Accounting and Auditing with Application

www.aaa.reapress.com

Acc. Aud. Appl. Vol. 2, No. 3 (2025) 216–227.

Paper Type: Original Article

Forecasting the Financial Bankruptcy of Iranian Listed Companies Using a Hybrid DEA–PCA Approach

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Citation:

Received: 07 March 2025 *Revised: 13 June 2025* *Accepted: 16 July 2025*	Shahriari, M. R., Zare-Talab, A., Mahmoudiar, M. A., & Sajjadi Jagharq, S. A. (2025). Forecasting the financial bankruptcy of Iranian listed companies using a hybrid DEA–PCA approach. *Accounting and auditing with application,* 2(3), 216-227.

Abstract

The topic of predicting company bankruptcy has attracted significant interest among financial researchers and experts. Given the significant impact of financial distress on companies' stakeholders, the development of accurate methods and models for forecasting bankruptcy and financial failure remains a key area of financial research. Investors consistently expect their capital to be secure and to receive returns that reflect the risks undertaken. Furthermore, the ability to predict financial crises in companies promptly to prevent capital losses is critical. To address this need, researchers have conducted extensive studies employing various models and methods to evaluate corporate financial performance and forecast bankruptcy. However, it is essential to note that no single method is sufficient on its own; the best outcomes are achieved by combining multiple approaches with expert professional judgment. One technique that has gained increased attention in recent years for facilitating financial decision-making processes is Data Envelopment Analysis (DEA), which has produced acceptable predictive results. In this study, 52 manufacturing companies listed on the Tehran Stock Exchange were selected from three sectors: food and pharmaceuticals, metals, automotive and machinery, and chemicals and petrochemicals. Specifically, the first group included 21 companies (10 bankrupt and 11 healthy); the second, 18 (10 bankrupt and 8 healthy); and the third, 13 (7 bankrupt and 6 healthy). The primary objective of this research is to evaluate the DEA model's ability to predict bankruptcy, i.e., to classify companies according to their financial distress status. To improve the performance of the DEA model, Principal Component Analysis (PCA) was used to reduce the dimensionality of its input variables.

Keywords: Data envelopment analysis, Principal component analysis, Stock market, bankruptcy.

1 | Introduction

The topic of predicting company bankruptcy has attracted significant interest among financial researchers. Traditionally, bankruptcy prediction has relied on financial ratios and multiple discriminant analysis models.

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10.22105/aaa.vi.76

The most well-known of these is Altman's [1] Z-Score model. According to one study, Altman's [1] model achieved prediction accuracies of 95% and 83% one and two years before bankruptcy, respectively.

Past research has employed artificial neural networks. These models have generally produced more accurate forecasts than other methods [2]. *Table 1* provides a brief overview of the key aspects of previous research into predicting corporate bankruptcy. The following study has been conducted in the field of Data Envelopment Analysis (DEA) in recent years:

Badi Zadeh and Farzipour Saen [3] developed a network DEA model to analyze undesirable outputs and calculate production line efficiency. Hua and Bin [4] examined the relationships between DMUs and sub-DMUs, assuming the presence of undesirable outputs. They also presented an NDEA model to calculate the total and partial efficiency of DMUs. Badi Zadeh et al. [5] developed a DEA network model to calculate efficiency in optimistic and pessimistic terms. Their proposed model could combine undesirable outputs and rank supply chains according to efficiency scores. They demonstrated the model's effectiveness through a case study. Najafi et al. [6] presented an integrated framework combining balanced scorecard and DEA models to measure efficiency over time, based on time-lagged Key Performance Indicators (KPIs), for a proposed BSC model. The causal relationships between the BSC model perspectives over time were initially mapped as a dynamic BSC. After identifying the NDEA structure, they developed a new objective function to measure the efficiency of nine refineries affiliated with the National Iranian Petroleum Refining and Distribution Company over time and with strategies [7].

Rahmani et al. [8] used a novel hybrid approach to evaluate the efficiency score of two-stage manufacturing processes, where the required model data are imprecise. Their proposed method considers the expected value intervals as fuzzy. It uses the convex combination of the two endpoints to measure the efficiency of each stage and the overall efficiency score for different values of α.

Since 1994, the DEA model has been incorporated into bankruptcy prediction models. This model has been found to be effective for bankruptcy prediction when used alongside other methods, such as regression [9]. In 2004, this model was used independently for prediction and demonstrated high accuracy. Subsequently, DEA models, which had previously been used only to measure efficiency within identical sets, received greater attention due to their high accuracy in predicting bankruptcy in early research and their other advantages. *Table 2* presents research conducted abroad in the field of bankruptcy prediction using DEA. Fewer studies have been conducted domestically in bankruptcy prediction than abroad. Only one study has been conducted on prediction using DEA. The following is a list of the most important domestic studies.

Other studies have generally used models designed abroad without changing the coefficients, which does not seem very accurate given the environmental differences (i.e., the differences in Iran's economic environment). Previous foreign and domestic studies have analyzed all companies together. Given the nature of the DEA, which requires all members of the Decision Making Unit (DMUs) to be homogeneous, this is a weakness of previous studies. For this reason, this study selects manufacturing companies listed on the stock exchange as the statistical population and places them in three categories: Food and pharmaceutical industries; metal and automotive industries; and machinery, chemical, and petrochemical industries. Manufacturing companies listed on the stock exchange increase the accuracy and generalisability of the analysis, thereby addressing the main problem of previous research. Using the Principal Component Analysis (PCA) technique also helps reduce the dimensionality of the inputs in the DEA model and prevent an artificial increase in DMU efficiency.

The advantages of this method include the simultaneous calculation of companies' efficiency, their ranking, and the prediction of their bankruptcy. Compared with other methods based on recent research, this method is more accurate. Further research is required to examine the predictive power of this model, and this research has also been conducted in this direction.

2 | Statement of the Problem

Many studies have been conducted on predicting corporate bankruptcy, yielding various results. These are discussed in more detail in the research background section. However, financial researchers have always been attracted to new methods and, of course, to old models in new formats. The simpler and more understandable these models are, the more they are favored. One model that has recently received more attention for predicting companies' financial futures is the DEA model proposed by Staňková and Hampel [10].

This model predicts whether a company will be healthy or bankrupt in the future by measuring its efficiency. A key issue in previous studies is that all companies were grouped for analysis. Given the nature of DEA, which requires all DMUs in the set to be homogeneous, this is one of the weaknesses of previous research. This study attempts to address this issue by categorizing companies. Categorizing allows the predictive ability of each category to be evaluated separately, providing a more comprehensive assessment of the model's effectiveness in predicting companies' financial status [11].

2.1 | Combining Data Envelopment Analysis and Principal Component Analysis

Since its introduction by Charnes et al. [12], DEA has been used as an effective tool for evaluation and modeling. In this method, the relative efficiency of each DMU is calculated by comparing it with similar units, using the weighted output ratio divided by the weighted input ratio [13]. However, the number of units that can be evaluated is limited by the number of input and output variables. Consequently, the greater the number of variables, the less powerful the analysis will be in distinguishing between efficient and inefficient units [14]. In such cases, it is therefore necessary to reduce the number of variables used in the DEA model. Obviously, such a reduction should have the least possible effect on distinguishing between efficient and inefficient units. Based on an empirical formula [15]:

$$(\text{output} \times \text{input}) \times 3 < \text{units under evaluation}. \quad (1)$$

If the DMUs are more than three times the sum of the inputs and outputs, the problem's dimensions need to be reduced. The outputs need to be reduced on purpose (Otherwise, a large number of units will be on the efficiency frontier, their efficiency will be unity, and incorrect results will be produced, which will lower the quality of the model). To this end, Jenkins et al. [14] employed the partial covariance matrix to eliminate highly correlated variables. Alternatively, Alder et al. [16] used the PCA method to replace the main outputs or inputs entering the DEA model with input- and output-oriented principal components. This approach has also been used to evaluate privatized airline networks, to measure airport quality [17], and to select DEA variables and models [18]. Bruce et al. [19] used a similar approach to that of Cinca et al. [18] to evaluate performance in the internet banking industry using PCA and DEA methods.

These studies led to the development of a combined DEA-PCA model to reduce dimensionality within each category, rank DMUs, and ultimately predict bankruptcy. To achieve this, information relating to inputs and outputs is first extracted. Then, the ratio of single outputs to single inputs is calculated, and the PCA method is applied to this ratio. Selecting the first few principal components appropriately achieves the necessary reduction in the number of variables. The selected principal components are then used as inputs in the DEA model. This method works well in many applications where the number of units to be evaluated is small compared to the number of input and output variables, to the extent that other methods cannot provide a meaningful analysis [20].

2.2 | Proposed Methodology

As mentioned in the introduction, previous foreign and domestic research has shown that, to predict bankruptcy using the DEA model, all companies are placed into a single group and analyzed. However, because the DEA requires all members of the set of DMUs to be homogeneous, this approach has been criticized as a weakness of previous research. For this reason, this research selects manufacturing companies listed on the stock exchange as the statistical population, grouping them into three categories: food and pharmaceutical companies; metal, automotive, and machinery companies; and chemical and petrochemical companies. The stock exchange increases the accuracy and generalisability of the analysis. This classification is based on production systems and similar risks for each category. For example, food and pharmaceutical companies in the same category have a continuous production system, similar raw material storage (Perishables), and similar product distribution and transportation. Consequently, they have similar financial and non-financial risks. The second category is also similar in terms of the main raw material (Metals) and production, storage, and distribution systems. The third category includes companies not in the first two groups, including chemical and petrochemical factories [21].

These factories are not dependent on the metal industry, and most of them operate on a continuous production system. They have also been empirically proven to be dependent on economic conditions and oil prices in terms of financial risks. Of course, companies listed on the stock exchange are classified in various ways in books and on websites. This general classification of manufacturing companies is just one example. First, inputs and outputs are extracted from existing sources for each category, namely the companies' financial statements (Profit and Loss Statement and Balance Sheet). Inputs include operating expenses, current liabilities, and financial expenses, while outputs include net profit, operating profit, and current assets. These inputs and outputs have been selected based on past research and available sources. These inputs and outputs have been selected based on past research and available sources [22].

Then, the ratio of each output to input is calculated separately for each company, yielding nine financial ratios. Given the incremental nature of these ratios, where the larger the fraction, the greater the utility, these ratios are considered a type of output. Therefore, the DEA model used in this study has no inputs. For this reason, we set the inputs of all DMU to the same value. In fact, setting any other constant value produces the same result. According to Mehregan's [15] empirical formula, we need to reduce the problem's dimensionality and deliberately reduce the number of outputs.

Otherwise, a large number of units will be on the efficiency frontier, falsely suggesting that they are all equally efficient, thereby lowering the quality of the model. Therefore, we use a dimensionality reduction technique to reduce the number of outputs for each category. The best technique for this is PCA. We use the PCA model's output as input to the DEA model. Given the nature of the inputs and outputs, the DEA model used in this study should be an output-oriented BCC model. Changes in inputs do not cause proportional changes in outputs, and returns to scale vary; therefore, the BCC model is more appropriate. Considering that DEA inputs are fixed in this study and the goal is to maximize output to increase efficiency, an output-oriented model should be used. The following are the multiplicative and enveloping BCC models, respectively.

$$
\begin{aligned}
&\min \sum_i v_i x_{ip} + v'_p = \phi_{p,} \\
&\text{s.t.} \\
&\sum_r u_r y_{rp} = 1, \\
&\sum_i v_i x_{ij} - \sum_r u_r y_{rj} + v'_p \geq 0 \text{ for all j}, \\
&u_r, v_i \geq \varepsilon, v'_p \text{ free.}
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
&\max \phi_p + \varepsilon\left[\sum_i s_i^- + \sum_r s_r^+\right], \\
&\sum_j \lambda_j y_{rj} - s_r^+ = \phi_p y_{rp} \text{ for all r},
\end{aligned}
\tag{2}
$$

$\sum_j \lambda_j = 1, \sum_j \lambda_j x_{ij} + s_i^- = x_{ip}$ for all i, $\lambda_j, s_i^-, s_r^+ \geq 0, \phi_p$ free.

The number obtained from the DEA model is an efficiency score between 0 and 1. Based on the breakpoint in the sample, a prediction is made about the company's bankruptcy risk or financial health. To use the calculated efficiency score for companies, a point between 0 and 1 must be introduced that best separates healthy companies from bankrupt ones (the model breakpoint), in such a way that classification error is minimized. If a company's efficiency number exceeds the breakpoint, it is considered healthy; if it falls below it, it is considered bankrupt.

The general assumption is that healthy, efficient companies have higher efficiency scores, close to 1. In fact, their score should be higher than that of inefficient companies, which should be close to zero. The goal is to measure the model's ability to predict bankruptcy 1 and 2 years before the event. To this end, the "year of occurrence" for each distressed company is first extracted from Law 141 of the Trade. To give healthy companies a specific year of occurrence, too, the distressed company's year of occurrence is determined, and then, among the healthy companies in the same group, companies of a similar size will also have the same year of occurrence.

Then, the required financial information for the 1 and 2 years before the year of occurrence is prepared and entered into the model. To determine the cut-off point, the financial information for the year of occurrence for each of the three groups is entered into the model to obtain the efficiency score for each group. A graph showing the distribution of efficiency scores for both the healthy and bankrupt categories is then drawn. The intersection point of these two graphs (Where the least classification error occurs) will be the cut-off point and the basis for prediction. As previously mentioned, if a company's efficiency number exceeds its category's cut-off point, it is considered healthy; if it falls below it, it is considered bankrupt.

In a previous study, the number 0.5 was chosen as the cut-off point without any specific calculation or rationale. That is, if a company's efficiency score was greater than 0.5, it was considered healthy; if it was less than 0.5, it was predicted to be bankrupt. However, this study uses the same method (For higher accuracy).

This comparison is made for one and two years before the year of occurrence to test the model's ability to predict past events. Finally, the model's accuracy is determined by examining the percentage of bankrupt and healthy companies it correctly predicted 1 and 2 years before the year of occurrence. Then, a proportion test at the 95% level is used to test the research hypotheses and see whether the model correctly classifies the companies according to the expected percentage.

$$\frac{(p - p_0)}{\left(\frac{p_0 q_0}{n}\right)^{0.5}}. \tag{3}$$

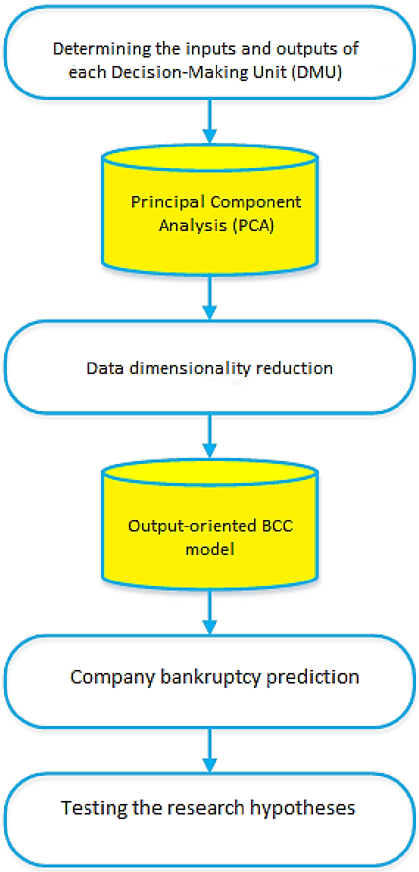
In this formula, p is the percentage of companies correctly classified by the model. P0 is the expected accuracy percentage, set at 0.5 based on previous research. Q0 is defined as 1-P0. At a 95% confidence level, we examine whether there is a significant difference in the predicted ratios across the three groups. If there is a difference, we can conclude that this model can help predict bankruptcy in some groups, but not necessarily in all.

$$\frac{p_1 - p_2}{\left(\left(\frac{p_1 q_1}{n_1}\right) + \left(\frac{p_2 q_2}{n_2}\right)\right)^{0.5}}. \tag{4}$$

In this formula, P1 and P2 correspond to two of the three groups, making a total of three pairwise comparisons for each year. *Fig. 1* shows the general research procedure based on the above explanation.

Fig. 1. Conceptual research model.

2.3 | Research Variables



The independent variables in this study are financial ratios used to classify companies as either bankrupt or healthy. The efficiency score obtained from the DEA model can also be considered an independent variable. Finally, a company's classification as healthy or bankrupt, which is a function of the efficiency score, is considered a dependent variable.

3 | Implementation of the Proposed Methodology and Analysis of the Findings

According to available information, 52 manufacturing companies listed on the Tehran Stock Exchange were selected into three groups: food and pharmaceutical companies; metal, automotive, and machinery companies; and chemical and petrochemical companies. Twenty-one companies (Ten bankrupt and eleven healthy) were in the first group, eighteen companies (Ten bankrupt and eight healthy) were in the second group, and thirteen companies (Seven bankrupt and six healthy) were in the third group. The names and information of these companies were extracted from the Kodal website.

First, to calculate the cut-off point for the companies in the first group, we entered the financial information for the year in which the companies in this group became bankrupt or healthy into the model. *Fig. 2* shows the distribution of efficiency scores for Financial health and bankrupt companies in the first group.

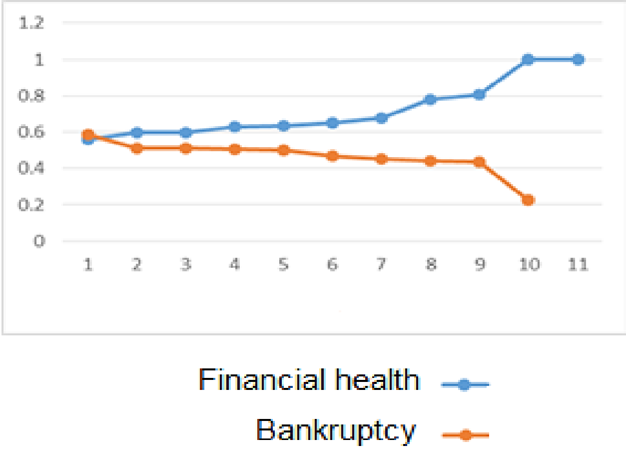


Fig. 2. Efficiency score distribution chart of the first group of companies.

According to *Fig. 1*, the cut-off point for this group is 0.59. As shown in the chart, as expected, the efficiency score of healthy companies increases and approaches 1 from the cut-off point onward. In contrast, the efficiency score of bankrupt companies decreases and approaches 0 (in fact, the lowest classification error occurs). As stated in Section 2, the process begins by extracting inputs and outputs from existing sources, namely the companies' financial statements (Profit and Loss Statement and Balance Sheet). Inputs include operating expenses, current liabilities, and economic expenses; outputs include net profit, operating profit, and current assets. The ratio of each output to input is then obtained for each company separately, of which there are nine in total. This number is very small due to the limited number of DMUs (Companies), which leads to errors in the DEA model. Therefore, they are reduced by PCA and then entered into the output-oriented BCC DEA model. Finally, an efficiency score is obtained, which is a number between 0 and 1.

Based on the calculations, the model correctly predicted 73% of healthy companies and 90% of bankrupt companies 1 year before the event. In the two years before the event, the model correctly predicted 73% of Financial health companies and 80% of bankrupt companies. *Fig. 3* shows the calculation of the breakpoint for the metal, automobile, and machinery companies group.

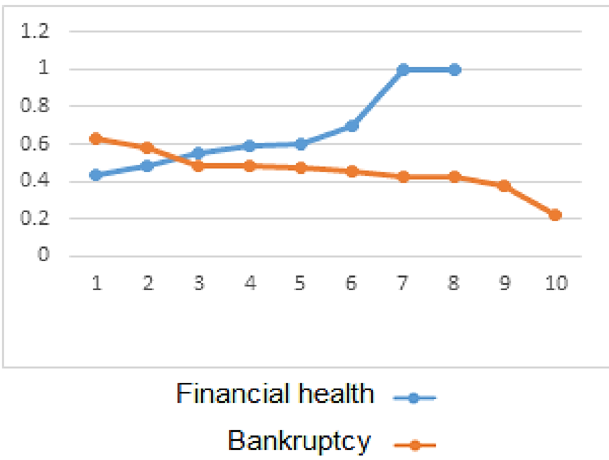


Fig. 3 Efficiency score distribution chart of companies in the second group.

As shown, the breakpoint value for this group is 0.52. One year before the event, the model correctly predicted 100% of healthy companies and 10% of bankrupt companies. Two years before the event, it correctly predicted 75% of Financial health companies and 80% of bankrupt companies.

Fig. 4 shows the calculation of the breakpoint for the group of chemical and petrochemical companies.

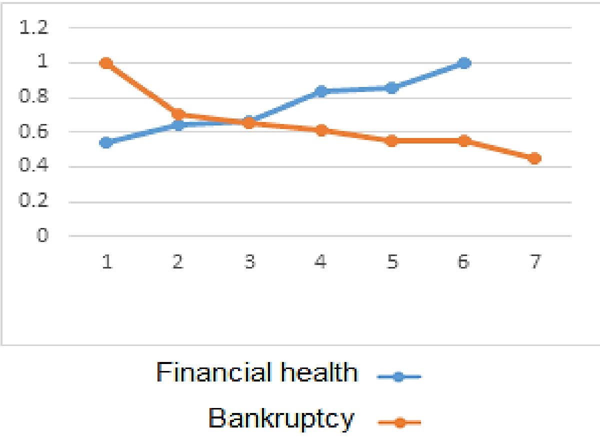


Fig. 4. Efficiency score distribution chart of third group companies.

As shown, the cut-off value for this group is 0.65. One year before the event, the model correctly predicted 83% of healthy companies and 85% of bankrupt companies. Two years before the event, it correctly predicted 34% of financial health companies and 71% of bankrupt companies.

At this stage, we will test the following hypotheses:

Hypothesis 1.

H0: It is not possible to predict bankrupt companies in the food and pharmaceutical industries on the stock exchange using a combination of DEA and PCA models.

H1: It is possible to predict bankrupt companies in the food and pharmaceutical industries on the stock exchange using the DEA-PCA model combination.

This hypothesis was tested using a 95% confidence interval test, and the results are shown in *Table 1*.

Table 1. Results obtained for Hypothesis 1.

Year	Percentage of Correct Predictions by the Model (Percentage)	Expected Percentage	Z Value	Result
One year before the event for healthy companies	73	50	1.526	H0 confirmed
One year before the event for bankrupt companies	90	50	2.530	H1 confirmed
Two years before the event for healthy companies	73	50	1.526	H0 confirmed
Two years before the event for bankrupt companies	80	50	1.897	H1 confirmed

As can be seen, the model can predict which companies in the first group (On the verge of bankruptcy) will go bankrupt one or two years before it happens. However, it cannot predict which Financial health companies will go bankrupt.

Hypothesis 2.

H0: It is not possible to predict bankrupt companies in the metal industry, or in the automobile and machinery sectors of the stock exchange, using the combination of DEA and PCA models.

H1: It is possible to predict bankrupt companies in the metal, automotive, and machinery industries on the stock exchange using the combination of DEA and PCA models. The results related to Hypothesis 2 are reported in *Table 2*.

Table 2. Results obtained for Hypothesis 2.

Year	Percentage of Correct Predictions by the Model (Percentage)	Expected Percentage	Z Value	Result
One year before the event for healthy companies	100	50	2.828	Confirm H1
One year before the event for bankrupt companies	10	50	-2.530	Confirm H0
Two years before the event for healthy companies	75	50	1.414	Confirm H0
Two years before the event for bankrupt companies	80	50	1.897	Confirm H1

According to the second hypothesis, the model can predict critical situations for the second group of companies over the previous two years, but not over the previous year. Regarding the companies' financial health, the model correctly predicted 100% in the previous year but could not produce reliable results in the two years before the event.

Hypothesis 3.

H0: It is not possible to predict which chemical and petrochemical companies will go bankrupt on the stock exchange using a combination of DEA and PCA models.

H1: It is possible to predict bankrupt chemical and petrochemical companies on the stock exchange using the DEA-PCA model combination. The results obtained for *Hypothesis 3* are presented in *Table 3*.

Table 3. Results obtained for Hypothesis 3.

Year	Percentage of Correct Predictions by the Model (Percentage)	Expected Percentage	Z-Value	Result
One year before the event for healthy companies	83	50	1.746	Confirm H1
One year before the event for bankrupt companies	85	50	1.852	Confirm H1
Two years before the event for healthy companies	34	50	-0.847	Confirm H0
Two years before the event for bankrupt companies	71	50	1.111	Confirm H0

For the third group of companies, the model predicted healthy and bankrupt companies accurately in the year before the event, but was unable to distinguish between them in the two years before that.

Hypothesis 4.

H0: There is no significant difference in the ability to distinguish between healthy and bankrupt companies across the three groups.

H1: There is a significant difference between the results obtained from the three groups when distinguishing between healthy and bankrupt companies. The results for Hypothesis 4 are reported in Table 4, which presents a comparative analysis of the three groups.

Table 4. Results obtained for Hypothesis 4.

Year	Comparison	Z-Value	Result
One year before the event	1 with 2	5.96	Confirm H1
Year	1 with 3	0.303	Confirm H0
	2 with 3	-4.546	Confirm H1
One year before the event	1 with 2	0	Confirm H0
	1 with 3	0.422	Confirm H0
	2 with 3	0.422	Confirm H0

As shown in the table, there is a significant difference in the results obtained from the three groups one year before the event. In contrast, there is no significant difference in the results obtained two years before the event. The following analyses can be presented considering the results obtained in the three groups:

Due to their structure, food and pharmaceutical companies lose customers continuously over time if they perform poorly and are unable to meet their needs. Losing customers is reflected directly in their financial indicators, so their financial performance can be used to predict their future performance.

It should be noted that, due to fluctuations in basic metal prices and exchange rates, financial crises are somewhat more difficult to predict in this group of companies. Also, the low cut-off point for this group is due to the companies in the sample having low efficiency scores in the year of occurrence. A low efficiency score in the sample means that the current results may differ slightly in other samples. Fluctuations in oil prices and exchange rates strongly impact companies whose raw material is oil or whose competitors are imported goods. The severe fluctuations in oil prices over the ten years covered by this study have caused instability among companies in groups two and three, which is perhaps why the model used in the study, which relies mainly on financial indicators, has not been very effective in predicting the financial situation and crises of these two groups.

4 | Conclusion

Various methods and models, such as Altman's [1], the multiple diagnostic method, and artificial neural networks, have been used to predict bankruptcy, yielding different results. Some methods have produced successful predictions, while others have failed. Using the DEA model with an efficiency score is a new method for predicting bankruptcy, and results have been mixed so far. Therefore, more research is needed to investigate the effectiveness of this model.

Although the DEA model is usually used to assess the efficiency of homogeneous or similar groups, in previous studies, all companies were placed in a single group for evaluation. In this study, it was decided to create smaller groups and evaluate manufacturing companies operating in similar fields separately. More financial indicators were also used than in previous studies. However, if the number of DMUs (I.e., manufacturing companies in each group) in the DEA models is close to the total number of inputs and outputs, this can cause problems with the model's results. Therefore, a method was needed to reduce the dimension; this is why the PCA statistical method was employed. The PCA statistical method increased the model's generalisability, as it allows more groups to use it.

A similar study, which evaluated all companies together using a DEA model, showed that bankruptcy could be predicted up to 2 years in advance. However, it was unclear which group of companies the model was most effective at predicting, and the results were general. In the current study, however, we see that the results for different groups vary, and that the BCC DEA model, using the PCA statistical technique, performs better at predicting the bankruptcy of food and pharmaceutical companies, with an accuracy of up to two years (Based on Law 141 of the trade). This model can predict the bankruptcy of chemical and petrochemical companies up to 1 year in advance. However, its performance in predicting company bankruptcies in the metal, automotive, and machinery industries is lower. Instead, it accurately predicts the health of companies in this group. The results of this study show that classifying companies by function and the risks they face, and evaluating them separately using the model, can yield acceptable results and provide researchers with more complete information. It is important to note that one should never rely solely on any bankruptcy prediction method, including the one proposed in this study, even if it has previously produced successful results, because predictions are never guaranteed. To increase the likelihood of a successful prediction, several mathematical and statistical methods and models should always be used alongside fundamental analysis (Interpretation and prediction of the future based on political, economic, military, and social issues).

Authors' Contributions

The authors carried out all aspects of the research and manuscript preparation. The authors have read and approved the final version of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

Funding

This research received no specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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