Failure Definitions and Financial Distress Prediction Models

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Contributor: Amélia Ferreira da Silva , José Henrique Brito , Mariline Lourenço , José Manuel Pereira

The concept of business failure has been under discussion in the academic and business world due to the economic and social relevance of the topic. The mere threat of a business going bankrupt affects the entire chain of business relationships. Therefore, predicting the bankruptcy of a business in advance is extremely important for investors, credit banks, suppliers, the state, employees, and other stakeholders of the organization. In this context, academics and professionals have sought to develop models for predicting business failure. The literature on this topic has evolved since the seminal works of Beaver (1967) and Altman, mainly based on the use of mathematics and statistics. However, with the emergence of artificial intelligence, the topic of predicting business failure has resurfaced with additional enthusiasm. This presentation addresses the evolution of business failure prediction models.

artificial intelligence | forecasting | business failure | financial sustainability

1. Failure Definitions

Grounded in the insights of Walsh and Cunningham [1], research into business failure dates back to the 19th century, but it has witnessed intensified and comprehensive investigation in recent years. Beaver [2] defines failure as an organization’s inability to fulfill its financial obligations, signifying its incapacity to meet creditor obligations, distribute dividends to shareholders, or avoid bankruptcy. Furthermore, Beaver et al. [3] characterize failure as the non-fulfillment of financial obligations, encompassing financial difficulties, which entails the failure to meet obligations on time and, on the other hand, the organization’s bankruptcy. Conversely, following the perspective advanced by Altman and Hotchkiss [4], a company can find itself in a state of economic failure for an extended period without defaulting on its obligations. In this view, the quality of managerial stewardship by the board of directors emerges as the primary determinant of failure. In concordance with Amankwah-Amoah et al. [5], business failure materializes when a company cannot recover from a period of decline, ultimately leading to its collapse. In a more general sense, business failure can be delineated as the cessation of operations due to an inability to adapt to external changes (Amankwah-Amoah and Wang [6]). However, as Pereira et al. [7] noted, it is essential to recognize that no singular concept of business failure exists, encompassing a spectrum ranging from legal bankruptcy to insolvency, suspension of payments, or persistent financial losses.

2. Financial Distress Prediction Models

In alignment with the diversity of failure definitions, a variety of models and methodologies exist for predicting business failure. This spectrum begins with the seminal univariate analysis model introduced by Beaver [2] and extends to multivariate discriminant analysis, logit, and probit models, as expounded by Pereira et al. [7]. Moreover, recent developments have given rise to models rooted in artificial intelligence techniques. Corroborating the assertion of Korol and Spyridou [8], establishing a financial early warning system is critical for organizations, leveraging reasonable forecasting models that empower stakeholders to evaluate financial risks capable of shaping organizational success or failure. It is imperative to recognize that each of the discussed models has advantages and drawbacks. Consequently, there is no universally superior technique, and selecting an appropriate model hinges on individual circumstances and one's conception of business failure, aligning with Pereira et al. [9].

The development of business failure models gained momentum in the 1960s, catalyzed by the imperative to scrutinize business failure and the ensuing economic and social ramifications for all stakeholders. The initial techniques employed encompassed statistical methodologies applied to companies' financial data, involving the utilization of a set of financial ratios (Maricica and Georgeta [10]). Pioneering contributions, such as those of Beaver [2] and Altman [11], played pivotal roles in this analytical domain. Regarding the most frequently employed technique for predicting business failure, multiple discriminant analysis is the prevailing approach in the corpus of analyzed studies (Alaka et al. [12]), Hausser and Booth [13], and Lenox [14].

Statistical techniques have historically served as the prevailing method for predicting business failure. These techniques, founded on a predefined threshold, classify companies as failures if their scores fall below the specified threshold or as non-failures if not. Nevertheless, as posited by Ooghe and Spaenjers [15], statistical techniques may yield specific errors, imposing costs on companies, such as type I errors (where failed companies are erroneously classified as non-failed) or type II errors (the converse situation). Pereira et al. [16] note that initial research sought to ascertain whether datasets contained sufficient information to forecast impending insolvency or aimed to discern the most effective predictive models. Subsequently, with more comprehensive models, such as artificial intelligence-based techniques, a quest for enhanced accuracy and reduced error rates in business failure prediction emerged.

Following Yeh et al. [17], the limitations of early business failure prediction models are twofold. Firstly, these models exclusively relied on financial ratios as independent variables. Secondly, they overlooked the significance of a company's managerial effectiveness as a critical variable for classifying failures. While widely adopted, statistical techniques often entail restrictive assumptions such as linearity, normality, and independence among variables (Wu [18]). Alternative methods rooted in artificial intelligence have been introduced to circumvent these limitations.

According to Shetty et al. [19], the 1990s ushered in a new phase in the evolution of business failure prediction models, introducing innovative methods, particularly artificial intelligence algorithms, including neural networks (Špiler et al. [20]) and decision trees. These artificial intelligence-based techniques offer promising alternatives to traditional statistical models, addressing their principal shortcomings (Dong and Chen [21]).

Neural networks (NN), as defined by Neves and Vieira [22], represent a prominent artificial intelligence-based method for business failure prediction. These networks, inspired by the architecture of the human brain, can learn directly from examples without prior knowledge of specific problems. A neural network comprises interconnected processing units, each with a calculation function (Tam and Kiang [23]). The learning process involves iterative adjustments to minimize errors until the network attains equilibrium, resolving the problem (Altman et al. [24]).

Neural networks offer several advantages over statistical models. They eliminate the need for a pre-established functional relationship among variables, as they can direct knowledge acquisition through the learning process. Furthermore, the collective behavior of multiple units, rather than individual units, contributes to their efficiency (Altman et al. [24]). Despite their advantages, neural networks are relatively slow learners and may yield complex, challenging-to-interpret results (Altman et al. [24]). Understanding the final rules neural networks acquire can also be challenging (Shin and Lee [25]). Numerous studies have compared the performance of neural networks with statistical techniques, revealing that neural networks may exhibit superior predictive capacity in specific scenarios (Altman et al. [24] and Gámez et al. [26]). It has been suggested that combining neural networks with multiple discriminant analyses may yield more accurate and comprehensible results (Altman et al. [24]). Noh [27] compared the bankruptcy prediction performance of the long short-term memory (LSTM), logistic regression (LR), k-nearest neighbors (k-NN), decision tree (DT), and random forest (RF) models. For the author, the results of this research provide useful information for selecting a suitable bankruptcy prediction model when the dataset has relatively few bankrupt companies.

Decision trees (DTs) constitute another machine-learning technique for business failure prediction. Decision trees map a hierarchy of classes or values based on conditional logic rules, leading to a classification. The main goal is to uncover relationships and dependencies between the variables, usually presented in the form of rules (e.g., “X → Y”).

Decision trees offer versatility and a high comprehension rate, facilitating the identification of critical factors for accurate company classification (Pereira et al. [7]). Moreover, they do not necessitate the transformation of variables or the imposition of constraints and can incorporate the costs of incorrect classification, ultimately reducing financial burdens (Gepp et al. [28]). However, decision trees have some drawbacks, including the arbitrary assignment of prior probabilities, rendering them less precise than statistical models. Additionally, they merely indicate the relative importance of variables, unlike statistical models that provide detailed significance levels (Gepp et al. [28]). Challenges include creating decision trees, which can be time-consuming, difficulty handling incomplete information, and the possibility of unexpected values (Pereira et al. [7]).

Support vector machines (SVMs) are an artificial intelligence-based method for business failure prediction. These machines employ a linear model to create an optimal separator for binary classification. The variables closest to this separator, referred to as support vectors, define the outcome, classifying companies as failures or non-failures (Alaka et al. [12]). SVMs excel in minimizing structural risk, offer a higher predictive capacity, and are adept at handling overlapping data (Yeh et al. [17] and Shetty et al. [19]). SVMs are lauded for their precision and stability in predicting business failure. Their simplicity facilitates integration with traditional statistical techniques, leveraging the strengths of both approaches (Min and Lee [29]). Kernel-based support vector machines (K-SVMs) enhance classification accuracy and outperform other prediction models (Shaw and Routray [30]). Genetic algorithms (GAs), a stochastic search technique inspired by natural genetics and evolution, also contribute to business failure prediction. GAs transform complex problems into simpler ones that can be treated as discriminant functions as mentioned by Gordini [31]. GAs excel in optimizing objective functions subject to rigid and flexible constraints and can explore non-linear solution spaces without prior information about the model (Shin and Lee [25] and Wu et al. [32]). GAs entail four key stages: initialization, selection, crossover, and mutation. In the initialization phase, a population of genetic structures, or chromosomes, is distributed in the solution space. The best-performing chromosomes are selected and copied to the next generation, gradually occupying a more significant portion.

As explained above, the burgeoning field of business failure prediction has witnessed a paradigm shift with the advent of artificial intelligence (AI) technologies. This research aims to investigate and compare the efficacy of business failure prediction models based on AI against those grounded in traditional statistical approaches. Based on the literature in the field, this research posits that AI-driven models outperform their statistical counterparts in accurately forecasting business failures.

AI-based models, particularly machine learning algorithms, offer a distinct advantage in handling complex and dynamic datasets. These models exhibit a capacity for nuanced pattern recognition, leveraging vast amounts of data to identify subtle indicators of financial distress that may elude conventional statistical methods. Moreover, AI models can adapt and evolve with changing market conditions, providing a more robust and responsive framework for business failure prediction. By harnessing the power of deep learning and neural networks, these models can uncover intricate relationships within financial data, offering a more comprehensive understanding of the multifaceted factors contributing to business failure.

Contrastingly, traditional statistical models often rely on predefined assumptions and linear relationships, limiting their ability to capture the intricacies of modern business dynamics. Statistical methods may struggle with non-linearity and fail to adapt to the evolving nature of markets, leading to diminished predictive accuracy.

Thus, based on the literature available, researchers can conclude that AI-driven business failure prediction models surpass statistical models.

References

1. Walsh, G.S.; Cunningham, J.A. Business Failure and Entrepreneurship: Emergence, Evolution and Future Research. Found. Trends Entrep. 2016, 12, 163–285.
2. Beaver, W. Financial Ratios as Predictors of Failure. J. Account. Res. 1966, 4, 71–111.
3. Beaver, W.; Correia, M.; McNichols, M.F. Financial statement analysis and the prediction of financial distress. Found. Trends Account. 2010, 5, 99–173.

4. Altman, E.I.; Hotchkiss, E. Corporate Financial Distress and Bankruptcy—Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt, 3rd ed.; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2006.
5. Amankwah-Amoah, J.; Adomako, S.; Berko, D.O. Once bitten, twice shy? The relationship between business failure experience and entrepreneurial collaboration. J. Bus Res. 2022, 139, 983–992.
6. Amankwah-Amoah, J.; Wang, X. Business Failures around the World: Emerging Trends and New Research Agenda. J. Bus Res. 2019, 98, 367–369.
7. Pereira, J.M.; Crespo Domínguez, M.Á.; Ocejo, J.L.S. Modelos de Previsão do Fracasso Empresarial: Aspectos a considerar. Polytechn. Stud. Rev. 2007, 7, 111–148.
8. Korol, T.; Spyridou, A. Examining Ownership Equity as a Psychological Factor on Tourism Business Failure Forecasting. Front. Psychol. 2020, 10, 3048.
9. Pereira, J.; Basto, M.; Ferreira-da-Silva, A. Comparative Analysis between Statistical and Artificial Intelligence Models in Business Failure Prediction. J. Manag. Sustain. 2014, 4, 114.
10. Maricica, M.; Georgeta, V. Business Failure Risk Analysis using Financial Ratios. Procedia Soc. Behav. Sci. 2012, 62, 728–732.
11. Altman, E.I. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. J. Finance 1968, 23, 589–609.
12. Alaka, H.A.; Oyedele, L.O.; Owolabi, H.A.; Kumar, V.; Ajayi, S.O.; Akinade, O.O.; Bilal, M. Systematic review of bankruptcy prediction models: Towards a framework for tool selection. Expert. Syst. Appl. 2018, 94, 164–184.
13. Hauser, R.P.; Booth, D. Predicting Bankruptcy with Robust Logistic Regression. J. Data Sci. 2022, 9, 565–584.
14. Lennox, C. Identifying failing companies: A reevaluation of the logit, probit and DA approaches. J. Econ. Bus. 1999, 51, 347–364.
15. Ooghe, H.; Spaenjers, C. A note on performance measures for business failure prediction models. Appl. Econ. Lett. 2009, 17, 67–70.
16. Pereira, J.; Basto, M.; Silva, A. Comparing logit model with discriminant analysis for predicting bankruptcy in Portuguese hospitality sector. Eur. J. Tour. Res. 2017, 16, 276–280.
17. Yeh, C.C.; Chi, D.J.; Hsu, M.F. A hybrid approach of DEA, rough set and support vector machines for business failure prediction. Expert. Syst. Appl. 2010, 37, 1535–1541.
18. Wu, W.W. Beyond business failure prediction. Expert. Syst. Appl. 2010, 37, 2371–2376.

19. Shetty, S.; Musa, M.; Brédart, X. Bankruptcy Prediction Using Machine Learning Techniques. J. Risk Financ. Manag. 2022, 15, 2–10.
20. Špiler, M.; Matejić, T.; Knežević, S.; Milašinović, M.; Mitrović, A.; Arsić, V.B.; Obradović, T.; Simonović, D.; Despotović, V.; Milojević, S.; et al. Assessment of the Bankruptcy Risk in the Hotel Industry as a Condition of the COVID-19 Crisis Using Time-Delay Neural Networks. Sustainability 2023, 15, 272.
21. Dong, J.R.; Chen, J. An evolutionary based wavelet network for business failure prediction. In Proceedings of the 2009 WRI Global Congress on Intelligent Systems, GCIS, Xiamen, China, 19–21 May 2009; Volume 3, pp. 274–278.
22. Neves, J.C.; Vieira, A. Improving bankruptcy prediction with Hidden Layer Learning Vector Quantization. Eur. Account. Rev. 2006, 15, 253–271.
23. Tam, K.Y.; Kiang, M.Y. Managerial Applications of Neural Networks: The Case of Bank Failure Predictions. Manag. Sci. 1992, 38, 926–947.
24. Altman, E.I.; Marco, G.; Varetto, F. Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience). J. Bank. Financ. 1994, 18, 505–529.
25. Shin, K.-S.; Lee, Y.-J. A genetic algorithm application in bankruptcy prediction modeling. Expert. Syst. Appl. 2002, 23, 321–328.
26. Gámez, M.A.F.; Gil, A.C.; Ruiz, A.J.C. Applying a probabilistic neural network to hotel bankruptcy prediction. Tour. Manag. Stud. 2016, 12, 40–52.
27. Noh, S.-H. Comparing the Performance of Corporate Bankruptcy Prediction Models Based on Imbalanced Financial Data. Sustainability 2023, 15, 4794.
28. Gepp, A.; Kumar, K.; Bhattacharya, S. Business failure prediction using decision trees. J. Forecast 2010, 29, 536–555.
29. Min, J.H.; Lee, Y.C. Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters. Expert. Syst. Appl. 2005, 28, 603–614.
30. Shaw, L.; Routray, A. A critical comparison between SVM and k-SVM in the classification of Kriya Yoga meditation state-allied EEG. In Proceedings of the IEEE International WIE Conference on Electrical and Computer Engineering, WIECON-ECE 2016, Pune, India, 19–21 December 2017; AISSMS: Pune, India, 2017; pp. 134–138.
31. Gordini, N. A genetic algorithm approach for SMEs bankruptcy prediction: Empirical evidence from Italy. Expert. Syst. Appl. 2014, 41, 6433–6445.
32. Wu, C.-H.; Tzeng, G.-H.; Goo, Y.-J.; Fang, W.-C. A real-valued genetic algorithm to optimize the parameters of support vector machine for predicting bankruptcy. Expert Syst. Appl. 2007, 32,

397–408.