Journal of Industrial and Systems Engineering
Vol. 17, No. 1, pp. 36-53
Winter (January) 2025

JISE

Application of Artificial Intelligence in Predicting Financial Dissatisfaction of Managers in Financially Distressed Companies of the Tehran Stock Exchange

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Abstract

Financial dissatisfaction is a critical factor influencing corporate success or failure. This study introduces two artificial intelligence (AI)-based models to predict factors contributing to financial dissatisfaction among managers of financially distressed firms. In the first phase, relevant data were gathered through a literature review. In the second phase, additional data were collected via questionnaires and interviews (Delphi method) with senior managers to ensure theoretical saturation. The Altman Z-score was then used to identify financially distressed companies. The study's statistical population included 166 senior managers from 50 financially distressed firms listed on the Tehran Stock Exchange. Data were collected through a structured questionnaire covering seven dimensions and 54 indicators. Two AI models- Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS)- were applied to analyze the predictive power of financial dissatisfaction factors. The first model was a multilayer perceptron (MLP) neural network, which used a hyperbolic tangent activation function. The second is an ANFIS framework with a five-layer Sugeno-type neural network including 143 neurons in the hidden layer and trained using the Levenberg-Marquardt algorithm. Comparative analysis revealed that both models effectively identified key financial dissatisfaction factors, but the ANN model outperformed ANFIS, achieving a mean correlation coefficient (R^2) of 0.98 (training) and 0.96 (validation), with a lower mean squared error (MSE) of 0.002120 and 0.003953, respectively. These findings highlight ANN's superior predictive accuracy, making it a valuable tool for assessing financial distress among executives.

Keywords: Dissatisfaction, Financial Distress, Artificial Intelligence, Tehran Stock Exchange

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ISSN: 1735-8272,

1- Introduction

The dynamic landscape in which companies operate has undergone significant transformations in recent years. Businesses have increasingly expanded their activities into the global economy, exposing them to heightened financial risks and economic uncertainties (Al-Hadi et al., 2016). Across numerous countries, the frequency of financial crises has risen abnormally, resulting in a substantial number of companies voluntarily declaring bankruptcy (Ugural & Aksoy, 2020). The ability to predict corporate distress and bankruptcy is of critical importance, as many small and medium-sized enterprises (SMEs) fail to achieve sustainable growth and collapse within the early years of their operations. Consequently, forecasting corporate growth and decline can mitigate the substantial financial losses that businesses and entrepreneurs incur (Ebrahimkhani et al., 2019).

Traditional models for predicting financial distress have been constrained by assumptions of normality, linearity, and homoscedasticity. These limitations have prompted researchers to adopt artificial intelligence (AI) techniques to address nonlinear, complex, and nonparametric problems in financial distress prediction (Daneshvar et al., 2020; Broby, 2022; Aliahmadi et al., 2022). However, the accuracy of previous predictive models remains a subject of skepticism, as they have predominantly relied on financial ratios as independent variables in forecasting financial distress and dissatisfaction among corporate executives. In addition to financial indicators, numerous non-financial factors can significantly influence financial dissatisfaction among executives in distressed firms (Soufi et al., 2020).

One of the primary challenges in predicting corporate financial distress is the lack of a comprehensive understanding of the key influencing variables. The presence of numerous variables often leads managers, creditors, researchers, and other stakeholders to either rely on prior studies or selectively choose certain variables from a broader set, based on subjective preferences rather than scientific rigor (Bruynseels & Willekens, 2012; Fallah & Nozari, 2021). The failure to systematically identify and incorporate critical financial and non-financial factors can result in ineffective predictive models, ultimately hindering the ability to anticipate financial crises and take preemptive corrective measures. By identifying and ranking these influential factors, researchers and practitioners can determine which elements play the most substantial roles in financial distress and dissatisfaction. Such insights allow decision-makers to focus on key indicators, take timely action to prevent financial distress, and implement strategic adjustments in corporate management (Waqas and Rohani, 2018). A well-structured ranking of these factors enables corporate stakeholders to prioritize critical financial distress signals and develop targeted strategies to mitigate potential financial crises. Effective distress prediction models not only contribute to reducing the incidence of corporate failures but also promote broader economic stability by preventing layoffs, preserving employment levels, and enhancing national economic output (Mselmi et al., 2017).

Conventional financial distress prediction models are typically based on restrictive assumptions such as linearity, normality, and the independence of predictor variables. These constraints often undermine the predictive power of traditional models and limit their applicability to real-world scenarios (Soufi et al., 2020). The strength of this research lies in its incorporation of a diverse set of microeconomic and macroeconomic variables, including managerial decisions, economic sanctions, financial crises, government performance, internal and external corporate challenges, and other relevant factors. This comprehensive approach enhances the predictive accuracy of the proposed AI-based model compared to previous models that have predominantly relied on financial indicators alone (Ashraf et al., 2019).

A review of existing literature within the Iranian context reveals a gap in research concerning the development of a holistic predictive model that integrates all relevant factors influencing financial dissatisfaction among executives in distressed companies (Gholamizadeh et al., 2023). Prior studies have primarily focused on financial ratios as the sole independent variables in distress prediction models. In contrast, this research aims to categorize and examine all relevant factors contributing to financial dissatisfaction among executives, representing a novel contribution to the field. Another distinguishing feature of this research is its use of expert interviews with senior executives from financially distressed companies, employing the Delphi method over a ten-year period in Iran. This extensive longitudinal analysis enables the identification of key financial dissatisfaction drivers, setting this study apart from previous research. Furthermore, a significant innovation of this study is the application of two optimized and robust AI models to enhance predictive accuracy.

This study aims to leverage AI techniques to identify and predict factors influencing financial dissatisfaction among executives in distressed firms. By integrating financial and non-financial indicators into AI-based models, this research seeks to overcome the limitations of conventional approaches and enhance forecasting accuracy. The primary objective of this study is to develop a predictive model capable of identifying and ranking influential factors affecting financial dissatisfaction among executives. Additionally, this research aims to assess the strengths and weaknesses of previously developed models and propose an optimized AI-based predictive framework. A key rationale for presenting this study as a critical research contribution lies in its methodological advancements over prior studies. Firstly, the theoretical foundation presented in this research has been significantly reinforced compared to previous studies. Secondly, this research simultaneously employs two advanced AI models: Adaptive Neuro-Fuzzy Inference System (ANFIS) and Artificial Neural Networks (ANN). In prior studies, the application of ANFIS models has been limited to training phases with only three learning algorithms. In contrast, this research extends beyond training and incorporates validation phases, integrating ANN-based multilayer perceptron (MLP) networks with optimized transfer functions to minimize prediction errors. These functions include hyperbolic tangent (Tanh), Boolean (Bolin), logarithmic sigmoid (Logsig), tangent sigmoid (Tansig), and linear purelin activation functions, enhancing predictive robustness. Lastly, this study identifies and compares the most effective algorithmic approaches in both AI models based on predictive power and minimal mean squared error (MSE), ultimately selecting the most accurate AI-based predictive model. The main question of the research is “What are the key financial and non-financial factors influencing financial dissatisfaction among executives in distressed firms, and how can AI-based models, specifically ANFIS and ANN, be optimized to enhance predictive accuracy?”

2- Literature Review

Financial dissatisfaction and distress encompass a broad spectrum of conditions where financial assets lose a significant portion of their nominal value. During the 19th and early 20th centuries, most financial crises were linked to banking sector failures, often coinciding with broader economic downturns (Jansen et al., 2024). Other financial distress scenarios include stock market crashes, speculative bubbles, and currency crises (Buachoom and Kasemsan, 2011). Given the complexity and multidimensional nature of financial distress, AI-based models offer a promising avenue for improving predictive accuracy and managerial decision-making (Raeeszadeh et al., 2016).

Despite the extensive research on financial distress prediction, a universally accepted definition of artificial intelligence remains elusive due to its vast and evolving scope (Salahi et al., 2023). AI can be categorized into strong AI and weak AI paradigms. The strong AI approach seeks to develop machines with comprehensive human-like cognitive abilities, such as consciousness, language comprehension, reasoning, and independent decision-making. In contrast, the weak AI approach focuses on designing systems that perform specific tasks mimicking human intelligence (Ghane et al., 2016). In summary, AI can be broadly defined based on four key attributes: thinking like humans, acting like humans, reasoning logically, and performing rational actions (Homayounfar et al., 2018; Nozari et al., 2024).

This study systematically reviews prior research on financial distress prediction, highlighting existing gaps and demonstrating the need for AI-driven models to enhance predictive accuracy. Table (1) provides an overview of previous studies in this erea, illustrating the evolution of financial distress prediction models and the significance of incorporating AI techniques to improve predictive outcomes.

Table 1. Summary of Researches on Financial Distress

Author	Findings
Kheradyar et al. (2018)	proposed an Adaptive Neuro-Fuzzy Inference System (ANFIS) based on Principal Component Analysis (PCA) to predict financial distress in companies. The results show that the ANFIS system based on PCA is capable of predicting the occurrence of financial distress in companies listed on the Tehran Stock Exchange.
Vaghfi et al. (2019)	Examined the factors influencing financial distress and its prediction through machine learning methods, including multi-objective genetic algorithm sorting and bee colony algorithms. The results indicate the indirect effect of the ratio of non-executive managers and institutional ownership, and the direct effect of earnings management and managers' overconfidence on financial distress, among other managerial variables.
Vaghfi & Darabi (2019)	Investigated the factors affecting financial distress and its prediction using artificial intelligence algorithms, decision tree methods, support vector machines, and Bayesian classification. The findings indicate the direct effects of inflation and financial risk, and the inverse effects of non-executive managers' ratio, annual stock returns, and operating cash flow ratio on financial distress.
Soufi et al. (2020)	Used a combination of artificial neural network techniques and genetic algorithms based on Zimenaski ratios for modeling financial distress prediction.
Botshekan et al. (2018)	Proposed a new approach for selecting variables affecting financial distress prediction using expert opinions and decision-making algorithms.
Gameel & El-Geziry (2016)	Based on studies, the use of neural networks (NNs) for predicting financial distress in companies has shown higher accuracy compared to statistical methods such as logistic regression and discriminant analysis.
Heydari et al. (2019)	Used Genetic Algorithm for predicting financial distress in companies. Their findings indicate that the genetic model not only predicts financial distress but is also understandable for users.
Khajouei et al. (2019)	Used a support vector machine to design a model for predicting financial distress in companies and compared the SVM model's results with MVA, LR, and Backpropagation Neural Networks (BPN). The results showed that the SVM model had higher accuracy with 88.01% for training data and 83.06% for testing data compared to other models.
Alexandropoulos et al. (2019)	Using Dense Deep Neural Networks (DDNN), it was shown that predicting bankruptcy in Greek companies provided significant results.
Matsumaru et al. (2019)	Using support vector machines, artificial neural networks, and multivariate discriminant analysis based on financial indicators, the study concluded that support vector machines are more accurate than other models in predicting corporate bankruptcy risk.
Inam et al. (2019)	By comparing and analyzing data mining techniques, they found that the neural network model performs better in predicting bankruptcy. They also concluded that profitability ratios and financial leverage have greater power in predicting bankruptcy and are the best variables for predicting financial distress.

3- Methodology

This research is of a mixed data type, descriptive in terms of method, applied in terms of purpose and result, longitudinal in terms of time dimension, and of a modeling nature. In the first stage, to collect conceptual data, write the theoretical foundations, define concepts, review previous research, and identify the research variables, a library method is used. This involves studying credible sources such as books, articles, conferences, the internet, and others related to the current topic, extracting necessary notes and concepts through note-taking, and referencing them in the theoretical section of the present dissertation. In the second stage, to identify and rank the factors influencing financial dissatisfaction among managers in financially distressed companies, interviews and questionnaires are used. A non-random, purposeful, and accessible sample from senior managers (CEO, CFO, middle managers in distribution, sales, production, etc.) of the sampled companies will be interviewed to identify the factors influencing financial dissatisfaction, continuing until the theoretical richness of the researcher is achieved.

Additionally, for designing a model to predict financial dissatisfaction among managers, variables and factors obtained from the interviews and questionnaires will be used. Therefore, interviews will be employed to identify the components influencing financial dissatisfaction. In this manner, the selected sample for the interview will respond to questions based on identifying the components influencing financial dissatisfaction among managers. After these components are identified by senior managers (of financially distressed companies), the secondary statistical sample will answer the questionnaire to rank the influencing components. The questionnaire is designed after the interview and identification of the components influencing financial dissatisfaction among managers. To achieve the main research objective, the work process is carried out in three main stages: selecting appropriate criteria for identifying financially distressed companies, identifying the variables and factors influencing financial dissatisfaction among managers in financially distressed companies, and finally, conceptual modeling.

4- Results

In this article, the Altman Z-Score index is used to identify financially distressed companies (Altman et al., 2015). To predict the occurrence of distress and bankruptcy, ratio analysis is used. This model consists of five financial ratios:

- Working capital to total assets (X1)
- Retained earnings to total assets (X2)
- Earnings before interest and taxes to total assets (X3)
- Book value of equity to book value of debt (X4)
- Sales to total assets (X5)

The model is formulated as follows:

$$\text{Z-Score} = 0.717\,X_1 + 0.84\,X_2 + 3.1\,X_3 + 0.42\,X_4 + 0.998\,X_5 \qquad (1)$$

The information extracted from the audited financial statements for the fiscal year-end (financial distress) is used to assess the status of the sample companies. This data is sourced from the statistical archive available on the official website of the Securities and Exchange Organization and Codal. By calculating the Z-Score for the sample companies in Table (2), it is determined that the lower the Z-Score, the higher the level of financial distress for the company. Companies with a Z-Score above 2.9 are considered healthy, while those with a Z-Score below 1.23 are considered bankrupt. A Z-Score between 2.9 and 1.23 is regarded as the "gray area" (distress), and this zone should be interpreted with caution (Mohammad Morfou et al., 2020).

In this research, the dependent variable is financial dissatisfaction among managers in financially distressed, and the independent variables include the factors that influence financial dissatisfaction among managers in financially distressed companies listed on the Tehran Stock Exchange. The collection of conceptual data, writing the theoretical foundations, defining concepts, reviewing previous research, and identifying the variables for this study are based on the library method. This involves studying credible sources such as books, articles, conferences, the internet, and other relevant materials related to the current topic, extracting necessary notes and concepts through note-taking, and utilizing them. Selecting the expert group is an important part of the Delphi method. The awareness of this group regarding the topic of interest guarantees high-quality Delphi results. Therefore, the members of the Delphi panel in this study were selected based on expertise rather than random selection.

In this study, an initial list of forty-five senior managers (CEO, CFO, Sales Manager, Production Manager, etc.) from the sample companies, who were considered experts, was chosen. For the interviews, thirty CEOs were selected from this list after being informed about the research topic and process. These participants had experience in other management levels, were familiar with most sections of the company, and most importantly, they were willing to dedicate the necessary time for the researcher. Additionally, for those experts who were not in their management posts during the study, arrangements were made for their participation. In the first phase, through reviewing sources and previous research, key factors affecting financial distress in companies were extracted as key points, which are represented in Table (2).

Table 2. Extracted Codes from Literature Review

Extracted Codes
Liquidity crisis
Inability to pay interest – decreased profitability
Improper risk management
Economic recession, financial and banking crisis – sanctions, slow economic growth – technological failure – currency fluctuations
Environmental pressures
Low-quality profit
Low sales-to-assets ratio
Increased trade barriers – poor financial performance
Decrease in sales
Negative economic growth, inflation
Fraud and corruption – financial statement manipulation
Inadequate economic structure – lack of competitiveness – fraud and corruption – volatility and reduced trade support – financing – lack of adequate capital – inefficient management
Sanctions and raw material supply – lack of competitiveness
Sanctions and increased investment risk
Currency devaluation
Environmental pressures – lack of appropriate company strategy
Decrease in GDP
Inefficient investment
Managers Overconfidence
Individualism in management – environmental pressures
Managerial conservatism – lack of cash flow forecasting
Inability to repay interest
Lack of competition
Insufficient working capital – inability to forecast cash flow
Managerial overconfidence – shortsightedness
Decrease in export income – reduction in long-term investment – decline in foreign exchange reserves
Decrease in board independence
Increased trade barriers – decline in sales-to-assets ratio – rising interest rates – loss of buyer confidence – tax laws – devaluation – decline in export income – reduction in foreign reserves – sanctions and reduction in long-term investments – excessive credit sales – technological failure – fraud and corruption
Inefficient investment
Limited knowledge – lack of innovation
Lack of an appropriate strategy – high management turnover – limited knowledge – insufficient managerial authority – lack of customer orientation

In the second phase of the research, semi-structured interviews were arranged. In these interviews, the researcher aimed to initially explore the experts' perspectives on the factors affecting financial dissatisfaction among managers and its relation to financially distressed companies. The main factors influencing managers' financial dissatisfaction in distressed companies were identified. Then, the findings from the literature review were shared with them to gather their opinions. A summary of these key points is provided in Table (3).

Table 3. Key variables in the First Phase of Delphi Method

Factors Affecting Financial Distress in Companies	
Company financing	Incorrect financial provision and cash flow forecasting
Company marketing	Weak company marketing due to lack of flexibility
Company debt – profitability	Inability to repay financial obligations
Economic sanctions	Increased transaction costs due to economic sanctions
	Inability to import goods and machinery due to sanctions
Speculation	Increase in speculation
Company innovation – customer orientation	Inability to adapt to market changes and technological advancements
Company sales	Lack of credit given by suppliers and creditors – sale of non-operational assets
Investment risk – raw material supply	High foreign investment risk – raw material supply at high rates due to sanctions
Goods value and the cost price of machinery	Low value of goods below cost price
	Machinery depreciation and obsolescence
	Increased internal disputes and conflicts
Raw material prices	Increase in raw material prices
Imports	Imposition of unfavorable tariffs on imports by the government
Bank loans – borrowing	Repeated borrowing by companies from banks instead of the capital market
Research and development	Reduction in company research and development expenditure
Retained earnings	Low ratio of retained earnings to total assets
Investments	Inefficient investment in profitable projects – risky investments
Financial and commercial health indicators	Low financial and commercial health indicators
Working capital	Insufficient working capital
Company management capability – public demand for company products	Inability to adapt to market changes and rapid technological advancements
	Ineffective resource management by the company
	Failure to recognize public demand
Company management – personnel issues – bureaucracy	Lack of innovation in company management
	Personnel problems and shortage of specialists
	Complex administrative bureaucracy, including tax and insurance laws
Support for trade in the country – external shocks – behavior in financial markets	Lack of government support for companies
	External shocks faced by companies
	Herd behavior and panic due to information asymmetry in financial markets
Economic, social, and political structures in the country	Poor economic, social, and political structures affecting the country’s economy
Country's financial and monetary system – capital market	Impact of banking sanctions on the financial and monetary system

Factors Affecting Financial Distress in Companies	
	Lack of interest in directing liquidity to the capital market for companies' financing needs
Value chain of goods	Changes in global value chains for goods and services
Inflation – competitiveness	Increase in inflation and inadequate provision of raw materials
	Excessive imports of goods similar to domestic products
Financial statements	Manipulation and distortion of financial statements
Economic conditions	International economic conditions – government decisions
Natural events and occurrences	Accidents and natural events such as floods and earthquakes
Trade unions and government interference – exchange rates	Imposed opinions by trade unions and government intervention
	Exchange rate instability
Cost control in companies	Lack of overall control and cost management in companies
Board members – company management	Lack of board members' participation in decision-making
	Failure to use specialists in company management
	Lack of training or management experience – poor managerial leadership
New technology – relationship between production and consumption	Failure to adopt new technology – misalignment between production and consumption

After the second phase and content analysis of the interviews, the factors influencing financial dissatisfaction among managers in financially distressed companies were extracted from the perspectives of these 30 specialists. These extracted codes were then compared with those from the literature review. Common codes were eliminated, and ultimately, 64 codes were identified as the main factors influencing financial dissatisfaction among managers (See Fig 1).

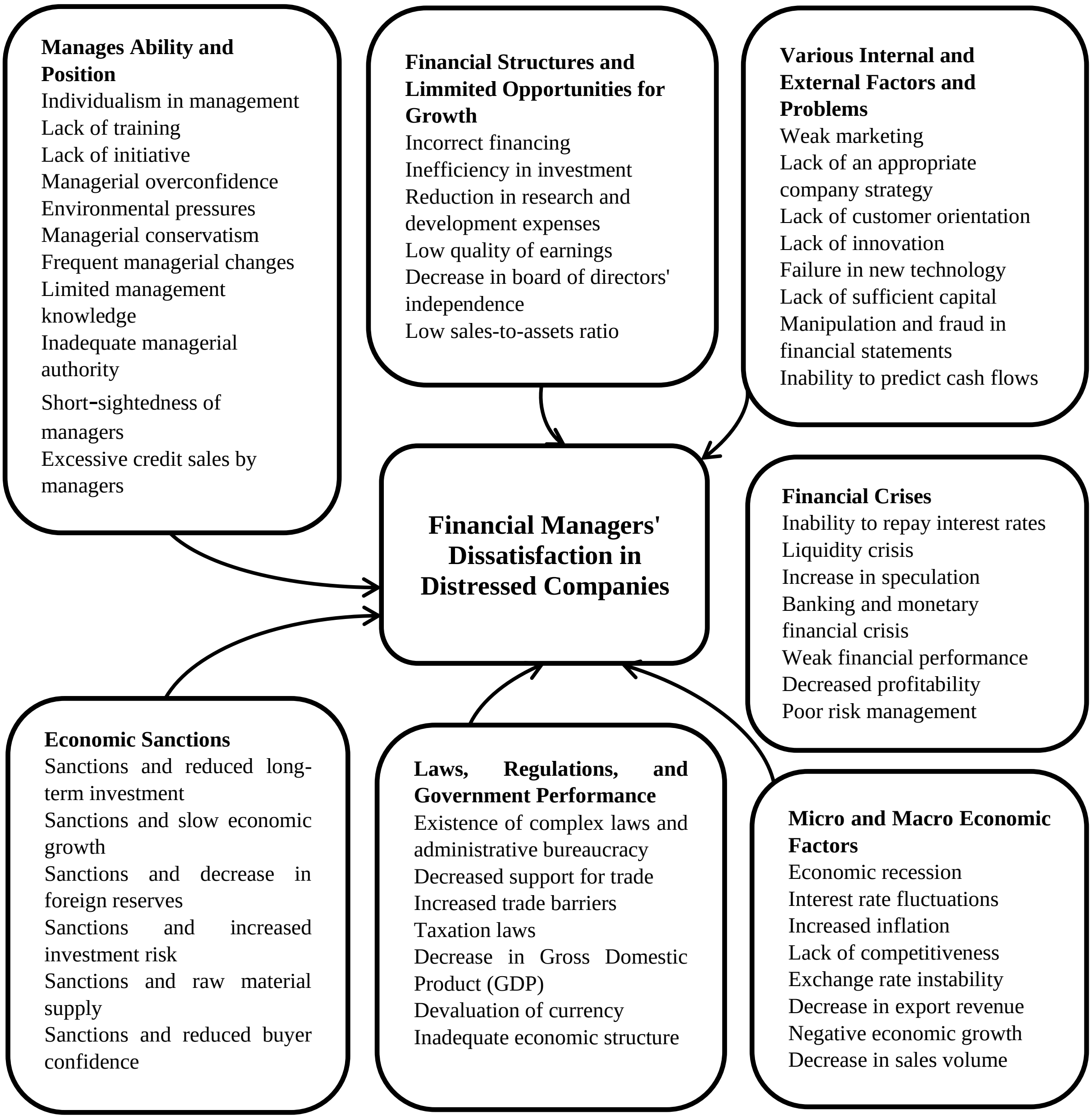

Fig 1. Conceptual Model

By identifying the variables affecting the financial dissatisfaction of managers in financially distressed companies and ranking these variables, as well as recognizing the strengths and weaknesses of artificial intelligence models, an artificial intelligence model has been designed. Modeling and simulating the factors influencing financial dissatisfaction of managers in financially distressed companies using Artificial Neural Networks (ANN), with its high learning capability, holds a special place. Therefore, in this section, the results obtained from modeling the financial dissatisfaction of managers in distressed companies using ANN are presented. In this study, the MATLAB software was used for the analysis. The collected data for implementing the artificial neural network is divided into three groups: training, testing, and validation data.

The first artificial intelligence model used in this study is neural network. After collecting the required data, it was divided into two sets: training data and evaluation data. The collected data is used to train the model, and the evaluation data is used to calculate the error rate of the algorithm on data that the model has not encountered before. In building a model based on a neural network, the first step is selecting the type of network. In this study, a multilayer perceptron (MLP) neural network has been used, as this type

of network is capable of classification and clustering and finding unknown mappings. After training the network in this study, the most optimized transfer functions were selected for the multilayer neural network with the lowest error rates. The hyperbolic tangent (Tanh), Boolean (bolin), Logarithmic sigmoid (Logsig), sigmoid tangent (Tansig), and linear (purelin) functions were used in layers one, two, three, four, and five, respectively. In the backpropagation rule, derivatives are crucial. The MLP learning algorithm requires nonlinear functions that can be continuously differentiated. The functions used in the hidden layers were selected because they meet these conditions and are simple to differentiate. It should be noted that the neural network model with activation functions is represented in Fig (3).
The results obtained from this model for each of the seven factors affecting financial dissatisfaction in distressed companies are presented in Table (4) under the five optimized functions used in the neural network.

Table 4. Performance of MLP neural networks with optimized activation functions

Factor	**Validation**		**Training**		**Function**	**Result (Rank)**
	MSE	**R^2**	**MSE**	**R^2**		
1	0.0099	0.94	0.0098	0.96	Tanh	1
	0.1098	0.88	0.0309	0.96	logsig	2
	0.1201	0.87	0.0387	0.96	purlin	3
	0.1405	0.87	0.0316	0.96	Tansig	4
	0.1689	0.84	0.0932	0.90	Bolin	5
2	0.0097	0.94	0.0095	0.97	Tanh	1
	0.1785	0.84	0.0299	0.96	logsig	3
	0.3021	0.74	0.0462	0.95	purlin	5
	0.2980	0.70	0.0813	0.91	Tansig	4
	0.1273	0.86	0.0812	0.91	Bolin	2
3	0.0091	0.94	0.0087	0.98	Tanh	1
	0.1852	0.84	0.0269	0.97	logsig	3
	0.2367	0.77	0.0906	0.90	purlin	5
	0.2136	0.77	0.0474	0.95	Tansig	4
	0.1377	0.85	0.0941	0.90	Bolin	2
4	0.0098	0.93	0.0089	0.97	Tanh	1
	0.2272	0.81	0.0390	0.96	logsig	3
	0.2164	0.80	0.0332	0.96	purlin	2
	0.2346	0.79	0.0448	0.95	Tansig	4
	0.2568	0.78	0.0856	0.91	Bolin	5
5	0.0099	0.91	0.0079	0.98	Tanh	1
	0.2316	0.77	0.0549	0.94	logsig	2
	0.2374	0.76	0.0513	0.94	purlin	3
	0.2443	0.76	0.0704	0.92	Tansig	4
	0.2928	0.76	0.0483	0.95	Bolin	5
6	0.0095	0.91	0.0091	0.97	Tanh	1
	0.1788	0.81	0.0415	0.96	logsig	2
	0.2527	0.75	0.0410	0.96	purlin	4
	0.1944	0.83	0.0827	0.91	Tansig	3
	0.2760	0.70	0.0960	0.90	Bolin	5
	0.0106	0.89	0.0093	0.97	Tanh	1
	0.2546	0.75	0.0741	0.92	logsig	4
7	0.2818	0.75	0.0820	0.92	purlin	5
	0.2025	0.82	0.0826	0.91	Tansig	3
	0.1781	0.82	0.0801	0.91	Bolin	2

After the evaluations conducted in this research using MATLAB software, the results for five functions under a multilayer perceptron network with the backpropagation error algorithm in the training and validation stages were examined based on two validation criteria: R^2 and MSE. For the R^2 validation criterion, a value above 0.90 is considered acceptable, and for MSE, if the value is smaller than 0.01, it is accepted. The neural network test results show that all factors, including management capability and position, various internal and external factors and problems, financial crises, financial structures, and growth opportunities and limitations, government laws, regulations, and performance, economic sanctions, and micro and macroeconomic factors, all influence financial dissatisfaction in managers during financial crises. Among the top artificial neural network models, the final neural network model with the hyperbolic tangent activation function and one hidden layer with the highest coefficient of determination (R2) of 0.97 and 0.92, and the lowest mean squared error (MSE) of 0.0090 and 0.0098, respectively, in the training and validation stages, was identified as the best model for predicting and estimating financial dissatisfaction in managers in distressed companies. To determine the effect of training iterations on the network's performance, the number of iterations was considered between 100 and 1000, and executing the networks with different iterations showed that the hyperbolic tangent function with 200 iterations provided the most suitable prediction. The output graphs for the hyperbolic tangent function for the factors affecting financial dissatisfaction of managers in distressed companies are depicted in Fig (2).

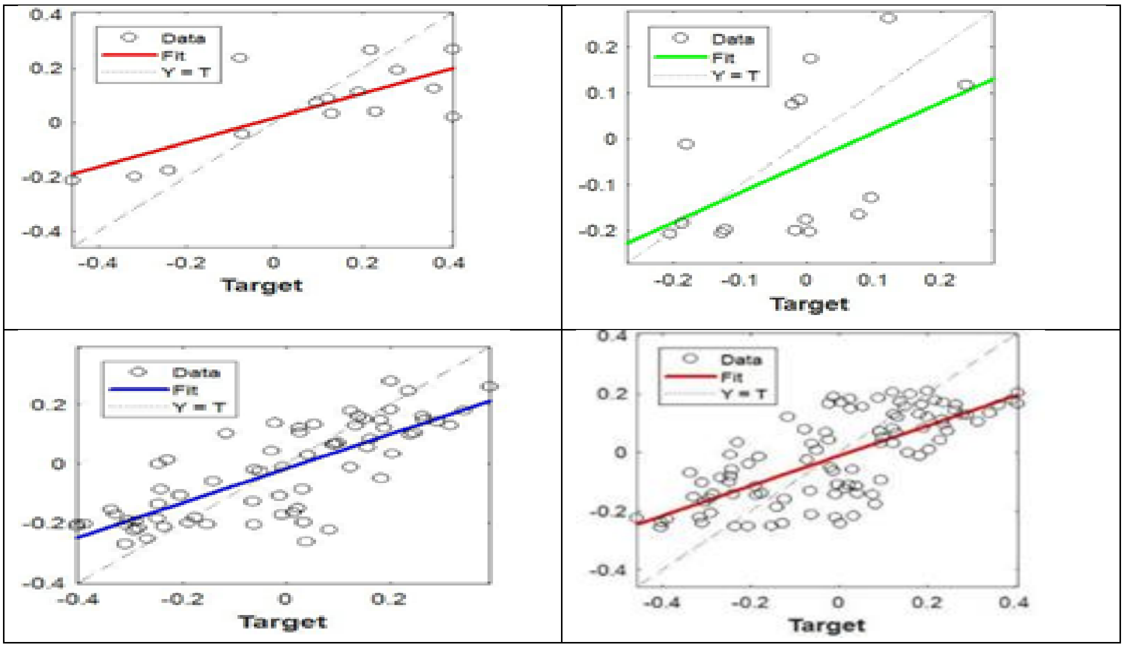

Fig 2. Output of the hyperbolic Tangent function for the factors

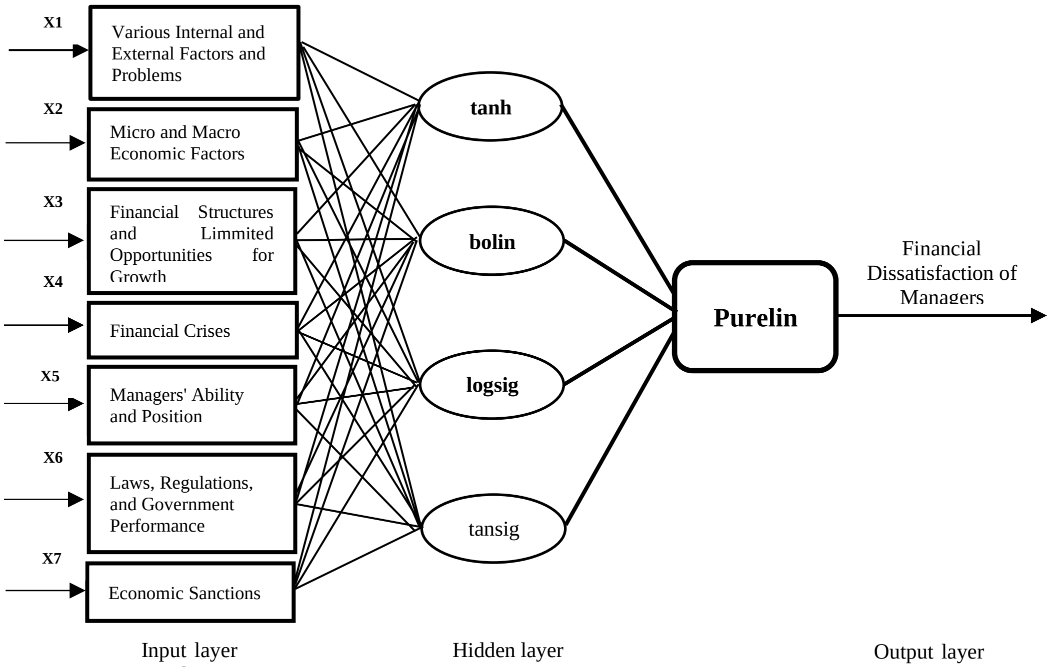

Fig 3. Model based on the neural network with activation functions

The second model used is the architecture of Adaptive Neuro-Fuzzy Inference Systems (ANFIS). This is the best fuzzy inference system used in ANFIS, with the Sugeno model being the chosen system. For simplicity, it is assumed that the fuzzy inference systems in question have two inputs, x and y, and one output. In the current study, after reviewing in MATLAB, among the training algorithms, the LM, GD, and GDX algorithms were selected due to their high correlation coefficient and low error rate. With different topologies, and considering that the initial weights are randomly assigned, leading to different outputs, the program was executed 30 times for each algorithm, and the average error and coefficient of determination values were presented in Table (5) using the simple averaging method.

After reviewing the results in this study using MATLAB, training algorithms LM, GDX, and GD were used in the adaptive neuro-fuzzy inference systems, which exhibited high correlation and low error rates. For evaluating the model, two validation metrics, R^2 and MSE, were employed. If the R^2 value is greater than 0.90 and the MSE value is less than 0.01, the factor is considered validated. The results of the neural network test show that all factors, including the capability and position of managers, various internal and external problems, financial crises, financial structures, opportunities and limitations of company growth, laws and regulations, government performance, economic sanctions, and micro and macroeconomic factors, influence financial dissatisfaction of managers during financial crises. As seen in Table (5), among the top ANFIS models, the five-layer Sugeno neural network with 143 neurons in the hidden layer and the Levenberg-Marquardt training algorithm with a correlation coefficient (R^2) of 0.98 and 0.96, and a mean squared error (MSE) of 0.002120 and 0.003953 for training and validation stages, respectively, was recognized as the best model for predicting and estimating financial dissatisfaction of managers in financially distressed companies.

Table 5. Performance of Adaptive Neuro-Fuzzy Inference Systems

Factor	Algorithm	Topology	Training		Validation		Result
			R^2	MSE	R^2	MSE	
1	LM	1-10-5	0.96	0.001483	0.94	0.001514	Approved
	GD	1-10-5	0.96	0.006997	0.95	0.007128	Approved
	GDX	1-10-5	0.96	0.002142	0.94	0.002413	Approved
2	LM	1-15-5	0.97	0.003190	0.96	0.003100	Approved
	GD	1-15-5	0.94	0.001244	0.93	0.001432	Approved
	GDX	1-15-5	0.91	0.006306	0.89	0.006517	Approved
3	LM	1-20-5	0.98	0.006438	0.97	0.006471	Approved
	GD	1-20-5	0.89	0.009761	0.87	0.009942	Approved
	GDX	1-20-5	0.91	0.009949	0.90	0.01	Approved
4	LM	1-25-5	0.97	0.001761	0.97	0.00760	Approved
	GD	1-25-5	0.94	0.001809	0.92	0.002014	Approved
	GDX	1-25-5	0.86	0.009022	0.84	0.014210	Approved
5	LM	1-30-5	0.99	0.000104	0.97	0.00612	Approved
	GD	1-30-5	0.96	0.008544	0.94	0.0094130	Approved
	GDX	1-30-5	0.96	0.004968	0.95	0.005713	Approved
6	LM	1-35-5	0.97	0.001761	0.95	0.002265	Approved
	GD	1-35-5	0.94	0.001809	0.92	0.002317	Approved
	GDX	1-35-5	0.86	0.009022	0.84	0.0014531	Approved
7	LM	1-40-5	0.99	0.000104	0.97	0.000605	Approved
	GD	1-40-5	0.96	0.008544	0.95	0.008952	Approved
	GDX	1-40-5	0.96	0.004968	0.93	0.005832	Approved

The images of Fig (4) below show some of the outputs from the MATLAB software, which were randomly selected from among the various combinations tested.

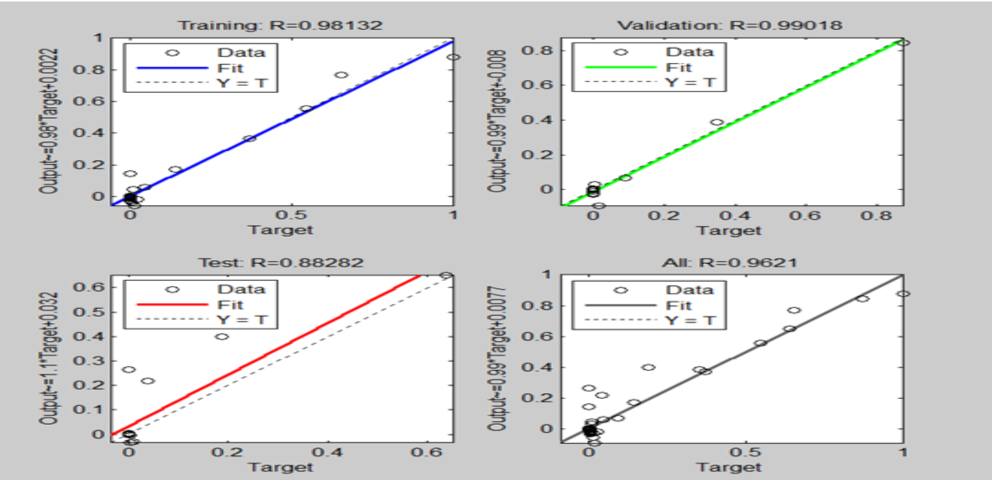

Fig 4. NN with the Levenberg-Marquardt Training Algorithm and 3-30-1 Architecture

As can be seen in Tables (4) and (5), the hyperbolic tangent activation function and the Levenberg-Marquardt learning pattern were identified as the best neural models. By comparing the two models of multi-layer perceptron neural networks with five transfer functions to the fuzzy adaptive inference network model with three learning algorithms, the Sugeno fuzzy adaptive inference network was ultimately chosen as the optimal model for predicting the financial dissatisfaction factors of managers in financially distressed companies, due to its high correlation coefficient (R^2) and low mean squared error (MSE) during both the training and validation phases, compared to the hyperbolic tangent function in the neural network. In this comparison, the highest correlation coefficient for the fuzzy adaptive inference network was 0.98 and 0.96 for training and validation, respectively, while for the hyperbolic tangent function, the correlation coefficient was 0.97 and 0.92 for training and validation. The results of this comparison are presented in Table (6).

Table 6. Comparison of the NN (Hyperbolic Tangent) ANFIS (Levenberg-Marquardt Algorithm) model

Factor	**ANFIS Model with Levenberg-Marquardt Algorithm (ML)**				**Multilayer NN with Hyperbolic Tangent Activation Function (Tanh)**			
	Validating		**Training**		**Validating**		**Training**	
	MSE	R^2	**MSE**	R^2	**MSE**	R^2	**MSE**	R^2
1	0.001514	0.94	0.001483	0.96	0.0398	0.94	0.0035	0.96
2	0.003100	0.96	0.003190	0.97	0.0371	0.94	0.0065	0.97
3	0.006471	0.97	0.006438	0.98	0.0301	0.94	0.0087	0.98
4	0.00760	0.97	0.001761	0.97	0.0657	0.93	0.0179	0.97
5	0.00612	0.97	0.000104	0.99	0.0773	0.91	0.0180	0.98
6	0.002265	0.95	0.001761	0.97	0.0853	0.91	0.0193	0.97
7	0.000605	0.97	0.000104	0.99	0.1226	0.89	0.0271	0.97

5- Conclusion

In this study, we aimed to identify the key factors influencing the financial dissatisfaction of managers in financially distressed companies and to propose a conceptual model based on these factors. Through content analysis of interviews, 54 relevant codes were extracted and categorized into seven components: the ability and position of managers, internal and external factors and challenges, financial crises, financial structures, growth opportunities and constraints, laws, regulations, and government performance, economic sanctions, and micro and macroeconomic factors. This categorization helped to better understand the complex factors that contribute to financial dissatisfaction in managers.

Furthermore, we sought to determine whether the identified factors have an equal impact on financial dissatisfaction among managers or if some factors have a greater influence. We also aimed to design a new, optimized model to predict financial dissatisfaction in managers of distressed companies using artificial intelligence techniques. To achieve this, we utilized MATLAB’s Tool Box environment to analyze the data, dividing it into training and validation datasets for implementing the artificial neural network. By using different activation functions in the network layers and iterating through various architectures, we were able to determine the best model for predicting financial dissatisfaction.

The first model in this study used a multilayer perceptron (MLP) with different activation functions such as Hyperbolic Tangent (Tanh), Bolin, Logarithmic Sigmoid (Logsig), Tangent Sigmoid (Tansig), and Purelin (linear function). The best performing architecture was found to use the Hyperbolic Tangent activation function in the hidden layers, with a single hidden layer architecture. The results showed that this model achieved the highest correlation coefficient (R^2) of 0.97 and 0.92 and the lowest mean square error (MSE) of 0.0090 and 0.0098 in the training and validation stages, respectively. This model was identified as the best for predicting and estimating financial dissatisfaction among managers in financially distressed companies.

The second model used in this study was the Adaptive Neuro-Fuzzy Inference System (ANFIS). This model was evaluated using learning algorithms such as LM, GDX, and GD, and demonstrated high performance with strong correlation coefficients and low error rates. Two criteria were used for validation: R^2 and MSE. If R^2 was greater than 0.90 and MSE was less than 0.01, the model was considered successful. The ANFIS model with Sugeno-type inference, utilizing the Levenberg-Marquardt learning algorithm, achieved the highest R^2 values of 0.98 and 0.96 in training and validation, with the lowest MSE values of 0.002120 and 0.003953, respectively. This model outperformed the MLP model, as indicated by the comparison of both models, confirming that the ANFIS Sugeno model is the most optimal for predicting financial dissatisfaction in managers of distressed companies. This result aligns with previous studies in both domestic and international research.

These findings have significant implications for financial managers and stakeholders, particularly in distressed firms. Understanding the key factors influencing financial dissatisfaction enables managers to proactively identify risks and implement measures to mitigate financial stress. AI-based predictive models, such as the ones developed in this study, provide a data-driven approach to forecasting dissatisfaction, allowing for timely interventions. By leveraging these insights, financial managers can make more informed decisions that enhance organizational stability and resilience. While this study provides valuable insights, it has some limitations. AI-based models rely on high-quality data, and inconsistencies may affect predictive accuracy. Additionally, industry-specific variations were not explored, which could impact financial dissatisfaction differently. Future research could develop hybrid AI models and incorporate real-time economic indicators for better adaptability. Comparing distressed and stable firms would offer deeper insights into dissatisfaction factors. Longitudinal studies could further enhance understanding by tracking financial dissatisfaction over time.

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