Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

Predictive Analytics for Hospital Resource Management

Mahtab Alam
Computer Science and Engineering
Integral University,
Lucknow, India

Irshad Ahmad
Computer Science and Engineering
Integral University,
Lucknow, India

Mohammad Dilshad Khan
Computer Science and Engineering
Integral University,
Lucknow, India

Dileep Kumar Maurya
Computer Science and Engineering
Integral University,
Lucknow, India

Balmukund Maurya
Computer Science and Engineering Integral
University,
Lucknow, India

***Abstract*—The predictive models of patient demand forecast, bed occupancy prediction, and workforce scheduling. By re-viewing recent literature, this work concludes that machine learning hybrids, combining statistical methods and deep learning architectures, achieve accuracy of 85–98% in hospital applica-tions. XGBoost and Long Short-Term Memory (LSTM) networks outperform conventional forecasting methods. However, imple-mentation barriers remain, including data fragmentation, lack of model generalization, and organizational unpreparedness.**

***Keywords*—Predictive analytics, machine learning, hospital resource management, patient flow forecasting, operational ef-ficiency.**

I. INTRODUCTION

The healthcare organizations around the world are facing parallel urges to improve the quality of care, curb the in-creasing expenses, and optimize utilization of the available limited resources including bed, medical equipment, drug stocks and clinical staff [2]. The traditional resource planning techniques that are founded on a historic average and intuition normally result into ineffective capacity utilization, excess wait time and substandard quality of care delivery [3].Predictive analytics can enable healthcare organisations to replace their reactive and crisis-based management perspective with a data-based perspective by analysing these massive volumes of operational data in real-time information sources, such as electronic health records, administrative systems, and facility management platforms [4]. This paradigm change will help the hospitals anticipate the demand variation of the patients, streamline the staffing process, harness the usage of the beds, and the overall functioning of the business. The recent past experienced healthcare crises and particularly the COVID-19 pandemic has demonstrated certain critical shortcomings in the traditional capacity planning models and demonstrated an urgent need to have complex and real-time forecasting solutions [5].

Identify applicable funding agency here. If none, delete this.

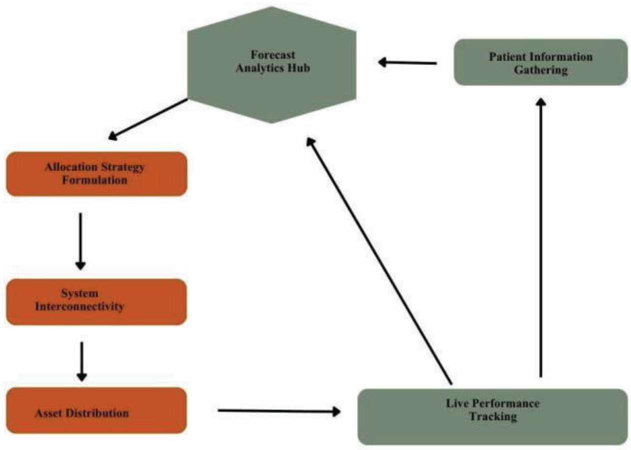

Fig. 1. Optimizing Resource Allocation in Hospitals using Predictive Analytics and Information Systems

II. THE HYPOTHETICAL FRAMEWORK AND THE MODERN METHODLOGY

The classical statistical techniques (ARIMA, Exponential Smoothing) were effective at capturing seasonality and trend, but ineffective at the multiple exogenous variables and the non-linear relationship between two or more exogenous time-series variables common with hospital activities. With the introduction of ensemble machine learning models, including Random Forest, Gradient Boosting and Support Vector Ma-chines, it was now possible to fit more complex relationships between operating characteristics and an outcome [7]. Models developed in recent deep learning, Long Short-Term Memory networks, and Transformer based models have revolutionized the way time series forecasting in healthcare is handled; they are effective at capturing long distance temporal dependencies and capture complex sequential structures [8].

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

III. PREDICTIVE ANALYTICS TECHNIQUES EMPLOYED

A. Machine Learning Models

Relapse, choice trees, and neural systems are a few of the machine learning strategies that are frequently utilized to see at healthcare information and make forecasts. Within the field of prescient analytics, relapse models are one of the most straightforward and most common strategies utilized. These models are used to figure continuous comes about, like the number of clinic visits, the length of remain for patients, or the filling rate of beds. One sort of show is direct relapse, which looks at the association between a subordinate variable (like quiet confirmations) and one or more autonomous components (like time of year, quiet information, and past admission rates). If you need to figure whether an understanding will be readmitted inside 30 days, for example, you'll be able utilize more complicated relapse methods like calculated relapse [17]. Another strong machine learning method used in healthcare for forecasting analytics is decision trees.

Step 1: Data Collection:

Mathematical Representation:

$$\text{Data} = \{X_1, X_2, \ldots, X_n\}, \quad X_i \in \mathbb{R}^d \tag{1}$$

where X_i represents the input feature vectors (e.g., patient characteristics, time, etc.), and d is the number of features.

Step 2: Model Selection and Training - Objective: Choose a machine learning model (e.g., regression, decision trees, or neural networks) and train it using the pre-processed data.

Mathematical Representation:

Linear Regression Model:

$$\hat{y} = w^T X + b \tag{2}$$

where $\hat{y}$ is the predicted output (e.g., patient admissions or resource usage), X is the input feature vector, w is the weight vector, and b is the bias term.

Decision Tree:

$$\hat{y} = \sum_{i=1}^{m} \alpha_i f_i(X) \tag{3}$$

where $f_i(X)$ represents the i-th decision rule, and α_i is the weight associated with each decision node.

Neural Networks: For a multi-layer perceptron (MLP):

$$\hat{y} = \sigma\left(W_2 \cdot \sigma(W_1 \cdot X + b_1) + b_2\right) \tag{4}$$

Step 3: Model Evaluation:

Mathematical Representation:

Mean Squared Error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{5}$$

where y_i is the true value and $\hat{y}_i$ is the predicted value.

Accuracy (for classification): Accuracy = (Correct Predictions / Total Predictions) * 100

Step 4: Deployment and Predictions:

Mathematical Representation:

For a new input X_{new}, predict the output $\hat{y}_{new}$:

$$\hat{y}_{new} = f(X_{new}) \tag{6}$$

where f is the trained model (e.g., linear regression, decision tree, or neural network) and X_{new} is the new input data (e.g., new patient information or resource availability).

IV. STATISTICAL METHODS

Step 1: Data Collection and Preprocessing Objective:

Collect and preprocess historical data. The data typically includes patient admissions, resource usage (beds, staff, equipment), and other relevant variables.

Mathematical Representation: Let X represent the input features (e.g., patient characteristics, resource usage, etc.), and Y represent the target variable (e.g., patient admission rates).

$$X = \{X_1, X_2, \ldots, X_n\}, \quad X_i \in \mathbb{R}^d \tag{7}$$

(input feature vector)

$$Y = \{Y_1, Y_2, \ldots, Y_n\}, \quad Y_i \in \mathbb{R} \tag{8}$$

(target variable)

Step 2: Model Development and Fitting - Objective:

Use statistical methods (e.g., linear regression, time series analysis) to fit a model to the data and make predictions.

Mathematical Representation:

$$Y_t = \alpha Y_{t-1} + \beta X_t + \epsilon_t \tag{9}$$

Step 3: Model Evaluation and Prediction

Mathematical Representation: Mean Squared Error (MSE) is used to evaluate the model's performance:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \tag{10}$$

where Y_i is the true value, $\hat{Y}_i$ is the predicted value, and n is the number of data points.

Once the model is trained and evaluated, use it to predict future outcomes (e.g., patient admissions, resource requirements):

$$Y_{pred} = f(X_{new}) \tag{11}$$

where X_{new} is the new input data, and f is the trained model.

V. CORE PREDICTION TARGETS IN HOSPITAL RESOURCE MANAGEMENT

A. Patient Demand Forecasting

Accurate prediction of patient arrival volumes and admission rates in the basic component of hospital capacity planning. The demand of the patients has made the time behaviour difficult in terms of daily cycles, weekly changes, season, and irregular interferences due to the weather, holidays, epidemics, and other health related activity of the people. The Temporal Fusion Transformers have been observed to perform better

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

in multi-horizon forecasting compared to the ARIMA and Prophet models particularly when exogenous variables such as calendar effects, weather conditions and syndromic variables are included as compared to the previously used models (Pokharial et al. 2019).

B. Bed Occupancy Prediction

Bed Occupancy and Length of Stay Prediction: Extreme Gradient Boosting models yielded an AUROC value of 0.87-0.88 to forecast 24-hour hospital discharge, which is far better than the baseline logistic regression models. [11]. With the Bayesian Model Averaging and Bidirectional LSTM, an accuracy of 98.06 percent and the means of the absolute error where 1.939 percentage error were found in predicting weekly bed occupancy. [12].

C. Workforce Planning

Workforce Planning and Optimization of Staffing: DeepAR was an autoregressive recurrent neural network algorithm, which proved successful in its ability to predict nursing work-force demand in a variety of units and specialties of a hospital [14]. The model was able to model complicated time trends such as trends, seasonal fluctuations, and abrupt interruptions caused by pandemic-related workforce changes. State of the art deep learning neural networks that forecast proxies of nursing care workload were more effective compared to older regression models, giving the opportunity to allocate staff in high-demand regions proactively [15].

VI. METHODOLOGIES AND PERFORMANCE COMPARISON OF MACHINE LEARNING

A. Tree-Based Methods

XGBoost forecasting hospital outpatient volumes demon-strated mean absolute percentage error of 4.2 per cent which is significantly lower than other SARIMAX and Random Forest baseline models [16]. The algorithm determined the predictive features that are important such as the availability of specialists, time-related determinants, and the surroundings such as air quality. Multi-task learning to make predictions of bed requirements in multiple hospital departments at the same time captured by MTL-XGBoost had better results in 11 of 12 departments with equal mean absolute percentage error values of 0.185-0.974 [17].

B. Deep Learning

LSTM networks are quite effective at time-based inter-pretation of hospital data. The variant of LSTM network, known as the Bidirectional LSTM network, or BiLSTM in short, considers the information as viewed in two directions. Actually, BiLSTM networks could anticipate the number of beds to be occupied with a precision of 98.06. This implies that they were in error 1.939 per cent of the time. After applying BiLSTM with certain methods such as grid search and Bayesian Model Averaging, we achieved some excellent predictions which not only informed us about how confident we were of the predictions but also informed us about how sure we were of our predictions.

C. Hybrid Models

Hybrid and Ensemble Approaches The hybrid ARIMA-ANN models of predicting elective surgery demand had a mean absolute error of 0.26-0.76 and a mean squared er-ror of 0.13-1.05 using two weeks of foresight [18]. Ge-netic Algorithm-Optimized Convolutional Neural Networks (GAOCNN) uses genetic algorithms to optimize the parame-ters of convolutional layers which are used to predict hospital readmission with 97.2 accuracy in diabetic patients and length-of-stay with 89-99.4 accuracy in various groups of patients [19].

VII. CORE APPLICATIONS IN HOSPITAL OPERATIONS

A. Emergency Department

Mean absolute error and the R 2 of Time Series Transformer Plus (TSTPlus) were 4.30 and 0.79 respectively in terms of predicting the number of ED boarding at six-hour horizons with just operational and contextual characteristics [20]. The hybrid VAE-GRU framework that involves the use of vari-ational autoencoders with the gated recurrent units showed better performance over LSTM, regular GRU, and CNN neural networks [21]. Deep learning systems that used both tabular data processing and natural language processing made 82 per-cent and 71 percent accuracy accrual hospitalization prediction and length-of-stay prediction, respectively, in the emergency setting [22].

B. ICU Capacity Planning

Mean absolute error— root mean squared error Since the study used LSTM models to predict ICU occupancy, the mean absolute error of 2.15 and root mean squared error of 2.96 [23] were obtained the time of pandemics, deep learning models that predict multivariate ICU bed demand showed a variation of about 3 beds in the number of beds predicted versus occupied in resource-limited conditions [24].

C. Operating Room Optimization and Surgical Services

Machine learning models trained on 1.17 million operations across 13 hospitals with a mean error of 34 minutes to predict the duration of a surgical procedure with 46 percent of estimates falling within 20 percent of actual time [25]. The major predictive variables were historical procedure physician duration, pattern of procedure terminology and time of day. In case of pediatric surgical services, median error in next-day census prediction was 7 percent when hierarchical modeling structures were used [26].

VIII. SUPPLY CHAIN AND INVENTORY MANAGEMENT

A. Pharmacy Forecasting

Pharmacy demand forecasting is an AI application that forecasts pharmacy demand to reduce inventory in order to strike a balance between the chances of a stockout and loss of wastage [27]. The comparison was made between models, among which the Support Vector Regression, the XGBoost,

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

the LSTM, and the GRU models predicted the dispensing of medication in general hospitals [28].

B. *Blood Inventory*

Multimodal platelet demand prediction, based on individual patient level was revealed to be specific (0.99) and less sensitive (0.37) to predict transfusion requiring patients [29]. Despite the fact that it has proven to be useful in the pretest tool category, the sensitivity is still in need of a better sensitivity in order to be used in clinical practice.

IX. DATA INTEGRATION AND FEATURE ENGINES

Proper predictive models require comprehensive intelligence (data integration) of different types of data, including elec-tronic health records (demographics, diagnoses, medications, vital signs), administrative data (admission/discharge times, insurance data), operational data (bed occupancy, staffing schedules), environmental (weather, seasonal signals) and ex-ternal data (disease surveillance, social determinants of health). The most prominent groups of features are temporal features (day of) represented by a week of the year, season, holiday, lagged (past volumes of admission, past occupancy) and de-rived (occupancy rates, staff to patient ratios), and interaction (synchronous weather and disease prevalence effects). The model of XGBoost outpatient volume prediction identified the number of specialists, time (year, quarter, month, weekday), and environment (temperature, PM2.5) variables as those with the most significant predictive ability [16].

X. THE CONSIDERATION OF IMPLEMENTATION FRAMEWORK AND ORGANIZATION

The idea behind the 8.1 Staged Implementation Approach is to implement changes step by step in order to ensure that all the stakeholders will truly adapt to the new procedure with-out experiencing much stress. Good execution of predictive analytics must be carried out in four stages:

- Phase 1: Foundation: Cross-functional teams formed, evaluate data quality and availability, and establish data governance, establish use case priorities based on opera-tional impact and feasibility.
- Phase 2: Pilot: Predictive models of top priority use case, derby and confirm relevance of prediction, can you develop prediction into pilot workflows, test user acceptability.
- Phase 3: Production: Production with proven models through the use of performance monitoring systems, remediation of retraining processes, extension to new applications.
- Phase 4: Constant Optimization: Check performance and satisfaction, apply feedback to the optimization of pro-cesses, develop advanced applications (prescriptive ana-lytics).

XI. CRITICAL SUCCESS FACTORS

- Data Infrastructure: Data governance, standardization, and integration work before advanced modeling inven-tions can take place in organizations that have discontin-uous and fragmented data systems.
- Clinical Engagement: Clinical champions who support the idea of integration into workflows significantly af-fect the achievement of success in implementation and acceptability among stakeholders.
- Workflow Integration: Predictions built into existing in-formation systems within hospitals make them easy to use and adopt versus the reporting systems.
- User-Centered Design: Prediction visualization and com-munication should correspond to user requirements. Fore-casts with confidence intervals, key drivers and suggested actions can be seen on dashboards, which make the board engaging [9].

XII. DIFFICULTIES, CONSTRAINTS AND OPPORTUNITIES

- Quality Data Problems: Hospital data is often full of errors, inconsistencies and lack of values, which signifi-cantly affect the performance of models [31]. There is not that much development of automated data quality monitoring in most institutions.
- Generalization and Transferability: When trained on one hospital, the model could be poor when used in other hospitals with other patients and operation processes [9]. Transfer learning and federated learning methods are still under research.
- Ethical and Fairness Implications: The issue of machine learning models and healthcare inequity is hat training data can reinforce the historical inequities [32]. Main-taining fair performance among the different groups of people will demand continuous monitoring and reduc-tion of bias. Key Barriers to Adoption: Due to limited data literacy, staff resistance to change, and workflow integration difficulties, organizational change can be seen as a significant barrier to adoption [33]. Implementing the change successfully involves change management and involvement of stakeholders.

XIII. RESULT AND DISCUSSION

When the information systems and prediction analytics are applied jointly to support the hospitals in deciding how to utilize their resources, things proceed with a lot of ease and patients receive improved care. By reducing wait times, hospitals are able to save on time over their resources by making more efficient use of the capacity of rooms by forecasting the number of patients they are going to need, ensuring that they have sufficient staff and ensuring that the required equipment is always available. Case studies demonstrate the ways to spend less and less, assist patients receiving higher-quality care, and involve the staff in making their jobs happier. Nonetheless, there are also issues with unifying information. The bed usage

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

rate went up from 85 to 90 percent, which means that the beds were used more efficiently. Predictive analytics probably helped hospitals get a better idea of how many patients would be admitted and how many would be sent home, which made better use of bed space.

EVALUATION PARAMETER	BEFORE PREDICTIVE ANALYTICS	AFTER PREDICTIVE ANALYTICS
Patient Wait Time (Minutes)	45	30
Bed Occupancy Rate (%)	85	90
Staff Utilization Rate (%)	75	80
Patient Readmission Rate (%)	18	15
Equipment Downtime (%)	12	08

TABLE I
HOSPITAL PERFORMANCE METRICS PRE- AND POST-IMPLEMENTATION

XIV. EMERGING OPPORTUNITIES

- Prescriptive Analytics: No more predictions, but actionable recommendations, with optimization algorithms to predictive model combinations to make resource allocation recommendations based on multiple conflicting goals [2].
- Cloud-Based Deployment: Cloud-based platforms (AWS SageMaker) offer scalable model deployment with response times as fast as 75 milliseconds with high accuracy in high computational loads [34].
- Explainable AI: SHAP value decomposition and attention weight visualization allows the prediction of each line by a line to be explained, which is critical to clinical validation and regulatory approval [30].

XV. CONCLUSIONS

Modern machine learning schemes, especially ensemble algorithms, statistical-machine learning models, and deep neural networks, significantly outperform the classical forecasting, and prediction accuracy of 85-98Technical capability in itself is, however, not enough to initiate successful implementation. Healthcare organizations have to manage data integration issues, provide clinical partic-ipation, build the competence of staff, and create gover-nance structures that will facilitate ethical and fair use. Companies that can implement through stages, focusing on the high-impact use cases, and at all times keep-ing the user-centered design approach have significantly higher success rates. Subsequent studies need to focus on creating generalizable models that can be transferred successfully to a wide variety of healthcare settings, developing glorifiable AI methods that would enable clinician trust, and dedicating further attention to health equity that would enable all populations to benefit from predictive analytics improvements. With the systematic deployment of predictive analytics in hospital operations, i.e., patient demand prediction to workforce planning, or supply chain optimization, the healthcare organizations will be able to realize significant gains in the efficiency of operations, the quality of care, and financial sustainability.

REFERENCES

[1] M.S. Ahmed, F.A. Zhinuk, S. Acharjee, S.Begum, M.I. Jobiullah and S. Islam, AI-driven predictive operations management: A business science framework for dynamic hospital resource optimization and clinical workflow efficiency. international journal of professional business review 2025
[2] E. Fagbenle, “Leveraging predictive analytics to optimize healthcare delivery, resource allocation, and patient outcome forecasting systems.” International Journal of Re- search Publication and Reviews, 2025.
[3] D. Rampengan, N. J. Permana, and D. Wuisan, “Machine learning in hospital bed management and patient flow: A comprehensive review of evidence synthesis and implementation guidance,” Journal of Cultural Analysis and Social Change, 2025.
[4] D. Bolarinwa, M. Egemba, and M. Ogundipe, “Developing a predictive analytics model for cost-effective healthcare delivery: A conceptual framework for enhancing patient outcomes and reducing operational costs,” International Journal of Advanced Multidisciplinary Research and Studies, 2025.
[5] K. Kasali and R. Oladapo, “Utilizing predictive analytics to improve healthcare access in the united states (u.s.),” World Journal of Advanced Research and Reviews, 2025.
[6] R. el-Bouri, T. Taylor, A. Youssef, T. Zhu, and D. Clifton, “Machine learning in patient flow: A review,” Progress in Biomedical Engineering, 2021.
[7] K. A. Taiwo, G. I. Olatunji, and O. O. Akomolafe, “Forecasting hospital resource demand using time series and machine learning models,” Gulf Journal of Advance Business Research, 2025.
[8] P. K. Rawat, “AI-enabled predictive analytics in US healthcare leveraging cloud-based data warehousing for disease forecasting,” International Journal For Multidisciplinary Research, 2025.
[9] T. M. Taylor, K. P. Lopez, and J. F. James, “Machine-learning models for emer- gency department patient-flow forecasting,” Journal of Frontiers in Multidisciplinary Research, 2025.
[10] A. Hu, S. Stockman, X. Wu, R. Wood, B. Zhi, and O. Y. Ch”en, “Enhancing uncertain demand prediction in hospitals using simple and advanced machine learning,” arXiv.org, 2024.
[11] J. Wei et al., “Predicting individual patient and hospital-level discharge using machine learning,” Communications Medicine, 2024.
[12] G. Avinash and S. Mishra, “Bayesian model averaging based deep learning forecasts of inpatient bed occupancy in mental health facilities,” Scientific Reports, 2025.
[13] J. Chen, Z. Chen, S. Yang, H. Jiang, and C. Xie, “Development of an interpretable machine learning model for predicting prolonged hospital stay in patients with acute exacerbation of chronic obstructive pulmonary disease: A retrospective cohort study,” BMC Medical Informatics and Decision Making, 2025.
[14] N. Ettehadi, T. J. Levy, P. Zhang, T. Corrigan, H. Tuchman, and T. P. Zanos, “An artificial intelligence-based probabilistic forecasting model for predicting nursing workforce demand in hospital units,” Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2025.
[15] Y. Baek, K. Han, E. Jeon, and H. Yoo, “Prediction of nursing need proxies using vital signs and biomarkers data: Application of deep learning models.” Journal of Clinical Nursing, 2024.
[16] L. Zhou, Q. Zhu, Q. Chen, P. Wang, and H. Huang, “Predicting hospital outpatient volume using XGBoost: A machine learning approach,” Scientific Reports, 2025.
[17] M. A. Bedada, I. Megdiche, E. Lamine, and D. Duval, “Multi-task learning approach for hospital bed requirement prediction,” ACS/IEEE International Conference on Computer Systems and Applications, 2024.
[18] X. Y. Leong, N. Jajo, S. Peiris, and M. Khadra, “Forecasting elective surgery demand using ARIMA-machine learning hybrid model,” European Journal of Artificial Intelligence and Machine Learning, 2023.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 04 , April - 2026

[19] A. Tavakolian, A. Rezaee, F. Hajati, and M. S. Uddin, “Hospital readmission and length-of-stay prediction using an optimized hybrid deep model,” Future Internet, 2023.
[20] O. Vural, B. Ozaydin, J. Booth, B. F. Lindsey, and A. Ahmed, “Deep learning-based forecasting of boarding patient counts to address emergency department overcrowding,” Informatics, 2025.
[21] A. Zidi, R. Jmili, I. Nouaouri, and I. B. Jaafar, “Optimizing emergency department patient flow forecasting: A hybrid VAE-GRU model,” International Conference on Control, Decision and Information Technologies, 2025.
[22] Y.-T. Lin, Y.-X. Deng, C.-L. Tsai, C.-H. Huang, and L. Fu, “Interpretable deep learning system for identifying critical patients through the prediction of triage level, hospitalization, and length of stay: Prospective study,” JMIR Medical Informatics, 2024.
[23] S. An, S. S, M. P, Poornima, and P. H. A. Khan, “AI-based smart healthcare system for optimized ambulance routing and predictive ICU bed availability,” 2025 9th International Conference on Computational System and Information Technology for Sustainable Solutions (CSITSS), 2025.
[24] A. Amal, T. Mounira, M. Feten, and K. Ouajdi, “Deep learning for multivariate ICU beds forecasting during global healthcare crisis: COVID-19 case study,” International Conference on Control, Decision and Information Technologies, 2025.
[25] S. Kendale, A. M. Bishara, M. Burns, S. Solomon, M. Corriere, and M. . Mathis, “Machine learning for the prediction of procedural case durations developed using a large multicenter database: Algorithm development and validation study,” JMIR AI, 2022.
[26] Y. B. Corren, J. Merrill, R. B. Wilkinson, C. Cannon, J. P. Bickel, and B. Y. Reis, “Predic ng surgical department occupancy and patient length of stay in a paediatric hospital setting using machine learning: A pilot study,” BMJ Health Care Infor- matics, 2022.
[27] S. S. Bhat, V. R. Srihari, A. Prabhune, S. S. Satheesh, and A. B. Bidrohi, “Optimizing medication access in public healthcare centers: A machine learning stochastic model for inventory management and demand forecasting in primary health services,” 2024 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), 2024.
[28] W. Punnahitanond, P. Kantavat, N. Prompoon, and T. Ananpiriyakul, “Forecasting drug dispensation using machine learning: A case study on a large public hospital,” 2025 8th International Conference on Artificial Intelligence and Big Data (ICAIBD), 2025.
[29] M. Engelke et al., “Predicting individual patient platelet demand in a large tertiary care hospital using machine learning,” Transfusion Medicine and Hemotherapy, 2023.
[30] R. Fa et al., “Prediction of prolonged length of stay from first 2 days of hospitalization data: A SHAP value-based variable selection method for a simplified model,” International Journal for Quality in Health Care, 2025.
[31] A. D. Orcid, T. Ndakondja, and A. Dongo, “Assessing the impact of artificial intelligence and machine learning on forecasting medication demand and supply in public pharmaceutical systems: A systematic review,” GSC Biological and Pharmaceutical Sciences, 2024.
[32] O. Ogundeko-Olugbami and O. Ogundeko, “AI-enhanced predictive analytics systems combatting health disparities while driving equity in u.s. Healthcare delivery,” World Journal of Advanced Research and Reviews, 2025.
[33] C. P. Singh, “Leveraging predictive analytics and artificial intelligence for optimal healthcare staffing: A focus on provider resource allocation,” Progress in Medical Sciences, 2023.
[34] S. Gupta, M. Gupta, P. Pahuja, Geeta, and R. Kumar, “Cloud-based predictive analytics for hospital resource optimization,” 2025 2nd International Conference on Computational Intelligence and Computing Applications (ICCICA), 2025.