Unraveling the Mystery of Default Prediction in the Textile Industry of Pakistan

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Abstract

Default events are inevitable in any economy and may have a considerable impact on the economic stability of a country. However, the prediction of defaults before any occurrence has always been a challenging task for the researchers around the world. In Pakistan, the textile industry experiences a high rate of default, which became a motivation to conduct a study on predicting the default in this sector. The data from 134 listed companies in the textile industry was analyzed between the time period (2000 and 2020), and segregated the industry into three sub-sectors (composite, spinning, and weaving with textile associated products) for better analysis. After reviewing the literature, five widely-used default prediction models were identified which led to perform a comparative study in order to validate their performance. Findings revealed that Grover's G-Score model was the best default predictor, followed by Springate's S-Score model, based on both model accuracy and model validation. However, it is important to note that the current study is limited to the textile sector and future studies could include other sectors and more advanced methods to improve accuracy. This study can be useful for investors and financial analysts in assessing the risk of default in the textile industry and making informed investment decisions.

***Keywords*:** default modeling, default prediction, risk assessment

Introduction

Financial distress pertains to a situation, wherein, a company is unable to fulfill its financial obligations due to factors, such as inadequate financial management, unfavorable competition, and deficient financial reporting methodologies (Tano & Nainggolan, 2019). Predicting the likelihood of companies' failure is important to prevent financial crisis and negative consequences on the economy and society (Bellovary et al., 2007). Financial distress can have adverse impacts on stakeholders, such as

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employees, creditors, shareholders, and customers, leading to high unemployment and crime rates (Chen et al., 2020).

It is crucial for senior management to continually monitor the reasons for financial distress in order to make timely and appropriate decisions regarding financial and investment alternatives (Venkata Ramana et al., 2012; Campbell et al., 2008). This is particularly important for manufacturing industries, such as in Pakistan, where financial sustainability is challenging due to various factors including fraud, mismanagement, and non-compliance with regulatory requirements. Identifying early signs of distress is essential for predicting a company's future health and preventing a decline in the manufacturing sector (Aslam u., et al., 2019).

In Pakistan, businesses face several challenges that can lead to financial distress, such as political instability, corruption, and compliance issues. The textile sector, which is a significant contributor to the Pakistani economy, has also faced financial crisis, with almost 50% of the defaulters during 2015-19 only from this sector (Rasool et al., 2020).

The growth rate of Pakistan's textile sector is experiencing a downturn due to multiple factors including global economic slowdown, security apprehensions, elevated manufacturing expenses, and devaluation of the national currency (Mushafiq et al., 2023). Among the different segments, knitwear, readymade, and bed wear continue to be the major contributors to textile exports, with a cumulative share of over 60%. However, the rise in inflation rates and high financing costs have also adversely affected the industry's growth (Halim et al.,2021). Political instability in the country has further worsened the situation, making it difficult for buyers and exporters to conduct business effectively (Sohail, M. T., et al., 2022).

In light of above explanations, the textile industry of Pakistan is on the verge of financial crisis and few firms are near credit default or financial distress (Rasool, N., et al 2020). Financial distress can have severe economic implications for a company, impacting various stakeholders, such as customers, shareholders, creditors, and employees. The resulting losses can lead to substantial social and economic costs not only for the organization but also for the entire country (Lizares & Bautista, 2020). Bankruptcies in the past few decades have destabilized the social and economic areas, leading to high unemployment and crime rates (Muñoz-Izquierdo et al., 2020). Accurately predicting financial distress is essential and it is becoming increasingly urgent to do so not only at firm level but also at industry and country levels (Cybinski, 2001).

In order to prevent further business failures and high costs associated with bankruptcy, it is important to use an appropriate model to predict financial distress and bankruptcy accurately (Parker, Peters, and Turetsky, 2002). However, studies conducted in Pakistan were limited in scope and confined to small sample sizes, with few techniques used to predict financial distress. Therefore, there was a need for more extensive research on financial distress and bankruptcy prediction in Pakistan to mitigate the risks and minimize the fear of business failure in the future. Hence, the current study fulfilled this need.

Numerous models have been proposed by researchers, however, there is no consensus as to which model is the best fit since different classifiers produce varying results depending on their perspective. The primary objective is to achieve the highest accuracy in default prediction modeling, which poses a challenging task for academics and practitioners alike (Kim et al., 2022; Гришунин & Егорова, 2022). Recent literature has identified three assessment criteria: categorical prediction correctness (Chye et al., 1989), discriminatory power (Beaver, 1966; Altman, 1968; Ohlson, 1980), and calibration and validation of the model (Kim et al., 2022). These criteria are frequently utilized to evaluate the performance of default prediction models.

Shareholders use auditor's reports to assess a company's financial well-being, however, studies show that these reports may not be as effective as financial distress prediction models in identifying financially troubled companies (Altman and Saunders, 1998). It is important to determine which financial ratios are better at forecasting business failure. Earlier studies have yielded conflicting outcomes on the effectiveness of traditional financial distress models, prompting the development and application of artificial intelligence techniques, such as decision trees, neural networks, and genetic algorithms alongside these models. However, (Jones et al., 2017) found that simple statistical models are more effective in predicting financial distress. Therefore, this study focused to analyze statistical techniques in order to predict financial distress (Marso & El Merouani, 2020).

The current study attempted to make valuable contributions to the existing literature. One of these was to evaluate five models' capability to forecast financial distress in Pakistan Textile industry. Secondly, it provided sub industry-specific results, for instance, Textile Composite, Textile Spinning and Weaving with sub Textile Products, which are less common in literature (Cultrera & Brédart, 2016). Thirdly, it compared validation results of the following models Altman (1968)'s Z-Score, Ohlson (1980)'s O-Score, Gordon L. V Springate (1978)'s S-Score, Jeffrey S. Grover (2003)'s G-Score and Zmijewski (1984)'s X-Score to determine which model is more effective in classifying distressed and healthy companies. These findings can assist policymakers in developing and implementing effective strategies to prevent financial distress.

The study is divided into four sections. Section 2 discusses the literature gap regarding default prediction models and their importance in achieving research objectives. Section 3 describes research methodology, tools, and techniques used to achieve these objectives. Section 4 presents the results obtained through the methodology, while section 5 provides the conclusion.

Literature Review

To meet their financial requirements, companies typically choose between internal or external financing options, such as equity or debt financing. External debt financing incurs a financial cost, and if a company fails to generate sufficient revenue to fulfill its financial commitments, it can fall into a state of financial distress, which may lead to bankruptcy. To comprehend the idea of financial distress, several theoretical analyses have been undertaken.

The cash management theory (Gitman, L. J., 1979) states that positive cash balances occur when inflows exceed outflows, while negative balances lead to financial distress and possible bankruptcy (Pandey 2005). The Gambler's Ruin theory (Feller, W. 1968) sees equity capital as a reserve that is depleted upon bankruptcy (Lim et al., 2012). The liquidity, profitability, and wealth theory relies on financial ratios to assess a company's financial health. Good ratios imply stability, while poor ratios indicate distress.

Rahma, F. A. (2022) used similar methods and samples but analyzed different industries, while (Sari, H. E., & Ariyani, V., 2022) focused on manufacturing companies in Indonesia. The studies have revealed that various financial distress prediction models can produce varying levels of accuracy. Zmijewski's model was identified as the most effective in predicting financial distress in the studies conducted by (Sari et al., 2022;

Setiawan et al., 2021), whereas (Rahma, F. A., 2022) found that Altman's Z-score method predicted more companies in financial distress.

Mutoharoh, A. F., et al (2021) used the Zmijewski model, with (Mutoharoh et al. 2021) applying it to European football clubs and finding it to be the most accurate, while (Agwata 2018) evaluated its effectiveness by using industry data from the Nairobi Securities Exchange. Agwata, J. A. (2018) compared the Altman and Zmijewski's models to detect distress in banks of Malaysia, Thailand, and Indonesia and determined that Indonesian banks performed better in terms of non-bankrupt status.

Both (Cahyani, 2017) and (Awais et al., 2015) evaluated financial distress prediction models. Cahyani, (2017) focused on a limited sample of Indonesian financing companies using the X-Score Zmijewski model, while (Awais et al., 2015) examined a larger sample of Indian companies under the insolvency and bankruptcy code using multiple models. Both studies stressed the need to assess model effectiveness by considering specific regions and industries and including qualitative and other quantitative variables.

Rasool et al. (2020) used multiple models including Z-Score, O-Score, Probit, and D-Score, and determined that Z-Score and O-Score models were the most robust in predicting financial distress. On the other hand, Lestari et al. (2021) employed four models, namely Altman (Z-Score), Springate (S-Score), Zmijewski (X-Score), and Grover (G-Score) to predict financial distress in different industries. Their study revealed that the Springate model was the most accurate in predicting financial distress.

Lutfiyyah and Bhilawa (2021) focused on English Premier League football clubs and used a sample of 37 clubs categorized into financial distress and nonfinancial distress. They compared the accuracy of their financial difficulty prediction model with the previous research and determined that the Zmijewski model has the highest accuracy rate of 72%. In contrast, Gerritsen (2015) examined the accuracy of accounting-based bankruptcy prediction models including the Ohlson (1980), Zmijewski (1984), and Altman (2000) models, on the Dutch professional football industry between 2009/2010-2013/2014. The sample size fluctuates between 30 and 36 clubs. The study determined that the Zmijewski Probit model performed most accurately, with an accuracy rate of 61% to 66%, and that the majority of clubs in the sample faced financial distress and potential bankruptcy.

Putri (2018) compared the accuracy of five models (Altman, Springate, Grover, Ohlson, and Zmijewski) over five years, finding significant differences in accuracy and the Zmijewski model being the most accurate. Husein et al. (2015) analyzed four models (Altman, Springate, Zmijewski, and Grover) by using Binary logistic regression and data from 132 companies listed on the Daftar Efek Syariah. All the models predicted financial distress, with the Zmijewski model deemed as the most appropriate for its leverage ratio indicator.

Ullah et al. (2021) found potential issues in the banking sectors of Pakistan and India using Altman's Z-score. Manalu et al. (2017) used Z-score and Zmijewski models to analyze the financial distress of shipping companies in Indonesia, and determined a relatively healthy industry. Multiple Discriminant Analysis (MDA) is a widely used model to predict financial distress, employed by researchers including (Rim and Roy 2014; Altman 2018), as discussed by (Ijaz et al., 2017).

Mushafiq et al. (2023) and Rubab et al. (2022) examined the relationship between financial measures and firm performance in non-financial and manufacturing firms, respectively. While, (Mushafiq et al., 2023) focused on the Altman Z-score and credit risk, (Rubab et al., 2022) and investigated the impact of financial distress. Both studies provided valuable insights for investors and policymakers.

Tung and Phung (2019) examined bankruptcy risk in multidisciplinary enterprises in a specific province in Vietnam, while (Joshi 2019) focused on the effectiveness of Altman Z-score in predicting the bankruptcy for a specific company, that is, Reliance Communication. Σέρμπος (2018) developed a predictive model for the viability of Greek technical firms using the data from Greek construction companies. All the three studies highlight the importance of financial measures in predicting bankruptcy risk and the potential applications of the Altman Z-score model in different industries and contexts. However, they differ in their specific focus and the types of firms and industries examined.

Westgaard and Wijst (2001) identified factors, such as solvency, liquidity, financial coverage, firm age, and size as crucial determinants of bankruptcy. Researchers, such as (Jones et al. 2017) used logistic regression to predict financial distress. Edwards (2013) highlighted the challenges faced by financially distressed businesses, such as higher capital costs and difficulty in obtaining credit, leading managers to invest in high-risk projects that may further harm the company's financial position and possibly result in bankruptcy.

Literature suggests that financial distress prediction models are useful tools to identify potentially bankrupt firms and guiding business development decisions. The studies reviewed in this summary indicate that there are significant differences in the accuracy and performance of various prediction models across different industries and regions. However, the Zmijewski model appears to be the most commonly used and consistently accurate across different contexts. It is worth noting that while these models are effective in predicting financial distress, they do not guarantee future outcomes and should be used in conjunction with qualitative analysis and expert judgment. Ultimately, the use of financial distress prediction models can aid in risk management and inform proactive measures to avoid financial difficulties.

Methodology

According to (Saunders et al. 2011), a sound methodology plays a crucial role to obtain reliable findings that are unbiased, realistic, and authentic. The data on textile sector was collected from 134 listed companies between (2000-2020) (more data could not be covered due to unavailability), which was subdivided into three categories. These categories included textile composite (46 companies), textile spinning (65 companies), and textile weaving with sub-products (23 companies). This sector was focused upon because it has been observed that 50% of default events occur within textile sector of Pakistan as further endorsed by (Rahma, F. A., 2022).

The data for the current study was obtained from public sources including the PSX, SBP, and PBS. To evaluate the accuracy of models, default data was gathered from credit rating agencies in Pakistan (VIS Credit Rating Company & Pakistan Credit Rating Company). It was used as an assumed default criterion, which considers a firm to be defaulted if its paid-up capital is eroded by 50% of the retained earnings (negative paid-up-capital to retained earnings ratio with 50% or above) -if defaults, then 1 else 0 (Dastile, X., et al 2020; Jones, S., & Wang, T., 2019).

Nevertheless, the current study has been split up in two segments. Firstly, model estimation and, secondly model validation. The details of both phases are as follows.

Model Estimation

Altman Z-Score Model

Altman (1968) introduced the MDA technique in 1968, which resulted in the Altman Z-Score formula. This formula classifies a company's possibility of distress, gray area, or health. Türk and Kurklu's (2017) research determined that the Altman model showed a higher accuracy rate of 69%, as compared to the Springate model which showed an accuracy rate of only 57%.

Following exhibits equation and tabular illustration

$$Z_{Score} = 1.20X1 + 1.40X2 + 3.30X3 + 0.60X4 + 0.99X5 \quad (1)$$

Code	Coefficient	Formulae	Author	Weights
Alt1	X1	Working Capital / Total Assets	Altman	1.20
Alt2	X2	Retained Earnings / Total Assets	Altman	1.40
Alt3	X3	EBIT / Total Assets	Altman	3.30
Alt4	X4	Market Value of Equity/Book Value of Total Debt	Altman	0.60
Alt5	X5	Net Sales / Total Asset	Altman	0.99

Note. Ranges of Altman model are as follows. If *z*-Score > 2.99 than safe area (healthy firms), If 1.91 < *z*-score>2.99 than grey area (near stressed) and *z*-Score < 1.91 than stressed.

Ohlson O-Score Model

Ohlson, (1980) developed a bankruptcy prediction model, based on a previous study conducted by Altman. This model aimed to predict the likelihood of a firm as bankrupt or not, for the period of (1970-1976). The model employed logistic regression analysis and consisted of nine variables, including various financial ratios. Ohlson's model differed from the previous model by incorporating more variables (Sayari, Naz et al., 2017). The calculation model was formulated by Ohlson in the following way, as quoted from his paper: "the model is a logistic probability model that expresses the probability of failure as a function of nine financial ratios."

$$O_{Score} = -1.34 - 0.41X1 + 6.03X2 - 1.43X3 + 0.0757X4 - 2.37X5 - 1.83X6 + 0.29X7 - 1.72X8 - 0.52X9 \quad (2)$$

Code	Coefficient	Formulae	Author	Weights
Ohl1	X1	Size	Ohlson	0.41
Ohl2	X2	Total Liabilities / Total Assets	Ohlson	6.03
Ohl3	X3	Working Capital / Total Assets	Ohlson	1.43
Ohl4	X4	Current Asset / Current Liabilities	Ohlson	0.08
Ohl5	X5	Total Assets > Total Liabilities	Ohlson	2.37
Ohl6	X6	Net Income / Total Assets	Ohlson	1.83
Ohl7	X7	FFO/Total Debt	Ohlson	0.29
Ohl8	X8	Default Dummy	Ohlson	1.72
Ohl9	X9	Change in Net Sales / Total Asset	Ohlson	0.52

Note. Ranges of Ohlson model are as follows. If O-Score > 0.38 than firm will bankrupt if O-Score < 0.38 than firm is financially healthy.

Springate S-Score Model

Gordon et al. (1978) developed "Springate S-Score" to predict financial distress by using four financial ratios, similar to Altman's MDA. Tahu (2019) examined the performance of the Springate and Altman models on eight companies and determined that the Springate model had a higher accuracy rate of 62.5%, with a lower type error of 37.5% as compared to the Altman model's accuracy rate of 50% with a type error of 50%. This indicates that the Springate model is a more effective predictor of financial distress than the Altman model.

The Springate model predicts a company's condition as either distressed or non-distressed (healthy) based on the results of the four financial ratios. These ratios are summarized in the model's formula, which takes into account the specific values of each ratio to determine a company's overall financial health.

$$S_{Score} = 1.030X1 + 3.07X2 + 0.66X3 + 0.4X4 \qquad (3)$$

Code	Coefficient	Formulae	Author	Weights
SPR1	X1	Working Capital / Total Assets	Springate	1.03
SPR2	X2	EBIT / Total Assets	Springate	3.07
SPR3	X3	Market Value of Equity/Book Value of Total Debt	Springate	0.66
SPR4	X4	Retained Earnings / Total Assets	Springate	0.40

Note. Ranges of Springate model are as follows. If S-Score > 0.862 than firm will bankrupt if O-Score < 0.862 than firm is financially healthy

Grover G-Score Model

Jeffrey S. Grover (2001) created a new bankruptcy prediction model, known as the Grover model. This model was developed by re-evaluating and re-designing the Altman Z-Score model including 13 new financial ratios. The same sample, used in the Altman Z-Score model, was also used in the current research. Finally, Grover produced 3 distinguished variables which are sufficient to predict default (Sari, 2013).

A study was conducted by (Verlekar and Kamat, 2019) on bankruptcy prediction models in the Indian banking sector, which specifically compared the Springate, Zmijewski, and Grover models. The study found that the Grover model was the most accurate in predicting financial distress as compared to the other two models. The results suggested that the Grover model could be a useful tool to assess financial health in the Indian banking industry.

$$G_{Score} = 1.65X1 + 3.404X2 - 0.016X3 \tag{4}$$

Code	Coefficient	Formulae	Author	Weights
Gro1	X1	Working Capital / Total Assets	Grover	1.65
Gro2	X2	EBIT / Total Assets	Grover	3.404
Gro3	X3	Net Income / Total Assets	Grover	-0.016

Note. Ranges of Grover model are as follows. If G-Score < -0.02 than firm will bankrupt if G-Score > 0.01 than firm is financially healthy

Zmijewski X-Score Model

Zmijewski, (1984) developed a financial distress prediction model that uses financial ratios to measure a company's performance, leverage, and liquidity. The model is based on a 20-year’s repeating study and utilizes ratios that have been previously used in research.

Salim and Sudiono (2017) conducted a study on coal mining companies listed on the Indonesia Stock Exchange (IDX) and found that the Zmijewski model was the most effective in predicting financial distress among the Springate and Altman models. The Zmijewski model had an accuracy rate of 78.95%, which was higher than the accuracy rates of the other two models.

The Zmijewski model uses financial ratios to determine if a company is in financial distress or not based on its performance, leverage, and liquidity.

The formula of the model considers specific values of these ratios to make prediction.

$$X_{Score} = -4.3 - 4.5X1 + 5.7X2 - 0.004X3 \quad (5)$$

Code	Coefficient	Formulae	Author	Weights
ZMI1	X1	Retained Earnings / Total Assets	Zmijewski	4.5
ZMI2	X2	Total Liabilities / Tier 1 Equity	Zmijewski	5.7
ZMI3	X3	Current Asset / Current Liabilities	Zmijewski	-0.004

Note. Ranges of Zmijewski model are as follows. If X-Score > 0.00 than firm will bankrupt if X-Score < 0.00 than firm is financially healthy

Model Validation

In the second phase of the current study, various tools were used to calibrate the results and evaluated the predictive models. Commonly used evaluation methods were selected from the literature review including Confusion Metrics, Accuracy, Type-1 Error, Type-2 Error, Precision, and Recall, F-Score. Several studies have suggested using specific evaluation tools, such as Precision, Recall, and F1-Score for model validation, including research by (Yıldırım et al., 2021).

Accuracy

In order to evaluate the performance of each model, the overall accuracy of the model is calculated. This represents the proportion of all samples that were correctly classified by the model. The formula to calculate accuracy is (True Positives + True Negatives) divided by (True Positives + True Negatives + False Positives + False Negatives), as stated by (Shrivastava et al., 2020).

$$\textit{Type-1 Error} = \frac{FP}{(FP+TN)}$$

$$\textit{Type-2 Error} = \frac{FN}{(TP+FN)}$$

$$\textit{Precision or Specificity} = \frac{TN}{(FP+TN)}$$

$$\textit{Recall or Sensitivity} = \frac{TP}{(TP+FN)}$$

$$\textit{F1-Score} = \frac{2 \times Recall \times Precision}{Precision + Recall}$$

Results and Discussion

Table 1

Descriptive Statistics for Composite Sector

Descriptive	Market Value of Equity / Book Value of Total Debt	Retained Earnings / Total Assets	Total Liabilities / Total Assets	FFO / Total Debt	Working Capital / Total Assets	Current Asset / Current Liabilities	Total Liabilities / Tier 1 Equity	Net Sales / Total Asset	Net Income / Total Assets	EBIT / Total Assets	Change in Net Sales / Total Asset
Mean	18.26	-0.10	0.68	0.26	-0.07	1.09	0.68	0.99	0.01	0.06	0.25
Standard Error	4.30	0.02	0.02	0.01	0.02	0.03	0.02	0.02	0.01	0.01	0.19
Median	3.47	0.01	0.64	0.24	0.00	1.00	0.64	0.93	0.02	0.07	-0.02
Standard Deviation	120.70	0.66	0.54	0.24	0.52	0.77	0.54	0.58	0.29	0.29	5.47
Sample Variance	14567.52	0.44	0.29	0.06	0.27	0.59	0.29	0.34	0.08	0.09	29.95
Kurtosis	406.48	94.16	124.43	5.62	140.91	92.62	124.43	8.34	404.08	483.59	754.17
Skewness	17.73	-7.96	9.34	1.02	-10.17	7.42	9.34	1.76	-14.74	-18.80	27.20
Range	3279.14	10.74	9.43	2.66	9.59	12.17	9.43	5.74	9.96	9.16	153.00
Minimum	-397.78	-10.03	0.03	-0.78	-8.82	0.05	0.03	0.00	-6.83	-7.17	-1.00
Maximum	2881.36	0.70	9.46	1.88	0.78	12.22	9.46	5.74	3.13	1.99	152.00
Sum	14389.62	-81.73	532.87	207.83	-56.03	856.08	532.87	782.63	8.64	46.78	195.97
Count	788	788	788	788	788	788	788	788	788	788	788

Table 2

Descriptive Statistics for Spinning Sector

Descriptive	Market Value of Equity / Book Value of Total Debt	Retained Earnings / Total Assets	Total Liabilities / Total Assets	FFO / Total Debt	Working Capital / Total Assets	Current Asset / Current Liabilities	Total Liabilities / Tier 1 Equity	Net Sales / Total Asset	Net Income / Total Assets	EBIT / Total Assets	Change in Net Sales / Total Asset
Mean	17.49	-0.11	0.68	0.26	-0.07	0.99	0.68	1.14	0.00	0.06	0.04
Standard Error	3.56	0.01	0.01	0.01	0.01	0.02	0.01	0.02	0.00	0.00	0.03
Median	2.91	0.03	0.65	0.23	-0.02	0.96	0.65	1.05	0.01	0.06	-0.04
Standard Deviation	118.46	0.45	0.29	0.25	0.27	0.53	0.29	0.62	0.10	0.11	1.06
Sample Variance	14031.68	0.20	0.08	0.06	0.07	0.28	0.08	0.39	0.01	0.01	1.13
Kurtosis	312.96	10.58	17.51	7.08	20.00	20.52	17.51	1.49	20.72	12.59	683.41
Skewness	16.22	-2.72	3.00	1.71	-3.46	3.26	3.00	0.93	-1.53	-0.94	23.64
Range	2810.64	4.04	3.29	2.60	3.20	5.87	3.29	3.71	1.74	1.76	32.39
Minimum	-48.08	-3.49	0.14	-0.52	-2.64	0.01	0.14	0.00	-1.03	-0.97	-1.00
Maximum	2762.56	0.54	3.43	2.09	0.55	5.88	3.43	3.71	0.70	0.79	31.39
Sum	19411	-121	755	290	-77	1099	755	1260	5	63	48
Count	1110	1110	1110	1110	1110	1110	1110	1110	1110	1110	1110

Table 3

Descriptive Statistics for Weaving and Other Textile Products Sector

Descriptive	Market Value of Equity / Book Value of Total Debt	Retained Earnings / Total Assets	Total Liabilities / Total Assets	FFO / Total Debt	Working Capital / Total Assets	Current Asset / Current Liabilities	Total Liabilities / Tier 1 Equity	Net Sales / Total Asset	Net Income / Total Assets	EBIT / Total Assets	Change in Net Sales / Total Asset
Mean	34.38	-0.12	0.64	0.31	-0.03	1.39	0.64	1.02	0.00	0.05	0.31
Standard Error	12.93	0.03	0.02	0.05	0.02	0.07	0.02	0.03	0.01	0.01	0.18
Median	3.08	0.03	0.62	0.25	0.01	1.01	0.62	1.03	0.01	0.06	0.01
Standard Deviation	250.34	0.54	0.40	0.87	0.35	1.29	0.40	0.57	0.11	0.12	3.41
Sample Variance	62667.95	0.30	0.16	0.76	0.12	1.65	0.16	0.32	0.01	0.01	11.62
Kurtosis	261.85	14.92	17.35	295.30	8.31	17.01	17.35	2.64	22.27	34.78	207.48
Skewness	15.22	-3.48	3.19	16.34	-2.43	3.63	3.19	0.82	-1.80	0.71	13.71
Range	4508.95	4.63	3.64	16.77	2.67	10.49	3.64	3.77	1.74	2.13	57.24
Minimum	-57.33	-3.97	0.03	-0.55	-2.01	0.06	0.03	0.00	-0.98	-0.90	-0.99
Maximum	4451.63	0.65	3.67	16.21	0.66	10.55	3.67	3.78	0.76	1.23	56.25
Sum	12894	-45	239	117	-12	520	239	381	0	19	115
Count	375	375	375	375	375	375	375	375	375	375	375

The textile composite sector has a high market value of equity as compared to total debt, indicating high earnings potential. However, low retained earnings to total assets ratio may limit growth. The sector carries high debt, which may increase financial risk, with low FFO to total debt ratio. Despite this, net sales to total assets ratio is high, indicating strong revenue streams. The sector has limited liquidity with a low working capital to total assets ratio. Companies may have satisfactory short-term liquidity with a current asset to current liabilities ratio of 1. Companies generate moderate returns on total assets with net income to total assets and EBIT to total assets ratios at 0.02 and 0.07, respectively. The sector has seen a slight decline in net sales.

The textile spinning sector has a median market value of equity to book value of total debt ratio of 2.91, indicating that investors have high expectations for future earnings potential. The sector has some relatively high retained earnings to total assets ratio, suggesting that companies are retaining earnings for future growth. However, the sector has some weaknesses as well, such as a high total liability to total assets ratio of 0.65 and a low FFO to total debt ratio of 0.23. The working capital to total assets ratio is negative but the current asset to current liabilities ratio is adequate. The sector has a high net sale to total assets ratio but low net income to total assets and EBIT to total assets ratios. The change in net sales to total assets ratio has a median of -0.04. Investors should consider these metrics when evaluating the performance and prospects of textile spinning companies.

The textile weaving and other products’ sector shows signs of financial stability and growth potential. It has a strong market value of equity relative to book value of total debt, and some high retained earnings to total assets ratio. With a moderate level of debt and leverage, the sector displays a moderate level of financial risk. The high FFO to total debt ratio indicates that the companies are generating enough funds from operations to cover their debt obligations. The sector also has adequate short-term liquidity. Although, the sector has modest returns on total assets, the slight increase in net sales over the analyzed period suggests potential for future growth and profitability improvements.

Table 5
Default Model Comparisons for Composite Sector

Validation	Z-Score	O-Score	S-Score	G-Score	X-Score
Accuracy	57.49%	71.95%	82.74%	85.91%	74.87%
Specificity	39.25%	60.53%	75.12%	88.41%	95.35%
Precision	49.73%	94.56%	90.93%	96.55%	99.64%
Recall	82.53%	73.17%	85.35%	85.26%	73.69%
F1 Score	62.06%	82.50%	88.05%	90.55%	84.72%
Type-I Error	35.15%	3.81%	6.35%	2.41%	0.25%
Type-II Error	7.36%	24.24%	10.91%	11.68%	24.87%
Total Observation	788	788	788	788	788
TP	274	521	501	532	549
FP	277	30	50	19	2
FN	58	191	86	92	196
TN	179	46	151	145	41

Table above summarizes the performance of various default prediction models in the textile composite sector, which consists of 46 listed companies. It is evident that the Grover model achieved the highest accuracy of 85.91%, implying a 14.09% error rate. The Springate and Zmijewski models followed with accuracies of 82.74% and 74.87%, respectively.

Upon closer analysis, the Springate model appears to be more reliable as it has a lower recall and Type-II error than the Grover model. Interestingly, the Zmijewski model had the lowest Type-I error at only 0.25%, indicating that it is good at correctly predicting non-default firms. However, it has a significantly high Type-II error of 24.87%, making it unsuitable for default prediction modeling since it could classify a firm as non-default when it is a default in reality. Therefore, relying solely on the X-Score statistic is not viable for default prediction.

Furthermore, it is noteworthy that Altman's Z-Score showed the lowest accuracy among all models, while Ohlson's O-Score showed the second-lowest accuracy at 71.95%. In contrast, the G-Score model was found to be the most appropriate model for default prediction in the textile composite sector. This model emphasizes capitalization through internal financing and profitability.

Conclusively, the Grover and Springate models have relatively high accuracy rates and could be used as alternative models for default prediction in the textile composite sector. However, the G-Score model is the most appropriate due to its focus on capitalization and profitability.

Table 6

Default Model Comparisons for Spinning Sector

Validation	Z-Score	O-Score	S-Score	G-Score	X-Score
Accuracy	57.57%	66.13%	81.89%	81.62%	69.64%
Specificity	41.59%	50.74%	76.26%	79.39%	100.00%
Precision	55.87%	90.85%	89.07%	91.67%	100.00%
Recall	73.43%	68.28%	84.35%	82.43%	68.48%
F1 Score	63.46%	77.96%	86.64%	86.80%	81.29%
Type-I Error	29.10%	6.04%	7.21%	5.50%	0.00%
Type-II Error	13.33%	27.84%	10.90%	12.88%	30.36%
Total Observation	1110	1110	1110	1110	1110
TP	409	665	652	671	732
FP	323	67	80	61	0
FN	148	309	121	143	337
TN	230	69	257	235	41

The Table above provides an overview of the performance of default prediction models in the textile spinning sector, which includes 65 listed companies. Among the six models evaluated, the Springate S-Score achieved the highest accuracy rate of 81.89%, indicating a relatively low margin of error in predicting defaults. However, it is worth noting that the S-Score also had a Type-II Error rate of 10.90%, meaning that around 122 out of 1,110 defaults were missed by the model.

Comparing the S-Score with other models, the G-Score had a similar accuracy rate of 81.62% but a higher Type-II Error rate of 12.88%, indicating that the model missed around 143 out of 1,110 defaults. In contrast, the X-Score had the lowest accuracy rate of 69.64% with a high Type-II Error rate of 30.36%, indicating that the model missed around 338 out of 1,110 defaults. However, it is worth noting that the X-Score did not produce any Type-I Errors, meaning that it did not falsely predict any non-defaults as defaults.

While comparing the Z-Score and O-Score models, it was found that the O-Score achieved a higher accuracy rate of 66.13% as compared to the Z-

Score's accuracy rate of 57.57%. However, the Z-Score had a lower margin of Type-II Error at 13.33%, as compared to the O-Score's 27.84%.

Overall, it can be concluded that the Springate S-Score model is the most suitable to predict defaults in the textile spinning sector due to its high accuracy rate and relatively low Type-II Error rate, despite being higher than desirable. The S-Score model focuses on factors, such as coverage, capitalization, and profitability in predicting defaults.

Table 7

Default Model Comparisons for Weaving and Other Textile Products Sector

Validation	Z-Score	O-Score	S-Score	G-Score	X-Score
Accuracy	56.47%	84.12%	74.71%	91.18%	87.65%
Specificity	32.32%	77.27%	46.55%	81.58%	100.00%
Precision	48.85%	96.18%	76.34%	94.66%	100.00%
Recall	90.14%	85.14%	89.29%	93.94%	86.18%
F1 Score	63.37%	90.32%	82.30%	94.30%	92.58%
Type-I Error	39.41%	2.94%	18.24%	4.12%	0.00%
Type-II Error	4.12%	12.94%	7.06%	4.71%	12.35%
Total Observation	170	170	170	170	170
TP	64	126	100	124	131
FP	67	5	31	7	0
FN	7	22	12	8	21
TN	32	17	27	31	18

The Table above displays the performance metrics of different predictive models in the textile weaving and other textile products sector (23 listed companies). The Table above presents a comparative analysis of various predictive models used in the textile weaving and other textile products industry. The models are evaluated based on their accuracy rates and Type-II Error rates, which indicate the proportion of actual defaults that the models fail to identify.

The G-Score model emerged as the best-performing model, with an impressive accuracy rate of 91.18% and a low Type-II Error rate of 4.71%. This indicates that the G-Score model is highly reliable in predicting defaults and is the most appropriate model for this sector. In contrast, the X-Score model showed a reasonably high accuracy rate of 87.65%, however, its Type-II Error rate was alarmingly high at 12.35%, indicating that it is less trustworthy in predicting defaults. The O-Score model had a slightly lower accuracy rate of 84.12%, and its Type-II Error rate was the highest at 12.94%, making it less suitable for default prediction.

The Springate model showed a sound accuracy rate of 74.71%, with a relatively low Type-II Error rate of 7.06%, making it the second-best model overall. Finally, the Altman's model had an accuracy rate of 56.47%, with a low Type-II Error rate of 4.12%, indicating that it is acceptable. However, it had a high Type-I Error rate of 39.41%, meaning that it is more conservative in predicting defaults.

Overall, the G-Score model is the best-performing model in predicting defaults in the textile weaving and other textile products sector, followed by the Springate model, which has a reasonable accuracy rate with minimal Type-II Error rate. The X-Score model ranks third with sound accuracy, however, it is less reliable in identifying actual defaults.

Table 8

Consolidated Results of Default Prediction Models' Comparison

Validation	Z-Score	O-Score	S-Score	G-Score	X-Score
Accuracy	57.55%	70.08%	81.30%	84.29%	73.96%
Specificity	38.86%	53.61%	71.14%	81.67%	98.20%
Precision	53.62%	92.25%	88.12%	93.71%	99.87%
Recall	78.22%	72.24%	85.35%	85.11%	72.71%
F1 Score	63.63%	81.03%	86.71%	89.20%	84.15%
Type-I Error	32.12%	5.37%	8.23%	4.36%	0.09%
Type-II Error	10.34%	24.55%	10.47%	11.35%	25.96%
Total Observation	2273	2273	2273	2273	2273
TP	844	1452	1387	1475	1572
FP	730	122	187	99	2
FN	235	558	238	258	590
TN	464	141	461	441	109

Finally, consolidated results of textile industry of Pakistan were reached based on 134 firms. The Table above shows total observation around 2273 (Unbalanced Panel Data) which was previously subdivided in three broad textile segments, for instance, textile composite, spinning, and weaving with sub-product.

After analyzing a dataset of 2273 observations from the textile industry of Pakistan, the accuracy and Type-II error rates of five models for default prediction were compared: Altman's Z-Score, Ohlson's Model, Springate's Model, Grover's Model, and Zmijewski's X-Score.

Altman's Z-Score, which only considers liquidity as a predictor of default, had the lowest accuracy rate (57.55%), though its Type-II Error rate was the lowest at 10.34%. Ohlson's model, which focuses on both liquidity and profitability, had an accuracy rate of 70.08% and a Type-II Error rate of 24.55%. Springate's model, which takes into account coverage, capitalization, profitability, and liquidity, had the second-highest accuracy rate at 81.30% and the second-lowest Type-II Error rate at 10.47%.

Grover's model, which emphasizes liquidity and profitability, had the highest accuracy rate among all models at 84.29%, with a negligible Type-II Error rate of 11.35%. Zmijewski's X-Score, which considers leverage, liquidity, and profitability, had the third-highest accuracy rate at 73.96%, however, its Type-II Error rate was sizeable at 25.96%.

Based on the analysis, it was concluded that Grover's G-Score model was the best performer to predict default in the textile industry of Pakistan. Springate's S-Score model was identified as the second-best model due to its low Type-II Error rate. Zmijewski's X-Score had the highest Type-II Error rate and Altman's Z-Score and Ohlson's model were least effective in predicting defaults. Therefore, Grover's G-Score and Springate's S-Score models were recommended as yardsticks for default prediction in the textile sector of Pakistan.

Discussion and Conclusion

The current study attempted to address the increasing default rates in the textile sector, which is negatively impacting the economy as a whole. Moreover, the study also aimed to explore the existing literature on default prediction models and identified the most recommended and robust models that have the potential to predict defaults or financial distress. The research determined that around 50% of defaults in Pakistan are from the textile sector, highlighting the urgent need for effective default prediction models.

To achieve the research objective, the study adopted five default prediction models including Altman’s Z-Score model, Ohlson’s S-score model, Springate’s S-Score model, Grover’s G-Score model, and Zmijewski's X-Score. These models show different characteristics while predicting defaults, however, they all consider liquidity as a critical factor in default prediction and financial distress prediction.

The research, then collected the data from all listed firms in the textile sector and subdivided it into three broad categories including textile composite, spinning, weaving, and textile associated products. A validation process was then conducted by using precision, recall, and F1 score. Furthermore, the results of the overall 134 listed firms were consolidated.

In the final phase, the results of each model were compared based on its accuracy and validation findings. Overall, the study provided valuable insights into default prediction models in the textile sector and suggested that liquidity and profitability are critical factors to be considered while developing such models. The findings may help stakeholders in the textile sector to make more informed decisions, which can ultimately lead to better financial stability and growth for the industry and economy.

Conclusion: The findings suggested that different default prediction models perform differently in the textile industry, depending on the segment and sub-product under consideration. In the textile composite sector, the Grover and Springate models have relatively high accuracy rates, however, the G-Score model is the most appropriate due to its focus on liquidity and profitability, these findings are aligned with (Sari, 2013; Verlekar and Kamat, 2019).

In the textile spinning sector, the Springate S-Score model is the most suitable to predict defaults due to its high accuracy rate and relatively low Type-II Error rate, despite being higher than desirable. The S-Score model focuses on factors, such as coverage, capitalization, and profitability in predicting defaults.

In the textile weaving and other textile products sector, the G-Score model emerged as the best-performing model, with an impressive accuracy rate and a low Type-II Error rate, making it highly reliable in predicting defaults. The Springate model also showed a reasonable accuracy rate with minimal Type-II Error rate, making it the second-best model overall, aligned with (Lestari, R. M. E., et al., 2021; Putri, D. P. S., 2018). Overall, the findings suggested that different models should be considered depending on the segment and sub-product under consideration for default prediction in the textile industry.

Limitations

The current study followed some limitations that should be taken into consideration. Firstly, all other default prediction models could not be covered, such as Shumway's Hazard model, Richard Taffler model, Joseph's V. Rizzi model, Joseph D. Piotroski model, and many others. Therefore, future studies may include these models to make a comparative analysis.

Secondly, the dataset was limited to the textile sector only. While findings are valuable for this sector, it may not be representative of other sectors. Therefore, future studies can include more datasets from other sectors to broaden the scope of the analysis and provide more comprehensive insights.

Overall, despite these limitations, the current research provided useful insights into default prediction models and their effectiveness in the textile sector. The findings can be useful for stakeholders in the industry, such as investors and creditors, to make informed decisions and mitigate their risk exposure.

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