BİNGÖL ÜNİVERSİTESİ İKTİSADİ VE İDARİ BİLİMLER FAKÜLTESİ DERGİSİ

Bingöl Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 10(1), 18-30

A Machine Learning Framework for Predicting Hospital Costs and Revenues Based on Healthcare Resources and Patient Waiting Times

Sağlık Kaynaklarına ve Hasta Bekleme Sürelerine Dayalı Hastane Maliyetlerini ve Gelirlerini Tahmin Etmek için Bir Makine Öğrenmesi Çerçevesi

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Abstract

Effective management of healthcare resources and patient waiting times is critical for operational efficiency and financial sustainability in healthcare institutions. This study proposes a machine learning (ML)-based framework for jointly estimating total cost and revenue by modeling the impact of five key healthcare resources (physicians, nurses, clerks, exam rooms, and triage areas) and patient waiting time. Three regression-based ML algorithms—Partial Least Squares (PLS), Random Forest (RF), and Gradient Boosting (GB)—were applied and compared using a simulated dataset. The GB algorithm demonstrated the best cost and revenue estimation performance, with R^2 values of 0.981 and the lowest MAPEs of 1.869% and 1.913%, respectively. The results indicate that non-linear models, such as GB, better capture the complex relationships between hospital operations and financial outcomes. This study highlights the potential of data-driven approaches to support strategic decision-making in hospital management, offering predictive accuracy and operational insight into resource allocation, cost containment, and revenue enhancement.

Öz

Sağlık kaynaklarının ve hasta bekleme sürelerinin etkin yönetimi, sağlık kurumlarında operasyonel verimlilik ve finansal sürdürülebilirlik açısından kritik öneme sahiptir. Bu çalışma, beş temel sağlık kaynağının (hekimler, hemşireler, memurlar, muayene odaları ve triyaj alanları) ve hasta bekleme süresinin etkisini modelleyerek toplam maliyet ve geliri birlikte tahmin etmeye yönelik makine öğrenmesi (ML) tabanlı bir çerçeve önermektedir. Simüle edilmiş bir veri seti kullanılarak üç regresyon tabanlı ML algoritması—Kısmi En Küçük Kareler (PLS), Rastgele Orman (RF) ve Gradyan Artırma (GB)—uygulanmış ve karşılaştırılmıştır. GB algoritması, maliyet ve gelir tahmininde en yüksek performansı göstermiş; sırasıyla 0,981 R^2 değerleri ile en düşük Ortalama Mutlak Yüzde Hata (MAPE) değerleri olan %1,869 ve %1,913'e ulaşmıştır. Bulgular, GB gibi doğrusal olmayan modellerin hastane operasyonları ile finansal sonuçlar arasındaki karmaşık ilişkileri daha iyi yakaladığını ortaya koymaktadır. Bu çalışma, veri odaklı yaklaşımların hastane yönetiminde stratejik karar alma süreçlerini destekleme potansiyelini vurgulamakta; kaynak tahsisi, maliyet kontrolü ve gelir artırma konularında öngörü doğruluğu ve operasyonel içgörü sağlamaktadır.

Keywords: Healthcare resources, waiting time, machine learning, cost, revenue.

Anahtar Kelimeler: Sağlık kaynakları, bekleme süresi, makine öğrenmesi, maliyet, gelir.

JEL Codes: I10; C15

JEL Kodları: I10; C15

Geliş Tarihi: 01/09/2025

Kabul Tarihi: 05/11/2025

DOI: 10.33399/biibfad.1775434

Araştırma Makalesi

1. INTRODUCTION

The quality and sustainability of healthcare services are directly related to the effective management of hospital resources (Lega, Prenestini, and Spurgeon, 2013). Essential healthcare resources, such as doctors, nurses, administrative staff, bed capacity, and triage areas, are critical to inpatient care (Heydari, Lai, Fan, and Li, 2022). Improper resource planning leads to both increased costs and decreased patient satisfaction. The importance of resource management, particularly in emergency rooms and intensive care units, is becoming increasingly evident amid rising patient volumes and limited staff (Atalan and Dönmez, 2024). Therefore, resource allocation and management are strategic issues for operational efficiency and financial sustainability.

One of the most frequently discussed hospital issues is patient waiting times (Lin, Goldstein, Hribar, Sanders, and Chiang, 2019). The length of waiting times directly impacts the speed of patient access to treatment and overall satisfaction (Soremekun, Takayesu, and Bohan, 2011). Furthermore, waiting times indirectly determine hospitals' cost structure and revenue potential (Brindley, Lomas, and Siciliani, 2023). Considering staffing and bed capacity in isolation can prolong patient treatment processes, leading to additional costs and potential revenue loss (Mihalj et all., 2022). Ineffective triage processes, particularly in emergency departments, jeopardize patient safety and increase operational costs (Fekonja et al., 2023).

Cost estimation in healthcare is a critical management tool for managers. Accurate cost estimates enable more efficient decisions in budget planning and resource allocation (Atalan and Dönmez, 2020). The healthcare resources also play a crucial role in determining hospital revenue. Hospitals are affected by numerous variables, including bed occupancy rates, personnel, and medication and medical supply costs (Bosque-Mercader and Siciliani, 2023). Traditional cost calculation methods often fail to fully reflect the dynamic and complex nature of healthcare processes (Yu, Xu, Hu, and Deng, 2023). Therefore, the need to develop more precise estimation methods has emerged.

Hospital revenue estimation is at least as important as cost estimation (Zalvand, Mohammadian, and Meskarpour Amiri, 2022). In healthcare, revenue is generally determined by the type and number of services provided per patient (Himmelstein, Ceasar, and Himmelstein, 2023). However, waiting times and resource constraints directly impact revenue potential (Mostafa and El-Atawi, 2024). Long patient waiting times lead to patient attrition or a perception of poor service quality, decreasing a hospital's overall revenue (Seif, Shah, Chandani, and Ali, 2025). Therefore, resource allocation and proper management of waiting times constitute a critical strategy for reducing costs and maximizing revenue (Oteri, Onukwulu, Igwe, Ewim, Ibeh, and Sobowale, 2023).

Machine learning (ML) has emerged rapidly in the healthcare sector in recent years (Atalan, Şahin, and Atalan, 2022). ML is a powerful tool for processing complex and high-volume data, extracting meaningful patterns, and building predictive models (Venkateswaran and Mm, 2025). ML algorithms in hospitals are increasingly used to predict patient density, waiting times, costs, and revenue (Tello et al., 2022). Regression, classification, and clustering algorithms, in particular, offer practical solutions for healthcare planning and management (Palei, Lenka, Jain, and Saxena, 2025). ML in healthcare is not limited to cost and revenue prediction (Siddique and Chow, 2021). ML is being applied in many different areas, including improving the quality of patient care, developing early diagnosis systems, resource planning, and predicting patient length of stay (Almeida, Brito Correia, Borges, and Bernardino, 2024). However, using ML to estimate the financial impact of operational processes, such as hospital resources and waiting times, is a relatively new approach in the literature. The primary motivation for this study is to develop models that predict both output variables, thereby reducing costs and optimizing revenue through effective management of existing resources.

Waiting time predictions are a critical factor in optimizing patient flow. When triage is not performed correctly, waiting for critically ill patients can negatively impact health outcomes, while prolonged waiting times for non-urgent patients reduce patient satisfaction (Corkery et al., 2021). ML algorithms learn from historical data to predict patient volume and wait times, enabling proactive resource management (Chigboh, Zouo, and Olamijuwon, 2024). This approach offers a more dynamic and adaptive solution than traditional statistical methods.

Balancing costs and revenues in hospital management is critical for long-term sustainability (Milojević, Knežević, Grivec, and Đokić, 2024). Optimizing resource utilization is essential to ensuring revenues cover costs (Gu, Wang, Chen, and Tang, 2022). ML-based models can inform strategic decisions by predicting future staffing levels, bed occupancy rates, and patient flow (Chuang et al., 2023). These models provide crucial input not only for short-term operational decisions but also for long-term investment planning.

This study's innovation lies in its integrated model, which utilizes ML algorithms to assess waiting times and resource utilization while estimating costs and revenue. While the literature typically focuses on cost or revenue estimation in isolation, this study combines these two dimensions to offer a more comprehensive approach. Furthermore, integrating the dynamic effects of essential healthcare resources such as doctors, nurses, clerks, beds, and triage areas into the models yields more accurate and predictive results than existing methods.

This study makes a unique contribution to the literature by presenting a comprehensive ML approach that jointly addresses the impact of hospital resource management and patient waiting times on financial outcomes. While most existing research focuses solely on cost estimation or revenue optimization, this study integrates both dimensions within a single modeling framework. Furthermore, modeling the effects of waiting time and the cost coefficients of resources such as doctors, nurses, clerks, examination rooms, and triage areas presents an innovative methodological approach that clarifies the complex relationships between operational and financial variables. This allows managers to develop strategic decisions focused not only on cost reduction but also on revenue enhancement. Consequently, rising cost pressures and patient expectations in the healthcare sector underscore the importance of data-driven decision-making in hospital management. ML-based revenue and cost forecasting models offer significant operational and financial advantages, enabling more efficient resource management. This article aims to contribute to the literature from theoretical and practical perspectives by focusing on applying these approaches in the healthcare sector.

This article consists of four main sections. It has a holistic structure that examines the effects of hospital resources (doctors, nurses, clerks, examination rooms, triage areas) and patient waiting time on total cost and revenue estimates. The introduction section details the innovative aspects of this study, including resource management in healthcare, cost-revenue dynamics, and machine learning approaches. The methodology section details the data collection processes, variable definitions, cost-revenue coefficient calculations, the machine learning algorithms (PLS, RF, and GB), and performance metrics. The results section analyses the algorithms' predictive performance and the effects of resources and waiting times on cost-revenue. The conclusion includes interpretations of the findings, recommendations for healthcare management, study limitations, and suggested areas for future research.

2. METHODOLOGY

This study aims to quantitatively estimate the impact of hospital resources (doctors, nurses, clerks, examination rooms, triage areas) and waiting time on both total cost (CTT) and total revenue (RPO) using ML-based regression models. The modeling strategy is two-stage: (i) estimating total cost and total revenue from resource and waiting time inputs separately (or with multiple outputs); (ii) comparing the resulting models in terms of performance, interpretability, and generalizability. In this context, Partial Least Squares (PLS), Random Forest (RF), and Gradient Boosting (GB) algorithms were applied. The independent and dependent variables used in the study are summarized in Table 1. Input represent direct resource usage and waiting time, while output represent cost and revenue components.

Table 1: The Features of the Dependent and Independent Variables Preferred in This Study

Variables	Type	Type of cost caused	Revenue	Coefficients for the cost and revenue
Physicians	Input	C_P	-	α_P
Nurses	Input	C_N	-	α_N
Clerks	Input	C_C	-	α_C
Exam Rooms	Input	C_{ER}	-	α_{ER}
Triage Area	Input	C_{TA}	-	α_{TA}
Waiting Time	Input	C_{WT}	-	α_{WT}
Patient Treated	Output	-	R_{PO}	α_{Po}
Total Cost	Output	C_{TT}	-	-

Each resource's cost to the hospital and waiting time is calculated using a coefficient for each resource (Atalan, 2022). The total cost to the hospital of resources and waiting time is given in Equation (1):

$$C_{TT} = C_P * \alpha_P + C_N * \alpha_N + C_C * \alpha_C + C_{ER} * \alpha_{ER} + C_{TA} * \alpha_{TA} + C_{WT} * \alpha_{WT} \tag{1}$$

The cost coefficients for health resources and waiting times were calculated based on the hospital's initial resource count (the start-up level). Equation (2) below was used for this calculation.

$$C_{TT}^{i} = R_{PO}^{i} + \zeta \tag{2}$$

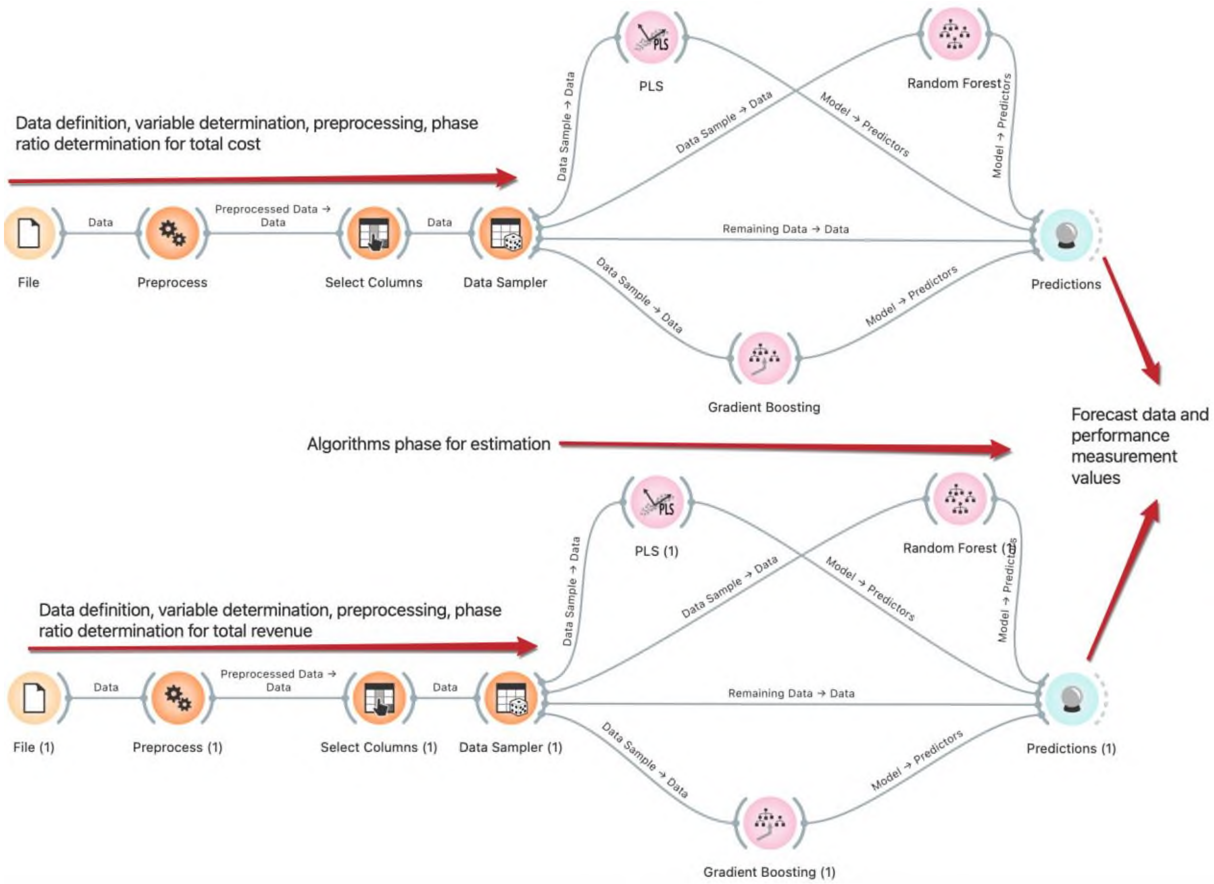
where, ζ represents the difference between the cost and the revenue of the number of healthcare resources required for the hospital's start-up activity and the waiting time. Thus, the coefficients α are iteratively optimized to provide the cost-revenue balance in the initial state.

In this study, we used the ML algorithms Partial Least Squares (PLS), Random Forest (RF), and Gradient Boosting (GB) to estimate total revenue and total cost. The Orange 3.39, an open-access version with Python as the backend, runs these algorithms (Demšar et all.,2013). The flowchart diagram of the algorithms used in the study is given in Figure 1.

Each model was trained on a separate branch, and predictions and performance metrics were compared at the output node. Scikit-learn-based implementations were used for the Python backend. All experimental conditions are documented, including the Python and Orange versions, library versions, seeds used, hyperparameter grids, and the CV (cross-validation) design.

PLS regression extracts latent components that maximize the covariance between inputs and outputs to produce stable predictions even in cases of high multicollinearity and $p \gg n$ (Mou, Zhou, Chen, Liu, and Li, 2025). This study chose PLS because of the high correlation among the source variables (number of doctors and nurses, beds, and examination room capacity). The number of components was selected using the RMSE_min (Root Mean Squared Error) criterion via cross-validation; the explanatory power of the variables and their relative importance in the model were assessed using VIP (Variable Importance in Projection) scores. The linear nature of PLS increased explainability by integrating the resulting coefficients into the cost-revenue equations.

Figure 1: The flowchart of the ML algorithms



RF is a nonparametric method that reduces variance by training multiple decision trees on bootstrap samples and averaging the predictions (bagging) (Alin, 2024). Selecting the best split from a randomly selected subset of features at each node split reduces correlation, improving overall performance. In this study, RF was chosen because it (i) captures complex, nonlinear interactions, (ii) provides an additional validation criterion with Out-of-Bag (OOB) error estimation, and (iii) allows interpreting the relative effects of waiting time and resource usage using feature importance scores (Gini or permutation-based). The hyperparameters for the number of trees (n_estimators), maximum depth (max_depth), minimum samples per leaf (min_samples_leaf), and feature subset size (max_features) were optimized using random search + CV.

GB is a method that reduces errors stage-wise and builds a strong model by aggregating weak learners (typically shallow decision trees) using gradient descent (Palaniswamy, Chitradevi, and Premalatha, 2025). This study optimized the learning rate, number of trees (n_estimators), maximum depth (max_depth), and subsample hyperparameters using early stopping criteria. GB was particularly evaluated for its ability to capture nonlinear cost–revenue relationships, waiting time threshold effects, and resource interactions. Small learning rates and shallow trees were used to manage the risk of overfitting.

The performance of each algorithm is measured using the following metrics: y is the actual value, $\hat{y}_i$ is the prediction, $\bar{y}_i$ is the mean of the observations, and n is the sample size (Ayaz Atalan and Atalan, 2024). MSE (Mean Squared Error) calculates the mean squared difference between the predicted and true values and penalizes significant errors more heavily. The mathematical formulation of MSE is defined as:

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

RMSE (Root Mean Squared Error) expresses errors in the original units by taking the square root of the MSE and displays the average error magnitude more intuitively. The RMSE is formulated as follows:

$$RMSE = \sqrt{MSE} \quad (4)$$

MAE (Mean Absolute Error) calculates the mean absolute value of the prediction errors and measures the mean deviation regardless of the direction of the errors. The MAE equation is given below:

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

MAPE (Mean Absolute Percentage Error) calculates the mean percentage error and shows the relative error between predictions and true values. The equation for MAPE is expressed as:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (6)$$

R^2 (Coefficient of Determination) indicates the extent to which the model explains the variability in the data; values close to 1 indicate strong explanatory power of the model. R^2 can be calculated using the following equation:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (7)$$

This methodology provides a systematic framework encompassing data collection, preprocessing, modeling, and evaluation, and addresses the impact of hospital resources and waiting times on cost and revenue estimation from a holistic perspective. The combined use of ML algorithms with diverse structural features, such as PLS, RF, and GB, enables modeling linear and nonlinear relationships, leading to more precise estimates of cost and revenue dynamics. Comprehensive evaluations using performance metrics (MSE, RMSE, MAE, MAPE, and R^2) demonstrate the generalizability and reliability of the models, while variable importance analyses and impact visualizations provide managerial implications. Thus, the developed methodology stands out as an innovative approach that will support hospital managers' strategic decision-making processes and has the potential to optimize resource allocation, thereby improving cost efficiency and increasing revenue.

3. RESULTS

This section compares the performance of three ML algorithms (PLS, RF, and GB) for estimating total cost and revenue based on hospital resources and patient waiting times. The models' accuracy was evaluated using performance metrics such as MSE, RMSE, MAE, MAPE, and R^2. The primary objective of these analyses was to determine which model provides more accurate and reliable estimates for both cost and revenue. Descriptive statistics of the actual data and prediction data corresponding to the testing phase of the ML models are given in Table 2.

Table 2: Descriptive Statistics of the Actual Data and Prediction Data Corresponding to the Testing Phase of the ML Models

Actual Data /Model	Variables	Mean	Standard Deviation	Variance	Minimum	Median	Maximum	Skewness	Kurtosis
$Revenue_{actual}$	Revenue (Any currency)	27.38	4.883	23.840	17.60	26.70	38.11	0.07	-0.73
PLS		27.29	4.798	23.018	15.82	26.54	37.33	-0.10	-0.63
RF		27.35	4.168	17.370	19.08	26.57	35.67	0.01	-0.98
GB		27.38	4.771	22.765	17.63	26.66	37.62	0.06	-0.86
$Cost_{actual}$	Cost (Any currency)	81.37	49.29	2429.1	9.00	99.00	149.0	-0.15	-1.66
PLS		73.54	36.68	1345.5	0.00	85.05	122.9	-0.44	-1.02
RF		81.22	49.21	2421.9	10.65	101.2	143.7	-0.14	-1.70
GB		81.66	49.43	2442.9	10.19	98.03	148.9	-0.14	-1.67

Table 2 presents a comparative analysis of the descriptive statistics for the income variable of the machine learning models used in the testing phase (PLS, RF, GB) and the real data. For the income data, the actual dataset had a mean of 27.38, a standard deviation of 4.883, and a variance of 23.840. The minimum and maximum values were 17.60 and 38.11, respectively, with a median of 26.70. A skewness value of 0.07 indicates that the distribution is close to symmetry, while a kurtosis value of -0.73 demonstrates that the distribution is flatter than a normal distribution. The mean income estimate in the PLS model was 27.29, a value quite close to the actual data. The RF and GB models also showed high similarity with mean values of 27.35 and 27.38, respectively. An examination of the models' standard deviation and variance values reveals that the RF model has lower variance and bias, resulting in a narrower distribution of its estimates. The skewness and kurtosis values for all models are close to those of the actual data, indicating that the distributional structure of the revenue estimates is largely preserved.

Regarding the cost variable, the actual data has a mean value of 81.37, a standard deviation of 49.29, and a variance of 2429.1. The minimum and maximum values are 9.00 and 149.0, respectively, and the median is 99.00. A skewness value of -0.15 indicates a slightly left-skewed distribution, while a kurtosis value of -1.66 indicates a flatter distribution than normal. The mean cost estimate in the PLS model is 73.54, a significant decrease compared to the actual data. The RF and GB models produced estimates very close to the actual data, with mean values of 81.22 and 81.66, respectively. When evaluated by standard deviation and variance, the RF and GB models are nearly identical to the actual data. In contrast, the PLS model provides cost estimates with lower variance, standard deviation, and a narrower distribution range. The closeness of the skewness and kurtosis values suggests that the RF and GB models demonstrate a higher fit than the PLS model in preserving the cost distribution structure.

The modeling results obtained in this article are summarized in Table 3. This table shows each model's error rates and explanatory levels for each target variable (total cost and total revenue).

Table 3. Performance Measurement Data of ML Algorithms

Output	Models	MSE	RMSE	MAE	MAPE	R^2
Total Cost	PLS	1.232	1.110	0.843	3.285	0.947
	RF	3.006	1.734	1.462	5.526	0.872
	GB	0.440	0.663	0.505	1.869	0.981
Total Revenue	PLS	2.136	1.462	1.102	4.351	0.909
	RF	3.392	1.842	1.483	5.508	0.855
	GB	0.447	0.669	0.518	1.913	0.981

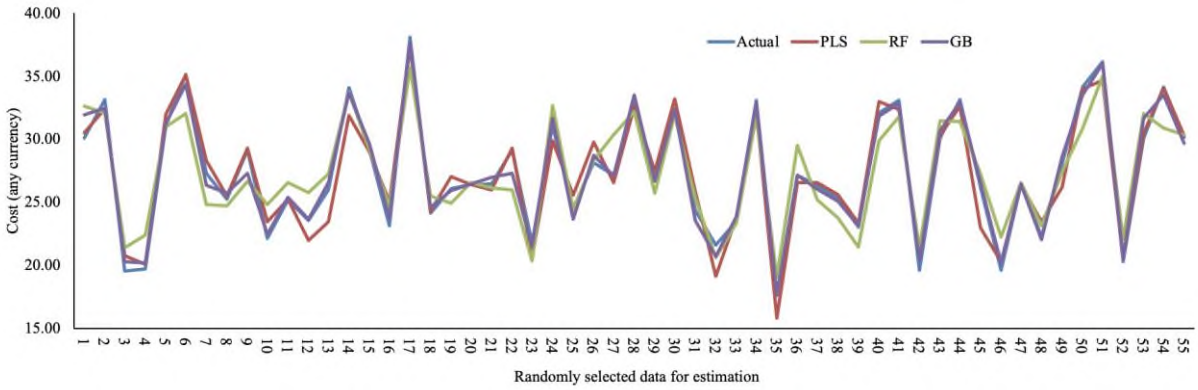
In total cost estimation, the GB algorithm stands out as the most successful model, with the lowest error rates (MSE: 0.440, RMSE: 0.663, MAE: 0.505, MAPE: 1.869%) and the highest explanatory power (R^2: 0.981). This demonstrates that the GB algorithm provides more sensitive and robust estimates of nonlinear relationships and resource interactions.

The PLS model, particularly given its high variable correlation, yielded highly successful results in total cost estimation (R^2: 0.947). Although based on linearity, this model was instrumental in understanding variable importance through VIP (Variable Importance in Projection) scores. The RF model, on the other hand, performed less well in cost estimation than the different models, with higher error rates (RMSE: 1.734, MAPE: 5.526%) and a lower R^2 value (0.872). This suggests that RF did not sufficiently learn some nuanced relationships in the dataset.

Similarly, GB performed best in total revenue estimation. With MSE (0.447), RMSE (0.669), MAE (0.518), and MAPE (1.913%) values, this model also offers high accuracy in revenue estimation. Furthermore, the R^2 value of 0.981 demonstrates that the model explains the data almost completely. The PLS model also achieved high explanatory power (R^2: 0.909) in estimating total revenue; however, the MAE and MAPE were slightly higher. This suggests that the model fell within some linear limits. RF also performed poorly in revenue estimation (R^2: 0.855, MAPE: 5.508%), revealing the model's overall structural limitations.

Figure 2 compares the ML-predicted values for the total cost variable with the observed values. The horizontal axis represents the order of data points (observations), and the vertical axis represents the cost values. Comparing each model's prediction curve with the observed cost values provides a visual impression of the model's predictive performance.

Figure 2: Comparison of total cost and estimated data



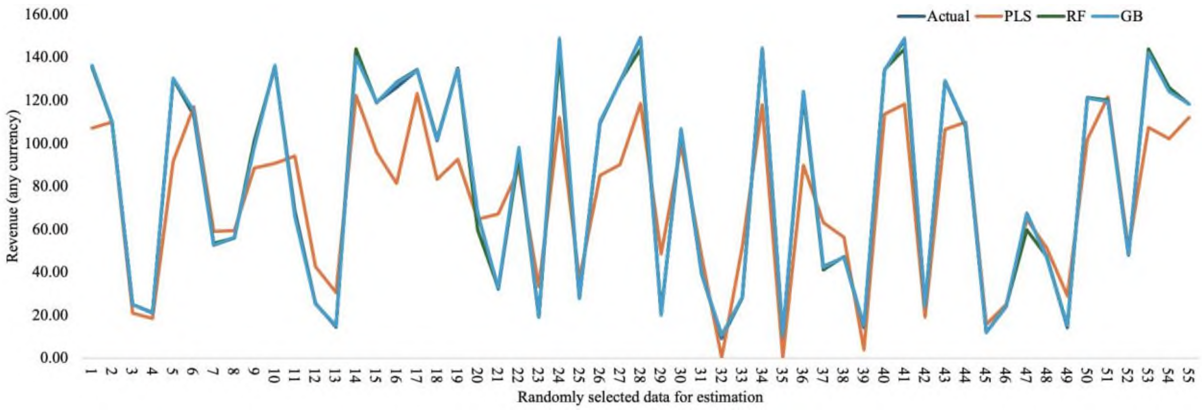
Examining the figure, it is observed that the GB algorithm's predicted values match the actual cost values almost exactly. The GB's prediction curve closely follows the actual curve, with only minor deviations across observations. This demonstrates that the GB effectively learns complex, nonlinear relationships and achieves high prediction accuracy. The PLS model followed general trends, making predictions that were quite close to the actual values, especially for low- and moderate-cost observations. However, in some high-cost cases, the PLS curve can deviate, leading to underestimation or overestimation. These deviations stem from the linear structure of the PLS model, which provides insufficient flexibility for data segments with high variance.

The RF model's curve shows greater fluctuations than those of the other two models and deviates significantly from the actual values at many points. This model tends to overestimate low-cost observations and underestimate high-cost observations. This suggests that RF is overly sensitive to dataset variations and may have under-learned some relationships. Figure 2 demonstrates that the GB model provides stable and highly accurate cost estimations, while

PLS performs moderately and RF performs limitedly. These differences are critical indicators for managers, helping them determine which model is more appropriate for use as a decision-support tool in operational planning.

Figure 3 visualizes the performance of the forecast models created for the Total Revenue variable. Actual revenue data is plotted on the same axis to compare the models' performance. Figure 3 demonstrates that the GB algorithm is the most successful cost and revenue forecasting model. The GB forecast curve parallels the actual data curve for nearly all observations. Even with fluctuating, high-variance data points, GB can make accurate predictions, and the deviation between the forecast curve and the actual values is quite small. This demonstrates that the GB algorithm effectively learns average trends and extreme values.

Figure 3: Comparison of total revenue and estimated data



The PLS model also demonstrated acceptable performance in revenue forecasting. While the forecast curve followed general trends, it occasionally underestimated, particularly in observations with high income levels. This suggests that the linear model structure may not fully reflect complex revenue dynamics. The RF model's revenue forecast curve, similar to the cost analysis curve, shows notable deviations. A tendency was observed to overestimate income values below the mean and underestimate income values above the mean. This model's erratic predictions, particularly in high-income cases, suggest it may not have generalized well enough to certain patterns during training. The overall assessment of Figure 3 shows that the GB algorithm provides the most consistent and reliable income estimates across the entire data range; PLS offers some accuracy but limited flexibility; and RF produces inconsistent, less accurate estimates in this data set. This analysis provides critical insight into which model is more appropriate and effective for revenue planning for healthcare institutions.

The findings demonstrate that the GB algorithm, in particular, performs superiorly in both cost and revenue estimation. The model successfully learned and incorporated the dataset's complex relationships and resource interactions into its predictions. The low MAPE and high R^2 values, in particular, demonstrate that the model can be a reliable tool for operational decision-making. Furthermore, its ability to model cost-revenue relationships based on waiting time and resource usage makes this algorithm strategic for healthcare management.

On the other hand, with its linear structure, the PLS model offers advantages in terms of explanatory power and allows for variable-based interpretation of cost-revenue relationships. While the RF model contributed to overall nonlinear structure estimation, it underperformed in this study due to the data structure and the level of detail regarding resource effects. Overall, the GB model is the most suitable and reliable forecasting model for both managerial decisions and clinical resource planning. This model is ideal for hospital strategic planning processes, particularly resource allocation and cost/revenue optimization.

This study has several limitations. First, the healthcare resources considered in the modeling process were limited to doctors, nurses, clerks, examination rooms, and triage areas. However, many resources that impact hospital operations, such as laboratory services, imaging units, intensive care units, medical device use, and medication consumption, can directly affect the cost and revenue structure. While excluding these elements from the model provides a generally valid estimation framework, it has limited representational power for real-world financial outcomes. Furthermore, the currency used in the study is not specific to any country but is defined in a unitary manner. This complicates comparisons between healthcare delivery models, unit cost structures, and revenue policies across different countries, limiting the model's generalizability for international comparisons.

Finally, this study presents a methodological framework developed and tested using simulated data. While this approach provided a controlled environment to precisely model the relationships between the selected healthcare resources, waiting times, and financial outcomes—free from the data quality issues and confidentiality constraints often associated with real patient data—it inherently limits the immediate generalizability of the findings to real-world hospital settings. The simulation assumes specific cost structures and interactions that may not capture the full complexity and variability of actual healthcare operations. Therefore, the results should be interpreted as a robust proof-of-concept demonstrating the potential of machine learning, particularly Gradient Boosting, in this domain. Future research is crucial to validate and adapt this model using empirical data from diverse healthcare institutions, incorporating a wider range of clinical resources and country-specific economic factors to enhance its practical applicability and external validity.

4. CONCLUSION

This study developed and evaluated an ML-based approach to predict total hospital costs and revenue using a limited yet essential set of healthcare resources and patient waiting times. The findings show that GB consistently outperforms both PLS and RF in terms of predictive accuracy and model robustness among the three algorithms tested. The superior performance of GB is attributed to its ability to learn complex, non-linear interactions between input variables such as resource utilization and waiting times. These insights suggest that advanced ML techniques can provide reliable, data-driven tools for healthcare managers to make more informed operational and financial planning decisions.

The study also revealed that while PLS provides interpretable linear modeling, its performance is constrained by high data variance or nonlinearity. Conversely, the RF model, though flexible at learning non-linear relationships, showed lower consistency and higher error rates, making it less reliable in this modeling context. Importantly, integrating cost coefficients and performance metrics allowed for a multidimensional evaluation of model suitability, making this study methodologically comprehensive and practically applicable. Hospital administrators can leverage the results to optimize staff distribution, manage waiting times more effectively, and better balance service quality and financial outcomes.

Despite the promising results, the study has limitations that should be addressed in future research. The resource types included in the model are limited to selected operational units and do not encompass high-cost clinical areas such as imaging departments, intensive care units, or surgical wards. Additionally, using a generic unit of cost and revenue, without country-specific currency or policy adaptation, limits the model's applicability to specific national healthcare systems. Lastly, using simulated rather than real hospital data may affect external validity. Future work should aim to integrate real-world datasets, expand the resource categories, and localize financial variables to enhance the model's generalizability and impact.

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Ethics Statement: The author declare that ethical rules are followed in all preparation processes of this study. In case of detection of a contrary situation, BİİBFAD Journal does not have any responsibility and all responsibility belongs to the authors of the study.
Author Contributions: Abdulkadir ATALAN contributed to all stages of the study. The author's contribution rate is 100%
Conflict of Interest: There is no conflict of interest.