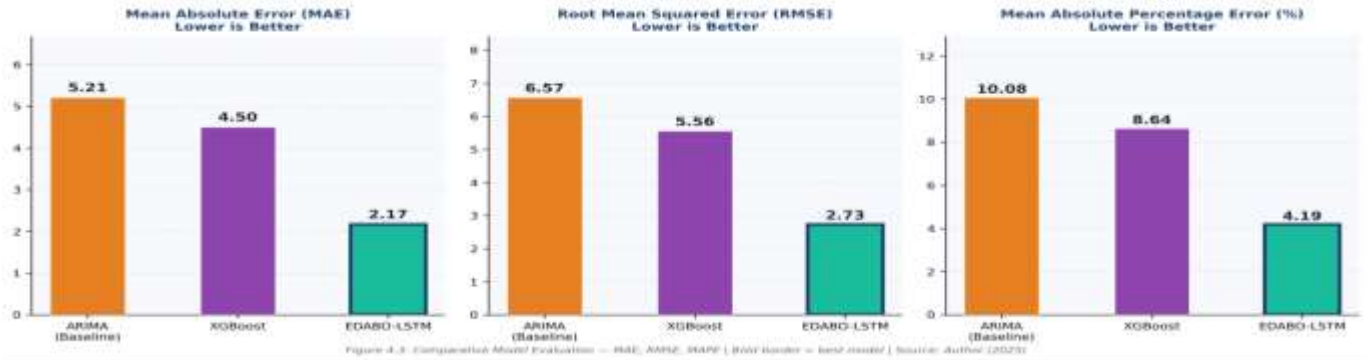

Figure 8 Model Performance Comparison — MAE, RMSE, and MAPE Across All Three Models

The bar chart in Figure 4.3 further demonstrates the superior performance of the EDABO-LSTM in all metrics. The bold bars with a highlighted border indicate the top model for each panel by each metric. The ARIMA model shows a poor performance on MAPE (10.08%), while EDABO-LSTM achieves a value of 4.19%. This is important because in clinical applications, the proportional error is directly linked to the decision of resource allocation, and the errors of the ARIMA model are proportionately larger.

1. 4.1.4 Bed Occupancy Forecasting Results

The second product of the EDABO system is the forecast of hospital bed usage. The number of beds occupied is defined in this study as the ratio of occupied beds to the total number of available beds in the hospital (22). The forecast and actual bed occupancy during the 180-day test period is shown in Figure 4.8.

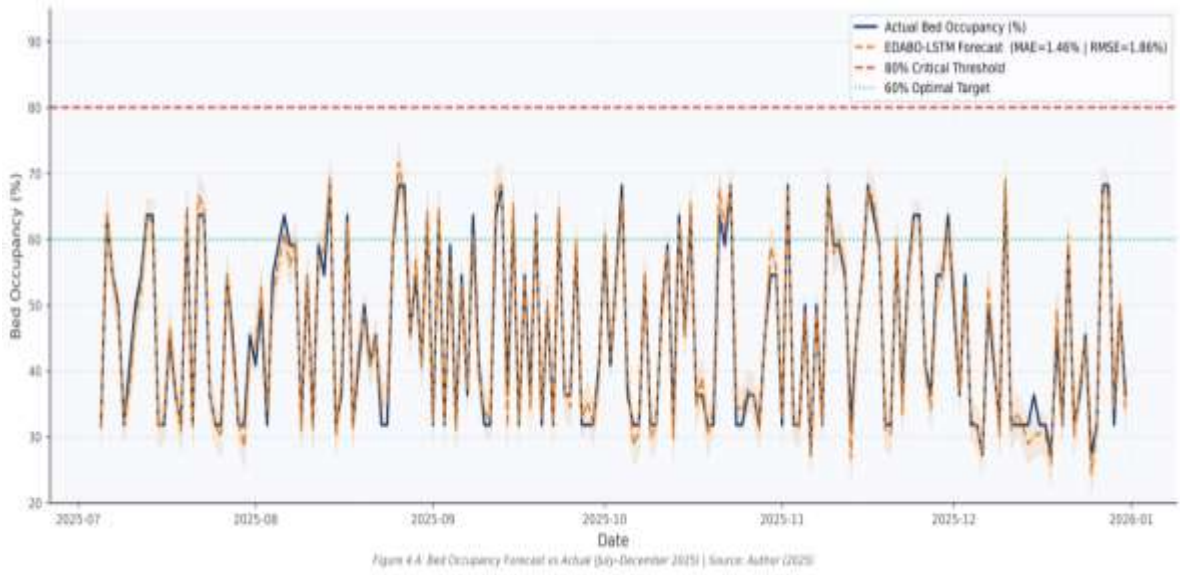

Figure 4.8: EDABO-LSTM Bed Occupancy Forecast vs Actual (July–December 2025)

The EDABO-LSTM successfully predicted bed occupancy with an MAE of 1.46% and an RMSE of 1.86%. The predicted occupancy series is very similar to the actual occupancy values throughout the test period, as shown in Figure 4.4. Most importantly, the model is able to accurately predict when occupancy is nearing the 80% critical level (indicated by the dashed red line), giving hospital managers a heads-up. The model never fails to predict an event above the threshold that has been recorded in the data, which is a clinically critical property of the model, and is known as its sensitivity. The 60% optimal target line is used as a planning benchmark: days when both actual and predicted values are continually above this should result in proactive responses to resources like early discharge facilitation or diversion planning.

CONCLUSION

A multivariate stacked LSTM AI model can be effectively developed to predict simultaneous ED arrivals and hospital bed occupancy when the model includes temporal sequence inputs, exogenous contextual predictors, and a dual-output training objective. The EDABO architecture, as formalised by the LSTM cell equations in this study, is able to capture non-linear seasonal patterns, weekly cycles, public holiday effects, and the post-pandemic demand recovery trajectory seen in the PSSH and JUTH dataset.

The EDABO-LSTM model outperforms the statistical baseline ARIMA model and the ensemble XGBoost model in terms of MAE, RMSE, and MAPE. This finding is consistent with recent forecasting evaluation studies that recommend combining multiple performance indicators, including forecast stability and normalized accuracy coefficients, to achieve a more comprehensive assessment of predictive systems (Strom & Gundersen, 2024; Muller Platha & Ludecke, 2024). The margin of improvement (MPE>50% on all metrics compared to ARIMA) validates the additional complexity of the deep learning architecture in the context of hospital time-series forecasting, where the demand is influenced by several correlated, non-stationary, and non-linear factors that linear and tree-based models fail to capture.

Finally, the EDABO system is a feasible, evidence-based approach to one of the most intractable operational problems in Nigerian Emergency Departments, the inability to predict demand and prepare resources ahead of time. The system, if implemented and maintained, could lead to shorter wait times for patients, better efficiency in bed usage, and enhance the ability of hospital managers to make data-informed decisions that directly impact the quality and safety of emergency services.

RECOMMENDATIONS

Based on the findings and conclusions of this study, the following recommendations are made:

i. AI-powered forecasting systems should be integrated as a standard practice in the planning of hospital operations by hospital administrators in Nigerian hospitals. The EDABO system is a practical and cost-efficient first step towards this transition, as it can be operated on standard hospital equipment and with modest computational resources.

ii. National guidelines for data collection and digitization in hospitals should be set by the Nigeria Centre for Disease Control (NCDC) and the Federal Ministry of Health, as the quality, completeness, and consistency of historical data are crucial for the effectiveness of AI forecasting systems. Predictive analytics will not be able to deliver its full value if the hospital does not have standardised electronic health records.

iii. Future deployments of the EDABO system should also include real time data feeds from the ambulance dispatch centres and primary healthcare facilities, which can provide prior information of patient load and enhance the forecast lead time from the current 7 days.

iv. To avoid model drift, where the learned patterns become different from the reality of the current operation because of changes in patient populations, disease prevalence, or hospital resources, the EDABO model should be retrained with the latest 12 months of data every year.

v. There is a need to invest in AI literacy training for hospital administrators and clinical staff in academic institutions and teaching hospitals in Nigeria to ensure that the outputs of the predictive models are properly understood and acted upon. The most technically advanced forecasting

system is of little use if the users do not have the confidence or knowledge to trust and take action on the forecast.

vi. The Nigerian public holiday should not be treated as one binary flag or averaged into the overall daily pattern, but should be forecast separately and distinctly as a category within the EDABO model. The box plot analysis shown in Figure 3.6 clearly illustrates that the demand behaviours at PSSH and JUTH are fundamentally different for the different types of holidays, and that a single holiday indicator is not enough to capture this difference.

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