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Short-Term Prediction in an Emergency Healthcare Unit: Comparison Between ARIMA, ANN, and Logistic Map Models

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Abstract

Emergency departments worldwide face challenges in managing fluctuating patient demand, which is often inadequately addressed by traditional forecasting methods due to the inherent nonlinearities of data. The purpose of this study is to propose a short-term prediction model for daily attendance in a private emergency healthcare unit in southern Brazil. The study employed seven years of historical data to compare the performance of ARIMA, Artificial Neural Networks (ANNs), and the chaotic logistic map model to forecast next-day arrivals in two specialties, general clinic and pediatric. The errors for the general practitioner and the pediatricians of the ARIMA, ANN, and logistic map models were, respectively, [0.31%, 2.54%, 2.17%] and [32.72%, 10.11%, 7.85%], measured by MAPE (mean absolute percentage error). The logistic map ranked second and first place, respectively, providing acceptable results in both cases. The main innovation is the successful application of a chaotic model, specifically the logistic map, exclusively for one-day prediction variables in the management of health and medical services. In particular, for the pediatrician, a most irregular time series, the logistic map provided the better outcome. For professionals, the study offers an accurate tool for optimizing the allocation of human and material resources and supporting daily strategic decisions. For scholars, it opens research avenues, addressing a gap in the body of knowledge on chaotic models that have not yet been extensively explored in healthcare service demand one-day forecasting.

Keywords: demand forecasting; ARIMA; Artificial Neural Networks; chaotic models; logistic map; emergency department; healthcare; short-term prediction

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1. Introduction

Healthcare systems worldwide encounter difficulties in efficiently managing emergency departments, which require new perspectives on the underlying factors that shape the random behavior usually observed in the arrival rates of patients with urgent needs [1]. The problem is notably significant in regions like Brazil, where emergency departments also function as medium-complexity health services [2], similar to the UK National Health Service (NHS) [3]. Such services must deliver immediate and precise medical care at affordable costs [4].

Usually, the demand for emergency services surpasses capacity, leading to stressful, challenging-to-manage queues. The consequence is patient dissatisfaction, caused by insufficient service or by service provided by non-physician professionals [5]. Recent overloads in the healthcare system underscore a need for strategic planning in allocating resources for emergency departments [4]. Additionally, the pressure is intensified by ongoing systemic inefficiencies, including insufficient staffing and a lack of resources, which became more pronounced during health emergencies like the COVID-19 pandemic [6].

Emergency care includes managing patients with acute illnesses or trauma, or those requiring advanced services. It also involves patients transported by mobile emergency services [1]. Due to cost control imposed by management [7], resource allocation and scheduling may significantly influence service quality [8]. Overburdening affects not only patient satisfaction but also the well-being of professionals working in high-stress environments [5].

Strategic resource allocation is a key factor in service management [1], as illustrated by studies of the UK's NHS, which emphasize efficiency while maintaining care quality [3]. Optimizing emergency department operations requires predictive modeling tools such as ARIMA and ANN to forecast patient inflow, enabling better preparation and resource allocation [7]. ARIMA models have limitations in capturing complex, nonlinear patterns inherent in healthcare data. ANNs are trained to minimize the squared difference between measured and predicted outputs, using backpropagation to adjust weight combinations and improve accuracy. Nonetheless, ANN may require more computational resources [8]. Such limitations suggest potential for alternative chaotic models, mainly due to their skills in handling erratic demand fluctuations.

At the time of this study, a search of Scopus and Web of Science revealed that ARIMA variations and ANN are the most commonly used time series modeling tools for healthcare management. A specific search in SCOPUS between 2015 and 2025, under the keywords "demand forecasting" and "healthcare", retrieved 110 documents (40 articles). A second similar search adding "chaotic models" OR "chaotic methods" OR "chaos" retrieved no articles, which means that, even if healthcare is a relevant theme, the use of chaotic methods is still a gap in the body of knowledge.

Thus, the research gap that this article aims to bridge is the use of chaotic models in healthcare management. The specific research question is as follows: Can a chaotic model satisfactorily predict the demand for arrivals in an emergency healthcare unit? The purpose of this article is to propose a method based on a chaotic model to predict the demand for emergency consultations in a Brazilian emergency healthcare unit. The research method is quantitative modeling. The study is limited to short-term forecasting, specifically one day, and to the simplest chaotic model, the logistic map. To enrich the analysis and allow comparisons, medium-term forecasts were also made using the ARIMA and ANN methods. This study uniquely and innovatively addresses the gap in forecasting emergency healthcare facilities by introducing chaotic models. Unlike previous studies, this research introduces the logistic map in healthcare short-term forecasting, an approach still unexplored. Unlike other methods, the logistic map captures intrinsic nonlinearities and sensitivity to initial conditions, allowing for improved accuracy in short-term predictions. This methodological innovation extends the applicability of chaos theory to practical decision-making in healthcare services, offering a low-complexity, high-performance alternative to conventional tools. By demonstrating its effectiveness in two medical specialties, the study not only fills a gap in the forecasting literature but also provides a replicable framework for healthcare contexts.

After the introduction, the article presents the methodology, related studies, results, and conclusions.

2. Materials and Methods

George Box and Gwilym Jenkins proposed ARIMA-based methods in the 1970s, relying on the premise that all prior values can explain part of the next values. Therefore, each value depends to some degree on all previous values. It remains to be determined how strong this dependence is [9]. The method uses an interactive procedure to fit a forecasting model based on random and cyclical patterns to minimize forecasting errors [10], integrating (I) autoregressive (AR) and moving average models (MA) [11]. In the notation ARIMA (p, d, q), p represents the order of the autoregressive component, d is the number of differences required to make the time series stationary (i.e., the number of times past values are subtracted to remove trends), and q denotes the order of the moving average component [4]. Applying d differences helps eliminate potential trends in the data, resulting in a stationary time series where variables fluctuate around a constant average level [12]. Equation (1) expresses the model:

$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots + \varphi_p y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \quad (1)$$

In which y_t = variable at time t φ = autoregressive parameter θ = moving average parameter e_t = residual error.

ANNs reproduce human central nervous system processes using computational resources, unveiling complex nonlinear relationships between outcome variables and their corresponding predictors. The model ANN consists of N layers that function like biological neurons and intensive connections through synapses. The computational elements used in ANN are called artificial neurons or processing elements [13].

The main function of an ANN is to assign weights by training the model with historical datasets. Learning is conducted by adjusting the connection strength [14]. The first and last layers are the input and output, respectively. Both provide information from the hidden layers and are used by the network to convert specific input patterns into appropriate output patterns through a nonlinear function. The network takes the form of a linear combination of the independent variables and their respective weights and bias terms (or intercepts) for each neuron. Execution occurs in steps: calculate y, calculate the error (the difference between predicted and actual values), and vary weights according to a rule to minimize the error [15]. Equation (2) shows the model.

$$y = x_0 + w_{1\times 1} + w_2 x_2 + \ldots + w_n x_n \quad (2)$$

In which y = the output or predicted value w_i = the variables' weights x_i = the independent variables or inputs x_0 = bias.

This study employs *MAE*, *RMSE*, and *MAPE*, represented by Equations (3)–(5), to measure the quality of the prediction [14].

$$MAE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n} \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n}} \quad (4)$$

$$MAPE = \frac{\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right|}{n} \quad (5)$$

In which y_i= real demand value in the i-th period $\hat{y}_i$= forecast value for the i-th period n = number of periods.

The next method involves chaotic systems. The outputs of a chaotic system vary according to nonlinear deterministic rules that, when applied repeatedly, produce data series that, at first glance, seem to be random [16]. Moreover, chaotic systems exhibit a sensitive dependence on input parameters. Small variations in the input produce more than proportional and unexpected changes in the output [17]. Such changes can be quantitative and qualitative and can radically alter the output pattern, even if the input variations are very small [18].

Models based on deterministic rules can describe chaotic patterns, even if the dataset is small. Initially, output patterns resemble random behavior, but a subjacent model applies, showing its deterministic formation law [19]. The initial conditions of the parameters heavily influence the output of a chaotic phenomenon that becomes unstable with time. The outcomes of a deterministic system, even with defined laws of evolution, become unpredictable due to the extreme sensitivity to perturbations and noise [16]. In short, noise, nonlinearities, and interaction between components amplify minimal parameter errors and create deterministic chaos [19].

Two properties help reconstruct the dynamics of chaotic systems: the embedding dimension and time delays [17]. The embedding dimension corresponds to the number of variables controlling the system, while time delays indicate how long changes in variables can affect the system. Chaotic behavior in time series suggests that reconstructing system dynamics is possible by rearranging the order of observations, which should unveil valuable hidden information [20].

Even if, among the already known chaotic models, the logistic map is the simplest, it is useful in modeling complex, nonlinear behavior [21]. The logistic map represents a positive feedback process arising from a recurrent deterministic rule, the quadratic function [22]. Equation (6) shows the model:

$$s_{(t+1)} = as_t(1 - s_t) \tag{6}$$

In which s_t = value at time t a = range from 0 to 4.

When a is less than 1, the result converges to 0. When $1 < a < 3$, the process tends towards a fixed value k, a stationary attractor given by Equation (7).

$$k = \frac{(a-1)}{a} \tag{7}$$

The process changes behavior when $3 < a < 3.57$ taking on cyclic attractor behavior. If $3.57 < a < 4$, the attractor takes on bifurcation behavior, the chaos edge. Since it originates from a deterministic rule, that region is called "chaos out of order" or "deterministic chaos." Chaotic behaviors arise if $a > 4$ [23].

3. Background: Related Studies on Prediction in Healthcare Service

A systematic literature review relying on Scopus and Web of Science databases considered only peer-reviewed English language papers published between 2016 and 2021 [24,25]. The search terms were "demand forecasting" (8102 papers), "demand forecasting models" (6047 papers), "health care demand forecasting" (262), and "emergency department demand forecasting" (80). The review excluded inadequate, inaccessible, non-English, and duplicate articles, resulting in the 29 articles shown in Table 1.

Table 1. Related studies.

Reference	Method	Independent Variables	Quality Measures
[26]	LR	Year	MAD
[27]	LR	Day of the week and time of day.	R^2
[28]	MLNB, SVM	Month, day of the week, time of day.	MAE, RMSE, RAE
[29]	FL, ARIMA, ANN	Month and day of the week.	MAPE, RMSE
[30]	ML	Day of the month, day of the week, time of day.	FSE

Table 1. *Cont.*

Reference	Method	Independent Variables	Quality Measures
[31]	ML	Day of the month and day of the week.	MAE, MAPE
[1]	ARIMA, ES, LR, STLF	Month of the year, holiday, day of the week, work shift, medical specialty, and demographics.	MASE
[32]	SARIMAX	Temperature and holiday.	MSE
[33,34]	GA, ANN, MLFS	Month of the year, day of the week, time of day, holidays, and climate features.	MAPE, RMSE
[4,35,36]	ARIMA	Month, day of the week, and time of day.	MAPE
[37]	SARIMA, ES	Day of the week.	MAPE
[38]	SARIMA	Month, gender, type of diabetes, and type of emergency.	MAE, MSE, MAPE
[5,39]	ARMA, ARIMA	Month of the year, week of the month, and day of the week.	RMAP, MAE, RMAE
[40]	ES, HWMS, SARIMA, MSARIMA	Month, day of the week, temperature, rainfall, air speed, relative humidity, and hours of sunshine.	MAPE
[41]	ARMA, ARIMA	Day of the week.	MAE
[11]	ARIMA, ARMAX, NLR	Day of the week and available operational resources.	MAE, RMSE, MAPE
[13]	ANN, NLR	Year, month, day of the week, holiday, and temperature.	R^2, RMAE
[42]	ANN	Year, month, and day of the week.	RMAE
[43]	WMA, LR, ANN, SVR	Month, day of the month, day of the week, and time of day.	MSE, MAPE
[44]	ARIMA, ANN	Month and day of the week.	MAE, RMSE, MAPE
[45]	ARIMA, ANN, ML	Month and day of the week.	RMSE
[46]	ANN	Day of the week and time of day.	MAD, MAPE
[47]	ML, VAE	Day of the week and time of day.	R^2, RMSE, MAE, EV
[48]	SARIMA, MSARIMA	Day of the week and time of day	MSE, MAPE, DS

Ref. [26] used LR to model psychiatric care and addiction services at Toronto Western Hospital between 2012 and 2016. The study used a discrete event simulation to balance demand and capacity based on projected waiting times. Ref. [27] used LR to compare peaks of demand and achieved reduced forecast errors in daily admissions predictions, including syndromic data. Ref. [28] used ML to predict the length of stay of patients in the pediatric emergency department of the regional hospital center in Lille, France. The NB, C4.5, and SVM methods achieved higher accuracy. Ref. [29] used FL, ARIMA, and ANN to predict daily, weekly, and monthly emergency department attendance for up to four months in four UK emergency departments. FL showed lower MAPE and RMSE. Ref. [30] compared twenty traditional, hybrid, and ML-based methods in two outpatient clinics at one medical center. ML-based and hybrid methods were more accurate, while the traditional methods achieved lower FSE on data following regular patterns. Ref. [31] compared machine learning algorithms to linear models in predicting short-term hospital demand regarding 1, 3, and 7 days. Linear models outperformed more advanced algorithms. Ref. [1] combined discrete event simulation, ARIMA, ES, LR, and STFL, assessed by MASE, to manage emergency demand at Princess Alexandra Hospital in England. Integration of the techniques enabled the management of emergencies caused, for example, by the closure of a nearby department. Ref. [1] modeled demand by medical specialty using ARIMA, ES, LR, and STLF. The authors used data from the National Health Service of England. STFL achieved the lowest MASE. Ref. [32] used ANN and SARIMAX to link independent variables (temperature and tourist arrivals) to demand at Rambam Hospital in Haifa, Israel. SARIMAX had the lowest MSE. The day of the week was the most important predictor. Refs. [33,34] developed an integrated deep ANN to predict patient flow in emergency departments at different triage levels. The model recorded lower MAPE and RMSE than LR, ARIMAX, ANN, and ML-based models. Ref. [35] developed a modified version of GA for resource selection and demand forecasting in an outpatient clinic in northeast China. A combination of GA and ANN outperformed LR, ARIMAX, and Shallow ANN by RMSE and FS criteria. The authors constructed an ARIMA model to predict the number of monthly visits to an emergency department. The ARIMA model

(0, 0, 1) produced better results, which were evaluated using MAPE. Ref. [36] modeled the presence of green patients (according to the Manchester protocol) in the emergency department of Passos, Brazil. The ARIMA (1, 1, 1) model showed the lowest MAPE. Ref. [4] used ARIMA for emergency demand at the hospital in Braga, Portugal. The ARIMA (1, 1, 1) (1, 0, 1) model obtained the lowest MAPE. Ref. [37] applied SARIMA, ES, and a combination of both in two internal medicine departments of a hospital in Chengdu. The combined model achieved the lowest MAPE. Ref. [38] developed a model for hypoglycemic and hyperglycemic cases that occurred between 2009 and 2015 in Outpatient Victoria, Australia. The SARIMA model (0, 1, 0, 12) showed the lowest MAPE (4.2%) and was useful for prehospital diabetic emergency management. Refs. [5,39] used ARMA and ARIMA models evaluated with RMAP to predict emergencies in the hospital of Troyes, France, and to create a new patient classification. Ref. [40] tested ES, HWMS, SARIMA, and MSARIMA, evaluated by MAPE at Hospital de Clínicas in Porto Alegre, Brazil. ES and SARIMA were the best for all patients and urgent patients. Ref. [41] forecast the multi-period bed demand using non-stationary inter-arrival times and patient-level duration. Ref. [11] compared ARIMA, ARMAX, NLR, and SVM to predict the total number of urgent patients assessed by MAE, MAPE, RMAE, and RMSE. Ref. [13] used LR-NLR and ANN to predict emergency department admissions at a public hospital in Istanbul. The independent variables were holidays and maximum temperature values. ANN-based models achieved lower MAEs. Ref. [42] used ANN to predict demand for medical specialties, including patient demographic characteristics assessed by MAE. Ref. [43] compared WMA, LR, ANN, and SVR in three Chilean hospitals. SVR provided the best results. Ref. [44] used ARIMA and ANN in an emergency department and assessed outcomes using MAE, RMSE, and MAPE. Ref. [45] compared ARIMA-, ANN-, and ML-based methods using data from the Medway Foundation Trust (MFT) in Kent, England. ML- and ARIMA-based models performed better on more erratic or stable data. Ref. [46] applied ANN in a U.S. emergency department. The multilayer perceptron (MLP) model achieved lower MAD and MAPE. Ref. [47] used an ML-based model to predict demand in the pediatric emergency department of the regional hospital of Lille, France. VAE performed better than recurrent neural network (RNN), long short-term memory (LSTM), bidirectional LSTM (BiLSTM), convolutional LSTM network (ConvLSTM), restricted Boltzmann machine (RBM), gated recurrent units (GRUs), and convolutional neural network (CNN). Ref. [48] compared ARIMA, MSARIMA, and a combinatorial model based on MSARIMA and a weighted Markov Chain to forecast three years of daily inpatient discharges at West China Hospital. The combined model outperformed the others, even if the authors raised concerns about some assumptions in weighting Markov Chain parameters.

The autoregressive method is the most frequent method in the sample (17 out of 29 studies). ANN, ML-based, and regression-based methods appear in ten, seven, and six studies, respectively. MAPE is the most commonly used quality measure, appearing in 15 studies, while MAE and RMSE appear in ten and eight studies, respectively. Chaotic models did not appear, reinforcing the existence of a research gap.

4. Results

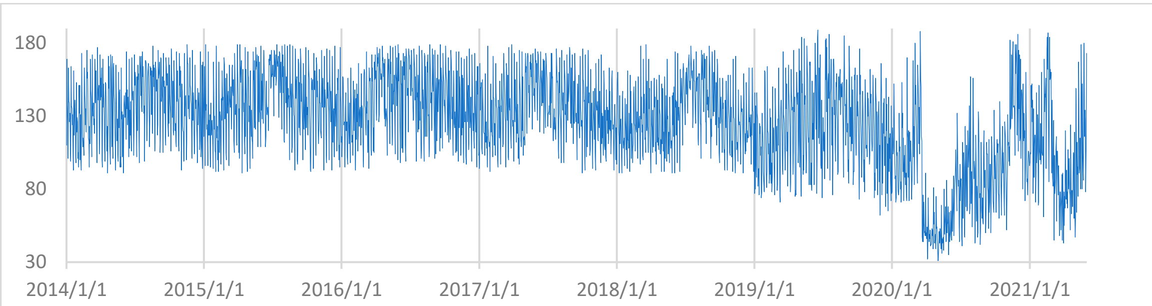
The research method is quantitative modeling [49]. This type of method uses logical and mathematical relationships to reproduce how natural systems behave [50]. The study analyzed 89 months of data from the emergency department of a private, nonprofit hospital in the southern region of Brazil. The data included the number of daily arrivals of the two most required specialties, general practitioners and pediatricians, which account for 58% and 24% of arrivals, respectively. The procedure employed the free software R version 4.2.1, a programming language and computational environment, to build the

ARIMA and ANN models [51]. ANN employed a backpropagation algorithm to reduce the error. The logistic map utilized the solver command of Excel®. Starting from an initial estimate for s0 (between 0 and 1) and a (between 3.57 and 4), the initial execution and feedback constant, the procedure generates an infinite chaotic series. Next, both the actual and the chaotic series are normalized to the interval [0, 1], and the RMSE is calculated. Using an evolutionary algorithm, the solver identifies the sequence of executions [s(1), s(2), s(3)...; s(1), s(3), s(5)...; s(1), s(4), s(7)...] that minimizes RMSE, updates the parameters, and estimates the next execution, the day after. A timeframe of nine executions provided satisfactory results for the next day. The solver typically requires about 20,000–40,000 iterations to converge.

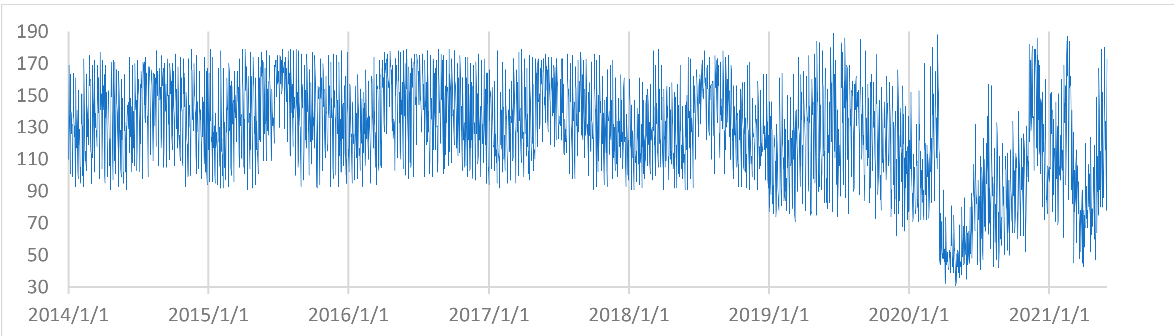
The calculation involved one-day forecast horizons as the focus is on short-term prediction. As ARIMA and ANN also offer seven, 14, and 30-day predictions, they appear in the study, even if they are not the research focus.

4.1. Data

The dataset spans from 1 January 2014 to 31 May 2021. As the research project is finished, more updated data is not available, which is less relevant for the study, as the main purpose is methodological. The COVID-19 pandemic period (March 2020 to December 2020) caused a notable reduction in the number of visits for both specialists. The training set trains the model until it achieves satisfactory performance based on quality measures, covering 1 January 2014, to 31 December 2020. The training data estimates the parameters of the prediction method, while the test data evaluates the accuracy of the models [14,32]. The test data covered 1 January 2021, to 31 May 2021. Figure 1a,b illustrate the daily number of patients visiting general practitioners and pediatricians, respectively. No trends or outliers appear, but seasonality reflects the day-of-month effect, particularly among pediatricians.



(**a**)



(**b**)

Figure 1. Daily number of arrivals. (**a**) General Practitioners (**b**) Pediatricians.

Autocorrelation also helps verify stationarity [52]. Autocorrelation in a time series is the correlation of a variable with itself at different time lags. It measures how y_t, the value at time t, is related to y_{t-k}, where k is the lag. A positive autocorrelation at lag k means past values strongly influence current ones in the same direction, while a negative autocorrelation means they move in opposite directions [4]. Partial auto correlation captures the correlation between a variable and a lag of the variable that is not explained by the correlation at all lags of a lower order, removing the effect of the observations [35]. Both showed a strong correlation within seven days for both specialists.

4.2. ARIMA

The study used the auto.arima, autocorrelation, and partial autocorrelation functions (ACF and PACF) from the R software prediction library, following previous studies [1,11]. Auto-arima reports the most appropriate parameters p, d, and q, based on Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) unit root tests (d) and the lowest AIC (Akaike information criterion) (p and q) [51]. The ARIMA (3, 1, 2) model for general practitioners showed the best performance, with a MAPE of 16.09%. PACF shows $p = 3$ given the modulus change at lag 3. ADF and KPSS tests indicated $d = 1$, ensuring stationarity. PACF shows that lags 1 to 6 move in the same direction until a new cycle of seven observations begins, shifting from negative to positive intensity. ACF shows $q = 2$, as a modulus change occurs from lag 2. For pediatricians, the auto.arima function yielded ARIMA (4, 1, 1) with a MAPE of 18.45%. PACF shows $p = 4$ given the modulus change at lag 4. The parameter $d = 1$ indicates stationarity. ACF shows $q = 1$, as the highest modulus occurs at lag 1 before a new cycle begins at seven observations.

Figure 2a,b show ACF and PACF for both specialties.

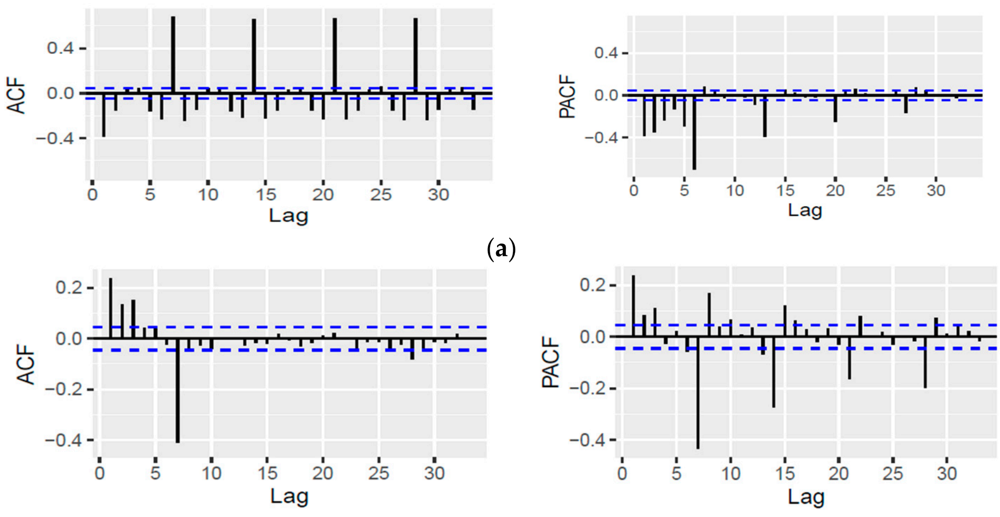
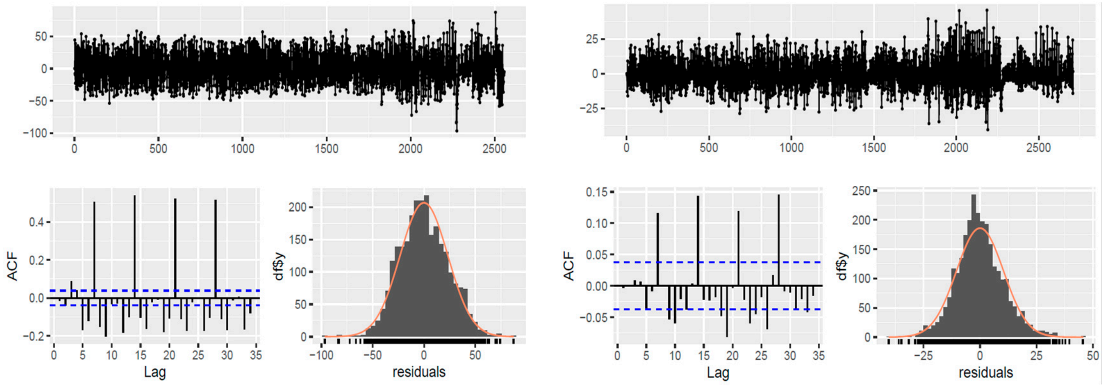


Figure 2. ACF and PACF for both specialties (source: R software, version 4.2.1). (**a**) General practitioners. (**b**) Pediatricians.

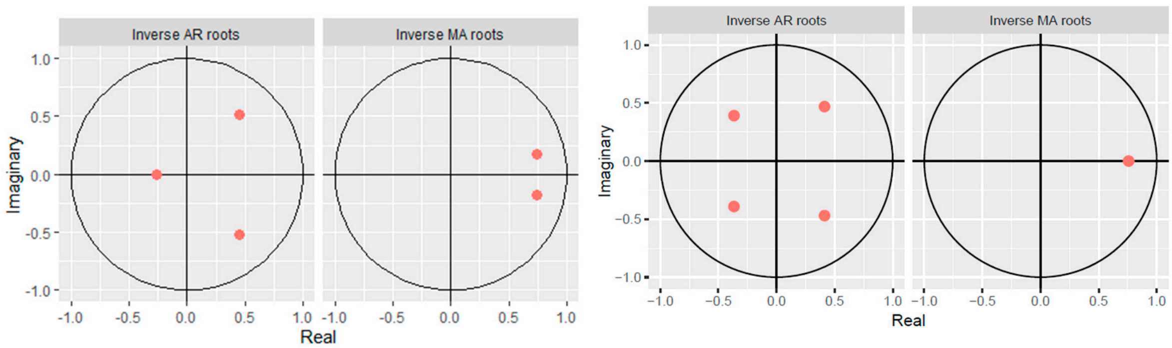
The procedure included normality and white-noise tests. The null hypothesis assumes uncorrelated residuals [35]. For the general practitioner, Figure 3a shows the ACF with autocorrelations near zero within 7-observation cycles, indicating residuals behave like white noise. For the pediatrician, Figure 3b shows residual autocorrelations within bounds over 7-observation cycles, also indicating white noise behavior without trend or seasonality. Both residual times show no trends or seasonality. Both residuals' histogram confirms normality.



(**a**) (**b**)

Figure 3. Residual plots (source: R software, version 4.2.1). (**a**) General Practitioners. (**b**) Pediatricians.

Finally, stationarity and invertibility require p and q to lie, respectively, within the complex and the inverse complex unit root circle [52]. According to Figure 4a,b, both models meet invertibility and stationarity conditions.



(**a**) (**b**)

Figure 4. Inverse roots for both models (source: R software, version 4.2.1). (**a**) General Practitioners. (**b**) Pediatricians.

Given the adequacy of the models, the last step is to verify the accuracy of the predictions. According to MAE, RMSE, and MAPE, the errors for the general practitioners and pediatricians were, respectively, [0.30, 0.30, 0.31%] and [13.62, 13.62, 32.72%].

4.3. ANN

This study used the nnetar function from the R software forecast library, which returns the model NNAR $(p, P, K)_m$. A comprehensive comparison with ARIMA and the structure of NNAR architecture can be found in detail in [53,54]. The values of p and P are selected based on the lowest AIC result. Based on different internal scenarios, the best parameterization is determined. The value of k is determined by the relation $(p + P + 1)/2$, rounded up to the nearest integer [50]. The notation NNAR (p, k) introduced by [52] indicates p delayed inputs and k nodes in the hidden layer, building a multilayer feed-forward network; outputs from one layer are inputs to the next. Node inputs combine through weighted linear combinations, modified by a nonlinear sigmoid function, which reduces extreme input effects, increases input–output sensitivity, and improves handling of nonlinearities. For both specialties, the model (1, 1, 2) achieved the best fit. For the general practitioner, the NNAR (30, 20) model used the last 30 observations as predictors with 20 neurons in the hidden layer. For the pediatricians, the NNAR (31, 20) model used the previous 31 observations with the same hidden layer size.

Given the adequacy of the models, the last step is to verify the accuracy of the predictions. According to *MAE*, *RMSE*, and *MAPE*, the errors for the general practitioners and pediatricians of the ANN model were, respectively, [2.42, 2.42, 2.54%] and [2.52, 2.57, 10.11%].

4.4. Logistic Map

Although not applied in the healthcare field, particularly in short-term prediction of medical visits, the logistic map is widely recognized as a useful tool for analyzing time series in complex systems [16,23]. By utilizing the Solver optimization function in Microsoft Excel®, the model obtained initial values of $s(0)$ and a as 0.521570 and 3.655899, as well as an optimal sequence [$s(1)$, $s(6)$, $s(11)$, . . ., $s(41)$]. Table 2 shows the temporal evolution of the logistic map for the general practitioner, with a step size of five positions. It also shows the squared error (SE) of executions. Equation (8) exemplifies the calculation by showing $s(1)$, according to Equation (6). Equation (9) predicts the next number of visits by calculating $s(46)$ and multiplying it by 106, the maximum actual number of arrivals, normalized as 1.

$$\mathrm{s}(1) = 3.65589 \times 0.52157 \times (1 - 0.521570) = 0.912272 \tag{8}$$

$$\textit{Next number}\text{ of arrivals} = 106.s(46) = 106.\ [3.655899 \times 0.550949 \times (1 - 0.550949)] = 95.87541 \tag{9}$$

Table 2. Temporal evolution of the logistic map for general practitioners.

Execution	*s*(Execution)	Visits (Norm)	SE	RMSE
1	0.912	1.000	0.008	0.06
6	0.804	0.802	0.000	
11	0.830	0.821	0.000	
16	0.753	0.717	0.001	
21	0.882	0.877	0.000	
26	0.899	1.000	0.010	
31	0.899	0.981	0.007	
36	0.900	0.943	0.002	
41	0.898	0.906	0.000	

Table 3 shows the temporal evolution of the logistic map for pediatricians, with a step size of five positions. The initial values of $s(0)$ and a are 0.111496 and 3.757890. Equations (10) and (11) calculate s(1) and the next number of arrivals by taking $s(46)$ and multiplying it by 55, the maximum actual number of arrivals, normalized as 1.

$$s(1) = 3.75789 \times 0.111496 \times (1 - 0.111496) = 0.372274027 \tag{10}$$

$$\textit{Next number}\text{ of arrivals} = 55.s(46) = 55.\ [\ 3.757890 \times 0.822332 \times (1 - 0.822332)] = 30.1969536 \tag{11}$$

Table 3. Temporal evolution of the pediatrician's logistic map.

Execution	*s*(Execution)	Visits (Norm)	SE	RMSE
1	0.372	0.309	0.004	0.09
6	0.328	0.291	0.001	
11	0.229	0.327	0.010	
16	0.939	1.000	0.004	
21	0.414	0.291	0.015	
26	0.620	0.709	0.008	
31	0.381	0.509	0.016	
36	0.384	0.455	0.005	
41	0.404	0.473	0.005	

Figure 5a,b illustrate the relationship between real normalized data and the logistic map outcomes for both models. The two R^2 close to 1 reinforce the models.

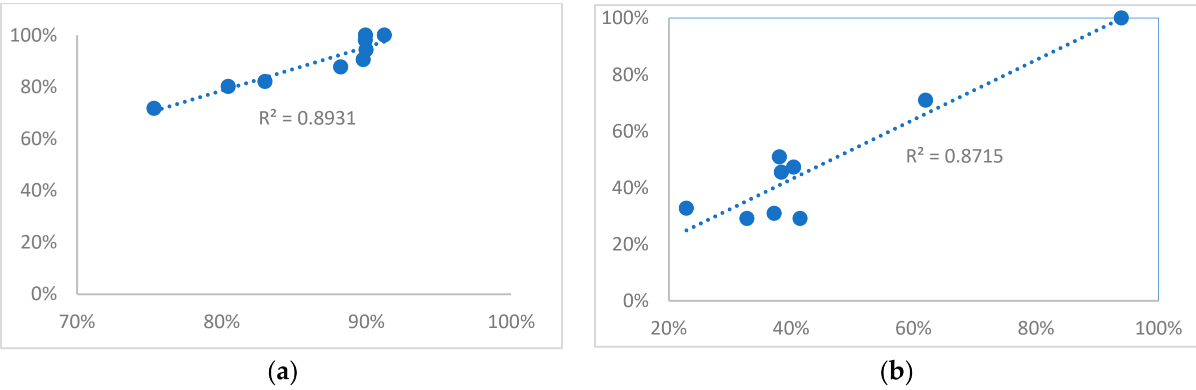


Figure 5. Actual norm data (y axis) and logistic map models' outcomes (x axis). (**a**) General Practitioners. (**b**) Pediatricians.

Given the adequacy of the models, the last step is to verify the accuracy of the predictions. According to MAE, RMSE, and MAPE, the errors for the general practitioners and pediatricians were, respectively, [2.12, 2.12, 2.17%] and [2.20, 2.20, 7.85%].

4.5. Result Comparison

Table 4 showcases the results obtained from the models, including predictions for seven, 14, and 30 days provided by the ARIMA and ANN models, even if those horizons are not the focus of the research.

Table 4. Summary of results.

Specialty	Method	Horizon	*MAE*	*RMSE*	*MAPE*
General Practitioners	ARIMA	One day	0.30	0.30	**0.31%**
		Seven days	27.32	34.59	28.13%
		14 days	24.65	30.34	25.38%
		30 days	22.48	28.19	23.14%
	ANN	One day	2.42	2.42	**2.54%**
		Seven days	24.34	26.45	25.03%
		14 days	20.8	24.28	20.93%
		30 days	17.63	20.43	17.17%
	Logistic Map	One day	2.12	2.12	**2.17%**
Pediatricians	ARIMA	One day	13.62	13.62	**32.72%**
		Seven days	17.17	17.36	41.99%
		14 days	14.67	15.82	35.90%
		30 days	15.89	16.84	38.88%
	ANN	One day	2.57	2.57	**10.11%**
		Seven days	1.95	2.62	7.47%
		14 days	4.05	5.98	14.87%
		30 days	6.24	8.78	22.12%
	Logistic Map	One day	2.20	2.20	**7.85%**

For general practitioners, ARIMA surpasses the logistic map, which slightly outperforms ANN. For pediatricians, the logistic map largely surpasses ANN, whereas ARIMA demonstrates a very low adequacy for this specific dataset. Despite utilizing a small number of observations, the logistic map yielded low, acceptable errors in both cases. An unexpected result is that short-term prediction for pediatricians is less accurate than for general practitioners. The reason for this difference should be investigated in the future, mainly why ARIMA yielded a very poor result.

5. Conclusions

The logistic map was selected for its capacity to represent nonlinear dynamics typical of short-term predictions. Unlike ARIMA, constrained by linearity, and ANN, which requires large datasets and tuning, it provides a simpler means of capturing chaotic behavior in healthcare management. Its adaptability enables efficient modeling under varying parameters, yielding robust forecasts. Such models are valuable because they accommodate the unpredictability of healthcare demand and reproduce complex dynamics where traditional methods often fail. Accurate short-term forecasts support the allocation of staff, materials, and costs in daily care, strengthening operational and patient management. To project next-day capacity, hospitals consider unoccupied beds at day's end and add patients expected to be discharged, underscoring the role of time series predictions. By contrast, less precise forecasts, such as 30-day horizons, risk misallocation of resources, operational inefficiencies, and financial losses.

The purpose of the study was to evaluate a short-term model for predicting daily attendance in an emergency healthcare unit. It compared two established forecasting methods, ARIMA and ANN, with a less conventional approach, the logistic map. The results showed that the logistic map could be an alternative for short-term prediction in healthcare management. The research question was as follows: Can a chaotic model satisfactorily predict the demand for arrivals in an emergency healthcare unit? The article provided a positive answer to the question.

The main contribution and innovation lie in the successful application of chaotic models, especially the logistic map, to the specific challenge of short-term forecasting demand for medical services. This contribution addresses a recognized gap in the existing academic literature, where the inherent nonlinear and complex patterns of healthcare demand have often posed difficulties for linear statistical models or complex machine learning techniques. The use of a chaotic model, designed to capture intricate dynamics, offers a new framework for understanding and predicting patient flow, moving beyond current limitations. To the best of our knowledge, this is the first use of the logistic map in forecasting emergency healthcare demand. Therefore, the contribution is twofold: it addresses a gap in applying chaos theory to healthcare and provides a resource-efficient forecasting tool for limited-capacity environments.

For practitioners in healthcare management, the findings offer a tangible tool for enhancing operational efficiency. The improved accuracy in short-term demand forecasting can directly support a more precise allocation of human resources, such as medical staff and support personnel, and material resources, including beds, equipment, and supplies. Better accuracy can lead to better patient flow, reduced waiting times, and a more balanced workload for staff, ultimately contributing to improved patient care experiences, cost reduction, and optimized resource utilization within emergency departments.

For scholars, this article opens avenues for further research. Future investigations could explore the applicability of other chaotic models, such as the Henon attractor or the Mackey–Glass model. Developing hybrid models that combine the strengths of chaotic approaches with traditional statistical methods or machine learning techniques could also yield more robust predictions. Research into incorporating external factors, such as weather patterns, public health campaigns, or local events, into chaotic models to enhance their predictive power would be valuable. Furthermore, studies focusing on adapting chaotic models for long-term forecasting or developing mechanisms for real-time adaptation to unforeseen changes would advance the field. Finally, research into the practical challenges and best practices for integrating advanced models into existing healthcare information technology systems would facilitate their broader adoption and impact. Upcoming studies should also investigate how to combine qualitative [55] and multicriteria approaches [56] with time series analysis. The method could introduce new influential, weighted factors [57], such as patient demographics, weather conditions, and local healthcare policies, alongside quantitative data.

The study faced limitations. Its scope was intentionally limited to short-term predictions, which means it does not fully explore the potential of chaotic models for long-term horizons. Furthermore, it utilized only the logistic map. Other chaotic models may exhibit different characteristics or offer alternative insights into the complex dynamics of patient demand. It also does not delve into the accuracy of the information system. The effectiveness of any forecasting model is also inherently dependent on the quality and availability of historical data. The study does not account for sudden, large-scale disruptions like natural disasters, pandemics, or mass incidents, which require adaptive response mechanisms rather than purely predictive ones. Finally, the practical implementation of advanced forecasting models can be affected by technological constraints within healthcare facilities, including access to specialized software, computational resources, or personnel with the necessary expertise, which was not tackled by the study.

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Abbreviations

Forecasting methods

ANN	artificial neural network
ARIMA	autoregressive integrated moving average
ARMA	autoregressive moving average
ARMAX	autoregressive moving average with exogenous inputs
ES	exponential smoothing
EV	explained variation
FL	fuzzy logic
GA	genetic algorithm
HWSM	Holt-Winters seasonal multiplicative
LR, NLR	linear, nonlinear regression
ML	machine-learning
MLFS	machine-learning feature selection
MLNB	machine-learning naive Bayes
MSARIMA	multivariate autoregressive integrated moving average
SARIMA	seasonal autoregressive integrated moving average
SARIMAX	seasonal autoregressive integrated moving average with exogenous inputs
STLF	short-term load forecasting
SVM	support vector machine
SVR	support vector regression
WMA	weighted moving average

Quality measures

DS	direction of symmetry
FSE	forecasting standard error
MAD	mean absolute deviation

MAE	mean absolute error
MAPE	mean absolute percentage error
MASE	mean absolute scale error
MSE	mean quadratic error
R^2: coefficient of determination	
RAE	relative absolute error
RMAE	relative mean absolute error
RMAP	relative mean absolute performance
RMSE	root mean square error

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