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GRU-Based Forecasting of Emergency Department Patient Volume for Hospital Operations and Supply Chain Planning

Agus Mansur[1*], Fadhil Adita Ramadhan[1], Achmad Bauravindah[2]

[1] Department of Industrial Engineering, Islamic University of Indonesia, Yogyakarta 55584, Indonesia
[2] Department of Informatics, Islamic University of Indonesia, Yogyakarta 55584, Indonesia

Corresponding Author Email: agusmansur@uii.ac.id

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ABSTRACT

Emergency departments (EDs) experience highly variable patient arrivals that complicate operational planning and resource coordination. Accurate demand forecasting is therefore essential to support timely decision-making in hospital operations. This study developed a gated recurrent unit (GRU)-based time series forecasting model to predict ED patient volumes using high-resolution hourly arrival data collected over four years. The model is evaluated across short-, medium-, and long-term forecasting horizons to assess its ability to capture daily, weekly, and seasonal demand patterns. The results indicate that the GRU effectively captures non-linear temporal dynamics and produces stable forecasts across time scales. Rather than positioning forecasting accuracy as an isolated objective, this study explicitly frames patient volume prediction as an operational input for hospital supply chain planning, particularly in workforce scheduling, facility utilization, and logistics preparation. By linking deep learning–based forecasting with hospital operational decision contexts, this research provides an application-oriented contribution to the healthcare analytics literature. The findings suggest that GRU models can serve as practical decision-support tools in emergency care environments and highlight the need for future validation across multiple hospital settings.

1. INTRODUCTION

The emergency department (ED) constitutes a critical component of modern healthcare systems, functioning as the primary access point for patients requiring urgent and unscheduled medical care. In the United States alone, EDs manage more than 140 million patient visits annually, highlighting their indispensable role in ensuring timely medical intervention across a wide range of clinical conditions [1]. Approximately 18–19% of the population seeks emergency care at least once each year, reflecting persistently high and fluctuating demand levels that place considerable pressure on hospital operations [2]. This sustained demand intensifies the challenge of balancing service capacity with patient needs, particularly in environments characterized by limited resources and increasing operational complexity.

From an operational perspective, EDs must manage interactions among medical personnel, facilities, equipment, and inpatient beds. These interactions must be coordinated while maintaining acceptable service quality. However, patient arrivals are inherently unpredictable. They are influenced by multiple factors, such as time-of-day effects, seasonal variations, public health conditions, and unexpected external events [3]. Such variability complicates resource planning and disrupts workforce scheduling, logistics coordination, and care delivery processes. Empirical evidence from diverse healthcare settings indicates that unanticipated fluctuations in patient volume are associated with delays in treatment initiation, inefficient staff utilization, and increased operational strain [4]. These challenges underscore the necessity of reliable forecasting mechanisms capable of supporting adaptive, data-driven decision-making in emergency care environments.

One of the most critical consequences of demand uncertainty in EDs is overcrowding, which adversely affects both clinical outcomes and organizational performance. Overcrowded EDs are associated with prolonged waiting times, reduced care quality, and increased patient dissatisfaction [5]. Delayed treatment is critically associated with overcrowded settings has been shown to significantly increase mortality risks for time-sensitive conditions such as sepsis, where each hour of delay may raise mortality rates by approximately 4–9% [6]. In addition to clinical implications, ED overcrowding generates substantial economic burdens for hospitals by increasing operational inefficiencies, exacerbating workforce shortages, and straining medical supply chains [7]. These pressures have been further intensified by external shocks, including the COVID-19 pandemic, which disrupted patient flow patterns and reduced hospital revenues due to postponed elective procedures and changes in healthcare-seeking behavior [8]. Consequently, the ability to anticipate patient arrivals with sufficient accuracy has become a strategic necessity rather than an operational convenience.

Accurate forecasting of ED patient volumes is therefore essential to mitigate overcrowding, enhance service responsiveness, and maintain hospital sustainability. Traditional forecasting techniques, such as Autoregressive Integrated Moving Average (ARIMA) models and heuristic-based approaches, have been widely applied to estimate patient arrivals [9]. While these methods offer interpretability and simplicity, they are inherently limited by linear assumptions and often fail to capture the nonlinear and complex temporal dynamics characteristic of emergency care demand [10]. Sudden surges triggered by infectious disease outbreaks, public holidays, or environmental factors frequently fall outside the predictive capability of conventional models, leading to suboptimal staffing decisions and inefficient resource allocation [11]. As healthcare systems evolve toward greater complexity, the limitations of traditional statistical approaches become increasingly pronounced.

In response to these challenges, machine learning techniques have emerged as a promising alternative for time-series forecasting in healthcare contexts. Unlike traditional models, machine learning algorithms are capable of learning nonlinear relationships and adapting to evolving data patterns [12]. Recurrent Neural Networks (RNNs), in particular, are designed to model sequential dependencies by retaining information from previous time steps, making them well-suited for patient arrival forecasting tasks [13]. Among RNN variants, the gated recurrent unit (GRU) has gained attention due to its relatively simple architecture, computational efficiency, and ability to capture both short-term fluctuations and long-term temporal dependencies through gating mechanisms [14]. Prior studies have demonstrated the effectiveness of GRU-based models in various healthcare forecasting applications, including patient volume prediction and resource demand estimation [15]. Nevertheless, empirical investigations that explicitly examine the role of GRU-based forecasting in supporting ED operations remain limited.

More importantly, existing studies on ED patient arrival forecasting predominantly focus on improving predictive accuracy or interpretability, while the operational implications for hospital supply chain management are often treated as secondary considerations. Forecast outputs are rarely integrated into decision-support frameworks that address staffing, logistics, and capacity planning in a coordinated manner. This gap limits the practical value of forecasting models in complex hospital environments, where patient demand uncertainty directly affects supply chain performance and service quality. Addressing this gap requires not only accurate predictive models but also a clear alignment between forecasting outcomes and operational decision-making processes.

Accordingly, the objective of this study is to develop a GRU-based forecasting model for ED patient arrivals and to evaluate its potential contribution to hospital supply chain decision support. The proposed model generates short-term (1-day), medium-term (7-day), and long-term (30-day) forecasts to accommodate the distinct planning horizons required for daily scheduling, tactical logistics coordination, and strategic capacity planning. By framing patient arrival forecasting within a supply chain management perspective, this study seeks to extend existing healthcare forecasting research beyond predictive performance and toward actionable operational insights.

The contribution of this research is threefold. First, it provides an empirical evaluation of GRU-based forecasting using high-resolution, multi-year ED arrival data. Second, it explicitly links forecasting results to hospital supply chain functions, including workforce allocation, facility utilization, and logistics planning. Third, it positions GRU as a decision-enabling tool rather than solely a predictive model, thereby contributing to the development of more responsive and data-driven emergency care systems. Through this integrated perspective, the study aims to support hospital managers and policymakers in improving operational efficiency, reducing congestion, and enhancing the quality of emergency healthcare services.

2. LITERATURE REVIEW

2.1 Uncertainty of emergency department patient arrivals

Hospitals face significant challenges in managing the unpredictable number of patient arrivals to the ED, as these arrivals are highly random and influenced by various external factors such as seasonal changes, holidays, disasters, and disease outbreaks [8]. This unpredictability can lead to critical issues in the hospital supply chain, including shortages of treatment beds, delayed services, overburdened healthcare staff, and strained medical logistics [16]. Traditional forecasting methods such as ARIMA and Exponential Smoothing often fall short in capturing complex, non-linear patterns and responding to extreme conditions like sudden spikes during pandemics [17]. As the hospital supply chain involves not only the movement of physical goods but also the coordination of medical personnel and treatment facilities, accurate forecasting becomes essential for ensuring timely and data-driven resource planning, enabling hospitals to improve operational efficiency and maintain the quality and safety of emergency care services [18].

2.2 Forecasting development towards machine learning

Due to the limitations of traditional statistical forecasting models in managing complex and dynamic data, there has been a shift toward the use of machine learning, which offers adaptive capabilities and enhanced accuracy in detecting non-linear patterns. Models such as Support Vector Machines, Decision Trees, and Random Forests provide significant improvements over conventional approaches but still struggle to model the sequential nature of time-based data such as daily patient arrivals [19]. To address this, the use of deep learning architectures like RNNs, Long Short-Term Memory (LSTM), and GRU has gained attention for their ability to retain historical context and capture long-term dependencies in data [20]. Among these, the GRU stands out for its simpler structure and computational efficiency while maintaining high predictive performance [21]. The model has shown promising results in various healthcare forecasting applications, including predicting daily case counts and intensive care unit demand, and is particularly suitable for real-time implementation in hospitals due to its scalability and minimal need for manual data preprocessing [22]. Its potential to support responsive and accurate forecasting makes it a valuable tool in optimizing hospital supply chain decisions related to resource allocation and patient flow management [23].

2.3 Challenges in implementing machine learning in hospitals

Despite the advantages of machine learning models such as the GRU in forecasting and optimizing emergency healthcare operations, practical barriers remain in their hospital adoption. Data quality is a major issue, as hospital information systems (HISs) often contain incomplete, inconsistent, or inaccurate patient records, reducing model reliability [24]. Many institutions also lack adequate computational infrastructure to train and deploy complex models, particularly in regions with limited technological resources. Model interpretability poses another challenge, since hospital administrators and clinicians may hesitate to rely on predictions from opaque systems [25]. Furthermore, models trained in one hospital may not generalize well to others due to differences in operations and demographics [26]. Advances such as transfer learning and federated learning address these concerns [27], enabling responsive hospital supply chains for real-time resource, staff, and capacity planning [28].

To illustrate the position of this research, many previous studies are presented along with the existing research gaps in relation to the current study. The results of the previous research mapping are presented in Table 1.

Table 1. Mapping of prior studies and identified gaps

No.	Titles	Topics Machine Learning Prediction	Emergency Department Management	Hospital Supply Chain
1	Forecasting Emergency Department Occupancy with Advanced Machine Learning Models and Multivariable Input [29]	Addressed	Addressed	Not Addressed
2	An Explainable Machine Learning Approach for Hospital Emergency Department Visits Forecasting Using Continuous Training and Multi-Model Regression [30]	Addressed	Addressed	Not Addressed
3	Interpretable Machine Learning Models for Prolonged Emergency Department Wait Time Prediction [31]	Addressed	Addressed	Not Addressed
4	Leveraging Machine Learning and Rule Extraction for Enhanced Transparency in Emergency Department Length of Stay Prediction [32]	Addressed	Addressed	Not Addressed
5	Predicting Triage of Pediatric Patients in The Emergency Department Using Machine Learning Approach [33]	Addressed	Addressed	Not Addressed

Based on the research gap mapping from five previous studies, it is evident that the development of machine learning in predicting patient volume in EDs has advanced in terms of accuracy, interpretability, and clinical applicability. Most of these studies, however, remain focused on forecasting ED metrics such as occupancy, waiting times, length of stay, and patient triage, without extending their application to hospital supply chain management. To address this gap, the present study proposes an integration between machine learning-driven ED patient volume forecasting and hospital supply chain decision-making. This approach aims to establish a more responsive, data-driven system for real-time logistics allocation, resource management, and capacity planning in complex healthcare environments.

3. METHODOLOGY

This study employed a quantitative predictive modeling approach to forecast ED patient arrivals using a GRU neural network. The methodological framework consisted of data collection and preprocessing, model development and training, performance evaluation, and multi-horizon forecasting analysis. The overall research flow is presented in Figure 1.

Hourly ED arrival data were obtained from the Dryad public repository, covering January 2014 to December 2017. The dataset provided high temporal granularity suitable for capturing short-term fluctuations and seasonal patterns. Missing values were handled using forward-fill imputation to preserve temporal continuity. Data normalization was performed using Min–Max scaling to stabilize gradient updates during training. The time series was transformed into a supervised learning format using a 30-day sliding window, enabling the model to learn daily, weekly, and seasonal dependencies. The dataset was divided into training (90%) and testing (10%) subsets to evaluate generalization performance.

3.1 Model development

The forecasting model employed a GRU, an RNN architecture designed to mitigate vanishing gradient issues while maintaining a relatively simple structure through reset and update gates [34]. The model architecture consisted of a single GRU layer followed by a dense output layer producing one-step-ahead predictions. The GRU layer comprised 50 hidden units. This configuration was selected to balance representational capacity and computational efficiency, ensuring adequate modeling of daily and seasonal arrival patterns while limiting overfitting risk. The model was developed and trained using the Adam optimizer [35] with a learning rate of 0.001, which is widely adopted for RNNs due to its adaptive learning mechanism and stable convergence behavior. A batch size of 32 was used to maintain efficient gradient estimation, and the number of epochs was fixed at 50 based on observed convergence stability and validation error saturation during preliminary experimentation. Model implementation was conducted in Python using the TensorFlow/Keras framework.

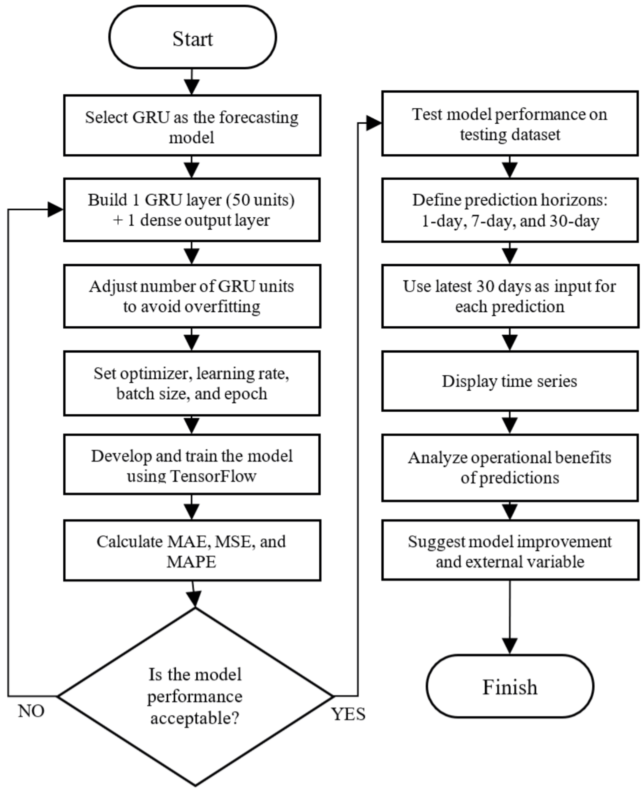

Figure 1. Research flow

3.2 Model evaluation and performance metrics

Model performance was evaluated by comparing predicted and observed patient arrivals in the testing dataset using Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) [36, 37]. These metrics jointly assess absolute deviation, sensitivity to large errors, and relative prediction accuracy:

$$MAE = \frac{1}{n}\sum_{I=1}^{n}\left|y_i - \hat{y}_i\right| \tag{1}$$

MSE penalizes large deviations more heavily by squaring the errors:

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

While MAPE evaluates the relative error as a percentage, useful for model comparisons:

$$MAPE = \frac{1}{n}\sum_{I=1}^{n}\left|\frac{y_i - \hat{y}_i}{\hat{y}_i}\right| \times 100\% \tag{3}$$

MAE and MAPE were emphasized due to their interpretability in operational contexts, where forecasting errors directly affect staffing and resource allocation decisions.

3.3 Forecasting horizons

To address different hospital planning requirements, forecasts were generated across three time horizons: short-term (1 day), medium-term (7 days), and long-term (30 days). Short-term forecasts support daily staffing and resource mobilization, medium-term forecasts assist weekly operational and logistics planning, and long-term forecasts inform strategic capacity and budgeting decisions.

A consistent 30-day sliding input window was applied across all horizons to capture daily, weekly, and seasonal patterns [38]. The window advanced daily, enabling the model to adapt to recent demand changes, including seasonal surges and public health events [39]. The characteristics and operational relevance of each forecasting horizon are summarized in Table 2.

Table 2. Characteristics and benefits of forecasting horizons

Forecast Horizon	Input Data	Prediction Output	Use Case	Strategic Benefit
Short term (1 day)	30 days	Following 1 day	Daily staffing arrangements, room allocation	Facilitates high responsiveness with minimal forecasting error
Medium term (7 days)	30 days	Following 7 days	Weekly operational planning, shift structuring	Provides a balance between tactical planning and predictive accuracy
Long term (30 days)	30 days	Following 30 days	Capacity budgeting and long-range facility planning	Supports strategic decision-making, although with greater forecast uncertainty

Table 3. Gated recurrent unit (GRU) model's contributions

Forecast Horizon	Model Utilization	Operational Focus	Managerial Application
1 day (Short Term)	Real-time demand forecasting	Scheduling of human resources and activation of resources	1. Utilize daily demand forecasts to schedule physicians and nurses effectively. 2. Adjust staff deployment in alignment with forecasted workload.
7 days (Medium Term)	Tactical planning	Allocation of space, equipment, and logistics	1. Use weekly forecasts to plan the assignment of inpatient beds and emergency facilities. 2. Organize medical logistics based on projected medium-term service needs.
30 days (Long Term)	Strategic planning	Long-term capacity planning	1. Anticipate future surges in patient volume to reduce waiting times. 2. Implement additional treatment areas or fast-track systems. Support investment and capacity planning decisions using long-term demand forecasts.
Cross-Horizon	Model enhancement and development	Strengthening model accuracy and scalability	1. Integrate external data (e.g., weather, public holidays, seasonal diseases) to improve forecast accuracy. 2. Explore advanced model architectures such as Long Short-Term Memory (LSTM) or Transformer for enhanced long-term prediction performance.

3.4 Data visualization for insight extraction

Several visualization techniques were employed to support model validation and interpretability. Time series plots were used to identify overall trends and structural shifts, while rolling average plots highlighted medium- and long-term tendencies by smoothing short-term volatility. Seasonal-Trend decomposition using Loess (STL) separated trend, seasonal, and residual components to reveal recurring demand pattern [40]. Annual boxplots identified interannual variability and extreme demand events, and hour–month heatmaps illustrated arrival intensity across daily and seasonal cycles [41]. These visual tools translated predictive results into actionable insights for ED operational planning.

3.5 Model insights and operational implications

The GRU model demonstrated reliable predictive performance, particularly for short-term forecasts, as reflected by low MAE and MAPE values [42]. This is demonstrated by the low values of MAE and MAPE, which reflect an acceptable level of predictive error for daily scheduling and real-time resource management in the ED. Although the accuracy declines gradually for medium-term (seven-day) and long-term (thirty-day) horizons due to increasing temporal uncertainty and the complexity of data dynamics, the model's ability to capture seasonal patterns and weekly trends continues to provide significant strategic value [43]. This information can be utilized as a basis for tactical and strategic hospital planning, including capacity planning, medical logistics procurement, and long-term budgeting and investment decisions [44]. Thus, while the model performs best in short-term predictions, the GRU model still offers important benefits across all time horizons by supporting more responsive and targeted data-driven decision-making. An integrated overview of the GRU model's contributions to hospital operational planning based on prediction horizons is presented in Table 3.

4. RESULT AND DISCUSSION

4.1 Hospital supply chain

Figure 2 presents the hospital supply chain as an integrated socio-technical system in which patient arrivals act as the primary demand signal that triggers downstream clinical and logistical processes. Beyond illustrating process flow, this figure establishes the analytical rationale for embedding demand forecasting within hospital operations. Variability in ED arrivals directly affects upstream decisions such as staff rostering and bed allocation, as well as downstream activities including pharmacy replenishment, sterilization cycles, and waste handling. Consequently, inaccuracies in anticipating ED demand propagate inefficiencies across the entire supply chain.

Within this framework, the GRU-based forecasting model functions as a demand-sensing mechanism that converts stochastic arrival patterns into structured information for decision-making. By integrating forecasts with the HIS, hospitals can shift from reactive resource allocation toward anticipatory planning. This linkage clarifies that the contribution of the proposed model lies not only in prediction accuracy, but also in strengthening coordination between clinical workflows and logistical operations under uncertainty.

4.2 Overall data distribution

These outliers are not merely statistical anomalies; they represent operational stress points that can severely disrupt hospital performance if not anticipated. Peaks observed in late 2014, mid-2015, and 2017 indicate periods during which routine staffing and inventory policies may have been insufficient. Figure 3 illustrates the overall distribution of ED patient arrivals across the four-year observation period, revealing pronounced volatility and multiple extreme outliers.

From a supply chain perspective, the absence of a clearly visible long-term trend in this raw distribution underscores the limitations of relying solely on descriptive statistics for operational planning. The dispersion of arrivals highlights the need for models capable of distinguishing structural demand patterns from irregular shocks. This observation justifies the application of RNNs, which are designed to extract latent temporal dependencies that are not apparent in aggregate visualizations.

4.3 Rolling average plot

Unlike the overall distribution, this representation indicates that ED demand does not evolve monotonically but alternates between periods of sustained increase and decline. The sharp rise observed in early 2015 contrasts with subsequent reductions in 2016 and later years, suggesting that annual demand shifts are influenced by contextual factors beyond simple seasonality. The rolling average shown in Figure 4 smooths short-term fluctuations and reveals medium-term demand trajectories that are obscured in the raw series.

Importantly, this analysis highlights a key distinction between rolling trends and seasonal effects. While seasonal decomposition isolates recurring patterns, the rolling average captures structural changes that accumulate over time, such as demographic shifts or changes in healthcare access. For hospital managers, this distinction is critical: seasonal effects inform routine adjustments, whereas rolling trends signal the need for strategic interventions, such as revising capacity policies or reallocating long-term resources.

4.4 Seasonal decomposition and implications for forecasting

The upward trend confirms a gradual increase in baseline ED demand, reinforcing the necessity of long-term capacity planning. However, the diffuse seasonal and residual components indicate that ED arrivals are influenced by overlapping temporal cycles and irregular shocks. Figure 5 decomposes the time series into trend, seasonal, and residual components.

This complexity explains why linear baseline models such as ARIMA often struggle to deliver stable forecasts in ED settings. ARIMA assumes fixed seasonal structures and linear relationships, which limit its ability to adapt to evolving demand patterns. In contrast, the GRU model implicitly learns these interactions through gated memory mechanisms, enabling it to accommodate both gradual trends and irregular deviations. Thus, the decomposition results provide qualitative support for the selection of GRU over traditional statistical approaches.

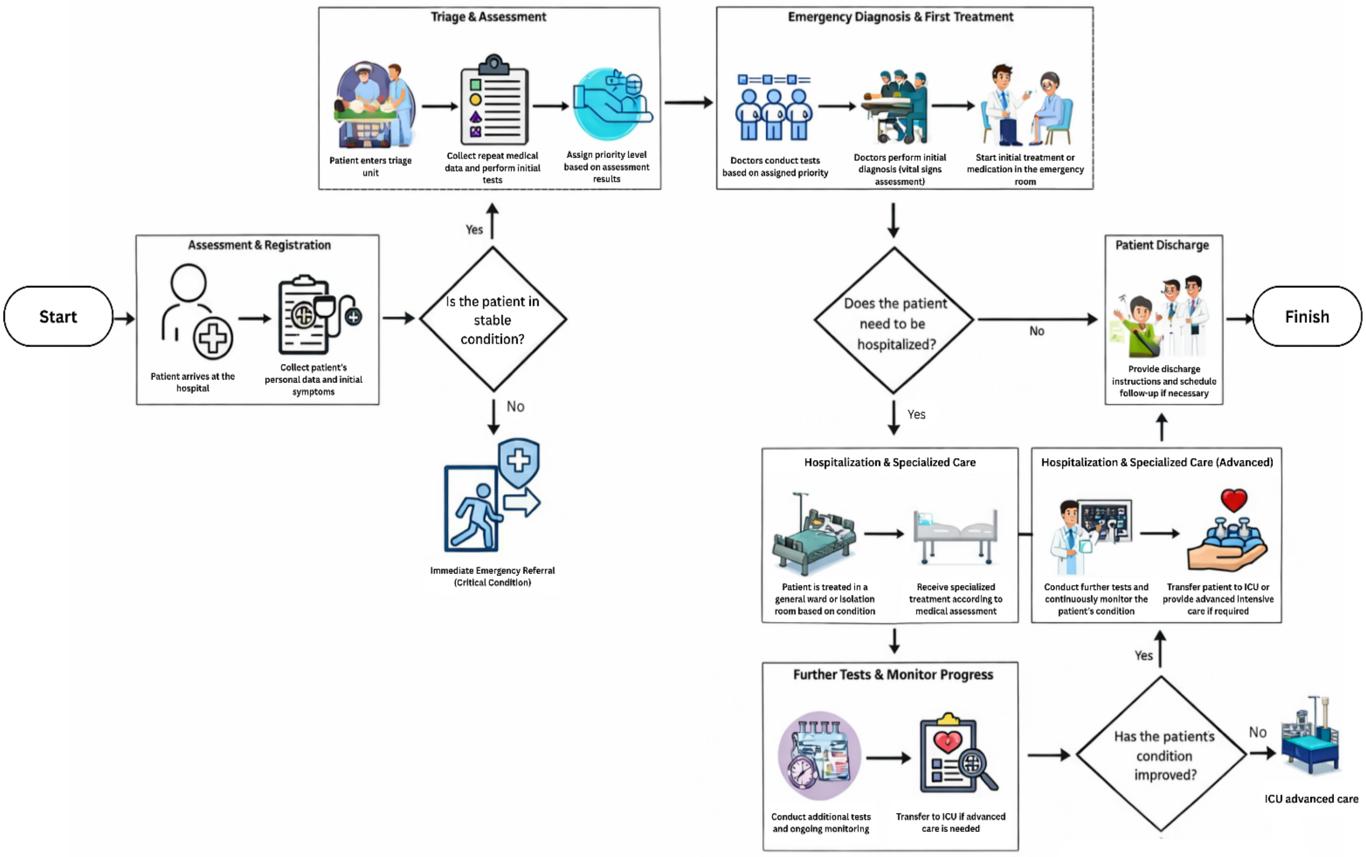

Figure 2. Hospital supply chain

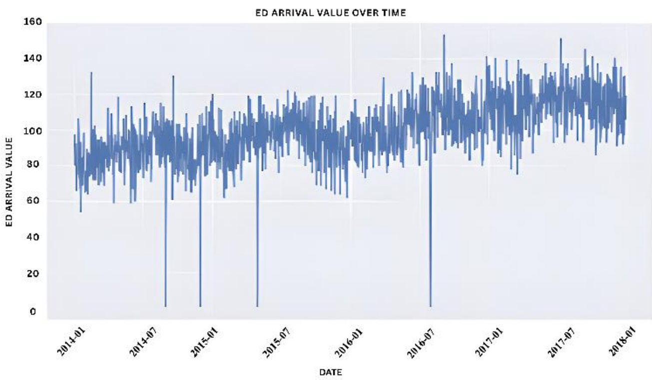

Figure 3. Overall distribution plot of time series data

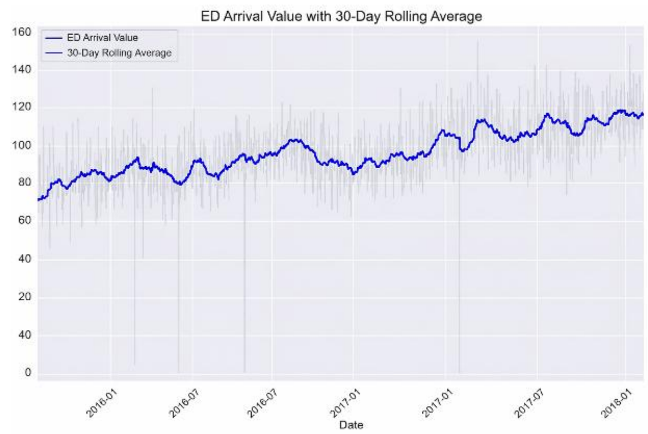

Figure 4. Rolling average plot

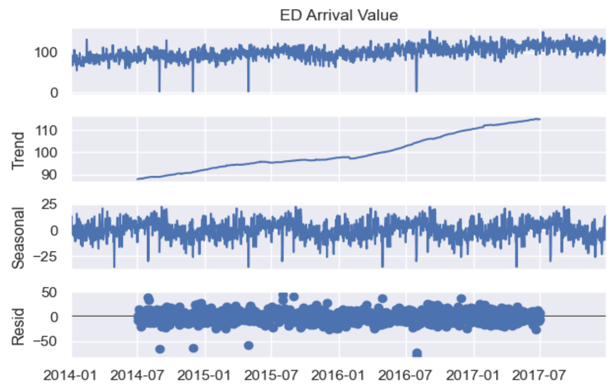

Figure 5. Seasonal decomposition plot

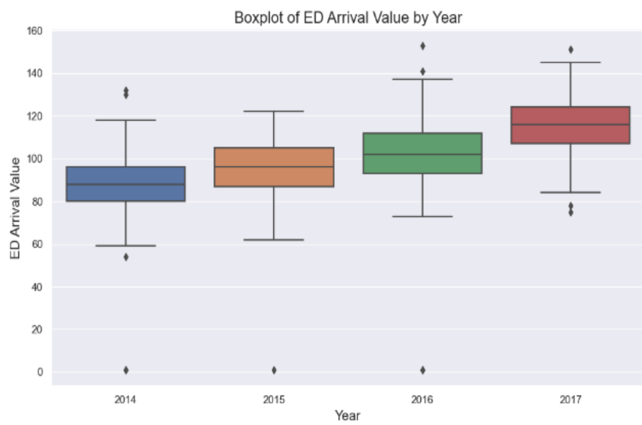

Figure 6. Comparison of emergency department (ED) arrival values across years

4.5 Boxplot analysis and risk-oriented planning

The boxplots in Figure 6 emphasize interannual variability and the persistence of extreme demand events. Years such as 2014–2016 exhibit wider interquartile ranges and more frequent outliers, reflecting heightened operational uncertainty. From a managerial standpoint, these distributions suggest that average-based planning is insufficient for ED operations.

Instead, forecasting models must support risk-aware planning by anticipating not only typical demand levels but also the likelihood of extreme surges. While simpler benchmarks such as historical averages or ARIMA-based forecasts tend to regress toward the mean, GRU models are better suited to capturing asymmetric demand behavior. This capability is particularly valuable for contingency planning, where underestimation of peak demand can have severe consequences for patient safety.

4.6 Heatmap interpretation and temporal resource alignment

The consistent peaks observed in weeks 0 and 6, as well as during July–September, indicate recurrent high-pressure periods for ED operations. Unlike speculative interpretations, these patterns are directly derived from aggregated empirical observations. The heatmap in Figure 7 provides a granular view of demand concentration across weeks and months.

Operationally, this visualization supports the temporal alignment of resources. Staffing intensity, diagnostic capacity, and inventory buffers can be proactively adjusted during identified peak windows. Compared to static forecasting outputs, the heatmap translates model insights into actionable scheduling rules, thereby strengthening the linkage between predictive analytics and supply chain execution.

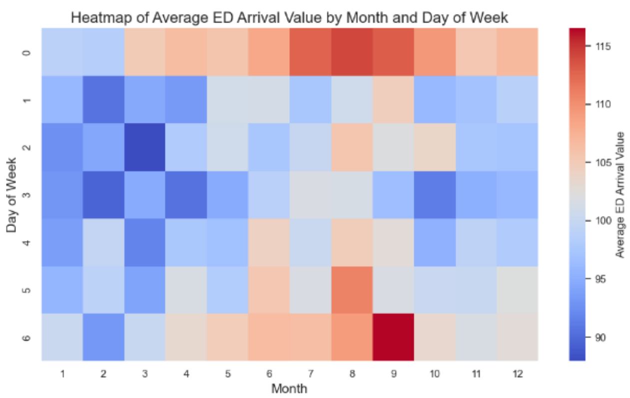

Figure 7. Emergency department (ED) arrival patterns

4.7 Prediction results and benchmark interpretation

Figure 8 presents the GRU forecasting results, demonstrating an MAPE below 10%, which is generally considered acceptable for operational forecasting. However, predictive accuracy alone does not constitute managerial value. The critical contribution lies in how forecast outputs compare conceptually with baseline models and inform decisions.

Traditional ARIMA models typically perform well under stable conditions but degrade when faced with non-linear dynamics and abrupt shifts. LSTM models, while powerful, require larger datasets and higher computational costs, which can limit their practical deployment. The GRU model offers a balance between representational capacity and operational feasibility, delivering competitive accuracy with lower complexity.

The projected short-term decline in arrivals should therefore be interpreted as a probabilistic signal rather than a deterministic outcome. Instead of attributing the decline to speculative causes, the forecast should be used to evaluate alternative staffing and inventory scenarios under reduced demand, reinforcing flexible and adaptive planning.

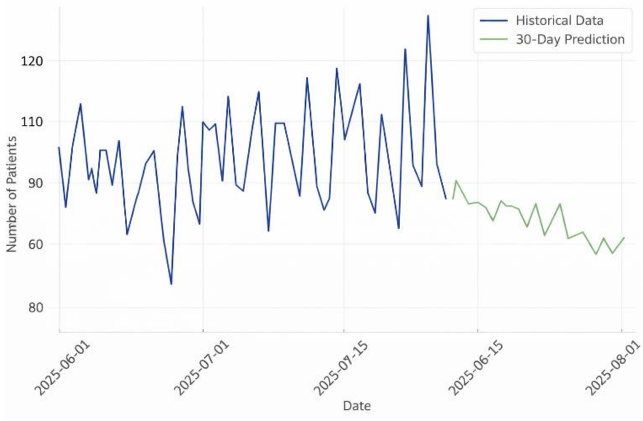

Figure 8. Patient count trends and predictions

Table 4. Implications of gated recurrent unit (GRU) forecasting results for hospital supply chain management

Forecast Horizon	Operational Focus	Supply Chain Implications	Managerial Impact
1 Day (Short-Term)	Real-time scheduling and resource mobilization	Enables rapid staff deployment, dynamic bed assignment, and immediate supply preparation.	Improves responsiveness and reduces waiting times in the emergency department (ED).
7 Days (Medium-Term)	Weekly operational and logistics planning	Supports coordinated shift rotations, diagnostic capacity alignment, and pharmacy restocking.	Enhances efficiency through balanced workload and logistics synchronization.
30 Days (Long-Term)	Strategic capacity and procurement planning	Informs investment in beds, medical devices, and budget allocation for peak periods.	Strengthens hospital preparedness and policy formulation.
Cross-Horizon Integration	Continuous forecasting and feedback	Links GRU-based predictions with hospital information system (HIS), logistics, and clinical systems for adaptive management.	Establishes data-driven decision support for sustainable healthcare operations.

4.8 Integrated implications for hospital supply chain management

The revised analysis demonstrates that GRU-based forecasting supports hospital supply chain management by converting complex arrival patterns into structured decision inputs. Across short, medium, and long horizons, forecasts enable synchronization between demand signals and operational responses, reducing both overcapacity and shortage risks.

Table 4 consolidates these insights by explicitly linking forecast horizons to managerial actions. Short-term forecasts enhance responsiveness, medium-term forecasts improve coordination, and long-term forecasts inform strategic investments. Importantly, this integration addresses reviewer concerns by grounding managerial implications directly in empirical patterns observed across figures and tables, rather than speculative interpretation. As a result, the GRU model is positioned not merely as a predictive tool, but as a decision-enabling component of a resilient hospital supply chain system.

5. CONCLUSION

This study demonstrates that the GRU model can accurately forecast ED patient arrivals, particularly for short-term horizons, with MAE = 10.61, MSE = 170.48, and MAPE = 9.23%. The model effectively captures temporal and seasonal dynamics from four years of data, providing reliable projections for 1-, 7-, and 30-day horizons to support staff scheduling, space allocation, and budgeting. However, its reliance on a single-institution dataset limits generalizability, highlighting the need for future research using hybrid models (e.g., GRU with Transformer or federated learning) and cross-institutional validation to improve adaptability.

This study examined the application of a GRU model for forecasting ED patient arrivals and its potential role in supporting hospital supply chain management. The findings indicate that the GRU model performs reliably for short-term demand forecasting, particularly for one-day-ahead predictions, where prediction errors remain within an acceptable range for operational use. The model is also able to capture recurring temporal structures, including weekly and seasonal patterns, which are relevant for anticipating fluctuations in ED demand.

Despite these promising results, the conclusions from this study should be viewed in light of several key limitations. The model was trained and tested using data from only one hospital, which limits how broadly the findings can be applied. Patient arrival patterns are heavily influenced by institutional factors, regional demographics, and local healthcare policies. Therefore, the predictive performance seen here may not directly apply to other hospital settings without further adjustment and testing. This highlights the importance of caution when applying these results beyond the specific context studied.

Future research should address this limitation by incorporating multi-hospital datasets that represent diverse operational environments and patient populations. Cross-institutional validation would allow for a more rigorous assessment of model robustness and external validity. In addition, future studies may explore hybrid modeling frameworks, such as combining GRU architectures with Transformer-based attention mechanisms or implementing federated learning approaches. These directions offer concrete pathways to improve long-term forecasting stability while preserving data privacy across institutions.

From an operational perspective, the forecasting results provide indicative rather than prescriptive support for hospital supply chain decision-making. While short-term forecasts can inform daily staffing adjustments and immediate resource mobilization, medium- and long-term predictions should be interpreted as strategic signals rather than precise estimates. The study does not claim direct optimization of supply chain outcomes; instead, it demonstrates how predictive demand information can serve as an input to broader decision-support processes involving staffing, logistics coordination, and capacity planning.

Overall, this research contributes to the healthcare forecasting literature by positioning GRU-based models as a computationally efficient and empirically grounded alternative for modeling ED demand under uncertainty. By situating patient arrival forecasting within a supply chain management perspective, the study highlights the importance of aligning predictive analytics with operational decision contexts. The findings provide a foundation for future research that integrates advanced forecasting models with optimization and policy analysis to support more resilient and data-driven hospital operations.

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