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Reducing Waiting Times to Improve Patient Satisfaction: A Hybrid Strategy for Decision Support Management

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Abstract: Patient satisfaction and operational efficiency are critical in healthcare. Long waiting times negatively affect patient experience and hospital performance. Addressing these issues requires accurate system time predictions and actionable strategies. This paper presents a hybrid framework combining predictive modeling and optimization to reduce system times and enhance satisfaction, focusing on registration, vitals, and doctor consultation. We evaluated three predictive models: multiple linear regression (MLR), log-transformed regression (LTMLR), and artificial neural networks (ANN). The MLR model had the best performance, with an R^2 of 0.93, an MAE of 7.29 min, and an RMSE of 9.57 min. MLR was chosen for optimization due to its accuracy and efficiency, making it ideal for implementation. The hybrid framework combines the MLR model with a simulation-based optimization system to reduce waiting and processing times, considering resource constraints like staff and patient load. Simulating various scenarios, the framework identifies key bottlenecks and allocates resources effectively. Reducing registration and doctor consultation wait times were identified as primary areas for improvement. Efficiency factors were applied to optimize waiting and processing times. These factors include increasing staff during peak hours, improving workflows, and automating tasks. As a result, registration wait time decreased by 15%, vitals by 20%, and doctor consultation by 25%. Processing times improved by 10–15%, leading to an average reduction of 22.5 min in total system time. This paper introduces a hybrid decision support system that integrates predictive analytics with operational improvements. By combining the MLR model with simulation, healthcare managers can predict patient times and test strategies in a risk-free, simulated environment. This approach allows real-time decision-making and scenario exploration without disrupting operations. This methodology highlights how reducing waiting times has a direct impact on patient satisfaction and hospital operational efficiency, offering an applicable solution that does not require significant structural changes. The results are practical and implementable in resource-constrained healthcare environments, allowing for optimized staff management and patient flow.

Keywords: patient satisfaction; healthcare operations efficiency; predictive modeling; simulation-based decision support; wait-time optimization

MSC: 62J05; 90B50; 90C90

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Citation: Morales, J.; Silva-Aravena, F.; Saez, P. Reducing Waiting Times to Improve Patient Satisfaction: A Hybrid Strategy for Decision Support Management. *Mathematics* **2024**, *12*, 3743. https://doi.org/10.3390/math12233743

Academic Editor: Prasenjit Chatterjee

Received: 31 October 2024
Revised: 22 November 2024
Accepted: 26 November 2024
Published: 28 November 2024

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1. Introduction

According to [1,2] and other authors, patient satisfaction and operational efficiency are two fundamental pillars in the management of modern healthcare systems. Prolonged waiting times in hospitals and healthcare facilities are a critical factor that negatively affects the perceived quality of care, patient satisfaction, and, ultimately, the operational performance of hospitals [3–5]. Several studies have shown that reducing waiting times can significantly improve the patient experience and optimize the use of limited resources, such as medical staff and hospital infrastructure [6–8]. In a context where healthcare systems

face increasing demands, optimizing service delivery times has become a priority for hospital managers.

Predictive methodologies and simulation models have gained traction in recent years as essential tools for improving decision-making in healthcare systems [9–11]. Accurate prediction of system times, including waiting and processing times across different stages of care, allows hospital managers to identify bottlenecks and allocate resources more effectively [12,13]. However, the challenge lies not only in accurately predicting system times but also in integrating these predictive insights into an optimization framework that can enhance operations and reduce inefficiencies without compromising service quality [14,15].

In this context, regression models have been widely used to predict system times in hospitals, including MLR and more advanced models such as ANN [16–18]. Each of these models offers specific advantages, such as the simplicity and interpretability of MLR or the ability to capture more complex nonlinear relationships through ANN and deep learning (see, e.g., [18–20]). However, recent studies suggest that combining predictive models with simulation and optimization can provide a more robust and effective solution for managing patient flow in hospitals, especially in environments with limited resources and fluctuating demand [21–23].

The aim of our paper is to build a methodology to reduce waiting times at critical care points and improve patient satisfaction through a hybrid prediction and simulation model. The novelty lies in the combination of an MLR model with simulation, which allows real-time decision-making, effectively optimizing resources in hospital environments. To achieve this, the hybrid approach combines predictive modeling with simulation-based optimization techniques to reduce total system times in the hospital. Using an MLR model as a basis, we simulate various operational scenarios, taking into account resource constraints such as medical staff availability and patient demand during peak hours. By simulating these scenarios, the proposed framework enables the identification of key bottlenecks and generates specific recommendations for optimal resource allocation and reduction of waiting times at critical stages such as registration, vital signs verification, and medical consultation (see, for example, [24–26]).

Over the past decade, simulation has become a crucial tool for improving healthcare system management without disrupting daily operations [27,28]. By integrating predictive models within a simulation platform, healthcare managers can foresee the impact of different operational decisions in real time, allowing for faster, data-driven decision-making. This approach offers a crucial advantage by enabling the evaluation of multiple scenarios without compromising service quality or causing disruptions to the workflow [29,30].

The structure of this paper is as follows: Section 2 provides a comprehensive review of the literature on predictive models and simulation in the hospital setting; Section 3 details the methodology used, with a focus on multiple linear regression and the simulation techniques applied. Section 4 presents the results obtained from the predictive models and simulation framework. Section 5 offers a detailed discussion, and in Section 6, we present the main conclusions of the paper.

2. Literature Review

In the healthcare field, patient satisfaction and the effectiveness of healthcare systems are closely related [31]. It has long been known that long waiting times have a negative impact on patient satisfaction and overall perception [32,33]. According to several studies, increasing operational efficiency, especially by reducing waiting times, is essential to improve patient satisfaction and the quality of treatment provided (see, e.g., [34]). This correlation between patient satisfaction and waiting time highlights the need to adopt efficient approaches that can alleviate bottlenecks and improve resource allocation in hospitals [4,35]. Therefore, healthcare services should prioritize optimizing system times to ensure that patient needs are met in a timely manner, which has been shown to help improve satisfaction levels [36–38].

Predictive modeling has emerged as a good tool in the patient care field to improve decision-making, particularly in predicting patient flow and waiting times [4,39]. Hospital managers can anticipate potential delays and adjust staffing and resources appropriately by using predictive models such as multiple linear regression and more sophisticated models such as artificial neural networks (ANN) that leverage past data [16,40]. According to [9], predictive models increase the accuracy of predicting healthcare outcomes, which is crucial for optimizing hospital operations. To fully realize their potential, predictive models should be incorporated within a broader decision-support framework [41]. According to [11], a hybrid technique combining simulation with predictive models provides a more complete solution by simulating various situations and predicting outcomes to increase system efficiency.

The application of simulation-based strategies in healthcare is well documented. Simulation allows healthcare services to experiment with various operational strategies, providing insights into how changes to one part of the system, such as staffing or resource allocation, can impact overall performance [13,25]. Research by [21,22] shows that simulation models can effectively reduce waiting times and improve resource management, particularly in high-demand settings such as emergency departments. The flexibility of simulation makes it a good tool for hospital management, allowing them to test different strategies before implementation [29]. By combining simulation with predictive analytics, healthcare services can achieve a holistic approach to managing patient flow, significantly reducing system times without compromising the quality of care.

Even with advancements in simulation and prediction model construction, there is a gap in their integration, particularly in frameworks for real-time decision-making [18,19]. The dynamic capabilities needed to react instantly to changes in healthcare environments are frequently absent from predictive models. However, although useful for testing scenarios, simulation models do not always offer the degree of predictive accuracy needed for long-term planning [23]. This disparity emphasizes the necessity of hybrid models that can effectively combine simulation and predictive analytics to offer a strong decision support system that can handle the pressing issues in healthcare [20]. Recent studies have highlighted the potential of hybrid models in achieving this balance, offering solutions that are both flexible and data-driven [42].

Authors such as [11,17] and others emphasize hybrid approaches of predictive models with simulations for waiting time management and how such integration can contribute to real-time operational optimization without disrupting hospital flow. Combining simulation and predictive modeling has two benefits: it increases prediction accuracy and gives hospital administrators a controlled setting in which to test out various operational tactics. In complex systems like hospitals, where resource limitations and variations in patient flow can have a major influence on system performance, this hybrid approach is especially advantageous [24]. According to research by [27], simulation can be used to enhance the general quality and safety of healthcare services in addition to optimizing patient flow. Healthcare systems can decrease wait times at crucial points in the care process, like registration and consultations, and increase patient satisfaction by incorporating simulation into predictive models [30].

A hybrid decision support system that combines simulation and predictive analytics is required to enhance healthcare delivery [28,43]. This strategy guarantees that medical institutions are prepared to manage both expected and unanticipated changes in patient demand. Authors such as [21] have shown that simulation-based optimization frameworks can better reallocate resources and pinpoint major bottlenecks that cause delays, hence reducing total system times. Additionally, the objectives of contemporary healthcare administration, which center on raising patient happiness through operational effectiveness, are in line with this hybrid approach. Incorporating machine learning methods into these hybrid models will probably increase predicted accuracy and system adaptability as research advances, providing healthcare institutions with a useful tool to satisfy demanding patient care requirements [28].

3. Materials and Methods

In this section, we show the data preprocessing process and the steps to follow for its preprocessing, including the handling of missing data and outliers, as well as the formulation to obtain the total system time based on the waiting times and the service process. The steps that allow us to prepare the data for the use of the methods used and the optimization strategies are described below.

3.1. Data Preprocessing and Postprocessing Process

The public data correspond to 500 patients from a public hospital in Pakistan who went through a healthcare system consisting of three key stages: registration, vital signs, and medical consultation. The total time each patient spent in the system was recorded, along with the waiting and processing times for each stage [44,45].

We implemented various preprocessing techniques, addressing the handling of missing data and outliers and preparing the data for use in predictive models. A brief description follows.

1. First, we inputted missing values in critical variables (such as times at registration, vital signs, and medical consultation stages). We chose to eliminate incomplete records to avoid bias.
2. Second, we applied the interquartile range (IQR) method to identify and handle outliers since these outliers can affect the distribution of the data and the accuracy of the predictive models.
3. Third, we calculated the waiting time at each stage (registration, vital signs, and medical consultation) as the difference between the end time of the previous stage and the start time of the next stage. We also calculated the processing time as the difference between the start and end of each stage. We assumed that each patient follows the same flow (registration $\rightarrow$ vital signs $\rightarrow$ medical consultation) without interruptions, which allowed us to calculate the total time in the system sequentially.
4. Fourth, we checked the distribution of the post-processing data. By removing outliers, we sought to ensure that the data followed a closer-to-normal distribution, especially during waiting and processing times.
5. Fifth, to simplify the actual complexity of the hospital flow, we considered that the waiting and processing times at each stage were independent of each other.
6. Sixth, we normalized the times between 0 and 1 to improve the convergence of the models and reduce the bias caused by different time magnitudes at each stage.

   Pre- and post-processing of the data allowed us to adequately prepare them for predictive and optimization analysis. This strategy allowed us to ensure that the methodology was built with high-quality data.

3.1.1. Handling Missing Data and Outliers

In the healthcare dataset, missing data are common, especially in recorded times for various stages of the patient care process. We addressed this issue by the following:

1. Eliminating records with missing values in critical variables: registration times, vitals times, doctor consultation times, and total system times. This decision was made to avoid introducing bias or inaccuracies caused by inputting essential variables.

   Let X be the dataset with variables X_1, X_2, …, X_n representing the waiting and processing times at different stages.
2. If $X_i \in \{T_{w,i}, T_{p,j}\}$ (wait time fo each stage i and processing time for each stage j), record X is removed if $\exists i \in \{1, 2, 3\}$ such as $X_i = 0$, where 0 represents missing values. After this step, only complete X $\in \{T_{w,i}, T_{p,j}\}$ records were retained, ensuring that all relevant information for each patient was available.
3. The presence of extreme outliers in the waiting and processing times could skew the results of our regression models. Therefore, outliers were identified using the interquartile range (IQR) method for each of the variables, and extreme values were

removed to ensure normal distribution and prevent model distortion. For each variable X_i, we calculated the interquartile range, and for the value of X_i that fell outside the range, we considered outliers and removed them.

4. The final dataset contained 480 complete cases that were used in this article.

3.1.2. Calculation of Waiting Times and Total System Time

The dataset records timestamps at different stages of the patient care process. From these timestamps, we calculate the waiting times and processing times as follows:

The waiting time for each stage is the difference between the end time of the previous stage and the start time of the current stage. The waiting times for registration, vitals, and doctor consultation are calculated as follows:

$T_{w,r} = T_{s,r} - T_{e,r}$, where w is the wait, r is registration, s is the start, and e is the end;

$T_{w,v} = T_{s,v} - T_{e,v}$, where v refers to vitals;

$T_{w,d} = T_{s,d} - T_{e,d}$, where d is the doctor.

Therefore, $T_{s,r}$, $T_{s,v}$, and $T_{s,d}$ are the timestamps for the start of each process. $T_{e,r}$, $T_{e,v}$, and $T_{e,d}$ are the timestamps for the end of each process.

The processing time for each stage is the time elapsed from the start to the end of the stage. The processing times for registration, vitals, and doctor consultation are calculated as follows:

$T_{p,r} = T_{e,r} - T_{s,r}$, where p refers to the process;

$T_{p,v} = T_{e,v} - T_{s,v}$;

$T_{p,d} = T_{e,d} - T_{s,d}$.

The total system time, T_t, is the sum of all the waiting and processing times across the various stages of the patient care process: $T_t = \sum_{n=1}^{3} T_{w,i} + \sum_{n=1}^{3} T_{p,j}$, where T_t is the total time a patient spends in the system, index i refers to the three stages of waiting (registration, vitals, and doctor), and index j refers to the three stages of processing (registration, vitals, and doctor).

3.2. Data Characterization

Figure 1 shows the distribution of waiting times for each of the stages. Although waiting times at each stage are concentrated at the beginning, there are cases in which patients wait a long time during all stages. Waiting times at the doctor stage are the longest, with waits of up to 50 min.

For the bottleneck analysis, we considered the T_t for each patient as a variable, that is, from their arrival until the end of their process with the doctor. In Table 1, we calculate the durations of the times for each stage and present the contribution of each one to the T_t.

In Table 2, we present a correlation matrix to evaluate the relationships between each stage with T_t. The analysis confirms that the highest correlation is between T_t and the doctor's times (0.469), confirming the bottleneck at that stage.

Table 1. Statistical summary of bottlenecks by stage (in minutes).

Summary Time	Total System (T_t)	Registration	Vitals	Doctor
Count	126	126	126	126
Mean	59.31	2.212	6.10	14.45
Std	32.89	2.17	5.74	9.31
Min	14	0	0	0
25%	13	1	3	7
50%	54.5	1	4	12
75%	78.5	3	7	20

Table 2. Correlation matrix of times per stage (in minutes).

Correlation Matrix	Total System (T_t)	Registration	Vitals	Doctor
`Total System` (T_t)	1.000	0.093	0.221	0.469
`Registration`	0.093	1.000	−0.027	−0.150
`Vitals`	0.221	−0.027	1.000	0.062
`Doctor`	0.469	−0.150	0.062	1.000

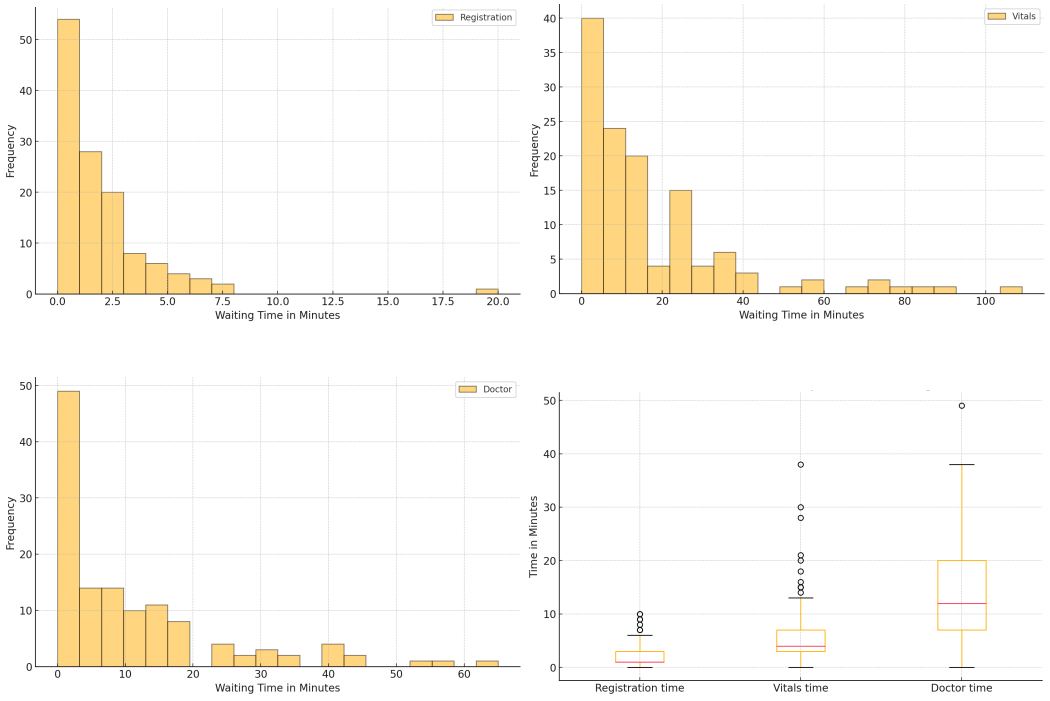


Figure 1. Distribution of time spent in each stage.

Now that we have determined the bottlenecks in the care process, after determining T_t, we present three predictive regression models and a decision support strategy to optimize system times in a patient care setting.

3.3. Multiple Linear Regression

MLR is a model that uses the waiting times and processing times of the three stages of the system under study to predict T_t. This section provides a detailed description of the formulation and implementation steps for this model.

The MLR model is expressed as a linear combination of several independent variables [40,46]. In this case, the independent variables are the waiting times and processing times at the three stages of the healthcare system, as presented in Section 3.1.2:

1. Registration stage: $T_{w,r}$ and $T_{p,r}$;
2. Vitals stage: $T_{w,v}$ and $T_{p,v}$;
3. Doctor stage: $T_{w,d}$ and $T_{p,d}$.

The general form of the MLR model is presented as follows:

$$T_t = \beta_0 + \sum_{i=1}^{3} \beta_i \cdot T_{w,i} + \sum_{j=1}^{3} \beta_{j+3} \cdot T_{p,j} + \epsilon, \quad (1)$$

where T_t is the dependent variable, representing the total time a patient spends in the healthcare system, β_0 is the intercept, representing the baseline time when all independent variables are zero, β_i are the regression coefficients for the waiting times, $T_{w,i}$, (where

$i \in \{1, 2, 3\}$ corresponds to registration, vitals, and doctor), β_{j+3} are the regression coefficients for the processing times, $T_{p,j}$, (where $j \in \{1, 2, 3\}$ corresponds to registration, vitals, and doctor), and ϵ is the error term (or residual), capturing the variance in T_t not explained by the independent variables.

It is important to mention that the first summation term, $\sum_{i=1}^{3} \beta_i \cdot T_{w,i}$, represents the combined effect of waiting times at each stage, and the second summation term, $\sum_{j=1}^{3} \beta_{j+3} \cdot T_{p,j}$, represents the combined effect of the processing times at each stage.

The MLR model operates under several key assumptions, which are essential to ensure the validity of the results [40]. We present its methodology below.

1. The relationship between the dependent variable T_t and the independent variables (waiting times and processing times) is linear.

$$E(T_t \mid T_{w,i}, T_{p,j}) = \beta_0 + \sum_{i=1}^{3} \beta_i \cdot T_{w,i} + \sum_{j=1}^{3} \beta_{j+3} \cdot T_{p,j}. \tag{2}$$

2. The residuals from one observation should not be correlated with the residuals from another observation. In other words, there should be no autocorrelation among the residuals. One way to check for autocorrelation in a regression model is by using the Durbin–Watson (DW) statistic.
3. The variance of the error term ϵ is constant across all values of the independent variables. This is known as homoscedasticity and is expressed as follows:

$$Var(\epsilon \mid T_{w,i}, T_{p,j}) = \sigma^2. \tag{3}$$

4. The error term ϵ follows a normal distribution, $\epsilon \sim N(0, \sigma^2)$.
5. The independent variables $T_{w,i}$ and $T_{p,j}$ are not highly correlated with each other. Multicollinearity could distort the estimation of the regression coefficients.

Now, we estimate the coefficients β_i and β_{j+3} using the ordinary least squares method (OLS) [47,48]. This method minimizes the sum of the squared residuals, which is the difference between the observed and predicted values of T_t.

$$\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_6 = arg \min_{\beta_0, \beta_1, \ldots, \beta_6} \sum_{k=1}^{n} (T_{t,k} - \hat{T}_{t,k})^2, \tag{4}$$

where $T_{t,k}$ is the actual total system time for the k-th patient, and $\hat{T}_{t,k}$ is the predicted total system time for the k-th patient based on the estimated regression coefficients.

3.4. Log-Transformed Multiple Linear Regression Model

The log-transformed multiple linear regression model (LTMLR) is derived from the original model, MLR (see Equation (1)). This type of strategy has also been used in health studies, such as [49,50]. We transform it using the natural logarithm, resulting in the following:

$$log(T_t) = \beta_0 + \sum_{i=1}^{3} \beta_i \cdot T_{w,i} + \sum_{j=1}^{3} \beta_{j+3} \cdot T_{p,j} + \epsilon, \tag{5}$$

where the components of the function are the same as in Equation (1), except that now $log(T_t)$ is the natural logarithm of the T_t.

We fit the model to revert the predictions from the log-transformed scale back to the original scale and apply the exponential function to the predicted values:

$$T_t = e^{\hat{Y}} = e^{\left(\beta_0 + \sum_{i=1}^{3} \beta_i T_{w,i} + \sum_{j=1}^{3} \beta_{j+3} T_{p,j}\right)}, \tag{6}$$

where $\hat{Y}$ = log (T_t) is the predicted log-transformed system time, and the exponential transformation $e^{\hat{Y}}$ brings the prediction back to the original time scale.

3.5. Artificial Neural Network Model

We have now developed an ANN model to predict T_t based on several input features, such as the waiting times and processing times at different stages of the patient care flow. For this ANN, we follow a multilayer perception (MLP) architecture with one hidden layer and the sigmoid activation function [17,51].

The input layer of the ANN receives the following variables, mentioned in Sections 3.1.2 and 3.3 (i.e., $T_{w,r}$, $T_{p,r}$, $T_{w,v}$, $T_{p,v}$, $T_{w,d}$ and $T_{p,d}$), and which represent the key factors that contribute to the T_t.

Neural Network Architecture

For the ANN model, we consider the following components: (1) input layer, i.e., it receives the input features (waiting and processing times and the number of neurons in this layer is six [it is equal to the number of input variables]); (2) hidden layer, i.e., it contains an experiment between 10 and 20 neurons, each neuron applies a sigmoid activation function to its input. The output of the hidden layer is calculated as follows:

$$z_k^{(h)} = \frac{1}{1 + e^{-(\sum_{i=1}^{n} w_{k,i}^{(h)} x_i + b_k^{(h)})}}, \tag{7}$$

where $w_{k,i}^{(h)}$ are the weights connecting the input variables to the neurons in the hidden layer, and $b_k^{(h)}$ is the bias term for each neuron in the hidden layer.

In our model, the final predicted value of T_t is produced by the output layer, which combines the outputs of the hidden layer using the following linear activation function:

$$\hat{T}_t = \sum_{k=1}^{m} w_k^{(0)} z_k^{(h)} + b^{(0)}, \tag{8}$$

where $w_k^{(0)}$ are the weights connecting the hidden layer to the output layer, and $b^{(0)}$ is the bias term in the output layer.

We use the sigmoid function as the activation function in the hidden layer to introduce nonlinearity into the model. The sigmoid function is defined as follows:

$$f(z) = \frac{1}{1 + e^{-z}}. \tag{9}$$

This activation function ensures that the output of each neuron in the hidden layer is between 0 and 1, allowing our ANN model to capture complex relationships between input variables.

For the loss function, we use MSE, which measures the squared difference between the predicted $\hat{T}_t$ and the T_t.

3.6. Statistical Metrics to Validate Regression Models

1. We measure the proportion of the variance of the dependent variable, T_t, that is explained by the independent variables of the model [52,53]. To do so, we calculate R^2 as follows:

$$R^2 = 1 - \frac{\sum_{k=1}^{n} (T_{t,k} - \hat{T}_{t,k})^2}{\sum_{k=1}^{n} (T_{t,k} - \bar{T}_{t,k})^2} \tag{10}$$

where $T_{t,k}$ is the actual observed value of the dependent variable for the k-th observation (in this case, the total time in the system, T_t); $\hat{T}_{t,k}$ is the predicted value of T_t

from the regression model for the k-th observation; and $\bar{T}_t$ is the mean of all observed T_t values.

2. We also obtained MAE as a measure of error to determine the absolute difference between the observed and predicted values of T_t.

$$MAE = \frac{1}{n}\sum_{k=1}^{n}|T_{t,k} - \hat{T}_{t,k}|. \tag{11}$$

3. Finally, we calculate RMSE as another error measure, which allows us to measure the square root of the average squared differences between the observed and predicted values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(T_{t,k} - \hat{T}_{t,k})^2}. \tag{12}$$

3.7. Strategy for Reducing Patient Wait Times: A Decision Support Management

We propose a decision support strategy to minimize T_t in patient care by leveraging optimization techniques and selecting the best regression model. We include multiple simulations to explore the impact of various constraints and resource allocations, making the strategy more comprehensive and adaptable. The details of its components are presented below:

1. The objective is to minimize T_t, which is influenced by waiting times and processing times at the three main stages of patient care: registration, vital signs, and medical consultation. In this way, we define the objective function as follows:

$$MinT_t = \beta_0 + \sum_{i=1}^{3}\beta_i \cdot T_{w,i} + \sum_{j=1}^{3}\beta_{j+3} \cdot T_{p,j}. \tag{13}$$

2. The key constraint in this optimization problem is the availability of resources such as staff, technological infrastructure, and time. These resources directly impact the possible reductions in waiting and processing times. Let R_i be the resources available for each stage i (registration, vitals, and doctor). Let $T_{w,i}^{min}$ and $T_{p,j}^{min}$ be the minimum feasible times for waiting and processing given available resources.
3. The constraints are (1) $T_{w,i} \geq T_{w,i}^{min}$ and (2) $T_{p,j} \geq T_{p,j}^{min}$.
4. Then, to optimize T_t, we introduce efficiency factors $\eta_{w,i}$ and $\eta_{p,j}$, where $\eta \in (0, 1]$, representing how much waiting and processing times can be reduced based on the resources available. In this way, the optimized waiting and processing times are $T_{w,i}^{opt} = \eta_{w,i} \cdot T_{w,i}$; and $T_{p,j}^{opt} = \eta_{p,j} \cdot T_{p,j}$.
5. Finally, the optimized T_t of the system becomes the following:

$$T_t^{opt} = \beta_0 + \sum_{i=1}^{3}\beta_i \cdot \eta_{w,i} \cdot T_{w,i} + \sum_{j=1}^{3}\beta_{j+3} \cdot \eta_{p,j} \cdot T_{p,j}. \tag{14}$$

4. Results

The results of our research show an evaluation of the performance of the developed regression models in terms of goodness of fit and prediction accuracy. We also present a simulation of the decision support strategy that links the model with a time optimization strategy to improve patient satisfaction.

4.1. Performance of Regression Models

We present, in Table 3, the performance metrics for our predictive models used to estimate the T_t in a healthcare setting. The model is evaluated using several statistical

measures, which indicate how well the model fits the data and how accurate its predictions are. The results confirm the MLR model presents the best performance.

Table 3. Comparative table of regression models (error metrics in minutes).

Model	R^2	MAE	MSE	RMSE
MLR	0.93	7.29	91.67	9.57
LTMLR	0.85	7.62	97.02	9.85
NN	0.86	7.05	190.04	13.79

4.2. Statistical Assumptions Results

We evaluate whether the MLR model meets the statistical assumptions. To do so, we check the aspects discussed in Section 3.3.

From Figures 2 and 3 and the information provided by Tables 4 and 5, we confirm that all these results indicate that the MLR model meets the key assumptions for linear regression, making it a robust and valid model for predicting T_t.

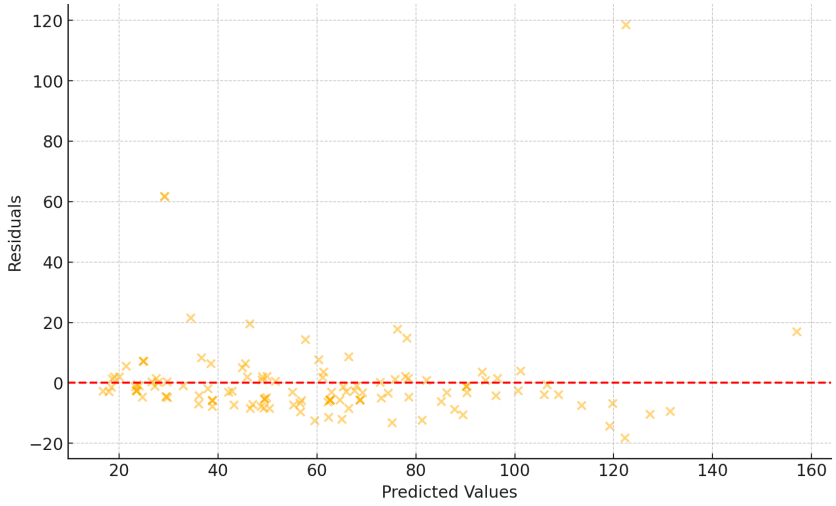


Figure 2. Residuals vs. fitted values (linearity and homoscedasticity).

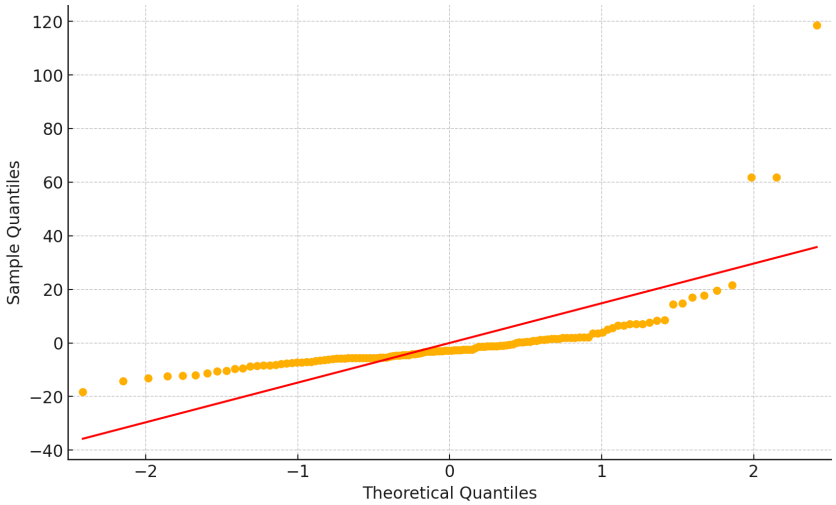


Figure 3. Q–Q plot of residuals (normality).

Table 4. Variance inflation factor (VIF).

Feature	VIF
Registration wait time	1.40
Vitals wait time	1.64
Doctor wait time	1.60
Registration time	1.78
Vitals time	1.83
Doctor time	2.68

Table 5. Summary of statistical test results.

Test	Value	Interpretation
Durbin-Watson	Close to 2	No autocorrelation in residuals (independence)
Breusch-Pagan Test (p-value)	>0.05	Residuals have constant variance (homoscedasticity)
Shapiro-Wilk Test (p-value)	>0.05	Residuals are normally distributed
Variance Inflation Factor (VIF)	All < 10	No multicollinearity

4.3. Decision-Making Framework

According to the strategy defined in Section 3.7, we propose an example to evaluate the reduction of patient total times in the system. Let us assume that we simulate resource constraints based on staff availability at each stage:

Stage 1: Registration has a staff of two, allowing for a minimum wait time of $T_{w,r}^{min} = 20$ min and a processing time of $T_{p,r}^{min} = 8$ min.

Stage 2: Vitals has a staff of three, reducing waiting time to $T_{w,v}^{min} = 15$ min and processing time to $T_{p,v}^{min} = 4$ min.

Stage 3: One doctor is available, limiting waiting time to $T_{w,d}^{min} = 30$ min and processing time to $T_{p,d}^{min} = 10$ min.

Now, we simulate a scenario where (1) the registration process achieves an efficiency of $\eta_{w,r} = 0.85$ (15% reduction in wait time) and $\eta_{p,r} = 0.9$ (10% reduction in processing time); (2) for vitals, $\eta_{w,v} = 0.8$ (20% reduction in wait time) and $\eta_{p,v} = 0.85$ (15% reduction in processing time); (3) for doctor consultation, $\eta_{w,d} = 0.75$ (25% reduction in wait time) and $\eta_{p,d} = 0.85$ (15% reduction in processing time).

We generate multiple scenarios with different levels of efficiency factors and resource availability. For each scenario, we calculate T_t using the MLR model. For each scenario, we calculate T_t^{opt} and compare it with T_t.

We assume the baseline times for a patient are (1) $T_{w,r} = 30$ min; (2) $T_{p,r} = 10$ min; (3) $T_{w,v} = 20$ min; (4) $T_{p,v} = 5$ min; (5) $T_{w,d} = 40$ min; (6) $T_{p,d} = 15$ min. We use the efficiency factors and the information above to determine the optimized times, which are presented below:

Registration: $T_{w,r}^{opt} = 0.85 \cdot 30 = 25.5$ min, $T_{p,r}^{opt} = 0.9 \cdot 10 = 9$ min.

Vitals: $T_{w,v}^{opt} = 0.8 \cdot 20 = 16$ min, $T_{p,v}^{opt} = 0.85 \cdot 5 = 4.25$ min.

Doctor: $T_{w,d}^{opt} = 0.75 \cdot 40 = 30$ min, $T_{p,d}^{opt} = 0.85 \cdot 15 = 12.75$ min.

The result of calculating the optimized time is $T_t^{opt} = 25.5 + 9 + 16 + 4.25 + 30 + 12.75 = 97.5$ min. Base Tt was $T_t = 30 + 10 + 20 + 5 + 40 + 15 = 120$ min. Therefore, the total system time reduction is $\Delta T_t = T_t - T_t^{opt} = 120 - 97.5 = 22.5$ min.

5. Discussion

In this work, we introduce a novel decision support strategy that integrates multiple regression models with simulation techniques to optimize total system times in healthcare. The proposed strategy offers a significant contribution to the field of healthcare operations management by providing a data-driven approach to reducing waiting times

and improving patient satisfaction. In contrast to traditional models, our approach leverages multiple predictive models and applies them in a simulation framework, allowing healthcare managers to evaluate and implement strategies in a controlled environment.

The results of the study demonstrate that the MLR model outperformed other models in terms of predictive accuracy, with an R^2 of 0.93, an MAE of 7.29 min, and an RMSE of 9.57 min. These findings are consistent with prior studies that have highlighted the robustness of MLR in healthcare settings (see, e.g., [42,54]). Additionally, the simulation results show that the proposed strategy effectively reduced total system times by an average of 22.5 min, with the most significant reductions observed in the registration and doctor consultation stages.

MLR is useful for hospital decision-making by providing coefficients that show the influence of each variable on total system time. However, in complex environments, wait times are not always linear, especially during peak hours or when resources are scarce. Additionally, factors like case severity also impact wait times, which MLR does not capture in a simple linear relationship.

We chose thrre types of models to meet the different needs of our study: MLR for its simplicity and interpretability, LTMLR to handle moderate nonlinear relationships and reduce distributional biases, and ANN to capture more complex relationships in the data. However, the limitations of each underscore that each model has areas where it could be ineffective, which is important to consider in the interpretation of the results and in the practical application of the study.

One of the limitations of this study is the reliance on a single dataset from a public hospital. While the models performed well within this context, additional research is needed to generalize these findings across different healthcare systems. Moreover, the simulation framework could be further enhanced by incorporating more complex variables, such as patient acuity and staff availability, to provide a more comprehensive analysis.

Additional limitations of our study include that it does not include detailed information on patients' clinical factors and their variability in system perception, which may affect patient satisfaction. Furthermore, the study does not consider external factors that may influence waiting times, such as disease outbreaks, health crises, or seasonal changes in patient volume.

Despite these limitations, the methodology presented in this paper offers a robust framework for reducing system inefficiencies and improving patient satisfaction. By integrating predictive modeling with simulation, healthcare managers can test various strategies and implement the most effective solutions without disrupting ongoing operations. Future research should explore the use of machine learning techniques to further enhance predictive accuracy and expand the applicability of the model to different healthcare environments.

6. Conclusions

In this work, we present an integrated decision support framework designed to minimize total system times in healthcare by leveraging predictive modeling and simulation techniques. The MLR model was identified as the most effective predictive model, achieving an R^2 of 0.93, an MAE of 7.29 min, and an RMSE of 9.57 min. The optimization framework built around this model demonstrated significant reductions in system times in 22.5 min, contributing to improved patient satisfaction and operational efficiency.

The contributions of this study are two-fold. First, we provide a comparative analysis of multiple regression models to determine the most accurate predictor of system times. Second, we integrate these models into a simulation-based optimization framework that enables healthcare managers to implement strategies for reducing waiting times and improving resource allocation.

Summarizing, the decision support strategy proposed in this paper offers a practical and effective solution for optimizing system times in healthcare. By reducing waiting times and improving resource allocation, the framework enhances both operational efficiency and

patient satisfaction, making it a valuable tool for healthcare managers aiming to improve service delivery.

Future research should investigate the application of advanced machine learning techniques to enhance predictive accuracy and broaden the model's applicability across diverse healthcare settings. For instance, approaches such as fuzzy multiple linear regression analysis could offer valuable insights. Furthermore, validation of the model across different healthcare systems and its adaptation to more intricate patient care workflows should be considered.

Incorporating real-time data into the simulation framework represents a critical avenue for improving the model's responsiveness to evolving healthcare dynamics. Additional directions for future work include the following: integrating patient demographic data to refine predictive accuracy; optimizing resource allocation based on patient profiles; conducting longitudinal studies to evaluate the impact of wait time management on patient satisfaction; developing a user-friendly interface that enables hospitals to intuitively utilize the simulation and predictive model in real-time.

Moreover, adapting the model to specialized areas within the hospital, such as emergency departments, intensive care units, or surgical units, could assess its versatility in varied clinical contexts. Finally, integrating alert systems responsive to epidemiological or climatic events could equip hospitals to anticipate and manage significant fluctuations in patient volume effectively.

Author Contributions: Conceptualization, F.S.-A. and J.M.; data curation, F.S.-A. and P.S.; formal analysis, F.S.-A. and J.M.; funding acquisition, J.M. and P.S.; investigation, F.S.-A. and J.M.; methodology, F.S.-A., J.M. and P.S.; project administration, J.M.; supervision, J.M. and P.S.; writing—original draft, F.S.-A., J.M. and P.S.; writing—review and editing, F.S.-A., J.M. and P.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the "ANID Fondecyt Iniciacion a la Investigación 2024 N° 11240214".

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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