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EMPLOYING ARTIFICIAL NEURAL NETWORKS AND MULTIPLE DISCRIMINANT ANALYSIS TO EVALUATE THE IMPACT OF THE COVID-19 PANDEMIC ON THE FINANCIAL STATUS OF JORDANIAN COMPANIES

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ABSTRACT

Aim/Purpose	This paper aims to empirically quantify the financial distress caused by the COVID-19 pandemic on companies listed on Amman Stock Exchange (ASE). The paper also aims to identify the most important predictors of financial distress pre- and mid-pandemic.
Background	The COVID-19 pandemic has had a huge toll, not only on human lives but also on many businesses. This provided the impetus to assess the impact of the pandemic on the financial status of Jordanian companies.
Methodology	The initial sample comprised 165 companies, which was cleansed and reduced to 84 companies as per data availability. Financial data pertaining to the 84 companies were collected over a two-year period, 2019 and 2020, to empirically quantify the impact of the pandemic on companies in the dataset. Two approaches were employed. The first approach involved using Multiple Discriminant Analysis (MDA) based on Altman's (1968) model to obtain the Z-score of each company over the investigation period. The second approach involved developing models using Artificial Neural Networks (ANNs) with 15 standard financial ratios to find out the most important variables in predicting financial distress and create an accurate Financial Distress Prediction (FDP) model.
Contribution	This research contributes by providing a better understanding of how financial distress predictors perform during dynamic and risky times. The research confirmed that in spite of the negative impact of COVID-19 on the financial

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	health of companies, the main predictors of financial distress remained relatively steadfast. This indicates that standard financial distress predictors can be regarded as being impervious to extraneous financial and/or health calamities.
Findings	Results using MDA indicated that more than 63% of companies in the dataset have a lower Z-score in 2020 when compared to 2019. There was also an 8% increase in distressed companies in 2020, and around 6% of companies came to be no longer healthy. As for the models built using ANNs, results show that the most important variable in predicting financial distress is the Return on Capital. The predictive accuracy for the 2019 and 2020 models measured using the area under the Receiver Operating Characteristic (ROC) graph was 87.5% and 97.6%, respectively.
Recommendations for Practitioners	Decision makers and top management are encouraged to focus on the identified highly liquid ratios to make thoughtful decisions and initiate preemptive actions to avoid organizational failure.
Recommendations for Researchers	This research can be considered a stepping stone to investigating the impact of COVID-19 on the financial status of companies. Researchers are recommended to replicate the methods used in this research across various business sectors to understand the financial dynamics of companies during uncertain times.
Impact on Society	Stakeholders in Jordanian-listed companies should concentrate on the list of most important predictors of financial distress as presented in this study.
Future Research	Future research may focus on expanding the scope of this study by including other geographical locations to check for the generalisability of the results. Future research may also include post-COVID-19 data to check for changes in results.

Keywords	financial distress prediction, COVID-19, ANN, MDA, Jordan

INTRODUCTION

The novel coronavirus (COVID-19), which originated in Wuhan in China, has spread to nearly every country on the globe, and to date, it has infected over 659 million people and resulted in over six million deaths (World Health Organization [WHO], 2022). Significant levels of mental health issues, anxiety, depression, and burnout among workers in companies during the pandemic were reported (Northwood et al., 2021). Schools and universities were no exception. Studies have reported that students, administrators, and teachers had lower levels of happiness and quality of life (Karakose, Yirci, et al., 2022; Odriozola-González et al., 2020), as well as a notable rise in loneliness and internet and social media addiction due to COVID-19 isolation (Karakose, Ozdemir, et al., 2022).

In terms of the global economy, the COVID-19 pandemic took a heavy toll on economies and financial markets. Estimates indicate that the pandemic decreased worldwide economic growth in the year 2020 by an annualized rate of approximately 3.2%, with global trade also falling by 5.3% (Jackson, 2021). Major adjustments in the capital structure of companies as a result of the COVID-19 pandemic started to be noticed, reviewed, and detailed (Goodell, 2020), which led to the reporting of massive drops in return on capital levels, as well as increased levels of risk due to the severe rise in COVID-19 cases (Ashraf, 2020; Zhang et al., 2020).

Like many other countries, the impact of the COVID-19 pandemic in Jordan was not noticed until 2020. Unlike in many other countries, Jordan's response to the pandemic was swift and draconian – the likes of which had not been seen since the early 1970s. The Jordanian government declared a state of emergency in March 2020, which resulted in massive restrictions along the borders, enforcement of daily curfews by the armed forces and other security forces, and imposing a mandatory quarantine on all incoming travelers. These strict measures massively reduced the number of new cases in the country and steered the country clear of a public health system collapse (Singh, 2020).

The aforementioned facts, coupled with similar lockdown measures in many other countries, had a huge toll on the Jordanian economy and workforce. Unemployment rates increased from 19% in 2019 to around 24% in 2020; a relative percentage increase of 26% (Department of Statistics, 2022). The International Monetary Fund (IMF) projected that Jordan's economy would shrink by 3.7% as a result of the pandemic (Abu-Mater et al., 2020). The service, hospitality, and tourism industries in the country were hit particularly hard, resulting in massive amounts of redundancies and reservation cancellations during peak seasons (Abu-Mater et al., 2020; Al-Nsour, 2021; Singh, 2020). The energy and construction industries were also adversely affected by the pandemic, leading to a decline in energy consumption, a drop in economic growth, an increase in unemployment levels, a rise in market instability, and an increase in financial distress within companies (Bsisu, 2020; Myyas & Almajali, 2022).

As is evident from the aforementioned statements, the COVID-19 pandemic has had a huge toll, not only on human lives, be it psychological or physical, but also on many businesses. This triggers the need for research exploring the economic and financial complexities the pandemic caused to companies. Such effort can be vital to identify the main financial variables that were affected by the pandemic, which allows focusing on their robustness to avoid future financial collapses.

This paper aims to understand the financial impacts of the COVID-19 pandemic in the Jordanian context by adopting a dataset comprised of companies listed on the Amman Stock Exchange (ASE) – as per the availability of data. The paper offers a significant contribution to the limited literature pertaining to the prediction of companies' financial health during the COVID-19 period, particularly in Jordan. It also provides decision-makers with the needed insight to plan any potential contingencies and develop suitable recovery strategies to control the long-term, negative implications of the pandemic. This was achieved through conducting a pioneering investigation focused on ASE companies using Multiple Discriminant Analysis (MDA) and Artificial Neural Networks (ANN) techniques. The constructed models assessed the financial status of companies listed on the ASE and presented the most important predictors of companies' financial distress.

The next section provides a chronological review of the literature on financial distress prediction, with a specific focus on ANNs as a useful technique in simulating connections between complex data, ending with the development of the research questions. Later, the methods and tools used in this study to collect and analyze data are presented, leading to the results, discussion, and conclusions.

LITERATURE REVIEW

EVOLUTION OF FINANCIAL DISTRESS PREDICTORS

Innumerable models have been developed over the years to deal with Financial Distress Prediction (FDP) using various techniques. They vary in methodologies; however, they generally aim to analyze variables and/or identify the most accurate predictions possible (Halteh, 2019).

FDP has been in existence ever since the early 1930s, pioneered by Fitzpatrick (1932), followed by Winakor and Smith (1935), who discovered that trends in financial ratios can cause financial distress. These studies were furthered by Beaver (1966) by forming the first statistical univariate analysis model. Beaver created a classification model using thirty financial ratios to identify the best cut-off point to minimize misclassification and defined a set of ratios with the best predictive power. Beaver's model was able to predict financial distress with an accuracy rate of over 80% for short-term predictions. Its accuracy, however, declined significantly for long-term predictions. Beaver's model was also criticized for the used ratios since they may result in contradictory predictions (Halteh, 2019).

Altman (1968) later founded the first multivariate statistical approach concerning FDP using Multiple Discriminant Analysis (MDA). Altman's model was developed to tackle the main challenge of Beaver's (1966) model, i.e., different ratios could result in contradictory predictions (Halteh, 2019). Altman formulated a single weighted score (Z) for each company based on five financial ratios. As per the result of the Z-weighted score, Altman was able to determine whether a company is healthy, distressed, or inconclusive. He classified a company as healthy if its corresponding Z-score was more than 2.99, distressed if its Z-score was less than 1.8, and inconclusive if its Z-score was between 1.8 and 2.99. Altman's model was superior to that of Beaver's, as the short-term accuracy surpassed 90%; however, this accuracy declines for long-term predictions (Halteh, 2019). MDA has been extensively used in many FDP studies, and despite being dated, it is still used in research, including Altman et al. (2017), Chung et al. (2008), Grice and Ingram (2001), Halteh (2019), Lee and Choi (2013).

Artificial Intelligence and Machine Learning in FDP

Artificial neural networks

Artificial Neural Networks (ANNs) are computerized techniques that are trained to simulate the cellular connections in the brains of humans (Hertz et al., 1991). ANNs consist of interconnected units that manage and assess the interactions between the units, which allows for handling complex data. ANNs assign weights to the inputs to accurately deduct the final outcome. This enables the model to overcome the issue of prespecifying interactions amongst independent variables (Dorsey et al., 1995).

Besides the ability to overcome the requirement for pre-specification of a functional form, ANNs do not require the inclusion of restrictive assumptions with regard to the properties of statistical distributions of the variables. ANNs are further able to operate with imprecise variables and can adapt to the presence of new cases in the dataset (Halteh, 2019).

ANNs have been recognized by many researchers as a useful technique to predict financial distress, to mention but a few: Ansari et al. (2020), Ciampi and Gordini (2013), Coats and Fant (1993), Le and Viviani (2018), Lee and Choi (2013), Odom and Sharda (1990), and Tan (2001). All these studies present results that show the empirical predictive superiority of ANNs when compared to MDA.

Decision trees

Decision trees are models that recursively divide a dataset into smaller partitions to create a set of tree-based classification rules. The rules are generated through a process of splitting data from a higher to lower level of the tree until it reaches leaf nodes that represent classification groups such as distressed or successful. In FDP, decision trees classify companies as either successful or distressed based on an expression compared to a cut-off point at each node (Halteh, 2019).

Decision trees have a drawback in that they do not provide precise probabilities of group membership, such as financial distress, except for a whole node. However, they have several benefits, including the ability to handle missing data, being invariant to monotonic alterations of input variables, and effectively handling outliers and mixed variables in the data (Halteh, 2019). Decision trees have been previously used in FDP modeling with varying levels of accuracy, but they tend to outperform MDA (Gepp & Kumar, 2015; Halteh, 2019).

Random forest

Random forest is a machine learning technique used for classification and regression analysis, which involves constructing multiple decision trees. The mode of the classifications from individual trees is used as output for classification, while the mean of the outputs from all trees is used for regression. It has several advantages over single trees, including its ability to handle mixed variables effectively, its invariance to monotonic transformations of input variables, its robustness to outlying observations, and its ability to adapt to various strategies for handling missing data (Chandra et al., 2009). Several studies have used random forests in FDP, and their results tend to outperform single trees and traditional statistical models (Fantazzini & Figini, 2009; Halteh & Tiwari, 2023).

Stochastic gradient boosting

Stochastic gradient boosting is a machine-learning technique used for regression and classification tasks. It involves constructing an ensemble of decision trees that are combined to make a final prediction. Stochastic gradient boosting models tend to provide a degree of accuracy that is typically not achievable by a single model or ensembles like bagging or conventional boosting (Halteh, 2019). This technique has been used in FDP modeling in previous studies and produced results that tend to be of remarkably high accuracy when compared to single trees and traditional models (Fantazzini & Figini, 2009; Halteh et al., 2018).

Machine learning techniques comparison

ANNs, decision trees, random forest, and stochastic gradient boosting are all machine learning algorithms used for classification and regression tasks. Despite being simple to understand and depict, decision trees may not be as accurate as alternative algorithms, especially for complicated datasets (Halteh, 2019). While they can handle complicated datasets and offer high accuracy, gradient boosting and random forest require greater computational power and more data processing. ANNs are especially helpful for issues involving vast volumes of data and intricate interactions between variables. Although some studies preferred using boosting machines and random forests (Barboza et al., 2017; Sakri, 2022), ANNs were found by other studies to have similar or higher empirical predictive superiority (Ahmad et al., 2017; Begum, 2022; Naidu & Govinda, 2018). Knowing this, coupled with the widespread use of ANNs in the financial prediction literature, this research has opted to adopt ANNs for FDP modeling.

Research Questions

As per the above-presented literature, this paper has the intent to investigate the impact of the COVID-19 pandemic on the financial health of companies listed on ASE. The paper also looks for the most predictive variables of financial distress preceding and during the pandemic. The paper thus investigates the following questions:

1. Did the financial distress of Jordanian companies increase during the year of the pandemic?
2. What are the most important predictors of financial distress, both pre and during the pandemic?
3. Did the financial distress predictors change pre and during the pandemic?

The following section provides an overview of the methodological choices that were used in this empirical study.

Materials and Methods

This research conducts a quantitative analysis of companies listed on the ASE using readily available archival financial data from the Capital IQ portal – a reputable database that provides online services. These services include collecting data on companies around the world and offering software applications that enable financial analysts to study company details, construct models, and execute other financial research tasks (Feldman & Zoller, 2016; Halteh, 2019; Halteh et al., 2018; Kahle & Stulz, 2013). Using online archival data allowed the extraction of wide-scale and comprehensive data and enabled the reproducibility of empirical tests in an efficient manner.

The initial dataset was downloaded from the Standard and Poor's (S&P) Capital IQ portal. It comprised 165 companies; however, after cleansing the data by omitting companies with missing information, the size of the final dataset was reduced to 84 companies. Financial data of the 84 companies was collected over a period of two years, 2019 and 2020. This was done to check the financial status of the companies in a pre-pandemic and mid-pandemic state.

Two approaches were conducted to assess the financial status of the investigated companies. The first approach involved the use of Altman's (1968) MDA model to obtain the Z-score of each company in the dataset over a two-year period. The second approach involved developing models using ANNs in order to find out the most important variables in determining financial distress and creating an accurate FDP model that can be applied to ASE companies. The employability of both approaches is discussed in detail below.

MDA Approach

Following the data collection and data cleansing processes, an MDA model was developed based on Altman's (1968) Z-score model. This was executed on each company over two years to compare the financial performance of companies before and during the COVID-19 pandemic. This was done by using the following equation:

$$Z = 1.2x_1 + 1.4x_2 + 3.3x_3 + 0.6x_4 + 1.0x_5$$

- Z: Discriminant score of a company;
- x_1: Working capital divided by total assets;
- x_2: Retained earnings divided by total assets;
- x_3: Earnings before interest and tax divided by total assets;
- x_4: Market value of equity divided by book value of total liabilities; and
- x_5: Sales divided by total assets.

This equation was derived from Altman's (1968) study. Note that x_1, x_2, x_3, x_4, and x_5 are operationalized measurements of the same five variables included in Altman's model: profitability, leverage, liquidity, solvency, and activity. The weights assigned to each variable in the equation are based on their relative importance in predicting financial distress, i.e., the higher the weight, the more important the corresponding variable is in predicting distress. These weights were also obtained from Altman's study, which was initially derived from the coefficients of the MDA analysis. The weights were selected based on the statistical significance of the ratios in predicting financial distress and optimizing the Z-score's capability to discriminate between healthy and distressed companies.

Despite multiple studies over the years adjusting the weights of the variables and/or including different ratios (Altman, 2013; Halteh et al., 2018; Jan & Marimuthu, 2015), more than 50 years later, Altman's model remains widely used in its original form for FDP because of its simplicity and relatively high predictive accuracy (Altman et al., 2017; Halteh, 2019; Panigrahi, 2019).

After the MDA, a count was conducted for every company in the dataset for the two years to ascertain the number of companies classified as distressed ($Z<1.8$). This classification criterion is based on Altman's (1968) study. Inversely, a count was conducted for every company in the dataset to ascertain the number of companies classified as healthy ($Z>1.8$). Note that the inconclusive category was not used when conducting the analysis; that is, companies that had a Z-score within the range of 1.8 to 2.99 were included in the healthy category. This decision was made based on four main reasons. First, to create a single dichotomous variable for efficient analysis. Second, excluding the companies that fell within the inconclusive category would result in a sample size that is too small to analyze effectively, thus leading to inaccuracies in results. Third, since this study focuses on the financial distress aspect of companies, this approach represents a conservative way of classification to ensure that only truly distressed companies are categorized as such. Fourth, this approach is more suitable for the current research context, Jordan, where there are a limited number of listed companies to be investigated. That said, it is important to acknowledge that this approach is not watertight, and other approaches could be used, such as excluding the inconclusive category altogether. However, as explained earlier, the decision to include the inconclusive companies within the healthy category was seen to be appropriate based on the characteristics of the research sample and context.

Subsequently, a comparison study was conducted to determine whether the Z-scores of the companies have been affected by the pandemic – this was done by performing two main analyses: Z-score comparison and ANN-based prediction.

Relative change and Z-score comparison

The Z-scores of the companies were compared between 2019 and 2020 and their differences were analysed using the relative change equation:

$$C = \left|\frac{y_2 - y_1}{y_1}\right| \times 100\%$$

- C = Relative change;
- y_1 = Final value; and
- y_2 = Initial value.

Following this, an analysis was conducted to determine whether the Z-score of the companies in the dataset have been affected by the pandemic; that is, comparing the Z-scores of the companies in 2019 and 2020, and checking whether the Z-score of companies has generally decreased, i.e., companies becoming more financially distressed.

ANN Approach

A binary variable was introduced to the dataset, which was formed using the Z-score derived for each company, as per the MDA model explained earlier. If the company's Z-score was less than 1.8, the company was deemed distressed, and a '1' was assigned to it. All other companies that did not meet this categorization were deemed healthy and thus assigned a '0'. This was done for the years 2019 and 2020. This dichotomous variable is represented as the dependent variable in the analysis.

Fifteen financial ratios were chosen in this study as the independent variables. The variables used in the study are standard accounting and financial variables that were selected based on their availability in the literature and their use in previous empirical research. Care was taken when choosing the variables to not include financial ratios that are included when calculating Altman's Z-score. This is because the Z-score was already chosen as the dependent variable; thus, including any financial ratio from the Z-score as an independent variable may cause those ratios to be misleadingly deemed of utmost importance when running the models since they would be a direct input into the dependent variable. For example, 'total assets turnover' (sales divided by total assets) was excluded from the list of variables since it was included in the calculation of the Z-score. The complete list of the variables used in ANN modeling is in Table 1.

Table 1. Complete list of variables used in ANN modeling

Number	Variable
1	Return on Assets (ROA)
2	Return on Capital
3	Return on Equity (ROE)
4	Return on Invested Capital (ROIC)
5	Gross Margin

Number	Variable
6	Selling, General & Administrative Expenses (SGA)
7	Earnings Before Interest, Taxes, Depreciation, and Amortisation Margin (EBITDA Margin)
8	Net Income Margin (NI Margin)
9	Fixed Assets Turnover (FA Turn)
10	Inventory Turnover (Inv Turn)
11	Current Ratio (CR)
12	Quick Ratio (QR)
13	Days Sales Outstanding (DSO)
14	Debt-to-Equity (TD/TE)
15	Liabilities-to-Assets (TL/TA)

After finalizing the ratios, a cross-sectional study was conducted; that is, separate ANN models were created for each of the two years during which companies were investigated. The data and the variables were imported into the SPSS statistical software where two ANN models were created: one for 2019 and the other for 2020.

The following settings were used to build the ANN models. These are standard practices in this type of modeling (Chollet, 2021; Elsken et al., 2019; Halteh, 2019):

- Training the model was based on randomly selecting 70% of cases and testing on the remaining 30%.
- Automatic architecture selection: minimum and maximum number of units in hidden layer, 1 and 50, respectively.
- Type of training used is batch.
- Optimization algorithm used is a scaled conjugate gradient.
- User-missing values were excluded.
- Stopping rules – maximum steps without a decrease in error is 1.
- Output layer – activation function is Softmax; Error function is Cross-entropy.

After reviewing and finalizing the above settings, the ANN models were ready to be executed to generate results.

RESULTS

MDA APPROACH

The results of this research indicate that, in 2019, approximately 43% of companies were classified as distressed, and 57% were classified as healthy. In 2020, around 47% of companies were classified as distressed – an increase in distressed companies of more than 8% when compared to the previous year. As for the healthy companies, 53% were classified as healthy – a drop of more than 6% when compared to the previous year. This shows that there was an increase in the number of distressed companies during the pandemic.

Table 2 presents the results of the companies classified as distressed or healthy for the years 2019 and 2020. The table shows the actual number of companies followed by the percentage they constitute from the total dataset, presented in parentheses. For example, “36 (43%)” in 2019, refers to 36 companies being classified as distressed, with 43% being the percentage representing that number of companies (36) from the total number of companies, i.e., 84 minus 36 divided by 84 yields 43%.

Table 2. Company analysis according to the Z-Score

Z-Score \ Year	2019	2020
Z < 1.8 (Distressed)	36 (43%)	39 (47%)
Z > 1.8 (Healthy)	48 (57%)	45 (53%)
Total	84 (100%)	84 (100%)

Table 3 presents the results of how the companies' Z-scores changed from 2019 to 2020. As the table shows, 53 out of the 84 companies in the dataset – approximately two-thirds of the companies – have a decreased Z-score in 2020 (pandemic year) when compared to 2019 (pre-pandemic year). These numbers confirm that COVID-19 had an adverse effect on the financial health of companies.

Table 3. Z-Score differences for companies between 2019 and 2020

Z-Score \ Year	2019-2020
Z-Score Decreased	53 (63%)
Z-Score Increased	31 (37%)
Total	84 (100%)

ANN Approach

Using the ANN technique, two models were created (one for 2019 and one for 2020) to achieve two main goals: (1) determine the most predictive variables for financial distress of companies, and (2) create accurate financial distress prediction models to predict the financial status of these companies.

2019 model

Table 4 shows the case processing summary of the model built using the 2019 data. The training was executed using the random selection of 77.3% of companies in the dataset, followed by testing on the remaining 22.7% of companies. Nine companies were automatically excluded due to missing data.

Table 4. Case processing summary

Sample \ Result	Number	Percent
Training Testing	58 17	77.3% 22.7%
Valid	75	100%
Excluded	9	
Total	84	

Table 5 shows the classification summary of the model built using the 2019 data. In the training phase, the model correctly classified 94.1% of healthy companies and 62.5% of distressed companies. These results yielded an overall correct prediction percentage of 81%. In the testing phase, the model was able to correctly classify 90% of healthy companies and 28.6% of distressed companies. These results yielded an overall correct prediction percentage of 64.7%. The low accuracy of correctly classifying healthy companies is likely due to the small sample size (only 7 companies). This claim is solidified in the 2020 model, as higher accuracy was achieved when a larger sample size was used.

Table 5. Case processing summary

Sample	Observed	Predicted		
		0	1	Percent Correct
Training	0	32	2	94.1%
	1	9	15	62.5%
	Overall Percent	70.7%	29.3%	81.0%
Testing	0	9	1	90.0%
	1	5	2	28.6%
	Overall Percent	82.4%	17.6%	64.7%

Figure 1 shows the Receiver Operating Characteristic (ROC) curve, which presents all possible thresholds, i.e., the true positive and false positive error rates. The area under the curve is a performance measure for the ROC, i.e., the closer the area is to 1, the more accurate the model is (Halteh, 2019). As is shown by the green and blue lines, which represent the model's accuracy, they encompass a large area of the curve, which is stated in Table 6 with a score of 0.875 (87.5%) of the area under the ROC curve.

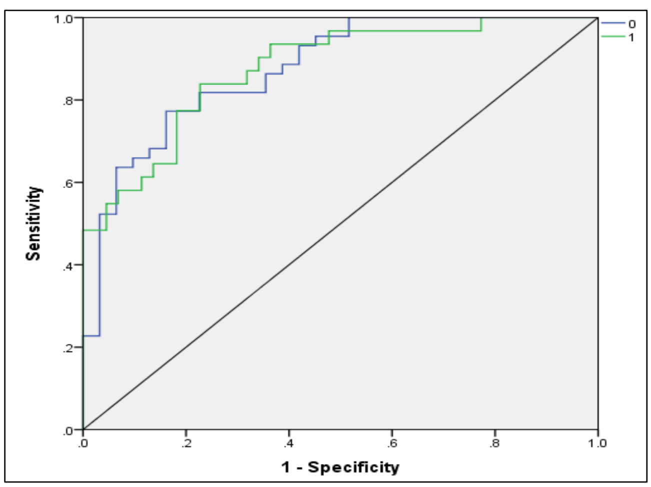

Figure 1. ROC curve for the 2019 model

Table 6. Area under the ROC curve

Year		Area
2019	0	.875
	1	.875

Figure 2 shows the normalized variable importance chart for the 2019 model. As is shown, the top three predictive variables chosen by the model are:

1. Return on Capital
2. Net Income Margin
3. Liabilities-to-Asset (Debt Ratio)

The normalized variable importance chart shown in Figure 2 identifies the most significant input variables that influence the model's performance. This aids in understanding the underlying structure of the data and helps decision-makers take informed actions. SPSS conducts a sensitivity analysis to compute the importance of predictors in neural network models. The sensitivity analysis systematically varies the input values and observes the resulting changes in the output variable to identify the most important predictors. Afterward, the absolute value of the weight of each input node is divided by the sum of the absolute values of all input node weights to calculate the normalized variable importance (IBM, 2019).

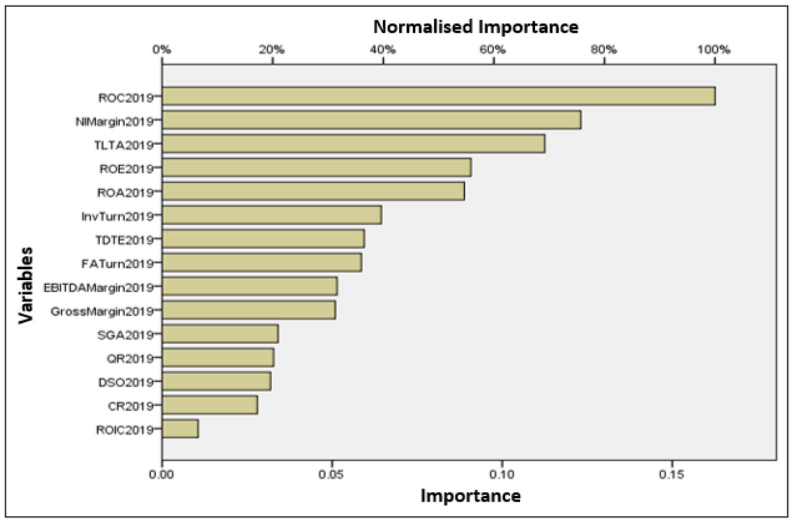

Figure 2. Normalised variable importance chart for the 2019 model

2020 model

Table 7 shows the case processing summary of the model built using the 2020 data. The training was executed using the random selection of 71.4% of companies in the dataset, followed by testing the remaining 28.6% of companies. Seven companies were automatically excluded due to missing data.

Table 7. Case processing summary

Sample \ Result	Number	Percent
Training Testing	55 22	71.4% 28.6%
Valid	77	100%
Excluded	7	
Total	84	

Table 8 shows the classification summary of the model built using the 2020 data. In the training phase, the model correctly classified 96.6% of healthy companies and 100% of distressed companies. These results yielded an overall correct prediction percentage of 98.2%. In the testing phase, the model was able to correctly classify 75% of healthy companies and 100% of distressed companies. These results yielded an overall correct prediction percentage of 86.4%.

Table 8. Case processing summary

Sample	Observed	Predicted		
		0	1	Percent Correct
Training	0	28	1	96.6%
	1	0	26	100.0%
	Overall Percent	50.9%	49.1%	98.2%
Testing	0	9	3	75.0%
	1	0	10	100.0%
	Overall Percent	40.9%	59.1%	86.4%

Figure 3 shows the ROC curve for the 2020 model. As is shown by the green and blue lines, which represent the model's accuracy, they encompass a large area of the curve, which is clearly stated in Table 9 with a score of 0.976 (97.6%) of the area under the ROC curve.

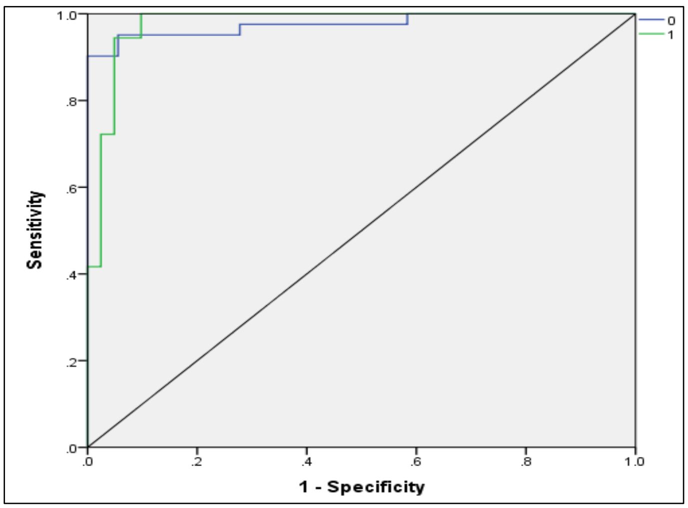

Figure 3. ROC curve for the 2020 model

Table 9. Area under the ROC curve

Year		Area
2020	0	.976
	1	.976

Figure 4 shows the normalized variable importance chart for the 2020 Model. As is shown, the top three predictive variables chosen by the model are:

1. Return on Capital
2. EBITDA Margin
3. Quick Ratio

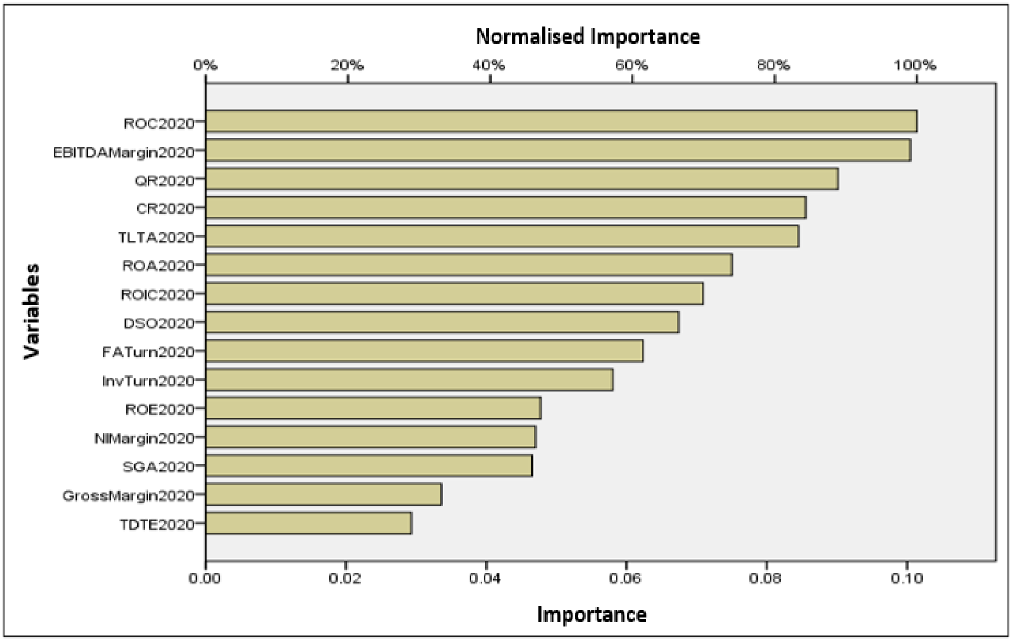

Figure 4. Normalized variable importance chart for the 2020 model

DISCUSSION

This study focused on the financial distress caused by the COVID-19 pandemic on a dataset comprised of companies listed on ASE. Being able to predict financial distress is vital to companies and involved stakeholders to take precautions and contingencies. Both ANNs and MDA techniques were used in this research to empirically quantify the impact of the pandemic on Jordanian companies. The results indicated that more than 63% of companies in the dataset have a worse Z-score when compared to the pre-pandemic year. More than 8% of companies have entered the distressed category, and more than 6% of companies exited the healthy category as a result of the pandemic. This confirms previous estimates that the pandemic decreased global trade in 2020 by 5.3% and led to shrinking worldwide economic growth by an annualized rate of around 3.2% (Jackson, 2021).

Models built using ANNs showed that the most important predictor of financial distress in 2019 and 2020 was Return on Capital, i.e., pre and during the pandemic year. This presents a significant contribution to the literature, indicating that although companies became more distressed during the pandemic year, the most important predictor of financial distress remained unchanged. Put differently, extraneous factors such as COVID-19 did not cause a major change in the most important financial distress predictor. Such insight supports the theoretical choice of Ashraf (2020) and Zhang et al. (2020) who focused on Return on Capital to reflect the negative impact of the pandemic on the financial performance of companies.

Other important variables in predicting financial distress, according to the models built using ANNs, include EBITDA Margin, Quick Ratio, Net Income Margin, and Liabilities-to-Assets. These variables are sensible since they include highly liquid ratios and other ratios showing the percentage of debt a company has with regard to its capital or income. For example, if a company has a low Quick Ratio, the higher its likelihood of financial distress, i.e., an inverse relationship between Quick Ratio and the likelihood of failure. A similar rationale applies to the other variables. These results should not only pave the way for researchers to further explore the above predictors but also encourage managers and decision-makers to focus on these ratios to make thoughtful decisions and take preemptive actions to avoid potential organizational failure.

CONCLUSION

This paper analyzed companies listed on the ASE over a two-year period, 2019 and 2020. MDA based on Altman's (1968) Z-score and ANNs were used to investigate the financial status of companies and how it was impacted during the year of the COVID-19 pandemic. Applying the Z-score, results show that, in 2020, there was an increase in distressed companies of more than 8% when compared to 2019. A drop of over 6% was also detected in healthy companies in 2020, and around 63% of companies have shown a lower Z-score in 2020 than in 2019.

As for the ANN approach, two financial distress prediction models were created in order to develop accurate prediction models of companies in the dataset, as well as identify the most important financial distress predictors. While the 2019 model was able to correctly classify 64.7% of companies and encompass 87.5% of the area under the ROC curve, the 2020 model had a higher predictive accuracy, which achieved a classification score of 86.4% and encompassed 97.6% of the area under the ROC curve.

This research contributes by providing a better understanding of how financial distress predictors perform during dynamic and risky times, i.e., COVID-19. The paper offers results that confirm the constancy of the most important predictive variable, i.e., Return on Capital, pre and during the pandemic year. This means that although financial distress increased in companies in 2020, the most important variable predicting financial distress remained steadfast. Such results indicate that standard financial distress predictors may be regarded as being impervious to extraneous financial and/or health calamities. Practically, using the insight into the main financial variables that were affected by the pandemic, the research contributes by helping decision-makers to plan any potential contingencies and develop suitable recovery strategies to control its long-term, negative implications.

As is known, no research is without limitations. More data availability could have better facilitated the scope of the study, however, the principles presented in this research can be applied to any company, anywhere, i.e., it is not limited to the Jordanian context. Including a higher number of companies, investigating more than two years, considering extra variables, and focusing on several geographical locations may also enhance the results of this research.

Future research may focus on expanding the scope of this study by including other geographical locations to check for the stability and generalisability of the obtained results. Comparisons between the financial impacts of COVID-19 on companies within various developing and developed countries may also be interesting. Other future research avenues may include incorporating post-COVID-19 data to check for any changes in results or may include exploring the role of government policies and initiatives in avoiding financial distress.

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