An LSTM Neural Network Approach to Resource Allocation in Hospital Management Systems

Ashish K Saxena
https://orcid.org/0009-0002-1647-9266

Rohit R. Dixit,
Siemens Healthineers
University of Texas at Tyler Tyler, United States
https://orcid.org/0000-0002-9888-6633

Attia Aman-Ullah,
PhD, School of Business Management,
Universiti Utara Malaysia, Sintok, Malaysia

Abstract

Hospital Management Systems (HMS) are essential for the coordination of clinical, operational, and administrative operations in healthcare settings. Central to these systems is resource allocation for operating efficiency and providing high-quality patient care. This research presents an innovative approach using a Long Short-Term Memory (LSTM) neural network to optimize resource allocation within HMS. The deep learning-based LSTM model analyzes historical and real-time data, learning from temporal patterns to predict resource requirements with high accuracy. The study evaluates the LSTM model's performance in comparison to actual data across various resource allocation scenarios, demonstrating the model's robust predictive capability and its potential as a decision-support tool. This model's integration with HMS is an initial move toward the delivery of healthcare services that are more flexible, effective, and patient-focused. This paper discusses the methodology, results, and significant implications of using LSTM networks in hospital management, advocating for their role in the future of healthcare systems. The proposed LSTM model can be applied in healthcare administration for aiming to minimize patient wait times, optimize staff allocation, and enhance patient outcomes.

***Keywords**: LSTM (Long Short-Term Memory) Neural Network, Resource Allocation, Hospital Management Systems (HMS), Predictive Analytics, Healthcare Optimization*

Introduction

Hospital Management Systems (HMS) constitute an integral framework within healthcare facilities, orchestrating a myriad of operational, clinical, and administrative functions [1]. At the core of an HMS lies the critical process of resource allocation—a decision-making and implementation process that is essential for efficient hospital operations and high-quality patient care [2]–[4]. Effective resource allocation within an HMS demands careful management of diverse elements including, but not limited to, human resources, medical equipment, bed allocation, and scheduling of services [5]. The intricacy of these tasks arises from their variable and interdependent nature, which must respond adaptively to the unpredictable flux of hospital demands. Ensuring optimal resource distribution is pivotal to preventing bottlenecks, reducing patient wait times, and enhancing the overall efficacy of healthcare delivery systems [6].

The evolution of Hospital Management Systems (HMS) has been significantly marked by the integration of advanced computational methods, addressing the challenges inherent in resource allocation and patient care optimization [7]. Historical literature reviews trace the progression from manual and semi-automated systems to the adoption of comprehensive computational tools, delineating a trajectory towards increasingly sophisticated HMS solutions. Emerging studies within the sector advocate for the application of artificial intelligence (AI) and machine learning (ML) techniques, reflecting a paradigm shift in the methodologies employed to manage healthcare resources [8]. Challenges such as dynamic patient influx, variable resource demands, and the need for real-time decision-making have catalyzed the exploration of predictive models and decision-support systems. Notably, the amalgamation of AI with operational research methods has led to the development of hybrid systems capable of adapting to the fluid and complex nature of hospital workflows. Such systems have demonstrated promise in addressing the multifaceted challenge of aligning resource availability with patient needs, which is a critical determinant of service quality and efficiency. As the sector moves towards a more patient-centric model, the capacity for anticipatory resource management and the personalization of patient care pathways stand out as focal areas of innovation. As hospitals transition to electronic health records (EHRs), the need for robust data governance frameworks has become increasingly apparent. These frameworks play a critical role in guaranteeing patient data availability, confidentiality, and correctness, all of which are essential for the efficient operation of computational HMS systems. Concerns regarding data security, privacy, and the ethical use of AI are recurrent themes within the literature, indicating the necessity for ongoing discourse and regulatory evolution in tandem with technological advances.

This study contributes to the field of computational Hospital Management Systems (HMS) by introducing a novel LSTM-based methodology for optimizing resource allocation efficiency. Our deep learning approach models and predicts hospital resource usage, offering HMS with improved decision-making and insightful operational analytics. The LSTM model forecasts resource needs with high accuracy with temporal patterns within hospital data in order to enable streamlined planning and optimized allocation. We address the real-world challenges of HMS with a rigorous approach, aiming to provide healthcare providers with an adaptable decision-support tool that anticipates the healthcare environment.

Literature Review

Different computational approaches in HMS

The integration of advanced computational approaches in Healthcare Management Systems (HMS) has been a significant driver of innovation, enhancing the efficiency and effectiveness of healthcare services. Lopez-Rubio et al. (2015) highlight the critical role of computational intelligence in managing vast datasets within healthcare organizations, enabling the extraction of valuable knowledge to improve services from both medical and managerial perspectives. This transformative impact is further underscored by Fang et al. [9], who discuss the challenges traditional health data management systems face in the era of "big data". They emphasize the necessity for advanced computational health informatics capable of handling data's volume, velocity, variety, and veracity. In exploring market dynamics, Montefiori and Resta [10] analyze healthcare market dynamics through Kohonen's Self-Organizing Maps, providing insights into the competitive dynamics between healthcare providers and patients. This approach showcases computational methods as essential tools for modeling hospital behavior and understanding demand mechanisms. Winslow et al. [11], delve into computational medicine, describing how models can encapsulate molecular networks and disease mechanisms specific to patients, thus fostering the personalization of therapies and advancing clinical care through a comprehensive understanding of health and disease. Ackerman and Locatis [12] review the application of advanced computing and networking in healthcare, demonstrating its relevance across various settings and specialties. This underscores the significance of network quality alongside technological advancements. The potential of deep learning in revolutionizing healthcare is presented by Esteva et al. [13], with applications ranging from medical imaging to electronic health record (EHR) data analysis and robotic-assisted surgery, illustrating deep learning's transformative potential in various medical domains. Huys et al. [14], explore the field of computational psychiatry, demonstrating how computational models grounded in neuroscience and machine learning can significantly improve outcomes for patients suffering from mental illnesses. Together, these studies illustrate a broad and impactful integration of computational intelligence, machine learning, and advanced networking technologies in healthcare, underscoring a trend towards more data-driven, personalized, and efficient healthcare solutions.

Deep Learning for HMS

Ravì et al. (2017) present a comprehensive review of deep learning applications in health informatics, including medical imaging, pervasive sensing, and public health. This study underscores deep learning's potential to automatically generate high-level features from data, which is crucial for predictive analytics and semantic interpretation in healthcare (Ravì et al., 2017). Benchmarking Deep Learning Models on Large Healthcare Datasets: Purushotham et al. [15], benchmark the performance of deep learning models against traditional ML models and prognostic scoring systems across several clinical prediction tasks using the MIMIC-III dataset. Their findings highlight the superior performance of deep learning models, especially when utilizing raw clinical time series data. A Review on Deep Learning Approaches in Healthcare Systems: Shamshirband et al. [16], investigate deep learning applications within healthcare systems, covering various network architectures and industrial trends. The paper emphasizes deep learning as a promising method for pattern recognition, vital for interpreting complex healthcare data. Deep Learning in Medical Imaging: Kim et al.

[17] discuss the revolutionary impact of deep learning in medical imaging, highlighting how artificial neural networks have outperformed traditional ML methods in tasks such as image classification, detection, and segmentation. This advancement facilitates improved diagnostics and patient care in radiology and pathology. Predicting Healthcare Trajectories from Medical Records: Pham et al. [18], introduce DeepCare, a dynamic neural network model capable of reading medical records to predict future medical outcomes. DeepCare models patient health trajectories, demonstrating efficacy in disease progression modeling and intervention recommendation. A Review on the Application of Deep Learning in System Health Management: Khan and Yairi [19], provide a systematic review of deep learning applications in system health management, discussing architectures, theories, and the potential of deep learning for fault diagnosis and prognostics. Despite its benefits, the paper also highlights the challenges and future research directions to further adopt deep learning in healthcare systems.

Hospital management system

Typical Healthcare System

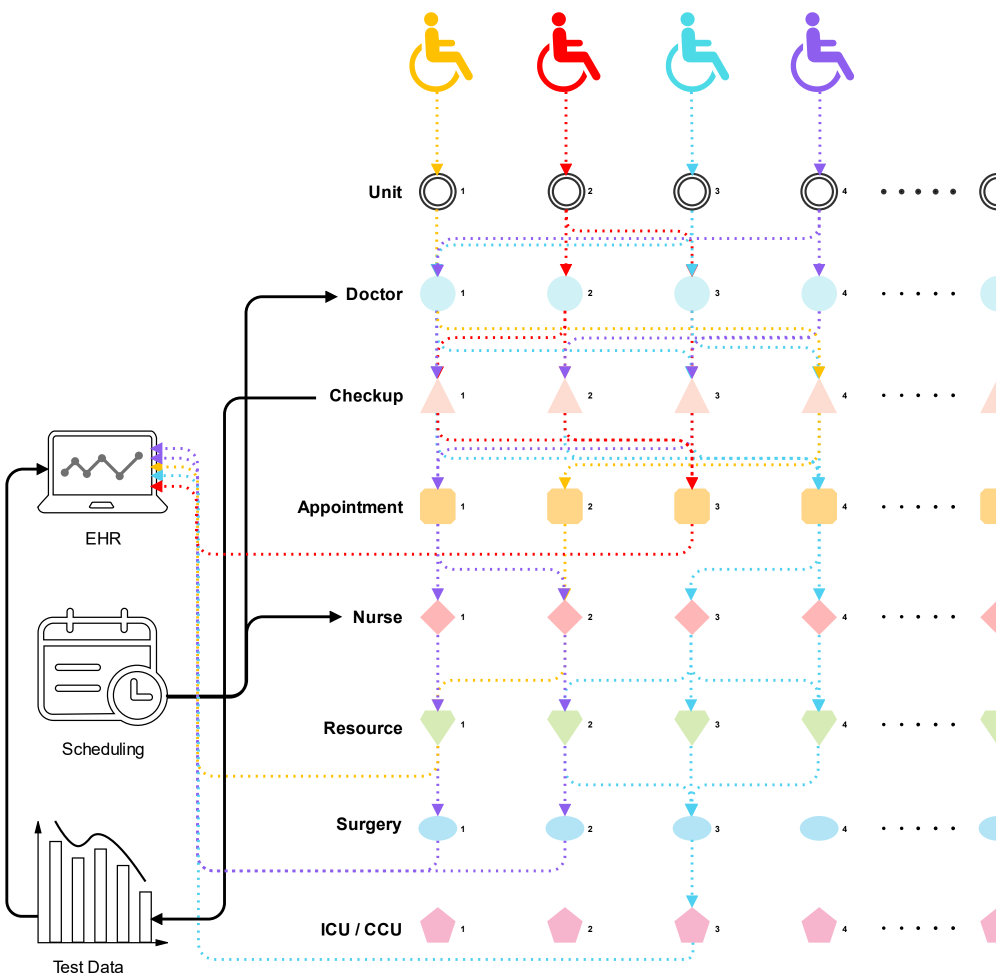

Figure 1. A simplified typical healthcare system

A typical hospital functions as an ecosystem where various specialized departments collaborate to ensure patient care. The emergency department acts as the first response to acute cases, while outpatient clinics handle non-urgent consultations. Admissions process patients needing inpatient care. Patient care units, including general and specialized wards, ICUs, and surgical suites, provide focused treatments, manned by teams of healthcare professionals. Supporting these frontline services are diagnostic units such as labs and imaging, and ancillary services, including nutrition and maintenance, which are crucial for comprehensive patient care. The administrative wing manages regulatory compliance, finances, and resources, ensuring smooth hospital operations. The operation of a typical healthcare system is shown in Figure 1.

Hospital management system

The literature on HMS discusses a transition from conventional management practices to more sophisticated, data-driven approaches. Past research highlights the utilization of various computational techniques and algorithms that aim to improve different components of the HMS, such as patient flow management, appointment scheduling, and inventory control. Studies have demonstrated the efficacy of predictive modeling and simulation methods in optimizing resource allocation, resulting in reduced patient wait times and increased service quality. Moreover, the adoption of electronic health records (EHRs) within HMS has facilitated the accumulation of extensive data, providing a rich foundation for employing advanced analytics to drive decision-making processes.

At the heart of HMS lies the Patient Management module, a critical component that manages patient-centric workflows, such as registration, appointment scheduling, bed management, and patient record maintenance. It serves as the backbone of the system, where the patient journey from admission to discharge is tracked and optimized for efficiency. The Electronic Medical Records (EMR) or Electronic Health Records (EHR) sub-modules are integrated into this system to ensure that patients' health information is recorded, updated, and accessible across different healthcare providers. The Clinical Management aspect of HMS focuses on the operational efficiency of medical services delivered within the institution. This includes managing intricate details within Lab Information Systems (LIS), Radiology Information Systems (RIS), pharmacy management, and surgery scheduling. These systems are designed to work in cohesion, facilitating seamless communication between various departments, thereby enhancing the quality of patient care delivered. Concurrently, Administrative Management captures the essence of the non-clinical operations of the hospital. It comprises modules for human resources, encompassing staff scheduling and payroll, inventory management for medical and non-medical supplies, financial reporting for an in-depth understanding of the hospital's economic health, and data analytics for strategic decision-making.

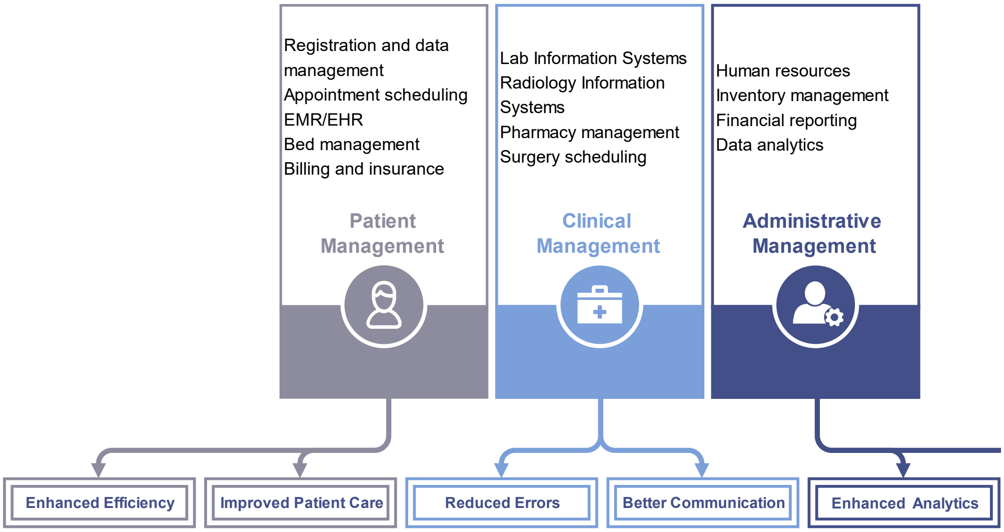

Figure 2. Core elements and benefits of HMS

The integration of these modules within an HMS is designed to bring about Enhanced Efficiency, primarily by automating routine tasks, thereby reducing manual labor and minimizing paperwork. Improved Patient Care is achieved through centralized access to medical records, enabling healthcare providers to make informed decisions. A reduction in Errors is facilitated by built-in checks and alerts, which are critical in a high-stakes healthcare environment. Better Communication between disparate hospital departments is ensured, aiding in the efficient coordination of care. Cost Savings are realized through optimized resource utilization and the elimination of redundant processes. Finally, Enhanced Data Analytics is provided by the system, furnishing hospital administrators with actionable insights derived from complex data sets, facilitating a data-driven approach to hospital management.

Methods

Data Collection

Our dataset comprises a comprehensive range of longitudinal data obtained from various departments within a healthcare facility. This includes but is not limited to patient admission and discharge records, staff schedules, inventory levels of medical supplies, and quantifiable patient care outcomes. The data spans a significant temporal range, capturing the dynamics of hospital resource allocation over extended periods. Such a dataset provides the groundwork for a rich analysis of resource allocation efficiency. Our preprocessing phase also includes transforming the collected data into structured sequences. These sequences are constructed to preserve the temporal order of events, reflecting the actual timing and order of resource allocation within the hospital. This structure is used for the LSTM network to understand and learn from the patterns inherent in the data.

LSTM Model

The LSTM (Long Short-Term Memory) network is a category of Recurrent Neural Network (RNN) capable of learning order dependence in sequence prediction problems. This is essential in complex problems like hospital resource allocation where the temporal sequence of events holds significant importance. The LSTM network architecture facilitates forward propagation of data through time, capturing and storing relevant information at each time step. The network comprises multiple LSTM units, each consisting of a cell state and three regulatory gates: input, output, and forget gates. These gates regulate the flow of information into and out of the cell, and between cells. The diagram in Figure 3 illustrates the LSTM model training components, including the Backpropagation Through Time (BPTT) for weight adjustment, Mean Squared Error (MSE) for loss calculation, and the Optimizer (Adam/RMSprop) mechanisms. The architecture showcases the input layer's role in feeding data into the network, followed by several hidden LSTM layers for processing the temporal sequence, culminating in a dense output layer for prediction output.

Training

Backpropagation Through Time (BPTT): This training algorithm is specifically designed for recurrent neural networks (RNNs) such as LSTM. The BPTT extends the conventional backpropagation algorithm by unfolding the network through time, allowing gradients to flow backward through each time step, updating the weights sequentially to reduce errors in prediction. This mechanism accounts for temporal dependencies in hospital management for capturing patterns over time.

Mean Squared Error (MSE) for Loss Calculation: MSE is selected as the loss function when targeting continuous efficiency metrics. It computes the average of the squares of the differences between the predicted and actual values, thereby quantifying the variance of the model's predictions. The squaring aspect of MSE ensures that larger errors are penalized more, which in turn drives the model to improve accuracy.

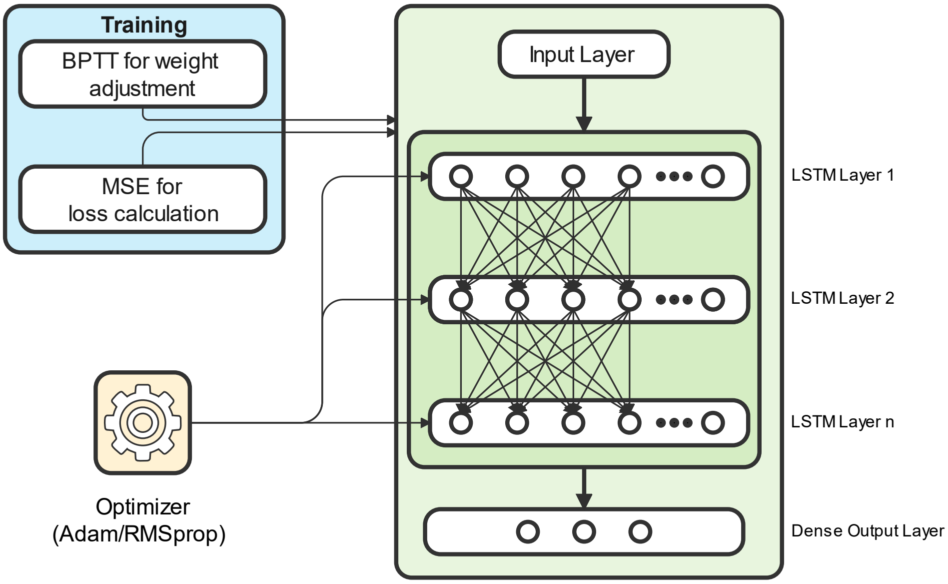

Figure 3. Schematic of LSTM Network Architecture for Resource Allocation in HMS

Optimization Strategy: The Adam optimizer, known for its efficiency in RNNs, will be utilized for adjusting the weights of the LSTM layers. Adam's advantage lies in its adaptive learning rate, which adjusts as per the learning's progression, thereby preventing the convergence at suboptimal weights.

Batch Training: Training the model in batches optimizes the computational resources because it leverages the inherent parallel processing power of modern GPUs for expediting the training phase without compromising the model's ability to learn from the data. The convergence of these components during training will result in an LSTM model adept at predicting the efficiency of resource allocation within a hospital setting. Through iterative refinement of weights and biases, the model will strive to minimize prediction errors, thereby serving as a reliable tool for hospital management decision support.

Hyperparameter Optimization

A series of experiments will be conducted to optimize the hyperparameters of the LSTM model, which include the learning rate, number of LSTM units, and the batch size. Optimization techniques such as grid search or random search will be employed to determine the optimal configuration that results in the best performance of the model. The goal of this optimization is to fine-tune the model to the specifics of our data and predictive task, ensuring that the model is not only accurate but also efficient in its predictions.

Results and Discussion

The predictive accuracy of the LSTM model was evaluated by comparing the predicted outcomes against the actual data. Two separate resource allocation scenarios were considered to assess the model's generalizability and precision. The results, as depicted in Figures 4 and 5, shows the correlation between the actual and the predicted values, alongside the residual errors associated with each prediction.

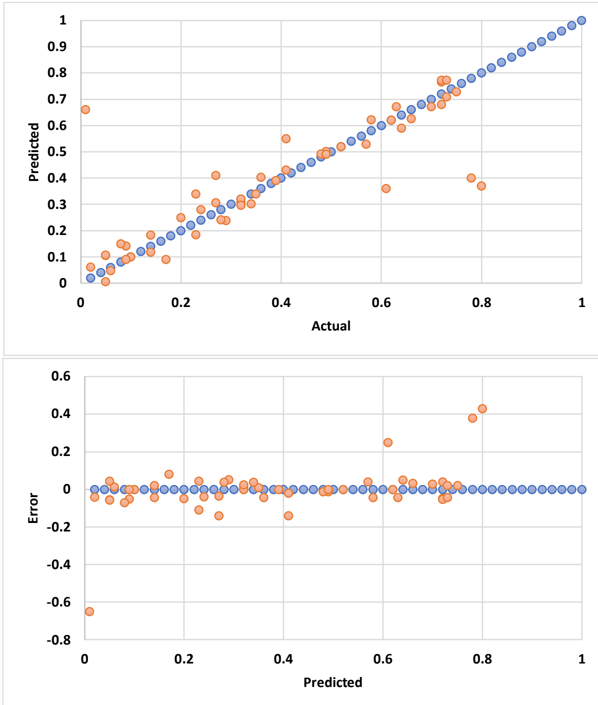

Figure 4. Comparative analysis of the LSTM model's predictions against actual data for Scenario 1, depicting both the concordance in predicted versus actual resource allocation efficiencies (left) and the distribution of residual errors (right)

For both scenarios, the LSTM model exhibited a robust predictive capacity, as indicated by the close alignment of the predicted values with the actual data. The distribution of residual errors, while present, remained tightly clustered around zero, suggesting minimal deviation from the actual values. This consistency shows the model's adeptness in learning from the temporal data and its application in forecasting resource allocation efficiency in a hospital setting.

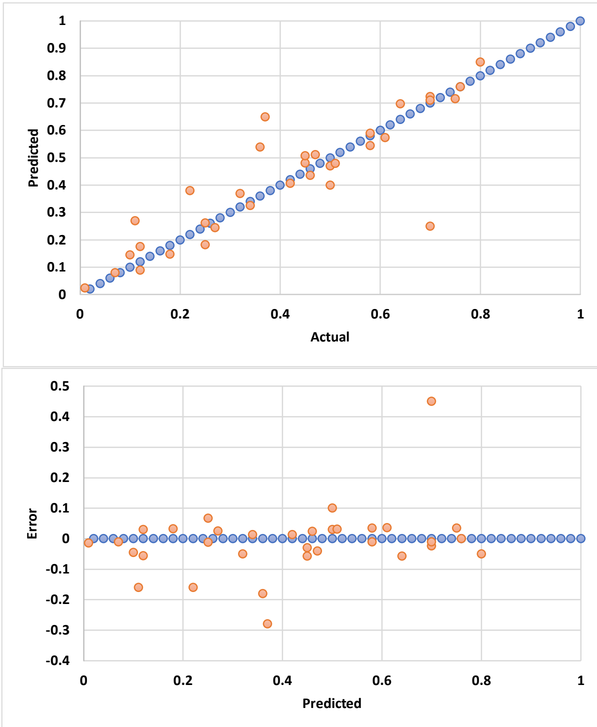

Figure 5. Evaluation of the LSTM model's predictions for Scenario 2, showcasing the correlation between predicted and actual values (left) and the corresponding residual errors, highlighting the model's prediction fidelity (right).

The model's capacity to accurately forecast resource allocation can significantly enhance operational efficiency, reduce patient wait times, and optimize staff scheduling.

Conclusion

This study has presented a significant advancement in the field of Hospital Management Systems (HMS) through the deployment of a Long Short-Term Memory (LSTM) neural network designed to enhance the efficiency of resource allocation. Our model demonstrates the potential of deep learning in healthcare management by methodically examining temporal data and finding essential patterns for projecting resource demands. The LSTM model demonstrated a high degree of predictive accuracy across multiple scenarios, indicating its robustness and adaptability to the complexities of hospital operations. The close alignment of predicted values with actual resource utilization illustrates the model's capability to serve as a reliable decision-support tool for the strategic planning and operational efficiency of healthcare facilities. As the healthcare business continues to generate vast amounts of data, the need and urgency of computational models that can analyze and use this information efficiently grows. This study adds to that account by presenting a model that not only accurately predicts outcomes but also gives insights that were not previously accessible to hospital administrators. Our findings reinforce the notion that computational models are not merely auxiliary tools but integral components capable of affecting the flow of healthcare delivery.

References

[1] K. Sahaf, M. B. E. N. Ali, S. Rifai, O. Bouksour, and A. Adri, "A model for measuring the impact of Hospital Supply Chain on the psychological state of cancer patients using PLS method," *Int. J. Logist. Syst. Manag.*, vol. 1, no. 1, p. 1, 2020.

[2] M. I. Fernandez, P. Chanfreut, I. Jurado, and J. M. Maestre, "A data-based model predictive decision support system for inventory management in hospitals," *IEEE J. Biomed. Health Inform.*, vol. 25, no. 6, pp. 2227–2236, Jun. 2021.

[3] C. R. Rosales, Michael J. Magazine, and U. S. Rao, "Dual sourcing and joint replenishment of hospital supplies," *IEEE Trans. Eng. Manage.*, vol. 67, no. 3, pp. 918–931, Aug. 2020.

[4] M. Marinelli, "Emergency healthcare facilities: Managing design in a post covid-19 world," *IEEE Eng. Manag. Rev.*, vol. 48, no. 4, pp. 65–71, Dec. 2020.

[5] A. S. Albahri *et al.*, "Based multiple heterogeneous wearable sensors: A smart real-time health monitoring structured for hospitals distributor," *IEEE Access*, vol. 7, pp. 37269–37323, 2019.

[6] S. Safdar, S. Ahmed Khan, A. Shaukat, and M. U. Akram, "Genetic algorithm based automatic out-patient experience management system (GAPEM) using RFIDs and sensors," *IEEE Access*, vol. 9, pp. 8961–8976, 2021.

[7] J. Ahmad, J. Iqbal, I. Ahmad, Z. A. Khan, M. I. Tiwana, and K. Khan, "A simulation based study for managing hospital resources by reducing patient waiting time," *IEEE Access*, vol. 8, pp. 193523–193531, 2020.

[8] R. Shahzadi, S. M. Anwar, F. Qamar, M. Ali, J. J. P. C. Rodrigues, and M. Alnowami, "Secure EEG signal transmission for remote health monitoring using optical chaos," *IEEE Access*, vol. 7, pp. 57769–57778, 2019.

[9] R. Fang, S. Pouyanfar, Y. Yang, S.-C. Chen, and S. S. Iyengar, "Computational health informatics in the big data age," *ACM Comput. Surv.*, vol. 49, no. 1, pp. 1–36, Mar. 2017.

[10] M. Montefiori and M. Resta, "A computational approach for the health care market," *Health Care Manag. Sci.*, vol. 12, no. 4, pp. 344–350, Dec. 2009.

[11] R. L. Winslow, N. Trayanova, D. Geman, and M. I. Miller, "Computational medicine: translating models to clinical care," *Sci. Transl. Med.*, vol. 4, no. 158, p. 158rv11, Oct. 2012.

[12] M. Ackerman and C. Locatis, "Advanced networks and computing in healthcare," *J. Am. Med. Inform. Assoc.*, vol. 18, no. 4, pp. 523–528, Jul. 2011.

[13] A. Esteva *et al.*, "A guide to deep learning in healthcare," *Nat. Med.*, vol. 25, no. 1, pp. 24–29, Jan. 2019.

[14] Q. J. M. Huys, M. Browning, M. P. Paulus, and M. J. Frank, "Advances in the computational understanding of mental illness," *Neuropsychopharmacology*, vol. 46, no. 1, pp. 3–19, Jan. 2021.

[15] S. Purushotham, C. Meng, Z. Che, and Y. Liu, "Benchmarking deep learning models on large healthcare datasets," *J. Biomed. Inform.*, vol. 83, pp. 112–134, Jul. 2018.

[16] S. Shamshirband, M. Fathi, A. Dehzangi, A. T. Chronopoulos, and H. Alinejad-Rokny, "A review on deep learning approaches in healthcare systems:

Taxonomies, challenges, and open issues," *J. Biomed. Inform.*, vol. 113, no. 103627, p. 103627, Jan. 2021.

[17] M. Kim *et al.*, "Deep learning in medical imaging," *Neurospine*, vol. 16, no. 4, pp. 657–668, Dec. 2019.

[18] T. Pham, T. Tran, D. Phung, and S. Venkatesh, "Predicting healthcare trajectories from medical records: A deep learning approach," *J. Biomed. Inform.*, vol. 69, pp. 218–229, May 2017.

[19] S. Khan and T. Yairi, "A review on the application of deep learning in system health management," *Mech. Syst. Signal Process.*, vol. 107, pp. 241–265, Jul. 2018.