VFAST Transactions on Mathematics
http://vfast.org/journals/index.php/VTM@ 2024 ISSN(e): 2309-0022, ISSN(p): 2411-6343
Volume 12, Number 1, January-June, 2024 pp: 311-322

Time Series Modeling and Forecasting of the Patients'Inflow and Admission in the Hospitals: A cases study of LUMHS Hospital Jamshoro Pakistan

Sakina Kamboh[1*], Mir Ghulam Hyder Talpur[2], Nawab Khan Chand[3], Liaquat Ali Zardari[4], Abdul Wasim Shaikh[5], Shakeel Ahmed Kamboh[6]

[1*]Department of Statistics, University of Sindh, 76080, Jamshoro ; [2]Department of Mathematics and Statistics, Institute of Business Management, Karachi; [3]Department of Natural Sciences, Begum Nusrat Bhutto Women University Rohri Bypass, Sukkur; [4]Faculty of Heritage, Aror University of Art, Architecture, Design and Heritage Sindh, RCW Rohri Sukkur; [5]Institute of Mathematics and Computer Science, University of Sindh, 76080, Jamshoro; [6]Departmet of Mathematics and Statistics, QUEST, 67480, Nawabshah

Keywords:*Statistical modeling, overcrowding, patients' inflow, patients' admission, time series modeling, ARIMA modeling, forecasting, LUMHS Jamshoro.* ***Subject Classification***:*Statistics, Distributions.*

Journal Info:
Submitted: May 27, 2024
Accepted: June 12, 2024
Published: June 26, 2024

Abstract The patients' crowding in the hospitals is an international phenomenon that demands much attention to avoid harm to the lives of patients. The quantitative based models have been successfully investigated to predict the crowding of patients. Thus, the main objective of this study is to probe a statistically feasible forecasting model capable of estimating the crowding of patients (patients' inflow and patients' admission specifically). As a case study, the Liaquat University of Medical and Health Sciences (LUMHS) Hospital Jamshoro was chosen. The patients' secondary data was collected form hospital and commercial computational software MATLAB was used to carry out all the calculations and manipulations by writing a concise user defined program (code). The Autoregressive Integrated Moving Average (ARIMA) modeling approach is adopted to investigate the best forecasting model. It is found that among the various six combinations of ARIMA (p,d,q) the ARIMA (1,0,1) are the best fit models for the patients' inflow and the patients' admission respectively; having the lowest AIC, BIC and p-values. Since the forecast accuracy contains minimal contains minimal errors thus forecast trends show very good results. The presented procedure can be helpful to manage the patients' volume in the hospitals and can also predict the future trend of patients' inflow and patients' admission with good accuracy.

***Correspondence Author Email Address:**
sakinakamboh85@gmail.com
DOI: 10.21015/vtm.v12i1.1840

1 INTRODUCTION

The patients' inflow and overcrowding due to surplus admission of patients in the various departments of the hospitals is an international phenomenon that has been extensively studied in the past decade. The overcrowding is resulted from the mismatch between existing capacity of the hospital and various input, throughput and output factors that continue to challenge the operational efficiency [2, 3, 16].The mismatch often brings the unwanted harm to the lives of patients either due to the unavailability of resources or long waiting lines. In literature, various techniques and measures have been proposed to address crowding and capacity of hospitals for managing patient flow efficiently. However, the priority is given to the quantitative approaches that have been using the various models to predict the crowding of patients [4, 7].

There are several key modeling methodologies presented in the current academic literature that attempt to analyze and forecast ED patient load and crowding. Most commonly used methodologies consist of formula-based equations, regression modeling, time-series analysis, queuing theory–based models, neural networks and discrete-event (or process) simulation (DES) models [8, 11, 14, 22, 28]. The Formula-based approaches use empirically determined equations based upon observed patterns and data [13]. Regression-based modeling offers a more robust approach to identify and describe variables that affect or forecast crowding, often offering a more mathematically justified approach compared to formula-based modeling methods. Time series analysis mainly uses recent historical time series data to model future ED behavior. Time-series models can use a number of different techniques such as auto-regression, moving average regression, exponential smoothing, and other variants and combinations of these techniques [16].Queuing theory makes basic assumptions about a system to create mathematical equations that describe system flow and thus can help to predict waits (i.e., crowding). At the most basic level, queuing systems consist of four components arrivals, servers, service principles (described as the queuing discipline" or rules as to whom a server serves next), and the flow or routing through the system [31]. Artificial neural networks (ANNs) have been recognized in recent years as one of the most accurate and widely used forecasting methods; ANNs are highly adaptive systems that are inspired by the functioning processes of the human brain. Essentially, they are systems that modify their internal structure in relation to a function objective and on the basis of new data [29].

Discrete-event simulation is a computer model that seeks to mimic" the behavior of a system or a queuing model. The simulation stores what is known as the event list, i.e., the desired model inputs, (e.g., patient arrivals, patient departures, staff breaks, laboratory and imaging studies, etc.). The simulation then steps from one discrete event (one step in the system flow) to the next, updating the system clock (which always moves forward in time) and system variables and recording relevant system data [1].Events are randomly generated by the program in real time, based on input probabilities. A conceptual Input-Throughput-Output model was introduced by [15] that can be useful for the evaluation of the factors affecting crowding in EDs. A multivariate analysis was conducted to determine the potential factors that contributed to the patient wait times and was reported by [5].

Their analysis revealed a strong relationship between the times, the day of the week, the month of the visit and the patients waiting time. Other factors such as volume of patients waiting number of patients that were registered, time to physician, number of patients awaiting triage and the number of patients at each acuity (6) level have also been reported to be important input factors [17, 18, 21, 33]. Some of common throughput indicators that reflect the efficiency of the ED process are the number of patients being treated the volume of patients awaiting their test results, the time to consultation and the length of stay in the ED. Similarly, there is extensive knowledge in the existing literature relate to the effective ways of measuring the output factors including number of patients admitted to the other units of hospitals, the number of patients discharged or waiting to be discharged, and the time of boarding [6, 9, 10, 12, 24].

The shortage of an adequate number of serious care beds can potentially lead to high acuity patients being stranded in the ED thereby increasing waiting times and limiting access for other individuals require immediate care. Other causes of ED crowding that have been found are the delays in medical test results and diagnostic imaging [25, 27, 32]. [26] Developed the patients flow simulation models using stochastic distribution methods. However, they have suggested that machine learning may be effective in predicting patient inflow. Gravity-type models to describe patient choices in inpatient and daycare hospital facilities effects as a function [20]. A discrete event simulation model was developed to study the hypothetical performance of a large University Hospital ICU on occupancy, rejection, and rescheduling rates for various scenarios [30].

The simulation model provided insights to foresee effects of capacity choices that should be made. [19] Developed a simulation model using Discrete Event Simulation (DES) methodology. By leveraging six different scheduling policies and machine learning techniques, their model dynamically identifies the most effective scheduling policy, based on a comprehensive dataset of ED visits in South Korea. Their simulation results claim an accuracy rate of 90%. Since the healthcare systems around the world face many challenges artificial intelligence (AI) is emerging as a key power for revolution. [23] Attempted to review for the motivation of the urgent need to harness AI's potential to mitigate various management problems in different healthcare domains. The have explored that AI empowers clinical decision-making, optimizes hospital operation and management.

Due to the increasing number of patients' arriving at hospital and fewer facilities or hospital bed capacity the prior prediction of patients crowding using statistical modeling may help the hospital management to manage the hospital resources in the best possible way. Therefore, the main goal of this study is to propose a forecasting model capable of estimating the crowding at LUMHS hospital Jamshoro. For testing and implementation purpose the primary data from the hospital was collected. The data consist of the information related to the patients flow and patients admitted in the hospitals.

2 METHODOLOGY

Hospitals using time series ARIMA approach [1, 16, 29] . The Auto Regressive (AR) model purely depends on its own time lags. Meaning to say that Y_t is a function of the various expressions of time lags such as Y_{t-1}, $Y_{t-2,...,}$ and a random error term is added due to the uncertainty. The AR model is represented symbolically as follows,

$$Y_t = \alpha + \beta_1 Y_{t_1} + \beta_2 Y_{t-2} + ... + \beta_p Y + t_p + \epsilon_1, \tag{1}$$

Where Y_t function of time lag; α is constant; β_1 coefficient of lag 1; Y_{t-1} lag 1 of Y; β_p coefficient of preceding lagged values; and the ϵ is the random error. On the other hand; a Moving Average (MA) model purely depends on the lagged forecast errors. Meaning to say that Y_t is a function of the various expressions of forecast error lags such as $\epsilon_{t-1}, \epsilon_{t-2}, ..\epsilon_{q-1}$. The MA model is represented symbolically as follows,

$$Y_t = \alpha + \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + ... + \phi_q \epsilon_t - q, \tag{2}$$

where α is constant and ϕ_q are the coefficients.The combination of AR and MA models referred to as ARIMA model and is defined as follows,

$$Y_t = \alpha + \beta_1 Y_{t-1} \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} \epsilon_t) \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + \ldots \phi_q \epsilon_{t-q}, \tag{3}$$

In general, an ARIMA model consists of the terms p, d and q; where the parameter p indicates the order of the AR, d indicates the number of differencing required to make the time series stationary and q is the order of the MA term. There can be various possibilities to identify the ARIMA model and the choices for p, d and q. The maximum likelihood estimation (MLE) similar to method of the least squares is used to find the values of the parameters of ARIMA model by maximizing the probability of obtaining the observed data.

In identifying the best ARIMA mode the Akaike Information Criterion (AIC) is used that helps to choose the combination for the p, d and q terms in the model. ARIMA (p, d, q) with lowest AIC values will be considered best. In addition to AIC; the Bayesian Information Criterion (BIC) is also used as a criterion for selection an ARIMA model. The ARIMA (p, d, q) with the lowest BIC values is preferred as the best model.

After obtaining the most suitable ARIMA (p, d, q) model for the patients' inflow and admission data the other performance metrics have been used to asses the model forecast accuracy criteria. For measuring and analyzing the goodness and models the metrics such as Mean Error (ME), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Sum of Square of Error (SSE), Mean Absolute Scaled Error (MASE), Coefficient of Determination R-Square and Adjusted R-Squared have determined using the formulas described by the following Equation (4-11) respectively.

$$ME = \frac{1}{N} \sum_{t=1}^{N} \left(Y_t - \hat{Y}_t \right), \tag{4}$$

where Y_t is actual value and $\hat{Y}_t$ is the estimated value of the dependent variable Y and N is the total number of observations.

$$MAE = \frac{1}{N} \sum_{t=1}^{N} \left(|Y_t - \hat{Y}_t| \right), \tag{5}$$

$$MAPE = 100 \times \frac{1}{N} \sum_{t=1}^{N} \left(|Y_t - \hat{Y}_t| \right), \tag{6}$$

$$MASE = mean \left(\frac{|e_j|}{\frac{1}{N-1} \sum_{t=2}^{N} |Y_t - Y_{t_1}|} \right), \tag{7}$$

where the $e_j = Y_j - F_j$ is the forecast error.

$$SSE = \sum_{t=1}^{N} \left(Y_t - \hat{Y}_t \right), \tag{8}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^{N} \left(Y_t - \hat{Y}_t \right)^2}, \tag{9}$$

$$R^2 = \frac{SSR}{SST}, \tag{10}$$

where SSR is the sum of squared regression and SST is the total variation in the observed data set.

$$\bar{R}^2 = 1 - (1 - R^2)\left(\frac{N-1}{N-(k+1)}\right), \tag{11}$$

where k represents the number of independent variables in the regression equation. The MATLAB have been be used to conduct data analysis and computational analysis respectively. The results of this study are presented and discussed in the next section.

3 RESULTS AND DISCUSSIONS

This section presents the statistical analysis and the results from method. First of all the descriptive statistical analysis of the patients' data is done in which we calculate the mean, minimum, maximum, range, standard deviation, standard error of the estimate. Furthermore, the correlation analysis was used to find out the association between patients' inflow and patients' admission. Then the ARIMA model is used for forecasting of patients flow and overcrowding in the hospital (LUMHS). Table 1 shows the important statistics for each shift and the daily average of patients' inflow and patients' admission over the year. The measured statistics reveal that the number of admitted patients is quite less than the patients' inflow. More crowding is observed in morning shift than other two shifts. Similarly, range of morning shift represents that most of the patients were admitted in the morning shift. The coefficient of correlation has also been determined to investigate the degree of association between the patients' inflow and admission in all the shifts.In Table 2 the highlighted values show that there is a moderate correlation between the inflow and admission of the patients in the hospital. The six different combinations of the p, d, q of the ARIMA model were investigated and among the six combinations the best one is selected on the basis of the model selection criteria. In Table 3 the model selection criteria consisting of AIC, BIC and p-values is compared. It can be observed that the ARIMA model ARIMA(1,0,1) is the best fit for the patients inflow I because it has the lowest AIC, BIC and the p-value is much less than 0.05. Table 4 lists the coefficients of the ARIMA (1, 0, 1) which are significant at 95% confidence level.In Table 1 N represents the Total Number of patients, SD represents Standard Deviation and SE represent the Standard Error.

Table 1 Descriptive analysis of the patients' Inflow and Admission data

Patients Data	N	Min	Max	Range	Mean	SD	SE
Patients inflow in morning I_1	325844	142	1450	1308	892.7	108.37	5.67
Patients Admitted in morning A_1	47755	24	166	142	130.8	16.73	0.87
Patients inflow in Evening I_2	282877	243	1231	988	775	95.69	5
Patients Admitted in Evening A_2	35553	22	133	111	97.4	11.91	0.62
Patients inflow in Night I_3	250279	139	1310	1171	685.6	112.24	5.87
Patients Admitted in Night A_3	25703	13	105	92	70.4	13.01	0.68
Patients inflow in all Shifts I	859000	580	391	3411	2353.4	233.37	12.21
Patients Admitted in all shifts A	109011	66	383	317	298.6	32.86	1.72

Table 2 Correlation Analysis of the Patients' Inflow and Admission data

Correlation (r)	**I1**	**A1**	**I2**	**A2**	**I3**	**A3**	**I**	**A**
I_1	1.0000	0.7772	0.3432	0.3628	0.3672	0.3777	0.7817	0.6767
A_1	0.7772	1.0000	0.3156	0.5564	0.3262	0.4401	0.6472	0.8850
I_2	0.3432	0.3156	1.0000	0.6763	0.2285	0.1346	0.6793	0.4591
A_2	0.3628	0.5564	0.6763	1.0000	0.1596	0.2435	0.5225	0.7422
I_3	0.3672	0.3262	0.2285	0.1596	1.0000	0.7592	0.7452	0.5245
A_3	0.3777	0.4401	0.1346	0.2435	0.7592	1.0000	0.5958	0.7082
I	0.7817	0.6472	0.6793	0.5225	0.7452	0.5958	1.0000	0.7548
A	0.6767	0.8850	0.4591	0.7422	0.5245	0.7082	0.7548	1.0000

Table 3 Model Selection Criteria for Patients Inflow, I

S. No	**ARIMA Model**	**AIC**	**BIC**	**p-value**
1	ARIMA (0,0,1)	4958.8	4962.7	5.5090E-224
2	ARIMA (0,1,1)	4958.1	4965.9	3.8001E-239
3	ARIMA (1,1,1)	4943.1	4954.8	2.1991E-232
4	ARIMA (1,0,1)	4934	4941.8	1.1365E-241
5	ARIMA (1,0,0)	4939.2	4943.1	5.8832E-230
6	ARIMA (1,1,0)	5010.3	5018.1	2.8010E-234

Table 4 ARIMA Model Specification for Patients inflow, I

Parameters	**Value**	**Standard Error**	**t-Statistic**	**p-value**
Constant	622.64	212.44	2.93089	3.5945E-03
AR (1)	0.735494	0.0911897	8.06554	1.08E-14
MA (1)	-0.387999	0.115474	-3.36005	0.00086228
Variance	42999.7	839.986	51.1909	7.54E-168

The following Eq. (12) is the estimated ARIMA (1, 0, 1) model for patients inflow I, which can be used to forecast the time series behavior of the patients inflow,

$$\hat{I}_t = 622.64 + 0.735494 I_{t-1} = 0.387999 \epsilon_{t-1}, \tag{12}$$

where $\hat{I}$ is estimated patients' inflow in time lag t, I_{t-1} is the patients' inflow in time lag 1 and ϵ_{t-1} is the random forecast error of lag 1. The model forecasting performance metrics are obtained and listed in the Table 5. The forecast errors are small and are in acceptable range, the MASE is below 1 which indicates the reliability of the model. Moreover, the coefficient of determination is about 95% indicating the significance of the model. The graphical representation of the actual time series behavior of the observed data, the estimated fit and the next year forecast for of the patients' inflow is exhibited in Figure 1.

Table 5 Model Forecast Accuracy Criteria for patients inflow I.

ME	**MAE**	**MAPE**	**SSE**	**RMSE**	**MASE**	R^2	**Adjusted** R^2
-0.0087087	118.11	6.1509	10.104	10.868	0.37827	0.95114	0.95101

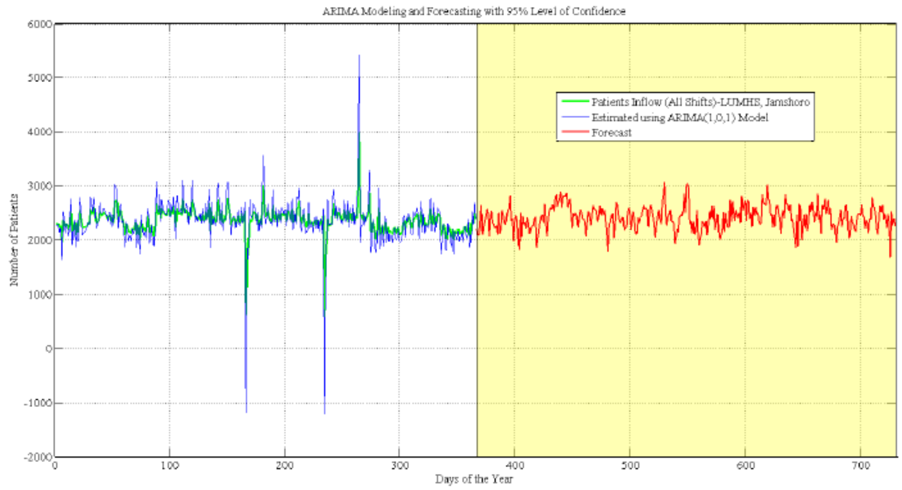

Figure 1. Time Series Forecasting of Patients Inflow, I

Next, just like the fitting of the patients' inflow model, the patients' admission model is also investigated by testing the six different combinations of the p, d, q of the ARIMA. For patients' admission, among the six combinations the best one is selected. In Table 6 the model selection criteria consisting of AIC, BIC and p-values is compared. It can be observed that the ARIMA model ARIMA(1,0,1) is the best fit for the patients admission because it has the lowest AIC, BIC and the p-value is much less than 0.05. Table 7 lists the coefficients of the ARIMA(1,0,1) which are significant at 95% confidence level.

Table 6 Model Selection Criteria.

S. No	ARIMA Model	AIC	BIC	p-value
1	ARIMA (0,0,1)	3518.1	3522	1.6810E-180
2	ARIMA (0,1,1)	3553.8	3561.6	1.2456E-181
3	ARIMA (1,1,1)	3517.2	3528.9	6.3262E-182
4	ARIMA (1,0,1)	3506.1	3510.9	2.3882E-186
5	ARIMA (1,0,0)	3508.2	3515.1	2.3412E-182
6	ARIMA (1,1,0)	3599.8	3607.6	3.1680E-181

Table 7 ARIMA Model Specification for Patients Admission

Parameters	Value	Standard Error	t-Statistic	p-value
Constant	173.033	47.9118	3.6115	3.4739E-04
AR (1)	0.42053	0.160713	2.61666	0.0092515
MA (1)	0.0300804	0.17357	0.173304	0.086251
Variance	864.712	27.9026	30.9904	7.09E-104

The following Eq. (13) is the estimated ARIMA (1, 0, 1) model for patients admission A, which can be used to forecast the time series behavior of the patients admission,

$$\hat{A} = 1.73.033 + 0.42053\hat{A}_{t-1} + 0.0300804\epsilon_{t-1}, \tag{13}$$

where $\hat{A}$ is estimated patients' admission in time lag t, A_{t-1} is the patients' admission in time lag 1 and ϵ_{t-1} is the random forecast error of lag 1. The admission model forecasting performance metrics are obtained and listed in the Table 8. The forecast errors are small and are in acceptable range, the MASE is below 1 which indicates the reliability of the model. Moreover, the coefficient of determination is about 95% indicating the significance of the model. The graphical representation of the actual time series behavior of the observed admission data, the estimated fit and the next year forecast for of the patients' admission is exhibited in Figure 2.

Table 8 Model Forecast Accuracy Criteria

ME	**MAE**	**MAPE**	**SSE**	**RMSE**	**MASE**	R^2	**Adjusted** R^2
-0.030343	20.477	8.4786	122.66	4.5251	0.40698	0.95338	0.95325

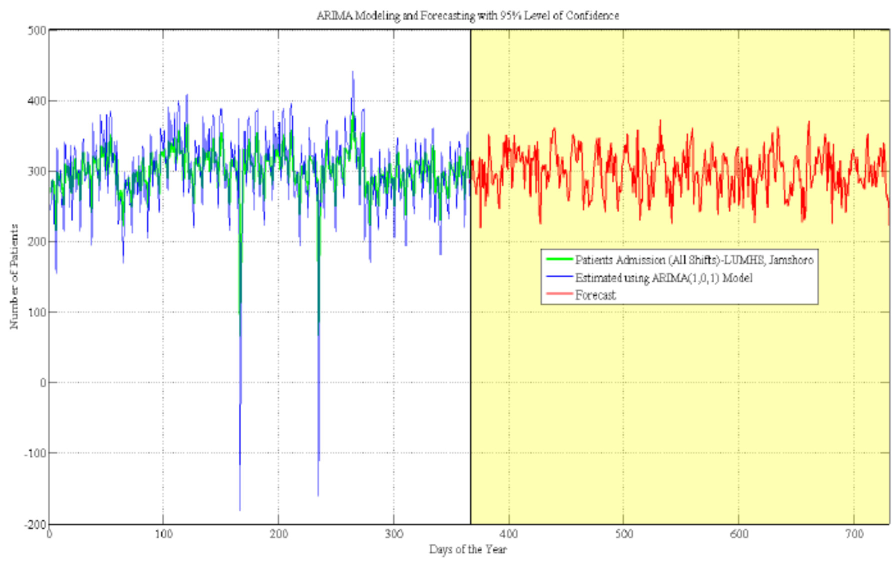

Figure 2. Time Series Forecasting of Patients' Admission

4 CONCLUSION AND FUTURE WORK

In this research paper, a time series forecasting model for the patients' inflow and patients' admission at LUMHS, Jamshoro was investigated using the ARIMA modeling. To obtain t results and goodness of the fit a user defined program (coding) was written on MATLAB and the various simulations were conducted for the observed data under consideration. Among the various combinations of ARIMA (p, d, q) it was found that ARIMA (1, 0, 1) is the best fit for the inflow and admission of the patients having lowest AIC, BIC, and p-values. The coefficients of the best ARIMA model were estimated with their statistical significance (95% confidence) and the model equation for every variable was particularly presented. Before forecasting by using the investigated ARIMA models for the patients' inflow and patients' admission the model forecast accuracy criteria was checked with various goodness metrics. The performance of investigated models was also found satisfactory with least errors and good level of significance. The results of this study can be helpful to manage the patients' volume in the hospitals and can also predict the future trend of patients' inflow and patients' admission with good accuracy. The outcomes of this study may provide some directions for future work in the area. The work can be extended for more variables such as number of patients discharged from the hospital, length of stay at hostel, bed occupancy level, number of patients left without seen, patients satisfactions, etc.

5 Author Contributions

Sakina Kamboh:, Proposed the main idea, objective and methodology of the paper, **Mir Ghulam Hyder Talpur**:supervision, provided the guidelines to formulate the ARIMA Model, **Nawab Khan Chand**: Contributed in literature review, **Liaquat Ali Zardari**:Contributed in error analysis of the model, **Abdul Wasim Shaikh**: proof reading, editing and rechecking of the results,**Shakeel Ahmed Kamboh**:Software suggestions and editing.

6 Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

7 Funding Information

No Funding

8 Author Information

ORCID:
Sakina Kamboh: 0009-0001-8845-3949
Mir Ghulam Hyder Talpur: 0000-0002-5273-6963
Nawab Khan Chand: 0009-0002-7171-5292
Liaquat Ali Zardari: 00009-0008-4659-279X
Abdul Wasim Shaikh: 0009-0008-8855-7626
Shakeel Ahmed Kamboh: 0000-0002-3468-1663

References

[1] Abraham, G., Byrnes, G. B. and Bain, C. A. [2009], 'Short-term forecasting of emergency inpatient flow', *IEEE Transactions on Information Technology in Biomedicine* **13**(3), 380–388.

[2] Abuhay, T. M., Robinson, S., Mamuye, A. and Kovalchuk, S. V. [2023], 'Machine learning integrated patient flow simulation: why and how?', *Journal of Simulation* **17**(5), 580–593.

[3] Ansah, J. P., Ahmad, S., Lee, L. H., Shen, Y., Ong, M. E. H., Matchar, D. B. and Schoenenberger, L. [2021], 'Modeling emergency department crowding: Restoring the balance between demand for and supply of emergency medicine', *Plos one* **16**(1), e0244097.

[4] Ba-Aoum, M., Hosseinichimeh, N., Triantis, K. P., Pasupathy, K., Sir, M. and Nestler, D. [2023], 'Statistical analysis of factors influencing patient length of stay in emergency departments', *International Journal of Industrial Engineering and Operations Management* **5**(3), 220–239.

[5] Chan, P. [2010], Predictive Modeling of Emergency Department Wait Times for Abdominal Pain Patients, PhD thesis.

[6] Cheng, I. S. [2016], 'Emergency department crowding and hospital patient flow: Influential factors and evidence-informed solutions'.

[7] Choudhury, A. [2019], 'Hourly forecasting of emergency department arrivals: time series analysis', *arXiv preprint arXiv:1901.02714* .

[8] Connelly, L. G. and Bair, A. E. [2004], 'Discrete event simulation of emergency department activity: A platform for system-level operations research', *Academic Emergency Medicine* **11**(11), 1177–1185.

[9] Eitel, D. R., Rudkin, S. E., Malvehy, M. A., Killeen, J. P. and Pines, J. M. [2010], 'Improving service quality by understanding emergency department flow: a white paper and position statement prepared for the american academy of emergency medicine', *The Journal of emergency medicine* **38**(1), 70–79.

[10] Erenler, A. K., Akbulut, S., Guzel, M., Cetinkaya, H., Karaca, A., Turkoz, B. and Baydin, A. [2014], 'Reasons for overcrowding in the emergency department: experiences and suggestions of an education and research hospital', *Turkish journal of emergency medicine* **14**(2), 59–63.

[11] Fatovich, D. M., Nagree, Y. and Sprivulis, P. [2005], 'Access block causes emergency department overcrowding and ambulance diversion in perth, western australia', *Emergency medicine journal* **22**(5), 351–354.

[12] Hamrock, E., Paige, K., Hauge, J., Parks, J., Scheulen, J. and Levin, S. [2014], 'Relieving emergency department crowding: simulating the effects of improving patient flow over time', *J Hosp Adm* **1**, 43–47.

[13] Hoot, N. R., LeBlanc, L. J., Jones, I., Levin, S. R., Zhou, C., Gadd, C. S. and Aronsky, D. [2008], 'Forecasting emergency department crowding: a discrete event simulation', *Annals of emergency medicine* **52**(2), 116–125.

[14] Hwang, U., Richardson, L. D., Sonuyi, T. O. and Morrison, R. S. [2006], 'The effect of emergency department crowding on the management of pain in older adults with hip fracture', *Journal of the American Geriatrics Society* **54**(2), 270–275.

[15] Jones, S. S., Evans, R. S., Allen, T. L., Thomas, A., Haug, P. J., Welch, S. J. and Snow, G. L. [2009], 'A multivariate time series approach to modeling and forecasting demand in the emergency department', *Journal of biomedical informatics* **42**(1), 123–139.

[16] Jones, S. S., Thomas, A., Evans, R. S., Welch, S. J., Haug, P. J. and Snow, G. L. [2008], 'Forecasting daily patient volumes in the emergency department', *Academic Emergency Medicine* **15**(2), 159–170.

[17] Kam, H. J., Sung, J. O. and Park, R. W. [2010], 'Prediction of daily patient numbers for a regional emergency medical center using time series analysis', *Healthcare informatics research* **16**(3), 158.

[18] Khashei, M. and Bijari, M. [2010], 'An artificial neural network (p, d, q) model for timeseries forecasting', *Expert Systems with applications* **37**(1), 479–489.

[19] Kim, J.-K. [2024], 'Enhancing patient flow in emergency departments: A machine learning and simulation-based resource scheduling approach', *Applied Sciences* **14**(10), 4264.

[20] Latruwe, T., Van der Wee, M., Vanleenhove, P., Michielsen, K., Verbrugge, S. and Colle, D. [2023], 'Improving inpatient and daycare admission estimates with gravity models', *Health Services and Outcomes Research Methodology* **23**(4), 452–467.

[21] Lee, C.-C., Lee, N.-Y., Chuang, M.-C., Chen, P.-L., Chang, C.-M. and Ko, W.-C. [2012], 'The impact of overcrowding on the bacterial contamination of blood cultures in the ed', *The American journal of emergency medicine* **30**(6), 839–845.

[22] Leegon, J., Jones, I., Lanaghan, K. and Aronsky, D. [2005], Predicting hospital admission for emergency department patients using a bayesian network, *in* 'AMIA Annual Symposium Proceedings', Vol. 2005, American Medical Informatics Association, p. 1022.

[23] Maleki Varnosfaderani, S. and Forouzanfar, M. [2024], 'The role of ai in hospitals and clinics: transforming healthcare in the 21st century', *Bioengineering* **11**(4), 337.

[24] Nwoke, U. A. [2013], 'Forecasting emergency department volumes using time series and other techniques'.

[25] Ouyang, H., Wang, J., Sun, Z. and Lang, E. [2022], 'The impact of emergency department crowding on admission decisions and patient outcomes', *The American journal of emergency medicine* **51**, 163–168.

[26] Pearce, S., Marr, E., Shannon, T., Marchand, T. and Lang, E. [2024], 'Overcrowding in emergency departments: an overview of reviews describing global solutions and their outcomes', *Internal and Emergency Medicine* **19**(2), 483–491.

[27] Ros Prat, I. [2015], Forecasting patients' admissions in an ed: The case of the meyer hospital, B.S. thesis, Universitat Politècnica de Catalunya.

[28] Schull, M. J., Vermeulen, M., Slaughter, G., Morrison, L. and Daly, P. [2004], 'Emergency department crowding and thrombolysis delays in acute myocardial infarction', *Annals of emergency medicine* **44**(6), 577–585.

[29] Schweigler, L. M., Desmond, J. S., McCarthy, M. L., Bukowski, K. J., Ionides, E. L. and Younger, J. G. [2009], 'Forecasting models of emergency department crowding', *Academic Emergency Medicine* **16**(4), 301–308.

[30] Sent, D., van der Meulen, D. M., Alban, A., Chick, S. E., Wissink, I. J., Vlaar, A. P. and Dongelmans, D. A. [2024], 'A quality improvement study on how a simulation model can help decision making on organization of icu wards', *BMC Health Services Research* **24**(1), 1–9.

[31] Steele, R. and Kiss, A. [2008], 'Emdoc (emergency department overcrowding) internet-based safety net research', *The Journal of emergency medicine* **35**(1), 101–107.

[32] Wachtel, G. and Elalouf, A. [2020], 'Addressing overcrowding in an emergency department: an approach for identifying and treating influential factors and a real-life application', *Israel Journal of Health Policy Research* **9**, 1–12.

[33] Wang, J. [2013], *On quantifying and forecasting emergency department overcrowding at Sunnybrook Hospital using statistical analyses and artificial neural networks.*, Library and Archives Canada= Bibliotheque et Archives Canada, Ottawa.