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A Neural Network Approach to Default Risk Modeling: Integrating Corporate Social Responsibility and Managerial Ability

Parvin sadri [1*]
Ava Aghaei [2]

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Abstract

This research aims to predict default risk by corporate social responsibility performance and managerial abilities through a neural network approach. It focuses on companies listed on the Tehran Stock Exchange from 2015 to 2022. The study is applied and employs non-experimental research methods to examine and describe variable relationships, ultimately pre-senting a model. It qualifies as a post-event study, utilizing historical data from actual finan-cial statements of companies and other reliable sources, with data collected through a library method. Data were gathered from financial statements, explanatory notes, and monthly re-ports of the stock exchange. A systematic elimination method was used to select 130 compa-nies as the statistical sample. Descriptive and inferential statistics, analyzed with MATLAB 2019 and Excel 2013, were employed to summarize the data. The findings indicate that social responsibility performance and managerial abilities, combined with artificial neural networks, effectively predict companies' default risk by developing a neural network model.

Keywords: default risk, managerial abilities, corporate social responsibility performance, neural network

[1]. *Department of accounting, Sav.C., Islamic Azad University, Saveh, Iran, parvin.sadri@iau.ac.ir* ***(Corresponding author)********
[2]. *Department of accounting, Sav.C., Islamic Azad University, Saveh, Iran. ava.agh1999@gmail.com*

Introduction

The performance strategy refers to how a company interacts with various stakeholders, including customers, employees, communities, and the environment. Studies have shown that companies with strong social performance are less likely to default, including customers, employees, communities, and the environment. Studies have shown that companies with strong social performance are less likely to default. Companies that act responsibly gain the trust and loyalty of their customers. This leads to increased sales and profitability, helping the company maintain its stability in challenging economic conditions. Additionally, the ability of managers to predict default risk is influenced through various channels; managers can significantly reduce the company's default risk by making appropriate strategic decisions. Companies with more capable managers are less likely to default and benefit from multiple advantages, including increased financial stability, enhanced company value, and gaining investor trust, Chen et al. (2023).

The subject of this research is an important and useful area for investigation, as it examines the impact of managerial decisions and social strategies on predicting risks arising from ethical and financial violations within organizations. This research can assist managers and organizations in improving decision-making processes and reducing potential risks associated with social performance and managerial capabilities. Default risk is the oldest financial risk; it occurs when one party in a financial contract fails to fulfill all or part of its obligations, whether intentionally or unintentionally. In such cases, it is said that "default" has occurred, Fallah-Pour & Tadi, (2016).

Various factors affect the likelihood of default. According to Biais & Gollier (1997), a buyer can reduce information asymmetry between themselves and the lender by improving the quality of financial reporting and disclosure, thereby receiving greater commercial credit from the seller and decreasing the seller's default risk, Ke (2013). Some recent studies indicate that companies benefit from investing in corporate social responsibility, (Albuquerque et al., 2019; Menz, 2010; Shi et al., 2024). With higher corporate social responsibility, the overall risk of a portfolio decreases; Jiraporn & Chintrakarn (2013), found that socially responsible companies have more favourable credit ratings. Managerial capabilities in utilizing company resources are effective in preventing stock price declines. One of the most important management duties is making correct decisions. Economically capable managers have a significant impact on the company. Competent managers should effectively control costs, minimize ancillary expenses, and maximize profits; thus, capable managers can reduce default risk by decreasing corporate debt, Chen et al. (2023).

Given the undeniable importance of credit rating and the necessity of having rating agencies in the country, it can be said that comprehensive research has not yet been conducted regarding the role of various factors of social responsibility performance (both quantitative and qualitative) and the ability of managers on default risk. Therefore, considering the significance of companies' commercial credibility in terms of their sales and financing, and consequently the future and return on their stocks, as well as the importance of social responsibility performance and managerial ability in decision-making and company credibility, this research aims to address the fundamental question: Can default risk be predicted using social responsibility performance and managerial ability through a neural network approach?

Corporate default risk is a critical challenge in the financial and economic sectors, with far-reaching implications for companies, banks, and economic institutions. It arises when a company fails to meet its financial obligations on time, such as loan repayments, bond interest payments, and other liabilities, leading to investor losses, diminished market confidence, and potentially large-scale financial crises. Corporate default risk is generally classified into two types: technical default, where contractual obligations are violated without an actual inability to pay, and actual default, where a company is genuinely unable to repay its debts. Several factors contribute to this risk, which can be categorized into three main groups: economic and environmental factors, including economic recessions, currency fluctuations, and high inflation, which erode revenues and drive up financial costs; financial factors, such as unstable capital structures and liquidity shortages, which weaken a company's debt repayment capacity; and managerial factors, including ineffective business strategies and poor financial decision-making, which heighten the likelihood of default. Effectively managing corporate default risk requires robust credit assessment methodologies, in-depth financial structure analysis, and proactive economic forecasting to safeguard against financial crises and maintain market stability.

Numerous studies have examined the factors influencing default risk, all of which have employed traditional methods for prediction, (Sefidpouosh-Khameneh et al., 2024; Zhang, 2022). However, in recent years, innovative meta-heuristic methods have been widely used in other financial discussions, yielding better results, (Xia et al., 2024; Yao et al., 2024). One reason for employing "artificial neural networks" is their non-linear nature in prediction; this non-linearity may manifest as complex relationships between independent or dependent variables at high or low thresholds affecting independent variables. Researchers have stated that continuous changes in the nature of financial relationships are a factor driving the shift from traditional approaches to artificial neural network approaches, leading to the abandonment of traditional techniques.

This research makes both theoretical and practical contributions. Theoretically, it advances literature on social information disclosure, corporate governance (managerial capabilities), and default risk. While many studies have explored factors influencing default likelihood, the effects of social responsibility performance and managerial capabilities through a neural network approach remain unexplored in Iran's literature. Thus, this research enhances existing knowledge. Building on Chen et al. (2023), the study has important practical implications. It investigates how social responsibility performance and managerial capabilities can substitute each other in managing corporate risk. Additionally, findings from developed countries cannot be directly applied to Iran due to its unique legal and structural context. The relevance of social reporting mechanisms and managerial capabilities in Iran necessitates further exploration of credit risk and default likelihood in manufacturing firms. Consequently, this study expands the literature on default risk in this domain. Lastly, since no prior research has analyzed default risk in relation to social reporting and corporate governance using a non-linear artificial neural network approach, addressing this gap is crucial for researchers, report developers, and stakeholders.

2 Theoretical Foundations

In the capital market, we witness various risks, one of the most significant being credit risk. Credit means that an agreed amount will be paid in the future, and in the event of non-payment, credit risk arises, which must be managed. Institutions that provide various facilities prevent the occurrence of this risk by implementing regulations. For example, by assessing the financial conditions of the counterparty and imposing restrictions, efforts are made to manage this risk as much as possible, Nabizadeh and Bahrami (2021). Credit risk occurs when one party to a transaction is unwilling or unable to fulfil its obligations on time. Credit risk is also referred to as the risk of non-performance of obligations. This risk is one of the oldest financial risks in the investment field. Despite the fact that operational risk has the potential to cause significant losses for economic companies, very few studies have been conducted on the impact of operational risk on the performance of companies concerning non-financial institutions, Ko et al., (2019).

Default risk is one of the most common types of risk in the investment process. In Persian, it is often referred to as the failure to pay promissory notes, drafts, and similar financial obligations. Essentially, default occurs when an individual or legal entity enters into a contract but fails to fulfil their obligations, either deliberately or unintentionally. In economic terms, default risk refers to the likelihood of non-fulfillment of contractual commitments in a transaction. For instance, if you lend money to a friend based on trust, there is always a risk of default. Why? Because the borrower may, for any reason, fail to repay the loan on the agreed date. Another example is an individual who takes out a loan from a financial institution and is required to make scheduled payments. Here too, default risk exists, as the borrower may be unable to meet their repayment obligations, resulting in default. As discussed, default risk is not limited to individual transactions; it can also have a significant impact on financial institutions. Consider how the default of multiple customers could inflict severe financial losses on a bank or lending institution. In such cases, several clients may fail to honor their contractual commitments, jeopardizing the financial stability of the institution, Xia et al., (2024).

Corporate social responsibility (CSR) involves companies voluntarily exceeding legal requirements to align with stakeholder expectations through enhanced reporting and information disclosure. In response to evolving demands, companies have integrated social responsibility into their core business practices, Hasas-Yeganeh et al., (2020). CSR can mitigate company risk in various ways, such as enhancing product differentiation, lowering systematic risk, and increasing overall value. According to stakeholder theory and resource-based theory, engaging in CSR fosters shareholder trust and diminishes risk. While some CEOs may see CSR costs as a threat to company value and thus avoid such expenditures, others may recognize CSR as an investment that fosters stakeholder risk management aligned with regulations and social norms. The perspectives of CEOs significantly shape CSR initiatives. Additionally, overconfidence can lead CEOs to overestimate their abilities and the likelihood of positive outcomes, influencing their reporting and investment decisions, Tseng & Demirkan, (2021).

Management ability comprises a range of skills and traits essential for managers to achieve company goals and strategies. These include strategic, communication, decision-making, financial, accounting, leadership, and systematic thinking skills. High management ability allows managers to utilize their knowledge and experience to enhance company performance, reducing stock price ambiguity and boosting investor confidence. Managers with strong capabilities can attract investors by providing clear and accurate information, facilitating the investment process. Executives who effectively manage resources are better positioned to meet their objectives. Their confidence in the financial reporting system encourages them to publish statements promptly and enthusiastically. Additionally, their comprehensive understanding of the business environment enables more efficient handling of complex financial reporting and auditing challenges. Thus, the significance of business unit management within the context of management ability is substantial, Mehrani et al. (2020).

Managers can optimize resource management through effective skills and decision-making, leading to improved financial performance, higher profitability, and better stock liquidity. Intelligent financial strategies, such as a balanced mix of bank credits and equity, can lower the cost of debt. A well-prepared auditor's report is crucial for financial transparency; when reliable, it boosts investor confidence in the company's financial information, enhancing stock liquidity. The report also identifies financial risks and deficiencies, allowing managers to tackle potential issues proactively. The combination of capable managers and trustworthy auditor reports builds investor trust, which can increase stock liquidity and elevate the company's market value. Firms with strong managerial skills and credible auditor reports are more likely to attract investments through rising stock prices or bond issuance, further reducing the cost of debt. By optimizing costs through improved profitability and operations, managers can diminish debt expenses, while the auditor's report fosters transparency, attracting capital at lower costs. Overall, both managerial capabilities and clear auditor reports are vital for enhancing stock liquidity and reducing the cost of debt, creating a comprehensive view of a company's financial health, Dalwai et al. (2023).

The social performance strategy influences companies' operations and debt financing, Kim & Yoo (2022). It helps firms achieve higher credit ratings, reduce financing constraints, and secure long-term bank loans, Su et al. (2016). Additionally, it is negatively correlated with default risk, with a stronger effect over the long term, as it enhances operational capabilities and decreases information asymmetry. However, some skeptics argue that this strategy may inadvertently increase default risk. In 2014, American companies contributed nearly \$18 billion, and in 2018, merchants on the Alibaba platform donated 266 million yuan through the "Public Welfare Child" project. Fortune Global estimates an annual expenditure of around \$20 billion on social performance activities. This raises questions about the actual impact of such strategies on default risk. Conversely, according to Hambrick and Mason (1984), upper echelons theory and Bertrand and Schoar (2003) fixed effects model, differences in managerial capabilities influence decision-making and default risk. Competent managers can effectively control costs and maximize profits while minimizing the social performance strategy's expenses (Demerjian et al., 2013; Koester et al., 2017). Companies led by capable executives can access external financing even during crises, bypassing underinvestment issues and fostering stakeholder trust in low-trust environments, Lins et al. (2016).

An artificial neural network is a concept for processing information, inspired by the structure of biological neural systems, and mimics the brain's processing methods. These networks serve as modern computational systems for machine learning and knowledge representation, enabling predictions from complex systems. The core idea is to develop new structures for information processing. In finance, neural networks are applied in algorithmic trading, high-frequency trading (HFT), credit scoring, risk assessment, fraud detection, transaction monitoring, portfolio management, market sentiment analysis, event prediction, option and derivative pricing, and financial forecasting. Their advantages include handling non-linear relationships, adaptability, and automation. Consequently, neural networks have become integral to modern finance, enhancing decision-making, risk management, and customer interactions, leading to more efficient financial operations.

Artificial neural networks are computational models inspired by the structure of neural networks in the human brain. These networks are composed of interconnected layers of processing units called neurons. Input data flows into the network through these neurons, which process the information using specific weights and generate the desired output. The application of neural networks in predicting default risk, based on strategies involving social performance and managerial capabilities, is highly significant. Due to their deep learning capabilities and ability to handle large volumes of data, neural networks can uncover hidden and complex patterns within datasets, enabling more precise analyses and improved predictions. By utilizing neural networks, researchers and managers can intelligently and automatically analyze social information and managerial performance, detect behavioural patterns related to supply chain risks, and develop optimized strategies to reduce default risk. This approach can significantly enhance decision-making processes, reduce costs, and increase efficiency in managing default risks. This study, therefore, seeks to establish a relationship between corporate social responsibility performance and managerial capabilities by employing artificial neural networks to predict company default risks.

The conceptual model of the research, grounded in theoretical foundations and previous studies, is illustrated in fig. 1.

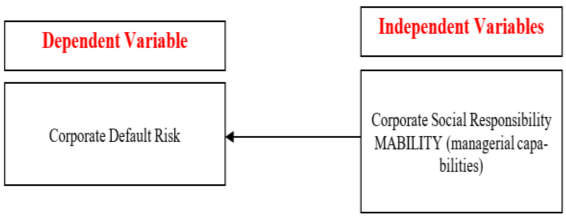


Fig. 1: Conceptual Model of the Research

2.1. Research Background

Fatahi (2023), conducted a study titled Managerial Ability and Trade Credit: Emphasizing the Role of Credit Ratings and Financial Constraints, examining the impact of managerial ability on trade credit. The study utilized financial data from 161 companies (1,610 firm-year observations) listed on the Tehran Stock Exchange, selected through a systematic screening approach and analyzed using multivariate regression methods. The research covered the peri-od from 2011 to 2020. Findings indicated that managerial ability has a significant positive effect on trade credit. Moreover, this effect is stronger in companies with lower credit ratings and higher financial constraints, suggesting that managerial ability plays a critical role in help-ing such companies navigate crises. The results imply that creditors value the managerial abil-ity of borrowing companies and are therefore more willing to extend credit to them. hrizad Firoz-Jah (2022), conducted a study titled Examining the Principles and Foundations of The-oretical Models for Predicting Default Risk in Companies Listed on the Tehran Stock Ex-change. The research defined risk as the probability of outcomes deviating from expectations and a form of uncertainty about the future, often reflected as gains or losses in financial man-agement. To minimize losses, avoid adverse events, maintain financial stability, and ensure operational capability, risk management methods can be employed for control and mitigation. According to the Basel Committee classification, credit risk, market risk, and operational risk are the three primary sources of risk, with credit risk being a significant contributor to risk in banks and financial institutions. Default risk, a key component of credit risk, has gained in-creased importance due to the growing frequency of financial crises. Default disrupts the lifecycle of companies, causing interruptions in supply chains, reduced productivity, and increased administrative costs. The objective of Gharizad's research was to evaluate and com-pare models for predicting the default risk of companies listed on the Tehran Stock Exchange. The study concluded that the latest model for predicting default risk is the Expected Default Frequency (EDF) model, which overcomes many of the shortcomings of the Merton and Ohl-son models. Chen et al. (2023), in a study titled The Impact of Managerial Ability in Corpo-rate Social Responsibility on Corporate Default Risk, explored the relationship between man-agerial ability in corporate social responsibility (CSR) and default risk. This study examined how managerial ability influences the relationship between CSR performance and default risk. The findings revealed a negative correlation between CSR performance and corporate default risk. Furthermore, the study analyzed the role of managerial ability and its effects on default risk, showing that CEOs with higher managerial skills can effectively leverage the benefits of CSR performance to reduce default risk. Li et al. (2018), in their research titled Environmen-tal, Social, and Governance Reporting and the Probability of Default Risk, investigated the impact of ESG (Environmental, Social, and Governance) practices on the default risk of Chi-nese listed companies from 2015 to 2020. Their findings indicated that higher ESG ratings reduce corporate default risk. The risk-reducing effect also strengthens with the extension of the default risk term structure. Additionally, they found that the impact of ESG ratings on default risk is less significant for manufacturing companies compared to non-manufacturing firms. A default risk prediction model was proposed by Goa et al. for peer-to-peer (P2P) companies using the LightGBM algorithm, integrated with linear blending, to analyse sample data, a leading P2P platform. The model achieves an 80.25% accuracy rate in predicting de-faults, with a precision value of 91.36%, recall of 75.90%, and accuracy of 84.36%, outper-forming traditional machine learning models like logistic regression and support vector ma-chines, Gao and Balyan (2022). The importance of managing credit default risk has grown as companies aim to identify and forecast future risks. A Graph Attention Network (GAT)-

based model was introduced by Zhou et al. for predicting credit default risk, incorpo-rating data such as credit default history, credit status, and personal profiles. By con-structing differ-ent graphs based on user similarities, the model uses GAT modules to capture both local and high-order rela-tionships, as well as linear and non-linear dependencies. Experimental results using real-world datasets show that the model ef-fectively predicts credit default risks, out-per-forming several baseline methods, Zhou et al. (2023).

3. Research Methodology

This study is applied in its objective and de-scriptive in nature, with a focus on explor-ing correlational relationships. It is catego-rized as a post-event study, utilizing histor-ical data, and is based on real financial statements from companies listed on the Tehran Stock Exchange, as well as other ac-tual data. The findings, derived through an inductive approach, are general-izable to the entire statistical population.

3.1. Population and Sample

The statistical population of this study con-sists of companies listed on the Tehran Stock Ex-change during the period from 2015 to 2022. To determine the sample, companies are first ho-mogenized using a systematic elimination method. After the population is homogenized, the sample is selected from this group. The criteria used in the systematic elimination process to ho-mogenize the population are as follows: Companies meeting these criteria are in-cluded in the sample, while those that do not meet the conditions are excluded.

Table 1: Sample selection based on the limitations and conditions of the population.

Number of Companies Listed on the Stock Exchange by the End of 2022	600
Number of companies that were not listed on the stock exchange between 2015 and 2022.	137
Number of companies whose financial year does not end in December.	96
Number of companies for which the necessary data to calculate the operational variables of the study is not avail-able.	55
Number of companies that have suspended operations or changed their operational period.	55
Investment companies, banks, and insurance companies.	127
Total	470
Number of companies for which data has been collected (final sample).	130

3.2. Model and Measurement Method of Re-search Variables

In this study, we aim to predict corporate de-fault risk using corporate social responsibility performance, managerial ability, and the ap-plication of artificial neural networks.

The model is derived from the study by Chen et al. (2023).

Default risk=f(CSR, MABILITY) **(1)**

In which:

Default risk: Corporate default risk

CSR: Corporate social responsibility perfor-mance

MABILITY: Managerial ability

3.2.1. Measurement Method of Research Variables

Output Variable

Default risk: Corporate default risk

The probability of default risk refers to the distance to default (DD), which represents the number of standard deviations by which the expected asset value at maturity deviates from the point of default. Therefore:

$$DD = \frac{\ln L - \ln A + \left(\mu - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \quad prob(Default) = \Phi(-DD) \qquad (2)$$

Where:
A is the market value of assets,
L is the value of liabilities,
μ is the drift rate,
σ is the annual volatility of asset value,
T is Time horizon,
One of the unknowns in the formula is the market value of a company's assets, which is not directly observable. What is observable is the book value of assets, which can differ from their market value for various reasons. For publicly traded companies, the market value of equity is observable and is calculated by multiplying the stock price by the number of shares outstanding.
The relationship between the value of equity and the value of assets at maturity can be explained as follows:

If the value of assets is less than the value of liabilities, the equity value will be zero, and all assets will go to creditors.

If the value of assets is higher than the nominal value of the zero-coupon bonds, shareholders will receive the remaining value.
The market value of assets can be calculated using the following equation:
Market Value of Assets=Market Value of Equity+ Value of Liabilities Market
The value of liabilities is also the book value of liabilities. To calculate the annual variance of the logarithmic changes in asset value, the variance of the asset return is computed using the Equ. 3:

$$\sigma^2 = \frac{\sum_{i=1}^{n}(R_i - \bar{R})^2}{n-1} \qquad (3)$$

where:
Ri: Return in period i
R¯: Mean (average) return, calculated as

$$\bar{R} = \frac{\sum_{i=1}^{n} R_i}{n}$$

n: Number of periods
To estimate the expected change in the value of an asset, using the obtained asset value figures, the expected return can be estimated through the Capital Asset Pricing Model (CAPM).

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f) \qquad (4)$$

E(Ri): Expected return of the asset
Rf: Risk-free rate (return on a risk-free asset, e.g., government bonds)
βi: Beta of the asset, measuring its sensitivity to market movements
E(Rm): Expected return of the market portfolio
E(Rm)−RfMarket risk premium (extra return expected for taking market risk)
In this research, the market return will be calculated based on the total stock market index.

$$Rmt = \frac{Imt - Im0}{Im0} \qquad (5)$$

Where Imt is the total stock market index at the end of time t, Im0 is the total stock market index at the beginning of time t, and β represents the accounting beta (systematic risk).

Input Variables:

CSR: Corporate Social Responsibility Performance

Various approaches exist for developing scoring programs to determine the level of disclosure in annual reports. Among these approaches, the unweighted disclosure index was used due to its frequent application in various studies for measuring the extent of CSR information disclosure (Rouf, 2011; Hossain, 2002; Samaha et al., 2012).

Development of the Disclosure Index:

1.Comprehensive List of Topics

Initially, a comprehensive list of CSR-related topics expected to be disclosed in companies' annual reports was identified. These included financial and non-financial topics potentially relevant to investors' decision-making.

- The initial topics of environmental and social information included in the disclosure index were based on studies by Williams (1999), Gao et al. (2005), and Aribi & Gao (2010).

2.Refinement for Local Context:

- Based on prior research, 45 factors were initially selected.
- Considering Iran's environmental, social, economic, and political conditions, the number of factors was reduced to 37.
- Eight factors were excluded due to limited applicability to Iranian companies

Categorization of Disclosure Items:

The disclosed items were divided into six categories:

- Environmental
- Products and Services
- Human Resources
- Customers
- Social
- Energy

Data Sources:

Subcategories were extracted from audited year-end financial statements, accompanying notes, and the board of directors' reports to the general assembly.

Unweighted Disclosure Index:

The unweighted disclosure index is the ratio of the number of items disclosed by a company to the total number of items it could potentially disclose.

- *Under this index,* all disclosure items are considered equally important for users.
- No preference is given to any specific user group.
- Each unique item is treated as a binary variable:
- If a company discloses an environmental or social information item in its annual report (regardless of its format, such as text, image, or graph), it scores **1.**
- If not disclosed, it scores **0.**

The unweighted disclosure model used to calculate the disclosure score for each company is expressed as follows:

Disclosure Score=Number of Items Disclosed by the Company/Total Number of Possible Disclosure Items

This formula has also been utilized in studies by Hussainey et al. (2019).

$$D_{Cor} = \sum_{j=1} \frac{d_j}{n} \tag{6}$$

Where Dcor represents the corporate social responsibility disclosure score of a company, dj is the total value of items disclosed by a company, and n is the maximum score a company could achieve (37 factors listed in the disclosure checklist).

MABILITY: Managerial Ability

Managerial ability is the portion of a firm's efficiency that is not influenced by the firm's inherent characteristics, Zarg Asl & Bistun Salehzadeh (2013). In this study, managerial ability is measured using the model proposed by Demerjian et al., (2013), which is based on accounting variables.

Model Overview:

The model calculates managerial ability by evaluating company efficiency as a dependent variable while controlling for the firm's inherent characteristics.

- Output: Revenue from sales is used as the output variable.
- Inputs: Seven variables are considered inputs:

1. Cost of goods sold (COGS)
2. General, administrative, and selling expenses
3. Net property, plant, and equipment
4. Operating lease expenses
5. Research and development (R&D) expenses
6.Goodwill
7.Intangible assets

These inputs comprehensively reflect management's discretion in achieving the desired revenue.

Efficiency Calculation:

The firm's efficiency is calculated using the following model:

$$\max_{v} \theta = \frac{Sales}{v_1 COGS + v_2 SG\&A + v_3 PPE + v_4 OpsLease + v_5 R\&D + v_6 Goodwill + v_7 OtherIn\tan} \quad (7)$$

In this model, all v-values are assumed to be constant (equal to 1). The calculated efficiency value ranges between 0 and 1, where maximum efficiency equals 1. Lower values indicate re-duced company efficiency.

Variables Used in the Model:

1. Sales: Revenue from sales.
2. COGS: Cost of goods sold for company i in year t.
3. SG&A: General, administrative, and selling expenses for company i in year t.
4. PPE: Net balance of property, plant, and equipment for company i in year t.
5. OpsLease: Operating lease expenses for company i in year t.
6. R&D: Research and development expenses for company i in year t.
7. Goodwill: Purchased goodwill for company i in year t.
8. OtherIntan: Net intangible assets for company i in year t.

The goal of calculating company efficiency is to measure managerial ability. However, since inherent company characteristics also influence efficiency calculations, managerial ability may not be accurately measured. These characteristics can cause efficiency to be overestimated or underestimated compared to the actual managerial ability.

Example of Influence from Inherent Characteristics:

- More capable managers, regardless of company size, typically have a better understand-ing of the company's and industry's future prospects.
- Managers of larger companies may inherently benefit from stronger bargaining power with suppliers.

To address this issue, Demerjian et al., (2013), divided company efficiency into two separate components:

1. Efficiency based on inherent company characteristics.
2. Managerial ability.

This division was achieved by controlling for five specific company characteristics:
1. Company size.
2. Market share.
3. Cash flow.
4. Listing age (years since the company was listed on the stock exchange).
5. Foreign sales (exports).

Each of these variables can either help managers make better decisions or, conversely, limit their managerial ability.

Calculation of Managerial Ability:
Managerial ability is computed using the following model:

$$FirmEfficiency = \alpha_0 + \alpha_1 Ln(TA) + \alpha_2 MS + \alpha_3 PFCF + \alpha_4 Ln(Age) + \alpha_5 FCI + \varepsilon \quad (8)$$

Where:
- **Firm Efficiency:** Company efficiency calculated using the previous model.
- **TA:** Total assets of the company, which can be extracted from financial statements.
- **MS:** Market share of each company, calculated using the following formula:
MS=Sales at the end of year t/Total industry sales at the end of year t
- **PFCF:** Indicator of positive free cash flow.
  - o If a company has positive cash flow, this variable equals 1; otherwise, it equals 0.
  - o **Free Cash Flow (FCF):** Net operating cash flow minus cash dividends paid and taxes paid.
- **Age:** The number of years the company has been listed on the Tehran Stock Exchange, calculated as the natural logarithm of the total years since its listing.
- **FCI:** Foreign currency indicator.
  - o This binary variable equals 1 if the company has export activities; otherwise, it equals 0.
- ε: The residual error from the model, representing the managerial ability score (Chen et al. (2023))

3.3. Data Collection Method
The data collection method used in this research is a library-based approach. The theoretical aspects of the study were gathered by reviewing various sources, publications, both internal and external, as well as utilizing the internet. The data was collected from primary sources provided by companies. Specifically, the required data for this research was gathered from library resources, using Rahavard Novin software, referring to the Tehran Stock Exchange, and examin-ing the financial statements of companies listed on the Tehran Stock Exchange between 2015 and 2022. In addition to studying the financial statements, data from the Tehran Stock Ex-change's information website were also utilized.

3.4. Analysis Method and Hypothesis Testing
Descriptive and inferential statistics were used for the analysis. Descriptive statistics were ap-plied to summarize the data, while the normality of the distribution of variables, reliability of variables, correlation between variables, and multicollinearity were also assessed. To test the hypotheses and

conduct inferential analysis, artificial neural networks were employed.

4. Data Analysis

The goal of this research is to develop a prediction model for default risk based on social per-formance strategy and managerial ability in companies listed on the Tehran Stock Exchange. Specifically, this chapter aims to identify a non-linear mathematical model that links default risk to the company's social performance strategy and managerial ability. The statistical population includes all active companies listed on the Tehran Stock Exchange, with a sample of 130 companies selected from 2015 to 2022. In this section, descriptive statistics are used to identify the distribution and concentration of the data, as the quality of the data is crucial for the development of the prediction model. The accuracy of the model depends on the input data, and it is important to create a comprehen-sive and complete model.

To extract the mathematical model, artificial neural networks are utilized to predict the risk of default. The collected data are analyzed and processed using Excel 2013, and the model is gen-erated with MATLAB 2019. For data analysis, descriptive statistics of the studied data are ana-lyzed and examined. The descriptive statistics table presents the values of descriptive factors for each variable separately, as well as for the total of the 8 years. The descriptive statistics for the extracted samples are provided in Table 2.

Table 2: Descriptive Statistics

Indicators	y	X1	X2
	Default risk	Corporate Social Responsibility	Managerial Ability
Mean	0.91	0.53	1.56
Median	0.99	0.56	1.05
Maximum	1	0.89	15.6
Minimum	0.5	0.0	0.022
Standard Deviation	0.125	0.191	2.21
Skewness	-1.25	-0.98	4.54
Kurtosis	0.239	0.906	24.06
Observations	1040	1040	1040

Based on Table 2, the average risk of default for the company is 0.91, with the lowest and highest values of the default risk variable being 0.50 and 1, respectively. The skewness coeffi-cient of the default risk is negative, indicating that the distribution is slightly skewed to the left. A slight kurtosis is also observed in the risk of default variable.

4.1. Neural Network Model Extraction

This study utilizes a multilayer neural network with a backpropagation algorithm to assess the factors influencing the risk of de fault. In feedforward neural networks, nodes are arranged in sequential layers, and the connections between them are one-directional. When an input pattern is introduced, the layers process it and pass the output to the subsequent layers. The backpropa-gation algorithm involves calculating the error from the difference between the network's output and the actual value, then feeding it back into the network. The network parameters are adjusted to provide more accurate outputs for future similar inputs and minimize errors. The key compo-nents of the artificial neural network are the neurons, which are categorized into input, output, and hidden neurons. These neurons are organized into input, output, and hidden layers. The input neurons receive data, while the intermediate and output layers process the information. In these units, mathematical operations are performed on the input data, and the results are passed on to the next layer. There is no strict rule for determining the number of neurons in hidden layers, and this decision is generally based on an empirical approach

4.2. Steps for Preparing and Training the Neural Network

1. Determining the Number of Input Variables

In this study, there are two input variables: social performance strategy and managerial capability.

2. Determining the Sample Size for Training, Validation, and Testing

The sample size consists of 1040 data points, collected from 130 companies over 8 years. From this, 70% is allocated for training, 15% for validation, and 15% for testing the network.

3. Defining the Neural Network Output

As there is only one output variable (risk of default), there will be a single processing unit in the output layer.

4. Number of Hidden Layers

Hidden layers are intermediate layers located between the input and output layers in a neural network. These layers are essential for enabling the network to learn and make complex decisions. They process the inputs from the previous layer and pass the results to the next layer. Each neuron in a hidden layer computes the weighted sum of the inputs and applies an activation function. This process introduces non-linearity, allowing the network to solve more complex problems. Hidden layers are crucial for the network's ability to generalize and learn from the data, enabling it to perform tasks beyond simple input-output mappings. The number of hidden layers is determined through trial and error.

5. Determining the Parameters for Network Design

At this stage, the parameters and internal elements of the model and learning algorithm are defined. The parameters of a neural network, primarily weights and biases, are learned during the training process and dictate the model's behavior. Hyperparameters, such as the learning rate and network architecture, are set before training and influence how the learning process progresses. Optimizing these parameters allows the network to make more accurate predictions based on input data. The specifications needed to train the neural network are shown in Table 3.

Table 3: Neural Network Model Specifications

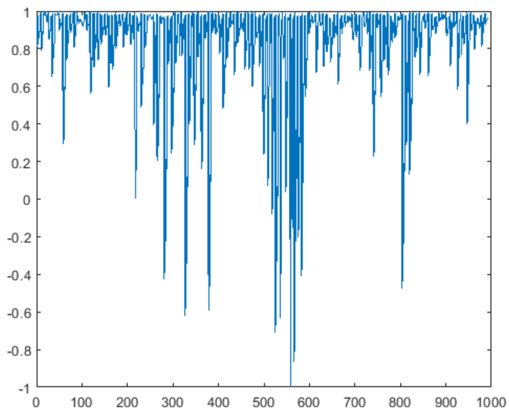
Neural Network Specifications	Specifications Used in the Network for This Research
Network Architecture	Feedforward
Training Algorithm	Levenberg-Marquardt backpropagation
Performance Function	Mean squared normalized error
Learning Rate	0.1

4.3. Simulation and Extraction of Results

As previously explained, the network consists of two input variables and one output variable. However, the number of hidden layers must be determined through simulation to understand how the number of layers affects the network's performance. This issue will be explored fur-ther, and an appropriate structure will be selected, with results extracted for that structure.

The desired output diagram for the default risk data is shown in Fig. 2. The default risk is calcu-lated using the relationships provided in previous sections. The network is trained using the rela-tionships specified for neural network learning, with data mapped in the range from -1 to 1. The neural network should be trained in such a way that it produces output values as closely as pos-sible to the desired output, as shown in fig. 2.

Fig. 2: Data Related to Calculated Default Risk



First, the effect of the number of layers on the network's performance is examined. The re-sults of this analysis are presented in Table 4.

Table 4: Comparison of Neural Network Performance with Different Numbers of Layers, Using 20 Neurons per Layer

No.	Number of Layers	Number of Training Iterations	Training Duration	MSE
1	1	1000	00.00	0.0798
2	2	1000	00.01	0.0792
3	3	1000	00.03	0.0730
4	4	1000	00.08	0.0716
5	5	1000	00.12	0.0668

As shown in Table 4, increasing the number of layers enhances the network's performance in terms of output accuracy. However, as the network becomes larger and more complex, the computational effort required to reach the desired results also increases, as clearly demonstrated in the table. To achieve an optimal structure in terms of both computational time and error, a 3-layer network is selected, which yields a Mean Squared Error (MSE) of 0.073. For the simula-tion, it is assumed that each hidden layer consists of 20 neurons.

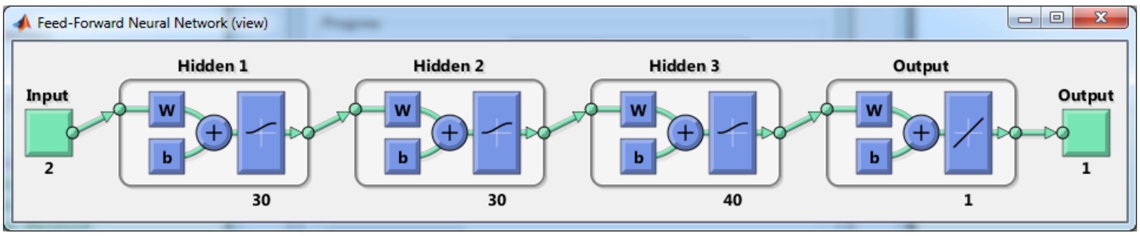
Another important factor to investigate is the effect of the number of neurons in each layer on the network's performance. In this case, the network with 3 layers, considered optimal in terms of computational efficiency and error rate, is used. The results of this simulation are pre-sented in Table 5.

Table 5: Comparison of Neural Network Performance with Varying Numbers of Neurons in a Single Layer.

No.	Number of Neurons in Layer 1	Number of Neurons in Layer 2	Number of Neurons in Layer 3	Training Duration	MSE
1	5	5	5	00.01	0.0888
2	10	10	10	00.02	0.0792
3	10	20	30	00.04	0.0770
4	30	30	40	00.15	0.0673
5	40	40	40	00.36	0.0679
6	50	50	50	03.29	0.0740
7	60	60	60	05.31	0.0619

As shown in Table 5, increasing the number of neurons reduces the error of the neural network, but it also increases the computational load, which is expected due to the larger and more com-plex structure. A higher number of neurons increases the degree of non-linearity, allowing for better training and a closer match with the desired output, thus reducing the network's error. In this simulation, it is assumed that there are only three layers. Based on Table 5, the optimal structure is one where the first and second layers have 30 neurons each, and the third hidden layer has 40 neurons. This configuration provides an optimal balance between mean squared error and computational time, as shown in the network structure diagram in Fig. 2.

Fig. 2: Optimal Structure Based on the Number of Layers and Neurons



In neural network training, the data is randomly divided into three categories: training data (70%), validation data (15%), and test data (15%). The training method used in this research is the Levenberg-Marquardt algorithm, which is one of the fastest supervised backpropagation algorithms. The mean squared error (MSE) criterion is used to assess the network's performance. During the training process, updates are continuously made in the training window. To stop the network training, two criteria are applied: the gradient and the number of validation checks. When the network reaches its minimum performance, the gradient becomes very small. If the gradient size is smaller than 1.00e-13, the training process is stopped, and the result is obtained. The number of validation checks indicates the repetitions in which the validation performance does not improve. If this number reaches 8, the training is terminated.

Fig. 3: Mean Squared Errors for Training, Validation, and Test Processes

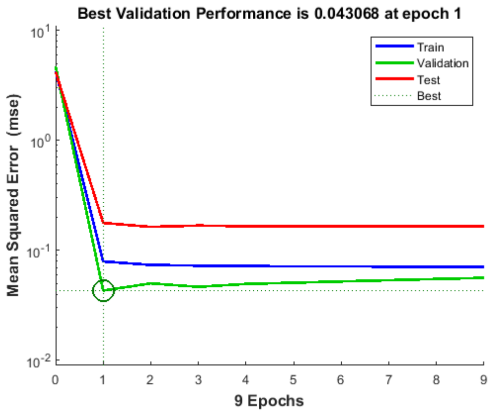
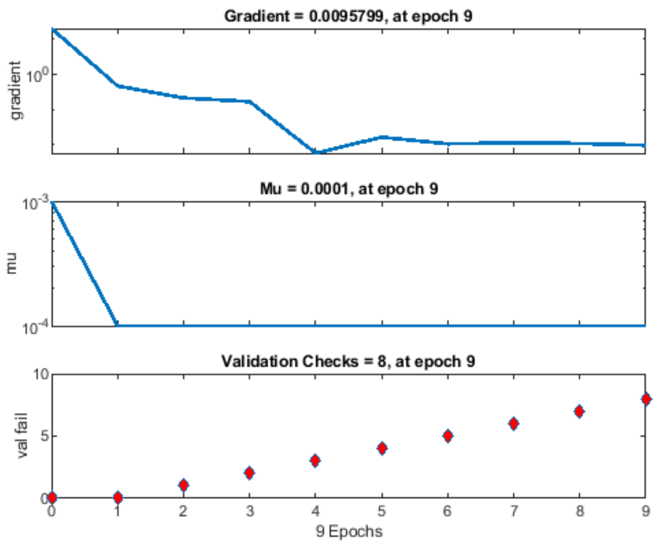


Fig. 3 illustrates the neural network performance. As shown in the figure, the mean squared errors for the three data sets—training, validation, and test—are displayed at each training stage. The best performance, with an error value of 0.043, occurs in the first training stage, which rep-resents the lowest error across all training phases. The gradient values during the training stages, as well as the number of validation checks throughout the training process, are presented in Fig. 4.

Fig. 4: Gradient, Control Parameter of the Training Algorithm, and the Number of Validation Checks at Vari-ous Training Stages



As depicted in Fig. 4, the gradient starts at a high value when the training process begins and gradually decreases during training. By iteration 9, it reaches the desired range, prompting the termination of the training process. The changes in the control parameter mu are also illustrated in the figure. Additionally, the number of validation checks is shown, with 8 successful valida-tion checks completed at iteration 9, which causes the training process to stop.

4.4. Default Risk Prediction Using Social Performance Strategy and Managerial Ability

The goal of this study is to develop a non-linear mathematical model to link default risk with social performance strategy and managerial ability. Based on the theoretical background and relevant literature, it is assumed that there is a meaningful relationship between the independent and dependent variables. However, this research uses a neural network to establish a non-linear relationship between these variables.

Typically, due to the complexity of input variables and the indices used for quantification, a linear relationship between the inputs and outputs is often approximated. However, this linear model may not be universally applicable. Neural networks, by contrast, can establish a more accurate representation of the relationship between the variables. Thanks to their intrinsic structure, neural networks are capable of developing models that work well across a range of outputs, even when the input-output relationship is too complex or variable for a linear model. For instance, when defining indices for each input and output variable, the changes may occur within a specific numerical range that varies across companies and years. This range may be too wide for a linear correlation to hold, but neural network models can effectively handle such variation.

The non-linear model derived from this research could serve as a useful tool for financial investors. By calculating the social performance strategy and managerial ability indices for each company, investors can determine the default risk index for that company, using the index as a reliable basis for decision-making.

5 Conclusion and Recommendations

In this study, by utilizing a neural network model, the aim was to find a nonlinear relationship between corporate social responsibility performance, managerial ability, and the risk of default in companies, to establish a precise relationship between these variables. Specifically, using a neural network enables the creation of a more comprehensive and complete model for the relationship between independent and dependent variables, which offers a more accurate prediction over a broader range.

5.1. Conclusion

Based on the tests and the extraction of the optimized artificial neural network model, the optimal nonlinear structure was identified to achieve the prediction model. This model is capable of providing more accurate predictions for the risk of default in companies, given the performance of corporate social responsibility and managerial ability. The accuracy of this model is evidenced by the very low error between the neural network output and the desired output, which is 0.04.

5.2. Theoretical Comparison

The results of the study show that corporate social responsibility (CSR) reporting can be regarded as a qualitative characteristic of a company, and even an innovative tool, that can influence its credit rating. It is argued that the increased disclosure of CSR performance information enhances the qualitative mechanisms of corporate governance (for example, improving managerial oversight and reducing search and information acquisition costs). More specifically, providing additional information on the environmental and social risks and initiatives undertaken by the company can help investors more accurately assess its value and mitigate information risk. Thus, CSR disclosure reduces information asymmetry, which in turn increases the seller's awareness of the buyer and simplifies the provision of commercial credit. As a result, buyers can improve the quality of financial reporting and disclosure, thereby reducing information asymmetry between themselves and creditors. This enables them to receive more commercial credit from the seller and lowers the likelihood of default risk.

Consequently, companies that are socially and environmentally responsible tend to have better credit ratings and lower default risk. Therefore, CSR disclosure can reduce a company's default risk by improving transparency and gaining the trust of society and stakeholders, which, in turn, strengthens brand credibility and loyalty. Additionally, managerial ability plays a role in influencing financial decisions within companies, making it a factor affecting both risk and returns. Since the CEO is the primary decision-maker, an increase in their ability enhances their sense of responsibility for controlling and monitoring decisions. This results in better alignment and more goal-oriented execution of plans, leading to a better understanding of the company's characteristics and more awareness of the opportunities and threats it faces. Consequently, managers become more sensitive to the decisions made and the control of their programs. This awareness of both internal and external company conditions, as well as the industry they are part of, helps to reduce business and non-business risks. Therefore, as risks decrease, the likelihood of default also diminishes. It is important to note that this relationship is not necessarily linear; rather, it is nonlinear. A neural network, inherently structured in a complex nonlinear way, is used to model this relationship. The network takes the input data and adjusts its coefficients to minimize the error between the output of the network and the desired result.

5.3. Comparison with Prior Research

In this context, Fatahi (2023), found that managerial ability impacts commercial credit. The findings of, Li et al. (2018), also demonstrate the effect of social performance indicators on credit risk. Shahrour et al. (2021) highlighted the relationship between corporate social responsibility (CSR) and default risk. Chen et al. (2023), also found that CEOs with higher managerial abilities can effectively leverage CSR performance to reduce default risk. Additionally, the study by Yari-Fard & Asl-Yazdi (2024), confirmed that artificial neural networks (ANN) models can predict default risk for the banking network facilities in Iran, which aligns with the findings of the present research. However, this study uniquely extracted a nonlinear relationship between default risk, CSR performance, and managerial ability using neural networks, which demonstrated extremely high predictive accuracy. It is important to note that while comparing results from studies conducted in different contexts and times by different researchers may not seem scientifically ideal, it is valuable in understanding the gradual progression of research in a specific area. The results of studies conducted in various locations and times inevitably reflect the distinct conditions under which they were carried out, and the consistency or inconsistency of these results in similar topics should take these differing conditions into account.

This research aimed to design a nonlinear model using neural networks to predict default risk based on CSR performance and managerial ability. Through the development of this nonlinear model, the study concluded that CSR performance and managerial ability could be used to predict default risk with high accuracy. The results obtained are consistent with the theoretical framework and the existing financial literature. Therefore, as a general conclusion, it1. can be inferred that CSR strategy indicators and managerial ability possess relatively high predictive capabilities for default risk using artificial neural networks. The developed model can serve as an effective tool for predicting default risk in companies, making it valuable for investors and researchers in the capital market.

The practical implications of this research are relevant to two primary groups: the first group includes users of financial information, such as investors, creditors, managers, and auditing firms. These stakeholders are directly involved with the financial outcomes and impacts of a company's default risk. The second group consists of researchers, policymakers, and accounting standard-setters or institutions like stock exchanges, who are interested in economic and financial issues. A significant portion of the results aligns with the theoretical foundations of the subject matter and fills gaps in the research, helping managers with effective decision-making and shareholders with investment strategies and policy development through default risk prediction. The use of neural network algorithms in identifying predictive models greatly enhances2. the accuracy of financial analyses. The de-3. signed neural network model shows that predicting default risk, despite its complex and nonlinear nature, is achievable, and this algorithm can be applied in various fields to assist investors and financial professionals in making informed decisions.

5.4. Recommendations Based on Research Findings

Based on the results obtained from this study and the extraction of a nonlinear model, the following recommendations are offered:

***Default Risk Prediction Model**:* The study developed a default risk prediction model for companies, utilizing corporate social responsibility (CSR) performance and managerial capabilities, through the use of artificial neural networks. These models, derived from nature-inspired metaheuristic methods, can serve as an effective tool for investors to evaluate companies. With their high accuracy, these models can replace traditional methods and analyses, providing more reliable and precise results in a shorter time frame for financial market participants. Furthermore, reducing default risk and improving credit ratings are likely to increase shareholder interest in a company's stock, leading to a rise in its market value over time. Therefore, it is recommended that company managers place greater emphasis on enhancing their abilities and capabilities, while ensuring the transparency of their actions and policies in CSR. Moreover, to ensure compliance with CSR reporting regulations, it is necessary to publish separate annual reports on CSR activities. It is suggested that the Tehran Stock Exchange examine ways to strengthen the enforcement of such reports.

Managerial Attention to the Model: It is recommended that company managers give careful attention to these models, as they can offer substantial benefits. By using these models, managers can quickly identify changes in default risk and take the necessary corrective actions to improve the company's creditworthiness in the shortest possible time.

5.5 Suggestions for Future Research

1. It is recommended that this study be conducted across various industries separately, with a comparative analysis of the results obtained from different sectors.

2. The model's comprehensiveness can be enhanced by incorporating more detailed information about companies and extending the analysis to cover additional years.

3. Future research could explore the prediction of default risk using a broader range of financial and non-financial factors, thus incorporating more diverse inputs.

4. Investigating default risk prediction using genetic algorithms and other model extraction techniques, and comparing these results with the model developed in this study, would be valuable.

5. The performance of metaheuristic algorithms in predicting default risk during economic recessions and expansions could be explored in future research.

6. Additionally, future studies could examine the combination of neural networks with optimization algorithms, such as ant colony optimization and bee colony optimization, and compare the results.

7. Due to the higher risk associated with growth companies compared to value companies, it is recommended that this classification be considered in future research.

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