VERİMLİLİK DERGİSİ
JOURNAL OF PRODUCTIVITY

Evaluation of Public Hospitals' Performance with Decision Tree Algorithms

Keziban Avcı[1]

ABSTRACT

Purpose: The study aims to evaluate a range of financial performance indicators calculated through structural, operational, and HVI measures for public hospitals in the Turkish healthcare sector using various decision tree algorithms.

Methodology: The study comprises threa phases. In the first phase, financial ratios were calculated from the hospitals' financial statements using the ratio analysis method. In the second phase, these ratios were used to calculate the HVI. In the third phase, the selected operational and financial indicators were analyzed with decision tree algorithms. The ID3, C4.5 and CART decision tree algorithms and AUC were used for predicting operational and financial indicators and performance assessment of decision trees.

Findings: It has been observed that decision trees created using the ID3 algorithm exhibit higher performance compared to other algorithms (AUC = 0.93). According to the results of the study, the number of beds significantly predicts the operational and financial performance of public hospitals and can be explained by the hospital scale. In addition, a strong relationship was found between operational and financial performance indicators with training status.

Originality: The study is original in demonstrating the effectiveness of the ID3 decision tree algorithm in predicting the performance of public hospitals.

Keywords: Financial performance, Operational performance, Public hospitals, Decision trees, K-means.
JEL Codes: I1, I11, C02, C38.

Kamu Hastanelerinin Performansının Karar Ağacı Algoritmaları İle Değerlendirilmesi

ÖZET

Amaç: Bu çalışma, Türk sağlık sektöründeki kamu hastaneleri için yapısal, operasyonel ve HVI ölçümleri yoluyla hesaplanan bir dizi finansal performans göstergesinin çeşitli karar ağacı algoritmaları kullanılarak değerlendirilmesini amaçlamaktadır.

Yöntem: Çalışma üç aşamadan oluşmaktadır. İlk aşamada hastanelerin mali tablolarından oran analizi yöntemi kullanılarak finansal rasyolar hesaplandı. İkinci aşamada HVI'nın hesaplanmasında bu oranlar kullanıldı. Üçüncü aşamada seçilen operasyonel ve finansal göstergeler karar ağacı algoritmaları ile analiz edildi. Operasyonel ve finansal göstergelerin tahmin edilmesi ve karar ağaçlarının performans değerlendirmesi için ID3, C4.5 ve CART karar ağacı algoritmaları ve AUC kullanıldı.

Bulgular: ID3 algoritması kullanılarak oluşturulan karar ağaçlarının diğer algoritmalara göre daha yüksek performans sergilediği görülmüştür (AUC=0,93). Araştırma sonuçlarına göre yatak sayısı kamu hastanelerinin operasyonel ve finansal performansını anlamlı düzeyde yordamakta olup hastane ölçeği ile açıklanabilmektedir. Ayrıca operasyonel ve finansal performans göstergeleri ile eğitim durumu arasında da güçlü bir ilişki bulunmuştur.

Özgünlük: Çalışma, ID3 karar ağacı algoritmasının kamu hastanelerinin performansını tahmin etmedeki etkinliğini göstermesi açısından orijinaldir.

Anahtar Kelimeler*:* Finansal performans, Operasyonel performans, Kamu hastaneleri, Karar ağaçları, K-ortalamalar.
JEL Kodları: I1, I11, C02, C38.

[1] Ankara Yıldırım Beyazıt University, Faculty of Health Sciences, Department of Healthcare Management, Ankara, Türkiye

Corresponding Author: Keziban Avcı, kezibanavci1@gmail.com
DOI: 10.51551/verimlilik.1494277
Research Article | Submitted: 01.06.2024 | Accepted: 19.11.2024
Cite: Avcı. (2025). “Evaluation of Public Hospitals' Performance with Decision Tree Algorithms”, *Verimlilik Dergisi*, 59(1), 133-142.

1. INTRODUCTION

In today's world, where many complex and ambiguous events arise due to volatility and uncertainty (VUCA), healthcare organizations face many difficulties in continuing their existence. It is critical for healthcare organizations to identify, measure, evaluate, and ultimately improve their key performance indicators to adapt to changes. (Adair et al., 2006). Indeed, it is observed that hospitals striving for success exert great effort to improve their performance (Li and Benton, 2003; Oner et al., 2016).

Performance measurement offers a solid empirical foundation for managers striving to improve organizational and financial capacities (Prentice, 2016). On the other hand, existing studies that focused on hospital management have been based generally on approaches to assess management by organizational structure and functions (Tsai et al., 2015). Most of these studies explore whether better management improves the efficiency and performance of healthcare organizations, and clinical engagement (Oner et al., 2016; Tasi et al., 2019).

Measurement is essential for management and performance indicators used in measurement influence the decisions to be made at strategic, tactical, and operational levels (Dai et al., 2018). At the same time, measuring and evaluating performance is crucial for delivering better healthcare services and improving health outcomes. World Health Organization (2013: 144) defines an indicator as “A quantitative or qualitative factor or variable that provides a simple and reliable means to measure achievement, to reflect the changes connected to an intervention or to help assess the performance of a development actor.”. In this context, indicators serve as indirect measures providing information about dimensions of care quality (The European Observatory on Health Systems and Policies, 2019: 33). Furthermore, performance indicators act as the communication protocol of healthcare institutions with the external world regarding health conditions. The use of standardized indicators for hospitals not only leads to better assessment but also increases transparency and trust for patients (Carini et al., 2020). However, there are no gold standards or indicators in hospital performance measurement.

Hospitals exhibit significant variability in size, type, teaching affiliations, demographic attributes, and service profiles. The primary determinants of hospital capacity include the number of beds, staff size, teaching status, and the nature of services provided. Numerous studies have explored the relationship between demographic factors, service composition, and capacity management decisions in hospitals (Li and Benton, 2003). Some studies emphasize the impact of hospital size and service mix on capacity decisions, highlighting that larger hospitals may not always be more efficient, despite trends in mergers and consolidations favoring size advantages (Goldstein et al., 2002). Conversely, smaller non-profit hospitals often demonstrate comparable cost efficiency to larger counterparts (Coyne et al., 2009).

Financial ratio analyses are commonly used in evaluating the financial condition of hospitals (Audi et al., 2016) Financial viability refers to an organization's ability to generate financial income flows above its expenses and sustain this ability for ongoing operations (Upadhyay and Smith, 2020). To measure this capability, the Hospital Financial Viability Index (HVI) is utilized as a strategic performance assessment tool, which is derived from the combined use of multiple financial ratios (Işıkçelik et al., 2022; Ozgulbas and Koyuncugil, 2009; Pegels, 1984). HVI comprises three components: the current ratio reflecting the hospital's liquidity status, the ratio of liabilities to assets measuring capital structure, and the ratio of operating expenses to operating revenues indicating profitability. Therefore, a single index provides insights into the organization's debt-paying ability, gains from operations, and capital structure (Karataş and Çinaroğlu, 2023; Pegels, 1984). As the index value increases, it signifies a decrease in the organization's financial viability, with a value greater than 1 indicating financial difficulties. According to this index, as the current ratio, an indicator of the organization's short-term debt-paying capacity, increases, the index value decreases. An increase in liabilities will raise the index value, negatively impacting the organization's financial viability. Similarly, an increase in the activity ratio, a profitability indicator, will raise the index value, signaling an unsustainable financial structure for the organization (Çelik and Korkmaz, 2023; Işıkçelik et al., 2022).

In a study examining the financial performance of a group of hospitals in Turkey for the years 2009-2019 using various techniques including HVI, it was found that the hospitals' use of external resources was high, profitability and short-term debt payment power were low, and costs and expenses were high. It was shown that the financial performance of hospitals the most favorable year was 2009 and the most unfavorable year was 2011 (Işıkçelik et al., 2022). In another study in which the HVI values of two private hospitals for the years 2017-2021 were calculated, the relationship between hospital profitability ratios and HVI values was analyzed. Accordingly, it was determined that there is a strong and negative relationship between HVI and gross profit margin and net profit margin and a very strong and negative relationship between HVI and operating profit margin and return on equity (Karataş and Çinaroğlu, 2023). Another study conducted with a group of hospitals covering the period between 2017 and 2021 showed that the financial viability capacity is highest in micro and then small-scale enterprises. Medium and large-scale enterprises, on the other hand, had financial problems; however, by 2021, it was determined that there were improvements in financial viability (Çelik and Korkmaz, 2023).

Ozgulbas ve Koyuncugil (2009) conducted a study to profile public hospitals based on their financial performance indicators. These indicators included equity-to-assets ratio, quick ratio, return on equity, return on assets, and total asset turnover. They utilized the CHAID algorithm for hospital classification; however, this approach led to an imbalance in hospital numbers within decision tree nodes (Ozgulbas and Koyuncugil, 2009). This study employed cluster analysis to overcome this limitation and identify similar hospital groups based on operational and financial performance indicators.

In light of the increasing emphasis on the importance of performance evaluation within healthcare organizations, this study aims to evaluate a range of financial performance indicators calculated through structural, operational, and HVI measures for public hospitals in the Turkish healthcare sector using various decision tree algorithms. The initial phase of the study comprised a comprehensive review of the relevant literature, while the subsequent phase detailed the research design and methodology. The third section presented the findings, and the fourth section discussed these results by comparing them with similar studies in the literature and providing recommendations.

2. METHODOLOGY

2.1. Research Design

The study included all public hospitals with 30 or more beds (n = 514) in Turkey. The data needed for the purpose was officially requested from the Ministry of Health (Public Hospitals Authority of Turkey) and the data obtained in accordance with the necessary permissions were used. Performance in healthcare organizations is often assessed based on financial sustainability, with a focus on financial indicators such as profits, liquidity, expenses, revenues, and market share (Jack and Powers, 2009; Tasi et al., 2019). Studies have shown that there is a positive relationship between health services characteristics and financial performance (Chaudary et al., 2015). Factors like hospital structure, resources, ownership type (e.g., for-profit vs. non-profit), and efficient utilization of assets play significant roles in determining financial efficiency and performance within the healthcare sector (Cinaroglu, 2020). In this context, it was decided to use the number of beds, number of consultations, teaching and service status variables as operational performance indicators in the study. Financial performance indicators were measured using ratio analysis and the HVI was calculated based on it. Figure 1 shows the flow chart of the research model. Accordingly, the study consists of three stages. First, ratio analysis was calculated from the financial statements of the hospitals and second stage HVI was calculated using the formula 4(debt-to-equity ratio × operation ratio 4)/current ratio (Ozgulbas and Koyuncugil, 2009; Upadhyay and Smith, 2020). In the third stage, the selected operational and financial indicators were analyzed with decision tree algorithms.

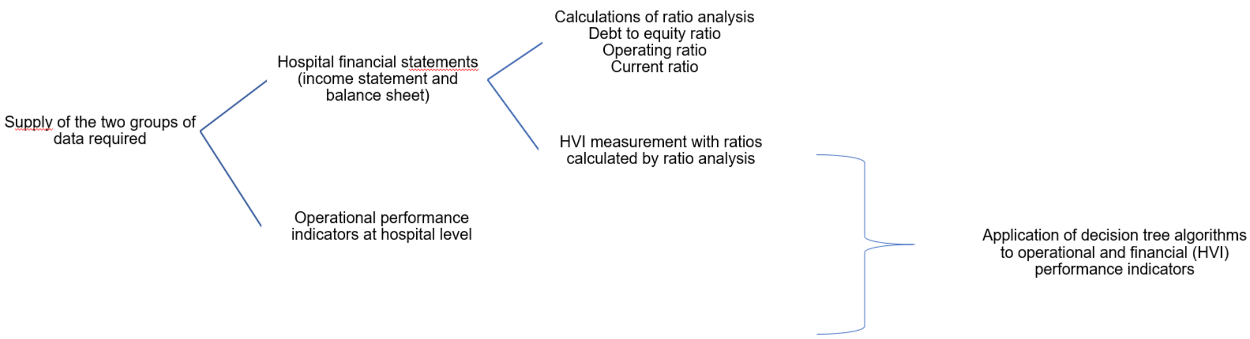

Figure 1. Flowchart of the research model

2.2. Analysis

2.2.1. Decision tree algorithms

A decision tree is a data representation model that originates from graph theory (Kantardzic, 2020). Graph theory is a mathematics-based theory applied to problem solving. Decision trees are used in data structures, databases, computer algorithms, machine learning, and data mining. This method produces a nonparametric classification and prediction model. Additionally, decision trees are nonlinear, supervised learning models that produce a tree-like structure theory for which a number of algorithms have been proposed (Liao et al., 2012). Among these is the Interactive Dichotomizer 3 (ID.3), which is an effective and popular method for finding decision tree rules. The information gained is exactly the metrics for selecting the best attribute in each step of the ID3 algorithm growth tree (Jin et al. 2009). C4.5 is another algorithm that uses decision trees and is an extended version of ID3. Both algorithms are popular in the machine-learning community. The difference between these two algorithms is that ID.3 uses binary splits, whereas C4.5 uses multi-way splits. The Classification and Regression Tree (CART) is another induction algorithm that uses decision tree models. It produces a regression tree when the outcome is continuous and a classification tree when the outcome is categorical (Kantardzic, 2020).

There are numerous performance measures to make a comparison between decision tree algorithms. The Area Under the ROC Curve (AUC) is one of these performance measures. This method is useful for organizing classifiers and visualizing their performance. The theoretical ROC curve is a plot of q = sensitivity versus p = 1 – [all possible threshold values]. The ROC curve area is typically located between 0.5 and 1.0. If this value is equal to 1.0, then the test is 100% accurate because both the sensitivity and specificity are 1.0; thus, there are no false positives or false negatives (Cook, 2017; Kantardzic, 2020).

In this study, before the analysis, MoH public hospitals were classified and grouped according to their operational and financial indicators. For classification, k-means clustering algorithm was used and all variables were standardised before clustering. While performing k-means clustering analysis, the number of clusters was optimised by using 10-fold cross validation. k-means is a typical clustering algorithm and is popular in practice because it is simple and generally very fast. It partitions the input dataset into k clusters. Each cluster is represented by an adaptively changing centroid (the cluster center), starting from initial seed-point values that are named. k-means computes the squared distances between the inputs (input data points) and the centroid and assigns inputs to the nearest centroid (Mishra et al., 2012). During the k-fold cross-validation process, the data is first partitioned into equal (or nearly equal) sized segments or folds. Subsequently, k iterations of training and validation are performed such that within each iteration, a different fold of the data is validated while the remaining k –1 folds are used for learning (Kantardzic, 2020).

3. RESULTS

3.1. Descriptive Statistics

Table 1 presents the descriptive statistics of hospitals, frequencies and percentages of categorical variables, mean values, and standard deviations of continuous variables. It can be seen that 13% are training hospitals and 86.8% are general hospitals. Furthermore, it can be seen that the average number of beds is 225.2 (±232.40), average number of consultations is 441,618.58 (±386,739.76), average bed occupancy rate is 61.23 (±19.15), average current ratio is 1.48 (±2.15), average debt-to-equity ratio is 3.40 (±5.16), average operations ratio is –1.04 (±0.18), average HVI is 15.27 (±5.52), average absolute liquidity is 0.10 (±0.18), average total assets turnover rate is 4.54 (±3.35), and average return on equity is –0.84 (±30.7).

Table 1. Descriptive statistics

Variable Group	*Variables*			
Operational	*Categorical*		*N*	*%*
	Training Status	Training	67	13
		Not Training	447	86.8
	Service Status	General	441	85.6
		Specialized	73	14.2
	Total		514	100
	Continuous	*N*	*Mean*	*Std. Deviation*
	Number of beds	514	225.23	232.40
	Total consultations	514	41,618.58	386,739.76
	Bed occupancy rate	514	61.23	19.15
Financial	Current ratio	514	1.48	2.15
	Debt-to-equity ratio	514	3.40	5.16
	Operations ratio	514	–1.04	0.18
	HVI*	514	15.27	5.52
	Absolute liquidity	514	0.10	0.18
	Total assets turnover rate	514	4.54	3.35
	Return on equity	514	−0.84	30.7

* HVI = 4 (debt-to-equity ratio × operation ratio)/current ratio

3.2. Correlations

According to the correlation analysis results presented in Table 2, the relationships between the variables in the model were examined before the clustering process. It was observed that most variables were significantly correlated. Correlation coefficients show that there is no significant linear relationship between the variables. Therefore, the data are suitable for clustering analysis.

Table 2. Correlations for operational and financial performance indicators in hospitals

		Training Stat.	Serv. Stat.	Num. of Beds	Tot. Num. of Cons.	Bed Occup. Rate	Abs. Liqu.	Tot. Assets Turn Rate	Return on Equity
Training Status	r	1							
Service status	r	0.12**	1						
Number of Beds	r	0.55**	0.10*	1					
Total Consultations	r	0.43**	−0.17**	0.74**	1				
Bed Occupancy Rate	r	0.20**	0.17**	0.26**	0.36**	1			
Absolute Liquidity	r	0.05	0.12**	−0.08	−0.02	−0.03	1		
Total Assets Turnover Rate	r	0.02	0.05	−0.02	−0.07	0.016	−0.12**	1	
Return on Equity	r	0.02	−0.10*	0.01	0.03	−0.03	0.02	−0.01	1

**p <0.01, *p < 0.05

3.3. Hospital Clusters

According to the k-means clustering results in Table 3, the number of hospitals in each of the four clusters is evenly distributed. The second cluster contains the highest number of hospitals.

Table 3. Number of hospitals in clusters

Clusters	*N*	*%*
Cluster	70	13.6
Cluster	162	31.5
Cluster	135	26.3
Cluster	147	28.6

The ANOVA results presented in Table 4 confirm that the four hospital groups differ according to the continuous variables used. The differences are due to the number of beds (F = 104.98, p < 0.01), total number of consultations (F = 89.52, p < 0.01), bed occupancy rate (F = 12.49, p < 0.01), absolute liquidity (F = 35.41, p < 0. 01), total assets turnover (F = 5.08, p < 0.01), return on equity (F = 7.33, p < 0.01) and HVI (F = 11.37, p < 0.01).

Table 4. ANOVA Results for differences between clusters according to continuous variables

Variables	*Sum of Squares*		*F*	*p*
Number of beds	Between	231.90	104.98	< 0.01
	Within	281.09		
Total consultations	Between	211.86	89.52	< 0.01
	Within	301.13		
Bed occupancy rate	Between	45.87	12.49	< 0.01
	Within	467.12		
Absolute liquidity	Between	111.69	35.41	< 0.01
	Within	401.30		
Total assets turnover rate	Between	19.72	5.08	< 0.01
	Within	493.27		
Return on equity	Between	27.96	7.33	< 0.01
	Within	485.04		
HVI	Between	42.08	11.37	< 0.01
	Within	470.91		

3.4. Classification of Performance Results Using Decision Trees

Table 5 presents the performance results of ID.3, C4.5 and CART decision tree algorithms. In this study, AUC is used as a performance measure. AUC = 1 means an excellent prediction performance (Kantardzic, 2020). According to the results, the ID.3 algorithm created with the data obtained has a high AUC performance (AUC = 0.9399). The AUC values of the C4.5 and CART algorithms created using the earnings ratio and Gini index were determined as 0.9322 and 0.9334, respectively.

Table 5. Performance results of different decision tree algorithms

Decision Tree Algorithms	AUC (Area Under the ROC Curve) Performance Results
Decision Tree_ID3	0.9399
Decision Tree_C4.5	0.9322
Decision Tree_CART	0.9334

In this study, ROC curve was used to test the prediction performance of decision trees; the ROC curve performance results are shown in Figure 2. Accordingly, it can be said that the decision trees constructed using the ID.3 algorithm (red line) are closer to the ROC curve (yellow line) than the other algorithms.

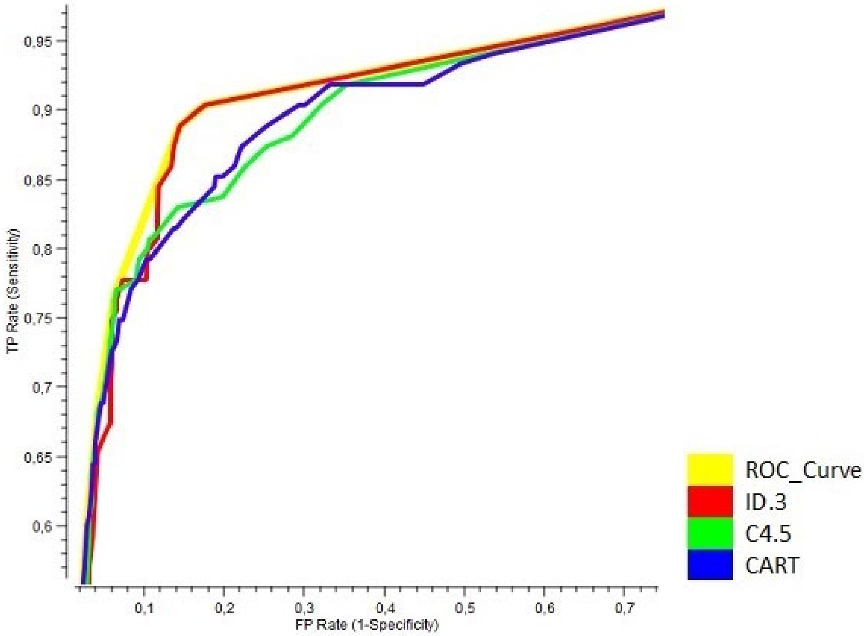

Figure 2. ROC curve performance results

3.5. Predictors of Operational and Financial Performance Indicators

According to Figure 3, the ID.3 algorithm classifies the operational and financial performance indicators of hospitals on the basis of the number of beds ($r = 0.55$, $p < 0.01$), which has a high correlation with educational status. Accordingly, the number of beds stands out as a significant variable in the data set. The dependent variable of this study is hospital groups and the independent variables are the categorical variables of education and service status and the quantitative variables of number of beds, total number of examinations, bed occupancy rate, absolute liquidity, total asset turnover, return on equity and HVI. The ID.3 algorithm generated seven nodes (groups).

The first group includes hospitals with the number of beds > 174 and return on equity > 5.45; the second group includes hospitals with the number of beds > 174, return on equity ≤ 5.45, and HVI > 12.22. The third group includes hospitals with the number of beds > 174, return on equity ≤ 5.45, and HVI ≤ 12.22. The fourth group includes hospitals with the number of beds ≤ 174, absolute liquidity > 0.11, and return on equity ≤ 0.66. The fifth group includes hospitals with number of beds ≤ 174, absolute liquidity > 0.11, and return on equity > 0.66. The sixth group includes hospitals with the number of beds ≤ 174, absolute liquidity ≤ 0.11, and return on equity > 3.02. The last (seventh) group includes hospitals with the number of beds ≤ 174, absolute liquidity ≤ 0.11, and return on equity ≤ 3.02.

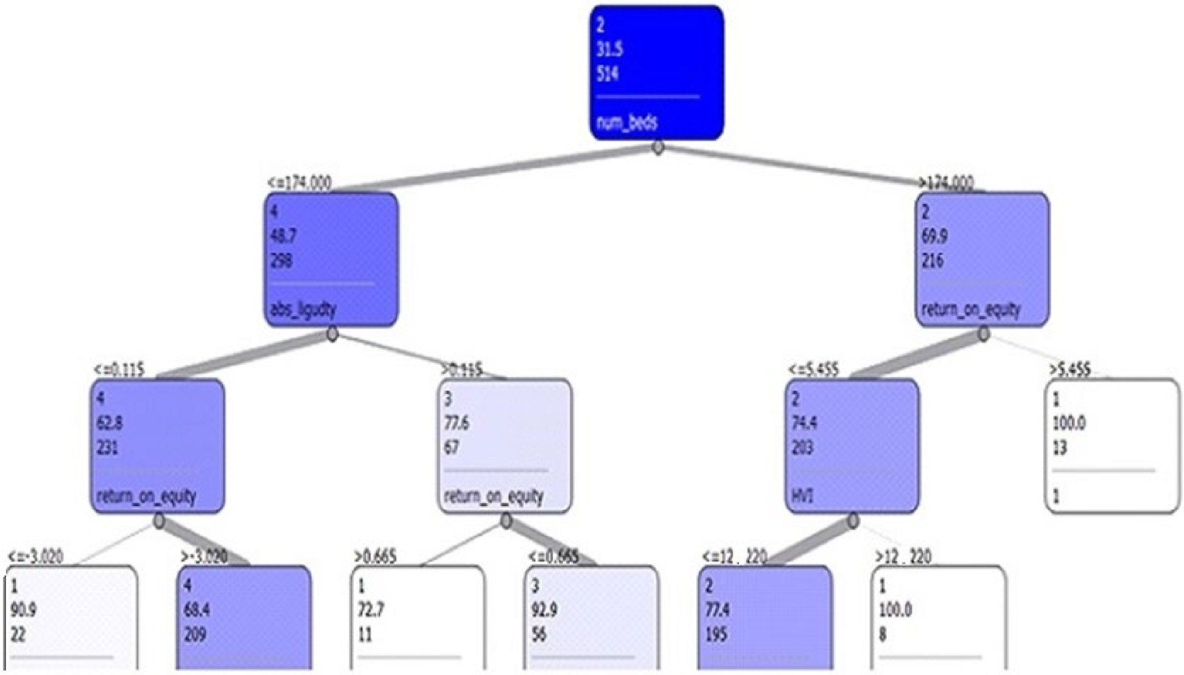

Figure 3. Classification Tree For ID.3

4. CONCLUSION and DISCUSSION

Performance measurement in healthcare means to define what hospitals actually do and compares that with the original targets or expectations of healthcare organizations. Healthcare organizations identify opportunities for improvement in organizational and financial performance management with measurement. Indicators, which serve as the foundation for measurement, are tools that possess a "normative" effect capable of influencing organizational behavior and decision-making, as aptly explained by Hauser and Katz (1998) with the concept of "organizations are what they measure". However, the selection of appropriate indicators is not a simple task. Nevertheless, it remains crucial for organizations to conduct measurement to evaluate operational efficiency, productivity, and profitability, as these assessments aid in understanding the extent to which organizational performance aligns with strategic objectives. This necessity is becoming increasingly critical in the present competitive business environment (Franceschini et al., 2019:143).

Managing the performance of a healthcare organization is vital in achieving its overarching objective of improving the overall health of the population. By doing so, the healthcare organization can effectively monitor the state of the sector and devise appropriate development plans. To evaluate progress toward organizational goals are used performance indicators that prioritize the assessment of outcomes, responsibilities, and goals. Performance indicators serve as valuable tools for healthcare managers in resource allocation and decision-making processes aimed at determining optimal strategies.

In this study, the performance of public hospitals in Turkey was evaluated through different decision tree algorithms using various financial performance indicators calculated based on structural, operational and HVI measures.

According to the results of the study, the number of beds can be a predictor of the operational and financial performance of public hospitals and can be largely explained by hospital size. However, it is noted in the literature that larger hospitals do not always perform better (Goldstein et al., 2002). In this respect, healthcare managers should not overlook the advantages of size in certain circumstances. Similarly, if hospital performance is poor, these hospitals are more likely to experience financial distress than hospitals that are relatively more efficient (Ginn and Lee, 2006).

The status of being a training hospital is considered another determinant of hospital performance. Training hospitals are usually located in urban areas and employ advanced expertise physicians. Consequently, they tend to become reference centers for the treatment of complex cases. This situation can also entail a high demand for patient care (Dimick et al., 2004). On the other hand, in a study investigating the influence of training status on average costs in Spanish hospitals, it was found that costs in training hospitals were 9% higher than those in non-training hospitals (López-Casasnovas and Saez, 1999). In another study, patients treated for cervical spine surgery in teaching hospitals were found to have longer hospital stays, higher costs, and mortality rates compared to patients treated in non-training hospitals (Fineberg et al., 2013). In a study found that in the United States, a strong relationship was found between operational and financial performance indicators and training status, and it claimed that training status is not a good indicator of inefficiency (Mutter et al., 2008). Similarly in this study, a strong relationship was found between operational and financial performance indicators with training status.

The continuity of operating profits and the successful management of the patient revenue cycle play a prominent role in the financial stability of healthcare organizations (Rauscher and Wheeler, 2008). (Rauscher and Wheeler, 2008). Success in the patient revenue cycle is a critical element to boost profitability, build equity capital, and remain financially viable over the long term. In this regard, hospitals need to embrace financial systems that can manage higher patient volumes and ensure patient access to financial information (Singh and Wheeler, 2012).

This study shows that the ID.3 decision tree algorithm can be used in the prediction of operational and financial performance indicators of public hospitals in Turkey. The research demonstrated that hospital size and operational performance metrics, particularly bed count, are predictive variables for the hospital's organizational and financial performance. Additionally, factors such as absolute liquidity, return on equity and HVI were identified as other determinants of hospital organizational and financial performance. Furthermore, this research highlighted that decision tree algorithms are a valuable technique for providing insights into solving complex operational and financial performance issues in hospitals

It is considered that the simple recursive model presented in this study could contribute to understanding the determinants of organizational and financial performance indicators in healthcare services. Healthcare managers in Turkey, if aiming to enhance the performance of public hospitals, should effectively manage their healthcare institutional capacities and aim for financial sustainability. In this context, it is recommended that strategies aimed at improving financial performance, such as optimizing liquidity to increase profitability, should be identified. Additionally, K-means clustering successfully classified the hospitals. However, this study has several limitations. Firstly, the analysis is restricted to a limited set of operational performance indicators. Secondly, there is an absence of clinical indicators pertaining to clinical performance. Although the measurement of financial performance using an index beyond simple ratio analysis is a strength of the study, the evaluation of financial performance with a broader range of indicators or multiple indices is a noted limitation. Finally, the data used in this study are from a single year, limiting the generalizability of the results.

In this context, it is recommended that future studies employ various machine learning algorithms, such as Random Forest. Additionally, considering the dynamic properties, number, and diversity of the variables used, there is a need for studies that utilize a broader and more diverse range of operational, clinical, and financial performance indicators to identify areas for improvement.

Conflict of Interest
No potential conflict of interest was declared by the author(s).

Funding
Any specific grant has not been received from funding agencies in the public, commercial, or not-for-profit sectors.

Compliance with Ethical Standards
It was declared by the author that the tools and methods used in the study do not require the permission of the Ethics Committee.

Ethical Statement
It was declared by the author(s) that scientific and ethical principles have been followed in this study and all the sources used have been properly cited.

REFERENCES

Adair, C., Simpson, E., Casebeer, A., Birdsell, J., Hayden, K. and Lewis, S. (2006). “Performance Measurement in Healthcare: Part II - State of the Science Findings by Stage of the Performance Measurement Process”, *Healthcare Policy/ Politiques de Santé*, 2(1), 56-78. https://doi.org/10.12927/hcpol.2006.18338

Audi, G.R., Kates, F.R., Capen, M.M. and Polito, A. (2016). “An Analysis of Organizational Structures within Southern Rural Multi-Hospital Systems in the United States”, *Journal of Health Care Finance*, 43(1), 1-14.

Carini, E., Gabutti, I., Frisicale, E. M., Di Pilla, A., Pezzullo, A.M., de Waure, C., Cicchetti, A., Boccia, S. and Specchia, M.L. (2020). “Assessing Hospital Performance Indicators. What dimensions? Evidence from an Umbrella Review”, *BMC Health Services Research*, 20(1), 1038. https://doi.org/10.1186/s12913-020-05879-y

Chaudary, S., Zafar, S. and Salman, M. (2015). “Does Total Quality Management Still Shine? Re-Examining the Total Quality Management Effect on Financial Performance”, *Total Quality Management & Business Excellence*, 26(7-8), 811-824. https://doi.org/10.1080/14783363.2014.895521

Cinaroglu, S. (2020). “Integrated k-means Clustering with Data Envelopment Analysis of Public Hospital Efficiency”, *Health Care Management Science*, 23(3), 325-338. https://doi.org/10.1007/s10729-019-09491-3

Cook, J.A. (2017). “ROC Curves and Nonrandom Data”, *Pattern Recognition Letters*, 85, 35-41. https://doi.org/https://doi.org/10.1016/j.patrec.2016.11.015

Coyne, J.S., Richards, M.T., Short, R., Shultz, K. and Singh, S.G. (2009). “Hospital Cost and Efficiency: Do Hospital Size and Ownership Type Really Matter?”, *Journal of Healthcare Management*, 54(3), 163-175. https://doi.org/10.1097/00115514-200905000-00005

Çelik, M. and Korkmaz, E. (2023). “İnsan Sağlığı Hizmetleri Sektöründe Yer Alan İşletmelerin Finansal Performanslarının Değerlendirilmesi”, *Artvin Çoruh Üniversitesi Uluslararası Sosyal Bilimler Dergisi*, 9(2), 352-367. https://doi.org/10.22466/acusbd.1337309

Dai, N. T., Kuang, X. (Jason) and Tang, G. (2018). “Differential Weighting of Objective Versus Subjective Measures in Performance Evaluation: Experimental Evidence”, *European Accounting Review*, 27(1), 129-148. https://doi.org/10.1080/09638180.2016.1234402

Dimick, J.B., Cowan, J.A., Colletti, L.M. and Upchurch, G.R. (2004). “Hospital Teaching Status and Outcomes of Complex Surgical Procedures in the United States”, *Archives of Surgery*, 139(2), 137-141. https://doi.org/10.1001/archsurg.139.2.137

Franceschini, F., Maurizio, G., Domenico, M. (2019). “Designing Performance Measurement Systems: Theory and Practice of Key Performance Indicators”, Springer International Publishing, Cham, Switzerland.

Fineberg, S.J., Oglesby, M., Patel, A.A., Pelton, M.A. and Singh, K. (2013). “Outcomes of Cervical Spine Surgery in Teaching and Non-Teaching Hospitals”, *Spine*, 38(13), 1089-1096. https://doi.org/10.1097/BRS.0b013e31828da26d

Ginn, G.O. and Lee, R.P. (2006). “Community Orientation, Strategic Flexibility, and Financial Performance in Hospitals”, *Journal of Healthcare Management*, 51(2), 111-121. https://doi.org/10.1097/00115514-200603000-00009

Goldstein, S.M., Ward, P.T., Leong, G.K. and Butler, T.W. (2002). “The Effect of Location, Strategy, and Operations Technology on Hospital Performance”, *Journal of Operations Management*, 20(1), 63-75. https://doi.org/10.1016/S0272-6963(01)00081-X

Hauser, J. and Katz, G. (1998). “Metrics: You Are What You Measure!”, *European Management Journal*, 16(5), 517-528. https://doi.org/10.1016/S0263-2373(98)00029-2

Işıkçelik, F., Turgut, M., ve Ağırbaş, İ. (2022). “Hastanelerde Finansal Performansın Farklı Analiz Yöntemleri İle Değerlendirilmesi”, *Süleyman Demirel Üniversitesi Vizyoner Dergisi*, 13(34), 505-519. https://doi.org/10.21076/vizyoner.948785

Jack, E. P. and Powers, T. L. (2009). “A Review and Synthesis of Demand Management, Capacity Management and Performance in Health-Care Services”, *International Journal of Management Reviews*, 11(2), 149-174. https://doi.org/10.1111/j.1468-2370.2008.00235.x

Jin, C., De-lin, L. and Fen-xiang, M. (2009). "An improved ID3 decision tree algorithm," 2009 4th International Conference on Computer Science & Education (2009), Nanning, China, 127-130, doi: 10.1109/ICCSE.2009.5228509.

Kantardzic, M. (2020). “Data Mining: Concepts, Models, Methods, and Algorithms”, 3rd Edition, (Editor: E. Hossain). Wiley-IEEE Press, New Jersey.

Karataş, Y.E. and Çinaroğlu, S. (2023). “Sağlık Alanında Faaliyet Gösteren İşletmelerin Konsolide Finansal Tablo Analizi”, *Hacettepe Sağlık İdaresi Dergisi*, 26(1), 149-174.

Li, L. and Benton, W. C. (2003). “Hospital Capacity Management Decisions: Emphasis on Cost Control and Quality Enhancement”, *European Journal of Operational Research*, 146(3), 596-614. https://doi.org/10.1016/S0377-2217(02)00225-4

Liao, S., Chu, P. and Hsiao, P. (2012). "Data Mining Techniques and Applications - A Decade Review from 2000 to 2011", *Expert Systems with Applications*, 39(12), 11303-11311. https://doi.org/10.1016/j.eswa.2012.02.063

López-Casasnovas, G. and Saez, M. (1999). "The Impact of Teaching Status on Average Costs in Spanish Hospitals", *Health Economics*, 8(7), 641-651. https://doi.org/10.1002/(SICI)1099-1050(199911)8:7<641::AID-HEC475>3.0.CO;2-L

Mishra, B.K., Nayak, N.R., Rath, A. and Swain, S. (2012). "Far Efficient K-Means Clustering Algorithm", *Proceedings of the International Conference on Advances in Computing, Communications and Informatics,* 106-110. https://doi.org/https://doi.org/10.1145/2345396.2345414

Mutter, R.L., Rosko, M.D. and Wong, H.S. (2008). "Measuring Hospital Inefficiency: The Effects of Controlling for Quality and Patient Burden of Illness", *Health Services Research*, 43(6), 1992-2013. https://doi.org/10.1111/j.1475-6773.2008.00892.x

Oner, N., Zengul, F.D., Ozaydin, B., Pallotta, R.A. and Weech-Maldonado, R. (2016). "Organizational and Environmental Factors Associated with Hospital Financial Performance: A Systematic Review", *Journal of Health Care Finance*, Fall 2016, 14-37.

Ozgulbas, N. and Koyuncugil, A.S. (2009). "Financial Profiling of Public Hospitals: An Application by Data Mining", *The International Journal of Health Planning and Management*, 24(1), 69-83. https://doi.org/10.1002/hpm.883

Pegels, C.C. (1984). "A Model for Evaluating Financial Viability of a Hospital", *Third International Conference on System Science in Health Care*, 701-704. https://doi.org/10.1007/978-3-642-69939-9_161

Prentice, C.R. (2016). "Why So Many Measures of Nonprofit Financial Performance? Analyzing and Improving the Use of Financial Measures in Nonprofit Research", *Nonprofit and Voluntary Sector Quarterly,* 45(4), 715-740. https://doi.org/10.1177/0899764015595722

Rauscher, S. and Wheeler, J.R.C. (2008). "Effective Hospital Revenue Cycle Management: Is There a Trade-Off between the Amount of Patient Revenue and the Speed of Revenue Collection?", *Journal of Healthcare Management*, 53(6), 392-404. https://doi.org/10.1097/00115514-200811000-00008

Singh, S.R. and Wheeler, J. (2012). "Hospital Financial Management: What is the Link Between Revenue Cycle Management, Profitability, and Not-for-Profit Hospitals' Ability to Grow Equity?", *Journal of Healthcare Management*, 57(5), 325-341. https://doi.org/10.1097/00115514-201209000-00007

Tasi, M.C., Keswani, A. and Bozic, K.J. (2019). "Does Physician Leadership Affect Hospital Quality, Operational Efficiency, and Financial Performance?", *Health Care Management Review*, 44(3), 256-262. https://doi.org/10.1097/HMR.0000000000000173

The European Observatory on Health Systems and Policies. (2019). "Improving Healthcare Quality in Europe Characteristics, Effectiveness and Implementation of Different Strategies", (Editors: W. Busse, Reinhard; Klazinga, Niek; Panteli, Dimitra; Quentin), WHO Regional Office for Europe, Copenhange.

Tsai, T.C., Jha, A.K., Gawande, A.A., Huckman, R.S., Bloom, N. and Sadun, R. (2015). "Hospital Board and Management Practices Are Strongly Related to Hospital Performance on Clinical Quality Metrics", *Health Affairs*, 34(8), 1304-1311. https://doi.org/10.1377/hlthaff.2014.1282

Upadhyay, S. and Smith, D. G. (2020). "Cash, Cash Conversion Cycle, Inventory and Covid-19", *Journal of Health Care Finance*, 46(4), 37-43.

World Health Organization. (2013). "WHO Evaluation Practice Handbook", https://iris.who.int/bitstream/handle/10665/96311/9789241548687_eng.pdf?sequence=1andisAllowed=y., (Access Date: 18.01.2024).