İŞLETME ARAŞTIRMALARI DERGİSİ
JOURNAL OF BUSINESS RESEARCH-TURK
2024, 16(3), 1582-1596
https://doi.org/10.20491/isarder.2024.1874

Predicting Financial Failure of Public Teaching Hospitals: An Application of Fuzzy Clustering Analysis*

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ARTICLE INFO

Keywords:
Financial failure
Fuzzy C Means clustering
Hospital
Turkey

Received 4 November 2023
Revised 10 September 2024
Accepted 15 September 2024

Article Classification:
Research Article

ABSTRACT

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Purpose – To develop a novel prediction model and determine the variables that best predict hospitals' financial failures.

Design/methodology/approach – A fuzzy C-means clustering analysis was conducted using financial ratios from MoH Hospitals' financial databases. Hospital Fuzzy Financial Health Scores (HF-HFS) then were calculated the as the degree of financial failure measured through the selected n-cluster model.

Findings – The results show that the number of teaching hospitals experiencing financial failure has increased. HF-FHS scores also were compared with the modified Altman Z scores a commonly used financial distress measure in the hospital service sector. The HF-FHS scores in good and poor financial conditions differ significantly. The HF-FHS scores were also strongly correlated with the Altman Z scores.

Discussion – The rising trend in the number of hospitals experiencing financial difficulties over the years may cause some hospitals in financial distress to fail to fulfill their obligations, which may disrupt the services provided. In such a situation, good management skills, which are the most important factor reducing the financial risks of hospitals, will not work after a certain point.

Conclusions – The findings indicate Fuzzy C Means clustering as a viable option to evaluate the financial failure of hospitals compared to more traditional methods such as Altman Z scores. Hospitals still face financial pressures due to market and structural factors such as the global budget repayment system, pricing and collection time, and insufficient competition conditions. Predicting hospitals' financial failures can help develop managerial policies and strategies to recognize and combat risks, improve performance, and improve the current situation of hospitals.

1.INTRODUCTION

Understanding underlying reasons for the financial distress of organizations is a central question that has attracted scholars from a large span of research disciplines. The elements of financial stress, defined as financial distress and financial failure in the literature, may result in adverse conditions that will lead to the inability to fulfill prior commitments. The failure to meet prior obligations may eventually lead to bankruptcy protection applications and termination of activity (Sun et al., 2014:41-56).

However, all organizations are not the same regarding bankruptcy since bankruptcy is legally impossible for some organizations, such as public hospitals. Thus, public hospitals may experience financial distress in which the resource collected from the government budget will remain insufficient for one fiscal period. For such a public hospital, financial indicators have come close to the verge of bankruptcy. Since no public hospitals may apply for bankruptcy protection, and be liquidated, or undergo termination of activity, they collect the required fund from the Treasury. This collection may lead to social security and budget deficits and later affect the country's macroeconomic performance. The appearance of budget and/or social security deficit is always possible in such emerging economies as Turkey, where 65% of all its hospitals are state-invested and operated. Therefore, the financial indicators of public hospitals need meticulous monitoring to determine the factors

* An earlier version of this study was presented at American Accounting Association Spark: Meeting of the Regions, USA, May 24 – 26, 2021.

Suggested Citation
Öner, N. (2024). Predicting Financial Failure of Public Teaching Hospitals: An Application of Fuzzy Clustering Analysis, *Journal of Business Research-Turk*, 16 (3), 1582-1596.

leading to financial failure. Consequently, it is essential to examine the factors leading to financial failure within the public hospital sector for emerging economies such as Turkey.

When one exemplifies financial failure as a medical prognosis, bankruptcy is not a heart-attack-like surprise ending that organizations die off. Instead, it is more like heart failure in which early symptoms show acute spasms due to the inability to meet short-term liabilities, which will later become chronic enough to lead to failures to meet essential obligations. As a result, the final stage will end with a fatality, i.e., bankruptcy. Therefore, predicting financial failure is crucial for even public hospitals, which won't be allowed to bankrupt, yet would become a substantial financial burden to the society and the country at large.

Despite the centrality of financial failure for public hospitals in Turkey, limited studies have explored underlying factors for failure (Erkılıç and Aksoy, 2020:1415-33). Even though there are some additional studies in the United States focusing on financial failure (Cleverley and Nutt, 1984:615; Ramamonjiarivelo et al., 2015:337-47; Langabeer et al., 2018:75-79; Puro et al., 2019:1-15), findings of these studies cannot be generalized to countries such as Turkey where public sector represents the majority of healthcare delivery services. Contrary to Turkey, the nonprofit sector holds the majority role in the U.S. Moreover, there is an overall lack of attention on the healthcare sector since research to date on financial failure mostly focused on industries such as banking (Iturriaga and Sanz, 2015:2857-69; Erdogan, 2008:2973-82), manufacturing (Koç and Ulucan, 2016:147-67), and industrial firms (Giannopoulos and Sigbjornsen, 2019:1114-28). Therefore, despite few efforts, there is a need to explore underlying factors for financial failure among public hospitals (Oner, 2020:7).

Selecting a proper method for assessing hospitals' financial outlooks is a critical issue. A useful method that enables categorizing public hospitals in terms of their levels of financial risk will be reasonable since the determination of each hospital's risk level is both an effortful and time-consuming task. In cluster-based risk determination, the overlapping texture of the limits of risk groups complicates classical clustering algorithms in the determination of real risk groups.

Classical clustering algorithms assume that each object ranging from black to white or from 1 to 0 is within or outside a particular cluster. However, not every loss will create a risk of bankruptcy for organizations, though bankruptcy refers to an exponentially increasing probability of loss (Apaydın et al., 2009:123-36). The fuzzy clustering method effectively solves financial problems with vague descriptions by establishing a membership model that will represent the relevant cluster best (Ostaszewski, 1993:104-105; Nabiyev, 2013:661-73). Fuzzy clustering aims to collect more information about the memberships of patterns (Dunn, 1973:32-57; Bezdek, 1981:1-13). In fuzzy c-means clustering, patterns may be included in a cluster with various membership values (Nayak et al., 2015:133-49). Accordingly, hospitals' financial success scores were used calculated by modified Altman Z-Score Model, as membership values so that hospital clusters would indicate an accurate interpretation on whether hospitals are financially risk-free, risky, or highly risky.

The purpose of the present study is to develop a prediction model for hospital failures and to determine the variables that will best predict the financial failures of public hospitals. In the literature, no researchers have used a combination of fuzzy c-means algorithm and Altman Z-Score Model to predict public hospitals' financial failures, which makes the topic worth studying.

1.1.Background

The level of community healthcare has lately been a critical welfare indicator for determining countries' macroeconomic levels of development. In underdeveloped and developing countries, hospitals are state-operated due to their high investment and operation costs. In developing countries such as Turkey, private healthcare services are still underinvested despite some former incentive regulations for private and nonprofit organizations. In Turkey, public hospitals comprise 65% of all hospitals. Contrary to other companies in the service sector, healthcare organizations aim to improve community health rather than maximize profit. With the most considerable portion

in the healthcare sector, public hospitals aim to improve community health through the effective deployment of resources. As a result, public hospitals are expected to provide medical services for anybody with or without health insurance (Villa and Kane, 2013:24-33).

In the case of Turkey, over the last few years, public hospitals have suffered from serious financial difficulties due to the rising costs of investment and operation, misleading tariffs and repayment policies of refunding institutions such as Social Security Institution (SSI), increase in the number of uninsured citizens; unutilized capacity; and competition. Furthermore, the improvements in medicine, biomedicine, electronics, computing, and programming have transformed hospitals into larger and more complicated facilities (Cagliano et al., 2011:695-708).

The underlying reasons for financial failure may vary by hospital. What is here to notice is the risk level due to hospital failure. Considering an assumption that financial failure stems from the same reason in every hospital, failure-induced levels of risk was expected will be the same for all hospitals. However, failure-induced levels of risk will be quite different because of each hospital's distinctive ability to resist such risks. Inferring from Beaver (1966:71-111) and Altman (1968:589-609), it is concluded that organizations with certain financial structures have more difficulties meeting liabilities and are more prone to bankruptcy.

1.2.Literature Review

There are many studies on financial failure; however, these studies concentrated mostly on banks and publicly-traded companies on a sectoral basis. Furthermore, very few researchers aimed to predict public hospitals' financial failures, and no researchers used a combination of fuzzy c-means algorithm and Altman Z-Score Model. Some of the notable studies were listed in this section.

Altman (1968:589-609) used five predetermined variables in a multiple discriminant model (MDA) and obtained robust predictions. Meyer and Pifer (1970:853-68) and Sinkey Jr (1975:21-36) used regression analysis for predicting bank failures. Martin (1977:249-76) used the logistic model for the early prediction of bank failures. Kolari et al., (2002:361-87) used the logistic regression model for variable categorization. Santos et al. (2006:37) used MDA for corporate bankruptcy predictions by data mining algorithm. Tsai (2009:120-27) used a t-statistic model to classify the rates being used for the detection of bankruptcy possibilities.

As for the studies on the prediction of hospital failures, Cleverley and Nutt (1984:615) used the financial flexibility index for determining hospital flexibility to detect the problem before the emergence of financial failure. Ramamonjiarivelo et al., (2015:337-47) used Altman Z-Score for predicting hospital failures to analyze if privatization could be a strategic alternative. Langabeer et al., (2018:75-79) predicted the levels of hospital failures via multivariate regression analysis. Puro et al., (2019:1-15) compared the bankruptcy prediction models of Altman Z-Score, Ohlson O-Score, and Zmijewski Score over a hospital financial dataset.

There is also some research conducted in Turkey on hospital failures. Tarcan (2010:23-46) used discriminant analysis to develop a prediction model for public hospital failures in Turkey. Yılmaz (2009:113) used a latent class regression model for developing a financial risk analysis model and determining the financial risk levels of public and private hospitals. Çil Koçyiğit (2011) used discriminant analysis and proposed a prediction model for financial failures. Civan and Dayı (2014:41) used Altman Z-Score and artificial neural nets in the public hospitals in Zonguldak Province and developed a failure prediction model. Erkılıç and Aksoy (2020:1415-33) predicted public hospitals' financial failures in Turkey via the logistic regression model. Oner (2020:84) predicted financial distress for the Turkish public, teaching, and university hospitals utilizing Altman Z-scores and machine learning algorithms. Overall, there has been no study using a combination of fuzzy c-means algorithm and Altman Z-Score Model to predict public hospitals' financial failures. This unique combination makes our study findings of particular value for the stakeholders of public hospital financial health.

2.METHODOLOGY

2.1.Data and Variables

Our sample includes 47 Turkish Ministry of Health (MoH) teaching hospitals from 2012 to 2014. Year-end consolidated financial statement data was collected from Turkish MoH hospital financial databases. In developing the final sample, the following criteria were utilized: hospitals having a minimum of 50 beds and serving for at least three consecutive years. To represent these teaching hospitals' financial conditions comprehensively, eight commonly-known and frequently-used financial ratios from four major financial dimensions were used, including liquidity, solvency, efficiency, and profitability (Oner et al., 2016:13-37) (See Table 1). Quick Ratio (Q.R.) and Account Payable to Net Sales Ratio (APS) were for the liquidity dimension. Financial Leverage Ratio (FLR) were selected for the solvency dimension. As for efficiency measures, Inventory Turnover Rate (ITR), Asset Turnover Ratio (ATR), Account Receivable Turnover (ART) and Operating Expenses to Sales (OPXR) were inclueded. For the profitability dimension, Return on Asset (ROA) was used (See Table 1). Finally, modified Altman Z-Scores for hospitals were calculated as a financial distress indicator. Modified Altman Z-Scores would allow us to compare the success of the Financial Health Scores for hospitals. The higher the Altman Z-Scores, the better the financial situation. The Financial Health Scores variable was obtained by using the Fuzzy C Means Algorithm. Financial Health Scores have been calculated for each hospital on a yearly basis. These scores range from 0 to 1. The higher the score, the better the financial situation.

Table 1. Included Variables

Variable	Abbr.	Description
Liquidity		
Quick ratio	Q.R.	(Current Assets – Inventories – Prepaids) / Current Liabilities
Account Payable to Net Sales Ratio	APS	Account Payable / Net Sales
Solvency		
Financial leverage ratio	FLR	Current Liabilities / Total Assets
Efficiency		
Inventory turnover rate	ITR	Cost of Goods / Average Inventory
Asset turnover ratio	ATR	Net Sales / Assets
Accounts receivable turnover	ART	Net Sales / Average Accounts Receivable
Operating expense to sales/revenue	OPXR	Operating Expense / Net Sales
Profitability		
Return of assets	ROA	Net Income / Assets
Financial Distress		
Modified Altman Z Score	AZ	Z= 6.56 X1 + 3.26X2 + 6.72X3 + 1.05X4 where X1 = Net Working Capital / Total Assets, X2 = Net Assets / Total Assets, X3 = Excess Revenue over Expenses / Total Assets, X4 = Fund balance / Total liabilities
Hospital Financial Fuzzy Health Score	HF-FHS	Generated financial scores through Fuzzy C Means Algorithm

2.2.Analytical Approach

As an analytical approach, FCM financial health scoring methodology was proposed and used by Gokten et al., (2017:385). The authors compared the Fuzzy Financial Health Scores (F-FHS)– generated by the FCM algorithm– with Piotroski's criteria scores (Piotroski, 2000:1-41) for 166 actively traded companies listed in the National Market of Istanbul Stock Exchange. In this study, the scores of the Hospital Fuzzy Financial Health Scores (HF-FHS) were comapared with the modified Altman Z scores- a commonly used financial distress measure in the hospital service sector. The analysis consists of 6 steps:

Step 1. Normalization and adjusting financial ratios: Financial ratios are primarily normalized with the min-max normalization method1. As a result of the normalization, all proportions are between 0 and 1.

$$X_{Normalized} = \frac{x_i - x_{Min}}{x_{Max} - x_{Min}} \quad (1)$$

Then the financial ratios were weighted according to their positive or negative effects on the hospital's financial situation. In this study, the increases in APS, FLR, and OPXR ratios are used as remaining percentages–the percentage value that completes to one– to normalize the values into the model since they negatively affect the financial situation in hospitals. For example, an FLR value of 0.63 was normalized as 0.27 in the model.

Step 2. Finding the optimum number of the clusters: At this stage, the optimum number of clusters was determined for models with different numbers of clusters by using the models' cluster validity indices. All these models were produced using the FCM algorithm. Although many cluster validity indices are used in the literature, four different indices, which are among the most commonly used ones, were used in this study. These are Partition Entropy (Bezdek, 1973:58-73), Xie-Beni Index (Xie and Beni, 1991:841-47), Kwon Index (Kwon, 1998:2176-77), and Fuzzy Silhouette Index (Campello and Hruschka, 2006:2858-75). The optimum number of clusters for each year is tested between 2 and 7 using indices formulas (See Appendix A). Bezdek et al., (1984:191-203) suggest that the FCM algorithm performs well between 1.5 and 2.5 fuzzification coefficient (m) (Cebeci, 2019:1-14). In this study, "2" , which is the midpoint of these two values , was determined as m (Cebeci & Cebeci, 2020:446:). While determining the optimum numbers of clusters, R "ppclust" (Cebeci et al., 2019; Cebeci, 2020:11-27) and "fcvalid" (Cebeci & Cebeci, 2020:446) packages were used. Euclidian was used as a measure of distance. "Inofrep" was used as an initialization method (Cebeci & Cebeci, 2020:446).

Step 3. Extracting predetermined cluster center vectors: FCM algorithm has been run for each year on the optimally determined cluster/s. The FCM method was used to obtain "V" matrices. Then, the cluster center vectors that were extracted from these "V" matrices were recorded for each year.

Step 4. Calculating Euclidian norms: At this stage, the norm value (hi) of the center vectors is calculated for each cluster obtained by the FCM method. Norm values indicate the contribution of the specified cluster relative to its financial status. The more norm value a cluster will have, the better the financial condition. On the contrary, a cluster with a lower norm value will indicate a worse financial situation.

Step 5. Calculating Financial Health Scores: Membership degree is obtained for each hospital in each cluster obtained with the FCM method. Membership degree ranges between 0 and 1 (See Appendix A). Membership vectors for each cluster membership are expressed as μi =[μ1+1, μ2+2,……. μc+i]. Financial Health Scores for each hospital is calculated with the formula:

$$\lambda_i = \mu_i h \ (2)$$

The calculated HF-FHS is normalized with the following formula.

$$HF - FHS = \frac{\lambda_i - \lambda_{Min}}{\lambda_{Max} - \lambda_{Min}} \ (3)$$

Step 6 Comparing HF-FHS and AZ Scores: The relationship between the HF-FHS scores obtained at this stage and the AZ scores (previously calculated) will be examined with the correlation analysis.

3.FINDINGS

Descriptive statistics for the study sample are provided in Table 2. The decrease in the Q.R. of hospitals and the increase in the FLR indicate that hospitals' liquidity status deteriorates over the years. Increasing FLR decreases the solvency of hospitals. The decrease in hospitals' OPXR, corresponds to increased ITR, ATR, and ART when evaluated in terms of efficiency over the years. On the other hand, in terms of profitability, hospitals are experiencing more difficulties over the years, and the severity of Financial Distress is increasing with each passing year.

Table 2: Descriptive Statistics

	2012		2013		2014	
	n=47		n=47		n=47	
Financial ratios	**Mean**	***SD***	**Mean**	***SD***	**Mean**	***SD***
Liquidity						
QR	0.59	*0.34*	0.40	*0.42*	0.41	*0.37*
APS	0.16	*0.07*	0.10	*0.05*	0.12	*0.06*
Solvency						
FLR	1.05	*0.48*	1.50	*0.78*	1.74	*1.10*
Efficiency						
ITR	12.12	*3.88*	22.61	*7.37*	29.15	*10.23*
ATR	4.92	*1.77*	7.54	*2.22*	7.48	*2.42*
ART	12.55	*6.04*	18.66	*7.07*	23.18	*6.96*
OPXR	0.46	*0.04*	0.15	*0.03*	0.14	*0.03*
Profitability						
ROA	-0.44	*0.45*	-0.51	*0.56*	-0.28	*0.49*
Financial Distress						
AZ	-4.82	*8.16*	-10.18	*11.43*	-11.11	*14.12*

QR: Quick ratio, APS: Account Payable to Net Sales Ratio, FLR: Financial leverage ratio, ITR: Inventory turnover rate, ATR: Asset turnover ratio, ART: Accounts receivable turnover, OR: Operating ratio, ROA: Return of assets, AZ: Altman Z Score

The Application of the Six-Step Analytical Approach

In Step 1 (Normalization and adjusting financial ratios), financial data obtained for each year of the study were normalized. Among the normalized variables, the increases in APS, FLR, and OPXR were transformed into 1-APS, 1-FLR, and 1- OPXR forms due to their negative impact on the financial status of hospitals.

In Step 2, the model was run every year with the Iterative FCM algorithm. In Table 3, the number of clusters for each year is modeled from 2 to 7. The lowest value in P.E., X.B., and KWON, and the highest in FSIL represents the optimum number of clusters. It is observed that the optimum number of clusters is 2 in terms of all validity indices in all years except 2014. Moreover, it was observed that the optimum cluster number in 2014 was 2 in terms of P.E. and FSIL indices and 3 in terms of X.B. and KWON indices. However, it is seen that the year 2014 is very close in terms of the number of X.B. and KWON indices 2 and 3 clusters. In this sense, considering the dominance of 2 as the optimum cluster number in other years, it was determined that the number of clusters should be 2 for all years.

Table 3: Cluster validity indices by number of clusters and years

Year	Validity Indicies	C=2	C=3	C=4	C=5	C=6	C=7
2012	PE	**0.526**	0.880	1.106	1.295	1.399	1.511
	XB	**0.449**	0.717	0.779	0.914	0.807	0.933
	KWON	**21.350**	34.457	37.908	44.993	40.416	47.240
	FSIL	**0.560**	0.407	0.410	0.332	0.411	0.323
2013	PE	**0.588**	0.950	1.186	1.379	1.477	1.587
	XB	**0.645**	1.614	0.873	1.699	0.875	0.869
	KWON	**30.561**	77.058	42.110	82.748	43.171	43.533
	FSIL	**0.476**	0.400	0.374	0.375	0.363	0.374
2014	PE	**0.556**	0.865	1.117	1.292	1.434	1.553
	XB	0.532	**0.520**	0.919	1.774	1.046	0.785
	KWON	25.241	**25.049**	44.835	87.615	52.381	39.753
	FSIL	**0.500**	0.435	0.331	0.366	0.292	0.211

PE: *Partition Entropy,* ***XB:*** *Xie-Beni Index,* ***KWON:*** *Kwon Index,* ***FSIL:*** *Fuzzy Silhouette Index*

In Step 3, each year's final cluster center vectors were obtained using cluster number 2, which was determined in the previous step. Table 4 also provides information about the final cluster vectors. The cluster sizes do not exhibit much change over the years. Vectors provide information about the characteristics of clusters. In all years, Cluster 1 has relatively more positive financial indicators. For example, the results indicate that the average normalized Q.R., 1-APS, 1-FLR, 1-OPXR, and ROA values in cluster 1 in all years are greater than Cluster 2. However, ITR, ATR, and ART values are relatively lower in Cluster 1, contrary to expectations. The vector norm values calculated in Step 4 show the extent to which the vectors belonged to which cluster contributed to the financial situation (Table 4). Cluster 1 has a higher norm value in all years, indicating that it is better than Cluster 2 in financial terms.

Table 4. Characteristics of the final prototype cluster for each year

			Liquidity		Solvency	Efficiency				Profitability	
Year	**Cluster**	**Size**	**QR**	**1-APS**	**1-FLR**	**ITR**	**ATR**	**ART**	**1-OPXR**	**ROA**	**Norm**
2012	Cluster 1	29	0.24	0.72	0.80	0.36	0.28	0.17	0.77	0.80	1.640
	Cluster 2	18	0.10	0.66	0.60	0.47	0.54	0.43	0.57	0.59	1.474
2013	Cluster 1	22	0.27	0.72	0.78	0.43	0.36	0.31	0.65	0.68	1.576
	Cluster 2	25	0.08	0.55	0.46	0.38	0.54	0.62	0.56	0.51	1.387
2014	Cluster 1	24	0.32	0.78	0.85	0.40	0.25	0.48	0.79	0.70	1.736
	Cluster 2	23	0.11	0.68	0.57	0.29	0.48	0.80	0.73	0.49	1.585

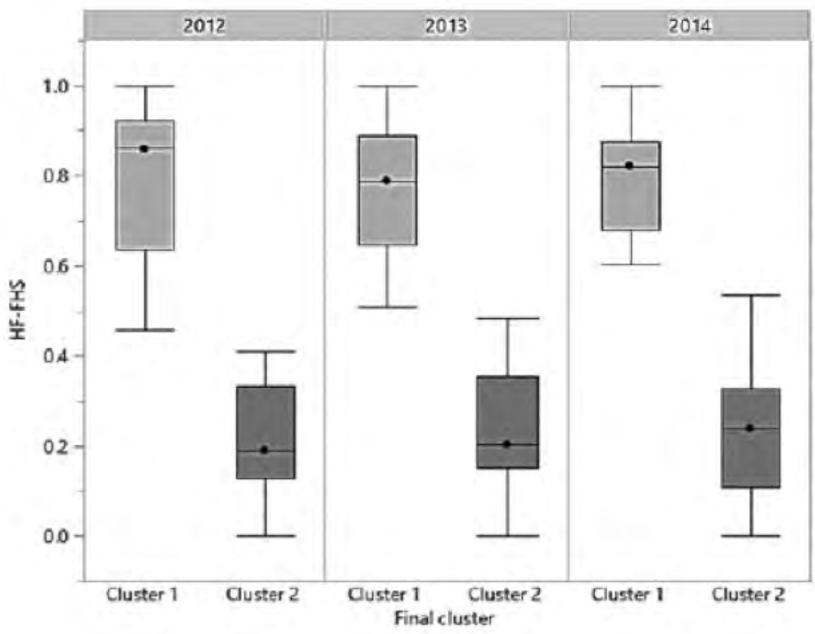
All ratios were normalized. QR: Quick ratio, APS: Account Payable to Net Sales Ratio, FLR: Financial leverage ratio, ITR: Inventory turnover rate, ATR: Asset turnover ratio, ART: Accounts receivable turnover, OR: Operating ratio, ROA: Return of assets

In Step 5, HF-FHS of the hospitals were calculated using formulas (2) and (3). In Figure 1, HF-FHS values of the hospitals are provided on a yearly basis. The risk scores from small to large are colored from light to dark gray. One hospital (H32) had the worst scores for three years. A number of hospitals (H6, H7, H11, H14, H20, H30, H35, H39, H40, H43, and H44) have relatively good financial scores over 3 years. While some hospitals (H1 and H10) improved over the years, some hospitals (H20, H25, H26, H27and H42, etc.) worsened their financial situation. While some hospitals (H5, H8, H15, etc.) protected their financial stability, some hospitals (H23, H34) experienced financial fluctuations.

ID	2012	2013	2014	ID	2012	2013	2014
H1	0.162	0.244	0.845	H25	0.991	0.553	0.208
H2	0.33	0.204	0.534	H26	0.674	0.197	0.093
H3	0.603	0.154	0.232	H27	0.684	0.166	0.058
H4	0.151	0.159	0.233	H28	0.847	0.566	0.663
H5	0.347	0.28	0.287	H29	0.31	0.877	0.735
H6	0.973	0.92	0.818	H30	0.935	0.991	0.815
H7	0.865	0.876	0.925	H31	0.513	0.408	0.244
H8	0.213	0.174	0.219	H32	0.063	0	0.084
H9	0.245	0.097	0.328	H33	0.244	0.239	0.38
H10	0.412	0.413	0.865	H34	0.167	0.486	0.273
H11	0.757	0.76	0.852	H35	0.641	0.834	0.9
H12	0.894	0.509	0.876	H36	0.468	0.261	0.247
H13	0.948	0.829	0.61	H37	0.925	0.724	0.527
H14	0.899	0.928	0.826	H38	0.632	0.322	0.239
H15	0.388	0.598	0.446	H39	0.86	0.84	0.851
H16	0	0.512	0.845	H40	0.718	0.815	0.919
H17	0.043	0.453	0.778	H41	0.537	0.762	0.767
H18	0.014	0.114	0.663	H42	1	0.395	0
H19	0.889	0.705	0.601	H43	0.936	1	0.958
H20	0.919	0.955	0.812	H44	0.856	0.718	1
H21	0.573	0.099	0.107	H45	0.168	0.075	0.278
H22	0.383	0.157	0.193	H46	0.167	0.386	0.494
H23	0.921	0.293	0.643	H47	0.458	0.147	0.054
H24	0.871	0.662	0.614				

Figure 1. HF-FHS Heatmap

In Figure 2, the Box-Plot graph shows the distribution of HF-FHS scores by years and final clusters. It is observed that the HF-FHS scores differ substantially across the final clusters produced by the FCM algorithm in all years (F_{2012}= 149.83 ($P<0.001$), F_{2013}=166.37($P<0.001$), F_{2014}=198.55($P<0.001$)). The HF-FHS scores of the hospitals in Cluster 1, which have a better financial situation, vary between 0.770 and 0.799 over the years, while the HF-FHS scores of the hospitals in Cluster 2, which have a worse financial situation, vary between 0.212 and 0.250. (See Appendix B).



Year	Level	Size	Mean	Std Error	Lower 95%	Upper 95%
2012	Cluster 1	29	0.786	0.029	0.727	0.844
	Cluster 2	18	0.212	0.037	0.137	0.286
2013	Cluster 1	22	0.770	0.030	0.709	0.830
	Cluster 2	25	0.237	0.028	0.180	0.294
2014	Cluster 1	24	0.799	0.027	0.744	0.854
	Cluster 2	23	0.250	0.028	0.194	0.306

Std Error uses a pooled estimate of error variance

Figure 2. HF-FHSs by clusters and years

In the last stage of the study, the correlation between HF-FHS scores found by FCM method and Altman Z scores was investigated. Figure 3 shows that there is a significant positive correlation between the two years scores ranging from 0.7482 and 0.7805.

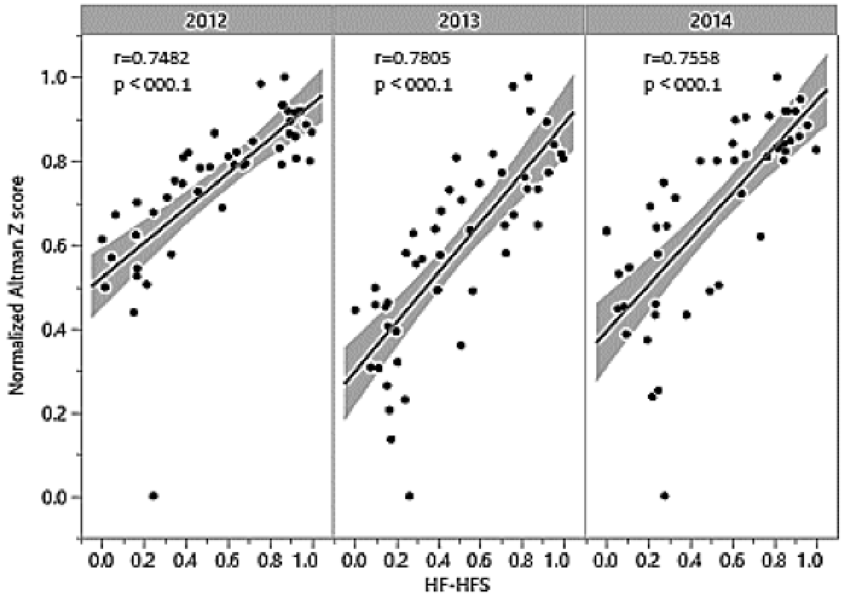


Figure 3. The relationship between HF-FHS and Altman Z Score by year

4.DISCUSSION

This study analyzed financial statement information from 47 public teaching hospitals for the years 2012-2014 by using Fuzzy Clustering Algorithms. In addition, models were developed to predict the financial failure of hospitals. Overall results suggest that between the years of 2012 – 2014, there has been an increase in the number of hospitals experiencing financial difficulties every year compared to the previous years (2012:0.38; 2013:0.53; 2014:0.48) (Figure 2). On the other hand, Their financial value is better for Cluster 1 than the hospitals classified in Cluster 2 (Table 4). Correlation between FCM and Altman Z scores also confirms the result (Figure 3).

The findings on differences between two clusters regarding the financial ratios also call for some interpretation based on the evolution of Turkey's healthcare system during the study years. The Cluster 2 hospitals (those experiencing financial difficulties) exhibited worse financial performance based on ratios including Q.R., APS, FLR, OPXR, and ROA compared to the other hospitals (Cluster 1). The ITR, ATR, and ART values achieved good financial results contrary to expectations (Figure 2). According to these results, the hospitals in Cluster 2 have Liquidity, Solvency, Profitability problems financially. Service sales/revenue volume of public teaching hospitals in Turkey is high. Therefore, it is considered natural that the ITR, ATR, and ART values, which are efficiency indicators, are higher than expected. Despite the high stock, asset, and collection rates that support service provision, profit rates remain very low or may result in loss from many service sales. This low-profit rate is due to the pricing of health services, which does not reflect the reality in Turkey; (Turk and Ertaş, 2018:272-97). Moreover, the reason for the low OPXR and ROA values of the hospitals in cluster 2 can be explained by the price-cost conflict.

Further evaluation of hospitals in the two clusters may provide additional insights into management practices. For example, comparing the financial risk status of the hospitals in Cluster 1 and Cluster 2, which have the same characteristics and operate in the same market, it can be said that hospitals in Cluster 1 exhibit better operational and managerial skills than the hospitals in Cluster 2. Because, in the healthcare market, where there is a pricing system that does not reflect the truth, the most critical reason why hospitals experience financial difficulties may be attributed to operational and managerial skills (Liu et al., 2011:31-68). Under these conditions, it is essential not to waste assets used in production, control costs and expenses, and collect receivables on time. The results of the study suggest that the hospitals in Cluster 1 meet these conditions compared to the hospitals in Cluster 2.

The overall increasing trend in financial disstress of hospitals across years for both clusters can be explained by the macroeconomic factors. Moreover, the rising trend in the number of hospitals experiencing financial difficulties over the years may cause some hospitals in Cluster 2 to fail to fulfill their obligations, which may disrupt the services provided. In such a situation, good management skills, which are the most important factor reducing the financial risks of hospitals, will not work after a certain point. Such an overall macroeconomic downfall can only be mitigated through macro-level policy changes or structural adjustments regarding the financial structures of hospitals (Langabeer et al., 2018:75-79).

This study findings provide some practical insights to the hospital managers. Considering the findings, it may be beneficial for hospital managers to explore more sophisticated analytical techniques similar to prefered models instead of relying only on financial ratios. Hospital managers would be able to assess the financial health of their organization and infer better-informed insights about operations and management by using methods that can rank and classify their risk by comparing them with generally accepted financial failure prediction methods such as Altman Z-score. In addition, the Ministry of Health officials should prevent the financial pressure on hospitals by pricing and reimbursement systems and other health policies, based on the increasing trend of financial problems in hospitals.

The use of only accessiable and outdated public teaching hospitals' financial reports while developing the financial failure prediction can be considered as a limitation of this study. Therefore, the findings cannot be generalized to other type hospitals and financial situations out of time horizon. However, the methodology that was used in this study can be applied to other types of hospitals and different time horizons to generate financial failure prediction models. Moreover, the financial prediction model was compared with the general financial parameter such as the Altman Z-score. The financial health score may differ when evaluated for a specific hospital in this context. Therefore, future similar studies may also examine other types of hospitals and may develop and use financial failure prediction models other than Altman Z-score.

5.CONCLUSION

This study has some limitations. Due to the small data set, results can not be generalized. The study period do not reflect the current status of the hospitals in Turkey. Moreover, this study theorizes financial failure as an output of some financial ratios. Thus, other organizational, operational, and environmental factors were not explored. On the other hand, the FCM method proposed in this study offers methodological robustness to reveal hospitals' financial status, proving correlations with the generally accepted financial failure prediction method, such as the Altman Z score. In addition, the FCM model is highly reproducible to update scores with new data. Hospitals still face financial pressures due to market and structural factors such as the global budget repayment system, pricing and collection time, and insufficient competition conditions. Hospitals experiencing financial difficulties can avoid this situation by using their assets efficiently, keeping their costs and expenses under control, collecting their receivables on time, paying their liabilities on time, and reducing their asset acquisition costs. Furthermore, predicting hospitals' financial failures through FCM models can help develop managerial policies and strategies to recognize and combat risks, improve performance, and improve the current situation of hospitals.

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APPENDICES:

Appendix A. Validity indices

Index	Formula
PE	$I_{PE}(U) = \frac{1}{n}\left(\sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}\, log_b(u_{ij})\right)$
XB	$I_{XB}(X;V,U) = \frac{\sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^2 \left\Vert x_j - v_i \right\Vert^2}{n\left(\min\limits_{1\le i,k\le c;\; i\ne k}\{\Vert v_i - v_k\Vert^2\}\right)}$
KWON	$I_K(X;V,U) = \frac{\sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^2 \left\Vert x_j - v_i \right\Vert^2 + \frac{1}{c}\sum_{i=1}^{c}\left\Vert v_i - \frac{1}{n}\sum_{l=1}^{n} x_l \right\Vert^2}{\min\limits_{i\ne k}\{\Vert v_i - v_k\Vert^2\}}$
FSIL	$I_{FSIL}(X;V,U) = \frac{\sum_{i=1}^{n}\left(u_{ij} - u_{ij'}\right)^{\alpha}\left(\frac{b_i - a_i}{\max(b_i, a_i)}\right)}{\sum_{i=1}^{n}\left(u_{ij} - u_{ij'}\right)^{\alpha}}$

In the formulas (Cebeci 2019);

vi : prototype (centres) vector for cluster *i*,

xj : feature vector for data point *j*,

d2(xj, vi) : Euclidean distances between prototype ***vi*** and the data point *xj*,

uij : fuzzy membership degree of data point *j* to the cluster *i*,

m : weighthing exponent for fuzziness,

c : an integer defining the number of clusters to be used in clustering.

Appendix B. Hospital cluster memberships vectors

ID	2012		2013		2014	
	Cluster 1	Cluster 2	Cluster 1	Cluster 2	Cluster 1	Cluster 2
H1	0.261	0.739	0.319	0.681	0.750	0.250
H2	0.398	0.602	0.289	0.711	0.493	0.507
H3	0.620	0.380	0.253	0.747	0.244	0.756
H4	0.252	0.748	0.256	0.744	0.245	0.755
H5	0.411	0.589	0.346	0.654	0.289	0.711
H6	0.921	0.079	0.819	0.181	0.728	0.272
H7	0.833	0.167	0.787	0.213	0.816	0.184
H8	0.302	0.698	0.267	0.733	0.234	0.766
H9	0.328	0.672	0.211	0.789	0.323	0.677
H10	0.465	0.535	0.444	0.556	0.766	0.234
H11	0.745	0.255	0.701	0.299	0.756	0.244
H12	0.856	0.144	0.516	0.484	0.776	0.224
H13	0.900	0.100	0.752	0.248	0.556	0.444
H14	0.860	0.140	0.826	0.174	0.734	0.266
H15	0.445	0.555	0.581	0.419	0.421	0.579
H16	0.129	0.871	0.517	0.483	0.750	0.250
H17	0.164	0.836	0.474	0.526	0.695	0.305
H18	0.140	0.860	0.223	0.777	0.600	0.400
H19	0.852	0.148	0.660	0.340	0.549	0.451
H20	0.876	0.124	0.846	0.154	0.723	0.277
H21	0.596	0.404	0.212	0.788	0.141	0.859
H22	0.440	0.560	0.255	0.745	0.212	0.788
H23	0.879	0.121	0.355	0.645	0.584	0.416
H24	0.838	0.162	0.628	0.372	0.559	0.441
H25	0.936	0.064	0.548	0.452	0.225	0.775
H26	0.678	0.322	0.284	0.716	0.130	0.870
H27	0.685	0.315	0.261	0.739	0.101	0.899
H28	0.818	0.182	0.557	0.443	0.600	0.400
H29	0.381	0.619	0.788	0.212	0.659	0.341
H30	0.890	0.110	0.872	0.128	0.725	0.275
H31	0.546	0.454	0.441	0.559	0.255	0.745
H32	0.181	0.819	0.139	0.861	0.122	0.878
H33	0.328	0.672	0.315	0.685	0.366	0.634
H34	0.265	0.735	0.498	0.502	0.278	0.722
H35	0.650	0.350	0.756	0.244	0.795	0.205
H36	0.509	0.491	0.332	0.668	0.257	0.743
H37	0.881	0.119	0.674	0.326	0.487	0.513
H38	0.643	0.357	0.377	0.623	0.250	0.750
H39	0.828	0.172	0.760	0.240	0.755	0.245
H40	0.713	0.287	0.741	0.259	0.811	0.189
H41	0.566	0.434	0.703	0.297	0.685	0.315
H42	0.943	0.057	0.431	0.569	0.053	0.947
H43	0.891	0.109	0.879	0.121	0.843	0.157
H44	0.825	0.175	0.670	0.330	0.878	0.122
H45	0.266	0.734	0.194	0.806	0.283	0.717
H46	0.265	0.735	0.424	0.576	0.460	0.540
H47	0.502	0.498	0.247	0.753	0.097	0.903