Using AI to Improve Operations in the Emergency Department

Taghreed A. Alahmadi*, Marwah J. Aljohani, Shrooq M. Alattas, and Salma M. Elhag

Department of Information Systems, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah, Saudi Arabia

Email: TALAHMADI0052@stu.kau.edu.sa (T.A.A.); MALJOHANI0422@stu.kau.edu.sa (M.J.A.); salattas0059@stu.kau.edu.sa (S.M.A.); smomar@kau.edu.sa (S.M.E.)

*Corresponding author

Manuscript received March 2, 2026; revised April 17, 2026; accepted May 12, 2026; published May 28, 2026

***Abstract*—Overcrowding in Emergency Departments (EDs) is a major problem in most hospitals, and long waiting times are one of its main causes. This problem is due to the complete reliance on manual processes, from registering the patient in the system to the triage and prioritization of examination. Thus, this paper proposes an electronic system as an alternative to manual procedures to mitigate the effects of overcrowding. The proposed system automates patient registration using an identity verification scanner and introduces an AI-based triage concept to support patient classification based on vital data entered by nurses. This approach assists in the classification of cases as emergency or non-emergency, and directly determines the course of action, either by immediately referring the patient to a doctor or waiting for the patient's turn to be examined. A Business Process Analysis (BPA) methodology was used to document and analyze both the current ("as-is") and proposed ("to-be") processes in the ED. A simulation was performed using the Bizagi Modeler to evaluate the performance of the proposed system. The results show that the redesigned process reduces the average patient waiting time in the ED by improving case periodization and workflow efficiency.**

***Keywords*—emergency department, automated AI triage, registration, ID scanning, vital signs, patient flow**

I. INTRODUCTION AND LITERATURE REVIEW

Crowding in Emergency Departments (EDs) is an ongoing, worldwide challenge for many health systems [1]. The implications of overcrowding in the ED include negative consequences for patient care and patient safety, including increased wait times for patients, delays in accessing critical medical care, elevated complications and morbidity rates, and decreased quality of care and patient satisfaction. Thus, this paper presents a novel technological solution that seeks to improve patient flow and reduce critical waiting times. The solution involves developing an automated registration and triage process that incorporates an AI-based concept to support patient classification.

A growing body of research has applied machine learning and deep learning techniques to forecast emergency department demand, including predicting patient arrival volumes [2], daily and hourly ED occupancy [3–6], patient flow and hospitalization likelihood [7–13], and long-term demand trends [14–18]. Additional studies have examined ED revisit risk [19], early sepsis detection [20], and surge response planning [21]. While these forecasting approaches offer valuable tools for capacity planning, they address a fundamentally different problem from the present study, which focuses on redesigning the internal patient flow process after arrival rather than predicting external demand. Akbasli *et al.* [22] examined 352,843 pediatric ED visits and developed 20 predictive models combining traditional Machine Learning (ML) with Deep Learning (DL). As a result, they achieved R^2 values up to 75%. These models improved physician allocation during peak hours by 30.4%, reducing patient-to-doctor ratios and waiting times. On the other hand, Tuominen *et al.* [2] used electronic health records and external variables, such as the weather and traffic, to compare advanced ML models (e.g., LightGBM, NBEATS, and DeepAR) with traditional forecasting models for 24 h inpatient stay prediction. Incorporating these variables improved prediction accuracy and highlighted the importance of multivariable inputs for ED planning. Likewise, Halwani *et al.* [23] used pediatric ED records from King Abdulaziz University Hospital (KAUH), incorporating patient demographics, triage levels, and clinical data. 6 ML algorithms were trained and evaluated. Gaussian Naive Bayes outperformed other approaches, as it demonstrated high predictive performance; however, its single-center design limited generalizability. Harrou *et al.*'s [3] Variational Autoencoder (VAE) model was employed for the daily and hourly forecasting of ED visits, with comparisons made against seven DL baselines: RNN, LSTM, BiLSTM, ConvLSTM, GRU, CNN, and RBM. The VAE model outperformed traditional DL models because of its flexible operation insights. Sharafat *et al.* [7] introduced PatientFlowNet, a DL model for forecasting patient flow in EDs, outperforming traditional models, including ARIMA and LSTM. On the other hand, Wang *et al.* [24] used 5 ML algorithms to predict prolonged ED waiting times, and found that 48.2% of ESI-3 patients experienced delays. Key factors included ED crowding and mode of arrival. Seo *et al.* [8] combined unstructured clinical text with hospital data, using ML models. As a result, they improved prediction performance by 6–10% in AUROC and 20–28% in AUPRC. In alignment with Ref. [8], Chen *et al.* [9] used a Bi-LSTM model with an attention mechanism to combine structured data and clinical notes, improving prediction and handling class imbalance. Their model outperformed baseline models, but lacked external validation. Thus, Tuominen *et al.* [4] used 158 features and forecasting models to improve ED arrival predictions, highlighting the importance of feature selection.

Porto and Fogliatto [1] examined the performance of 6 ML algorithms for predicting ED visits, and determined that the XGBoost model outperformed other methods consistently, in both short- and long-term forecasts of prediction accuracy. In particular, feature engineering markedly improved predictive performance despite excluding some key external variables. Moreno-Sánchez *et al.* [10] developed 2 interpretable

doi: 10.18178/ijfcc.2026.15.1.630

XGBoost models that estimated the likelihood of a patient needing hospitalization and predicted the required ward at the triage stage, achieving adequate performance (AUROC = 0.78) to aid in early resource allocation. Guo *et al.* [14] addressed the challenge of ED predictions by creating individual forecasting models for 16 distinct reasons for hospitalization, and showed that aggregated cause forecasts increased the accuracy in predicting ED visits by 3.81–23.54% compared to forecasting overall ED visits. Çiftçi and Sir [15] evaluated time series and ML models for ED demand forecasting during the COVID-19 pandemic. The SARIMA model fit best in terms of short-term forecasting (83.93% correlation), despite the limited time span of the data used. Vollmer *et al.* [5] created a unified ML framework for ED demand forecasting and observed that penalized linear models performed as well as or better than complex algorithms, as they produced reliable forecasts (1, 3, and 7 days) appropriate for near real-time applications. Youssefi *et al.* [16] developed a reliable daily ED demand predictor based on a deep neural network leveraging LSTM networks that outperformed most statistical alternatives, achieving a low average MAPE error of 4.89% for one-day predictions. Tabar *et al.* [6] proposed 2 models built on the use of generalized additive models and exponential smoothing for the reliable and probabilistic hourly forecasting of ED arrivals with up to 48 h lead time. As a result, their models performed better than all the benchmarks. Cusidó *et al.* [25] created a predictive model featuring the Gradient Boosting Machine (GBM) algorithm to quantify the probability of a patient being admitted. Maddigan and Susnjak [17] explored ML models for forecasting daily demand in urgent care clinics up to 3 months ahead. They demonstrated that clustering methods consistently improved prediction accuracy (by 23–27%) over both in-house and statistical models, despite the difficulty in generating reliable long-term forecasts during the COVID-19 period. James *et al.* [18] proposed a Multi-Granular Stacked Regression (MGSR) model for accurate long-term (monthly) ED demand forecasting in the UK. Their model achieved high accuracy (MAPE 3%) by accounting for service capacity and population health factors.

Peck *et al.* [11] developed a performance model for predicting the number of ED admissions per hour. The LEGOLAS model, a PPM approach to predicting hospital admissions based on events recorded during patient movement within the ED, was presented. Meanwhile, Lim *et al.* [26] proposed an early warning system capable of detecting emerging trends in ED attendance and providing timely alerts for proactive operational planning. On the other hand, Tan and Mills [27] combined 2 systematic literature reviews, one on Artificial Intelligence (AI) and the other on sensors. Their analysis of standard ED design in Chinese hospitals, based on modern hospital building design, demonstrated that a more advanced and innovative approach to AI design could be applied to Chinese resuscitation units, operating rooms in the ED, and intensive care units in the ED. In summary, AI techniques offer notable advantages in emergency clinical decision-making, resource optimization, and patient monitoring. Petravić *et al.* [28] discussed models for predicting patient arrival at EDs. The strength of their study lies in the comprehensive synthesis and analysis of 30 studies, the classification of 10 sets of extrinsic variables, and 53 prediction methods. Hao *et al.* [19] proposed a decision tree-based model with discriminatory and validated EMR features to estimate a patient's ED readmission risk after 30 days. Additionally, Greco *et al.* [20] conducted an 18-month EMR study. ML has been proposed primarily for the early identification of septic patients by detecting predictive patterns in data beyond linear relationships. ML models can handle the abundance and complexity of patients' digital data, accurately predicting which patients will develop sepsis. In their systematic review of ED demand prediction models, Chase *et al.* [21] compiled 30 studies that used statistical techniques and ML algorithms to predict visit volume and optimize resource allocation. Lee *et al.* [12] developed a computational approach using AI to accurately predict urgent patient outcomes, using digital data readily available in most EDs. In addition, Pasquadibisceglie *et al.* [13] introduced a model to predict the reception of patients in the ED. Table 1 summarizes the literature review.

Table 1. Summary of related studies

Ref.	Result	Limitation
[22]	Improved physician allocation by 30.4%.	The single-center design limited generalizability.
[2, 4, 24]	Increased accuracy with multivariable inputs.	The single-center design limited generalizability.
[23]	High-performance Gaussian Naive Bayes (accuracy = 98.4%).	The single-center design limited generalizability.
[3]	VAE outperformed traditional models.	The single-center design limited generalizability.
[7, 9]	Outperformed traditional models.	The single-center design limited generalizability.
[8]	Improved prediction by 6–10% in AUROC and 20–28% in AUPRC.	Single-hospital and text quality issues.
[1, 10, 14]	Improved machine-learning models outperformed traditional methods in predicting the number of visits to the emergency department.	The data used did not include all influential variables, such as air quality or epidemic events, and some models were not widely tested.
[5, 15]	Statistical models (such as SARIMA) and penalized linear models may perform similarly to or better than complex models in short-term forecasting.	The data were limited to short periods; lower interpretability.
[6, 16]	The use of neural networks and probabilistic prediction models improved the accuracy of daily and short-term forecasting.	Relying on data from only one hospital or limited variables.
[25]	The admission prediction model helped reduce waiting times.	The risk of overfitting and poor interpretability
[17, 18]	Both clustering methods and multi-granular stacked regression improved medium and long-term forecasting.	Long-term forecasts were affected by unforeseen factors (such as the pandemic).
[11, 21]	The best-performing model (XGBoost) achieved a Mean Absolute Error (MAE) of 2.63 and 2.64 for the 2 hospitals, respectively, outperforming traditional forecasting methods, such as ARIMA	Lack of external validation across diverse settings
[20, 26]	This study advanced emergency healthcare management by introducing a proactive surge detection framework	The findings have limited generalizability because of the small sample size.

[13, 19, 27, 28]	2 systematic literature reviews were combined, one in AI and the other in sensors. The experimental results show that LEGOLAS achieved higher accuracy.	The need for its application across different environments.
[12]	The model achieved a validation AUC of 0.8004, indicating adequate discriminative ability to predict hospital admissions.	The results were not implemented or tested in other hospitals to evaluate their effectiveness in practice.

II. Methodology

The chosen research methodology is based on the Business Process Analysis Methodology (BPAM), a structured approach that is critical for the systematic evaluation and improvement of workflows in organizations. BPAM undergoes various sequential stages to move from diagnosing the as-is state to implementing an improved to-be state (Fig. 1).

A. Process Discovery ("As-Is" Model)

Process discovery is the initial stage that encompasses the complete "as-is" model of the current manual patient flow process (Fig. 2).

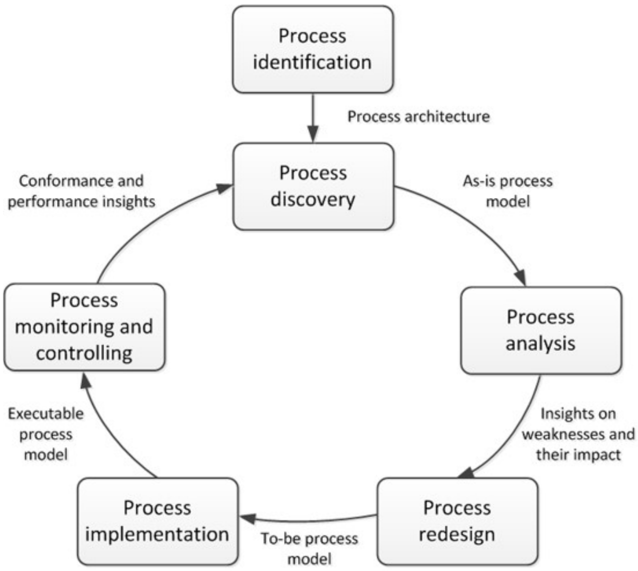

Fig. 1. Phases of the BPMN process analysis.

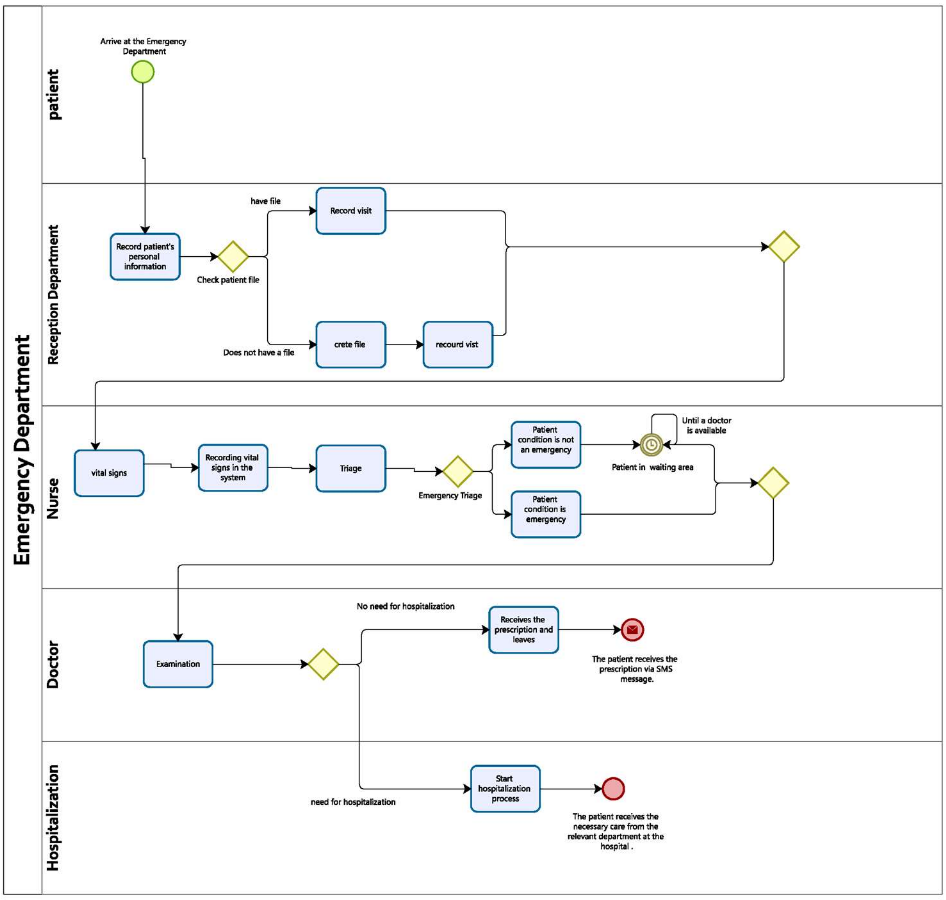

Fig. 2. "As-is" business process model.

B. *Process Analysis*

The process analysis stage is crucial for achieving a clear understanding of the current system's limitations before proposing solutions. By systematically dissecting the "as-is" process model, this analysis identifies the root causes of inefficiency and their measurable impact on Key Performance Indicators (KPIs).

1) *Qualitative analysis*

The qualitative analysis identifies issues that warrant prioritization. Fig. 3 and Fig. 4 present the 2 qualitative approaches employed: Pareto analysis diagrams and cause-effect (fishbone) diagrams, respectively.

2) *Quantitative analysis*

For the quantitative analysis, simulations were performed using the Bizagi Modeler to evaluate the performance of each ED process task, as described in the Simulation Setup subsection below. Table 2 presents the resulting KPI values for the as-is model.

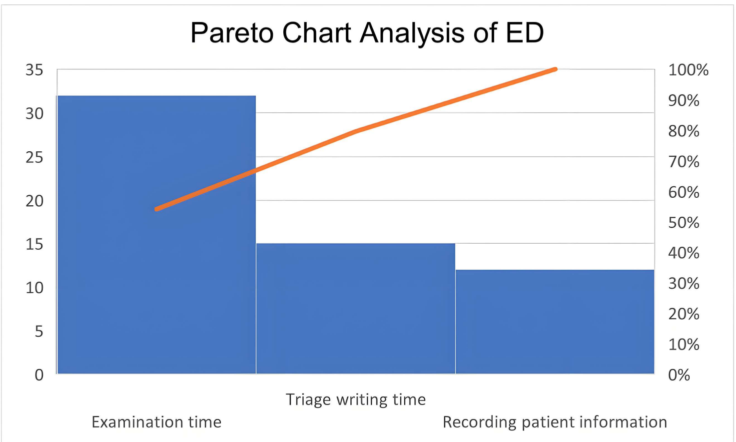

Fig. 3. "As-is" process Pareto diagram.

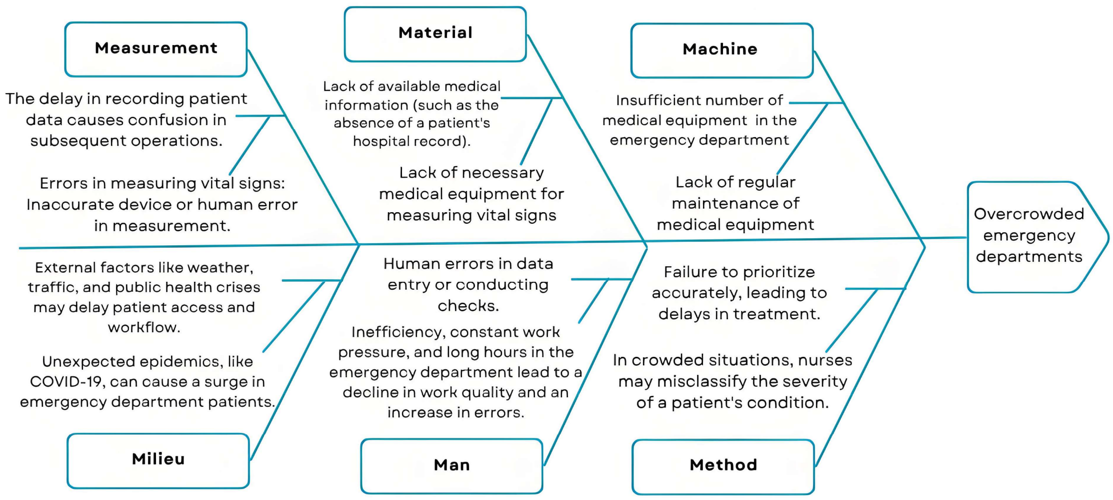

Fig. 4. "As-is" fishbone diagram.

Table 2. KPIs and simulation results (time) for the "as-is" and "to-be" models

KPI	Goal	Avg. Time in min ("as-is")	Avg. Time in min ("to-be")
Triage waiting time	Reducing the time spent triaging patients after taking their vital signs	15 min	1 min 30 s
Recording patient information	Developing a reception system to reduce the time required to register patient data upon arrival at the ED.	12 min	6 min
Examination time	Reducing the examination time.	32 min	25 min

C. *Simulation Setup*

In this study, the dataset was derived from a Bizagi-based process simulation rather than from observational hospital records. The simulation inputs were the modeled emergency department activities, including arrival, registration, vital signs recording, triage, waiting, physician evaluation, and disposition. The simulation assumed a predefined workflow with controlled resource and processing-time settings. The output variable was defined as the simulated surge or congestion outcome, represented by the patient's routing path and waiting-time behavior. It is important to note that this simulation is intended for process comparison analysis and does not represent a fully parametric random model.

D. *Process Redesign ("To-Be") Model*

Based on the root causes identified in the analysis, a "to-be" model is proposed to eliminate limitations in manual processes (Fig. 5).

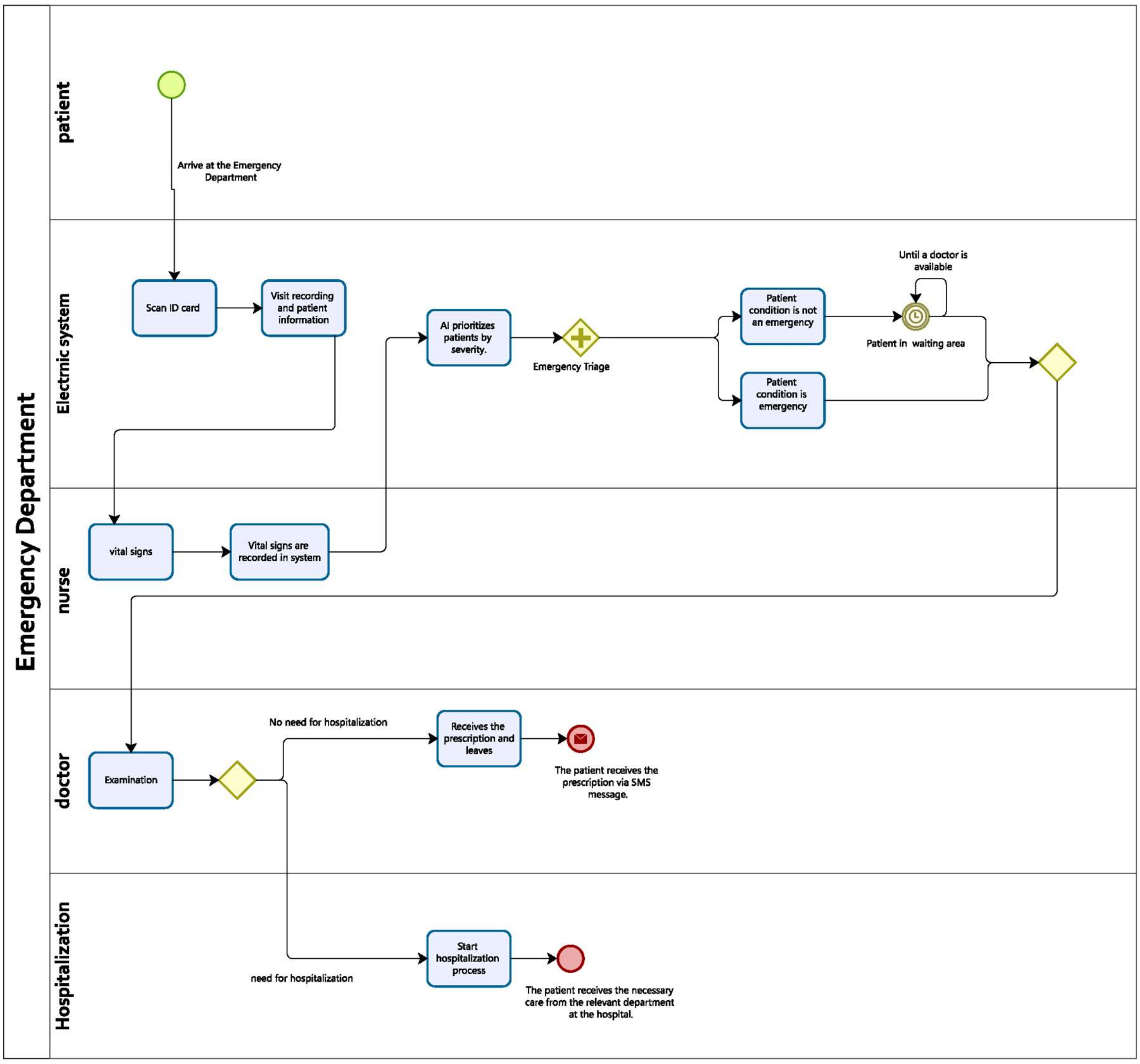

Fig. 5. "To-be" business process model.

E. Process Implementation

The process implementation phase transforms the "to-be" model into an effective and executable format, integrating the automated registration system and AI-based triage concept into the redesigned workflow (Fig. 5).

F. Process Monitoring and Controlling

The Six Sigma DMAIC framework is a managerial approach to monitor, reduce variance, and eliminate defects in a proposed AI-enhanced ED system. Full DMAIC results are reported in the DMAIC Summary section.

III. Results

A. Simulation Results

Table 2 presents the simulation results for the as-is and to-be process models across 3 key performance indicators. The most substantial improvement was observed in triage waiting time, which decreased from 15 min to 1 min and 30 s—a reduction of 90%. This improvement is directly attributable to the AI-based triage classification system, which eliminates the manual decision-making delay that follows vital signs recording. Patient registration time was reduced from 12 min to 6 min (50%), reflecting the efficiency gains from automated ID scanning at the point of arrival. Examination time decreased from 32 min to 25 min (21.9%), which can be attributed to improved patient prioritization upstream, allowing physicians to manage cases more efficiently. Collectively, these results demonstrate that the proposed to-be model substantially improves patient flow and reduces delays across the ED workflow.

B. SWOT Analysis

A SWOT analysis was conducted to provide a strategic overview of the proposed to-be model (Fig. 6). While not a quantitative validation tool, the SWOT analysis contextualizes the system's broader feasibility and sustainability within a hospital setting.

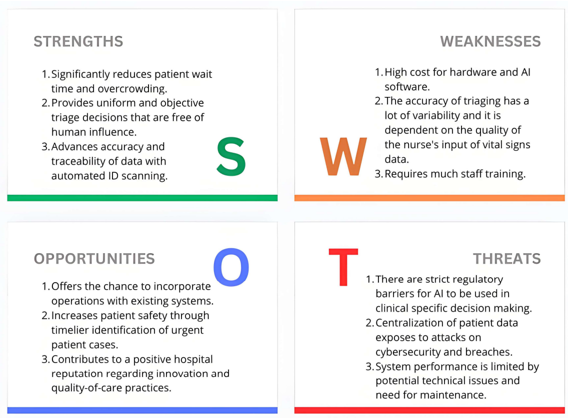

Fig. 6. SWOT analysis of the proposed ("to-be") model.

C. DMAIC Summary

The Six Sigma DMAIC framework was applied to monitor the proposed system and control process variance. In the Control phase, ongoing monitoring is supported through statistical process control, as illustrated by the KPI histogram in Fig. 7, which confirms that triage waiting times in the to-be model remain consistently within acceptable bounds.

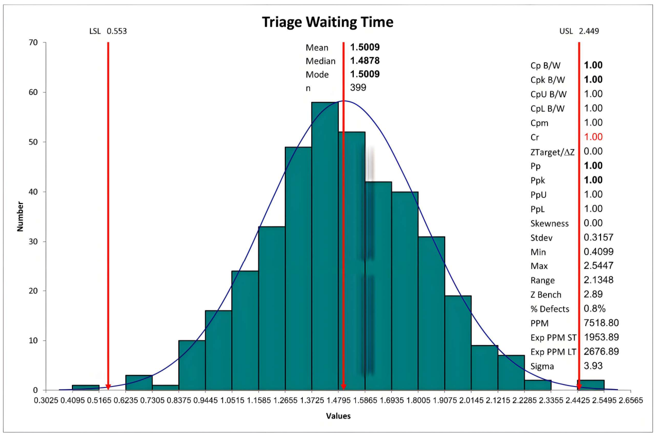

Fig. 7. Histogram of the KPIs to monitor and control.

IV. Conclusion

This study addressed the persistent problem of overcrowding in emergency departments, which results in prolonged waiting times, compromised patient safety, and reduced care quality. A novel, to-be process model was proposed as an alternative to existing manual procedures, incorporating automated patient registration via ID scanning and an AI-based triage concept to classify patients by severity based on vital signs data entered by nursing staff.

Using the Business Process Analysis Methodology (BPAM) and process simulation via the Bizagi Modeler, the proposed model was evaluated against the current as-is process across 3 key performance indicators. The results demonstrate that the redesigned process reduces triage waiting time by 90% (from 15 min to 1 min 30 s), registration time by 50% (from 12 to 6 min), and examination time by 21.9% (from 32 to 25 min). These improvements confirm that automating intake workflows and integrating AI-driven decision support can substantially enhance patient flow efficiency in the ED.

This study has several limitations. The simulation was conducted using the Bizagi Modeler with predefined workflow parameters and does not draw on real patient records from a specific hospital. As a result, the generalizability of the findings to real clinical environments should be interpreted with caution. Additionally, the AI-based triage component is conceptual in this study—it has not been implemented or validated against actual clinical data—and factors such as system integration complexity, staff acceptance, and infrastructure readiness were not modeled.

Future work should focus on implementing and validating the proposed system using real patient data from an actual ED setting to confirm the simulation findings. Additionally, the AI classification component warrants development into a deployable tool, with clinical validation across multiple hospital sites and patient populations to assess its robustness and generalizability.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

T.A.A., M.J.A., and S.M.A. equally contributed to the conception of the work, literature search, methodology, data analysis, and writing of the original article. S.M.E. supervised and critically reviewed the article for editing. All authors have approved the final version of the article.

References

[1] B. M. Porto and F. S. Fogliatto, "Enhanced forecasting of emergency department patient arrivals using feature engineering approach and machine learning," *BMC Medical Informatics and Decision Making*, vol. 24, Art. no. 377, 2024.

[2] J. Tuominen, E. Pulkkinen, J. Peltonen *et al.*, "Forecasting emergency department occupancy with advanced machine learning models and multivariable input," *International Journal of Forecasting*, vol. 40, no. 4, pp. 1410–1420, 2024.

[3] F. Harrou, A. Dairi, F. Kadri *et al.*, "Forecasting emergency department overcrowding: A deep learning framework," *Chaos, Solitons & Fractals*, vol. 139, Art. no. 110247, 2020.

[4] J. Tuominen, F. Lomio, N. Oksala *et al.*, "Forecasting daily emergency department arrivals using high-dimensional multivariate data: A feature selection approach," *BMC Medical Informatics and Decision Making*, vol. 22, Art. no. 134, 2022.

[5] M. A. C. Vollmer, B. Glampson, T. Mellan *et al.*, "A unified machine learning approach to time series forecasting applied to demand at emergency departments," *BMC Emergency Medicine*, vol. 21, Art. no. 9, 2021.

[6] B. R. Tabar, J. Browell, and I. Svetunkov, "Probabilistic forecasting of hourly emergency department arrivals," *Health Systems*, vol. 13, no. 2, pp. 133–149, 2024

[7] A. R. Sharafat and M. Bayati, "PatientFlowNet: A deep learning approach to patient flow prediction in emergency departments," *IEEE Access*, vol. 9, pp. 45552–45561, 2021.

[8] H. Seo, I. Ahn, H. Gwon *et al.*, "Prediction of hospitalization and waiting time within 24 hours of emergency department patients with unstructured text data," *Health Care Management Science*, vol. 27, pp. 114–129, 2024.

[9] T. L. Chen, J. C. Chen, W. H. Chang *et al.*, "Imbalanced prediction of emergency department admission using natural language processing and deep neural network," *Journal of Biomedical Informatics*, vol. 133, Art. no. 104171, 2022.

[10] P. A. Moreno-Sánchez, M. Aalto, and Mark van Gils, "Prediction of patient flow in the emergency department using explainable artificial intelligence," *Digital Health*, vol. 10, 2024.

[11] J. S. Peck, J. C. Benneyan, D. J. Nightingale *et al.*, "Predicting emergency department inpatient admissions to improve same-day patient flow," *Academic Emergency Medicine*, vol. 19, no. 9, pp. E1045–E1054, 2012.

[12] J. T. Lee, C. C. Hsieh, C. H. Lin *et al.*, "Prediction of hospitalization using artificial intelligence for urgent patients in the emergency department," *Scientific Reports*, vol. 11, no. 1, Art. no. 19472, 2021.

[13] V. Pasquadibisceglie, A. Appice, D. Malerba *et al.*, "Leveraging a large language model (LLM) to predict hospital admissions of emergency department patients," *Expert Systems with Applications*, vol. 287, Art. no. 128224, 2025.

[14] P. Guo, W. Y. Loh, K. Maung *et al.*, "High-dimensional point forecast combinations for emergency department demand," arXiv Preprint, arXiv: 2501.11315, 2025, doi: 10.48550/arXiv.2501.11315.

[15] S. Çiftçi and G. D. B. Sir, "An application for forecasting the number of applications to the emergency department with time series analysis and machine learning methods," *Pamukkale University Journal of Engineering Sciences*, vol. 29, no. 7, pp. 667–679, 2023.

[16] M. Yousefi, M. Yousefi, M. Fathi *et al.*, "Patient visit forecasting in an emergency department using a deep neural network approach," *Kybernetes*, vol. 49, no. 9, pp. 2335–2348, 2020.

[17] P. Maddigan and T. Susnjak, "Forecasting patient demand at urgent care clinics using machine learning," arXiv Preprint, arXiv: 2205.13067, 2022, doi: 10.48550/arXiv.2205.13067

[18] C. James, R. Wood, and R. Denholm, "A multi-granular stacked regression for forecasting long-term demand in emergency departments," *BMC Medical Informatics and Decision Making*, vol. 23, no. 1, Art. no. 29, 2023.

[19] S. Hao, B. Jin, A. Y. Shin *et al.*, "Risk prediction of emergency department revisit 30 days post discharge: A prospective study," *PLoS ONE*, vol. 10, no. 1, Art. no. e0117633, 2014.
[20] M. Greco, P. F. Caruso, S. Spano *et al.*, "Machine learning for early outcome prediction in septic patients in the emergency department," *Algorithms*, vol. 16, no. 2, Art. no. 76, 2023.
[21] V. J. Chase, A. E. M. Cohn, T. A. Peterson *et al.*, "Predicting emergency department volume using forecasting methods to create a 'surge response' for non-crisis events," *Academic Emergency Medicine*, vol. 19, no. 5, pp. 569–576, 2012.
[22] I. T. Akbasli, A. Z. Birbilen, and O. Teksam, "Artificial intelligence-driven forecasting and shift optimization for pediatric emergency department crowding," *JAMIA Open*, vol. 8, no. 2, Art. no. ooae138, 2025.
[23] M. A. Halwani, G. Merdad, M. Almasre *et al.*, "Predicting triage of pediatric patients in the emergency department using machine learning approach," *International Journal of Emergency Medicine*, vol. 18, Art. no. 51, 2025.
[24] H. Wang, N. Sambamoorthi, D. Sandlin *et al.*, "Interpretable machine learning models for prolonged emergency department wait time prediction," *BMC Health Services Research*, vol. 25, Art. no. 403, 2025.
[25] J. Cusidó, J. Comalrena, H. Alavi *et al.*, "Predicting hospital admissions to reduce crowding in the emergency departments," *Applied Sciences*, vol. 12, no. 21, Art. no. 10764, 2022.
[26] K. H. Lim, F. N. H. L. Nguyen, R. W. L. Cheong *et al.*, "Enhancing emergency department management: A data-driven approach to detect and predict surge persistence," *Healthcare*, vol. 12, no. 17, Art. no. 1751, 2024.
[27] S. Tan and G. Mills, "Designing Chinese hospital emergency departments to leverage artificial intelligence—A systematic literature review on the challenges and opportunities," *Frontiers in Medical Technology*, vol. 6, Art. no. 1307625, 2024.
[28] L. Petravić, K. G. Rogina, T. Albreht *et al.*, "Prognostic models for predicting patient arrivals in emergency departments: An updated systematic review and research agenda," *BMC Emergency Medicine*, vol. 25, Art. no. 106, 2025.