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Original Research

Financial Reporting Readability: A New Artificial Neural Network and Multi-Indicator Decision Making Approach

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ABSTRACT

The desirability of the financial reporting can greatly help the users of financial information in making investment decisions. The purpose of this research is to measure the readability of financial reporting using a multi-indicator decision-making model and the artificial neural network method and the role of information presentation time in its improvement. In this research, various indicators have been used to measure the readability of financial reporting, and the quality of reporting is obtained through the ranking of companies by the stock exchange. In this research, the number of 149 companies admitted to the Tehran Stock Exchange in the period of 2010-2020 was examined, and to measure the financial readability through structural equations and Stata software, and to test the hypothesis of the research, the regression model and Eviews econometrics software were used. In this study, we have tried to Use machine learning techniques and optimization tools as a way to derive adaptive-robust nonlinear models that can reduce the risk of model error as much as possible. The findings of the research show that the time of providing information has an impact on the readability of financial reporting. The obtained outputs from the estimation of the artificial neural networks and results obtained from estimation, using of this method with evaluation scales concerning random amount and comparing it with adjusted R, we found that there is meaningful relation between the associated variables and return. However, such network has the least error than other networks. The results show an overall improvement in forecasting using the neural network as compared to linear regression method. In other words, our proposed system displays an extremely higher profitability potential. The obtained result can be argued that the more the company's information is provided by the managers to the company's shareholders and investors on time and at the right time, the more readable and understandable the financial reports will be.

1 Introduction

Annual financial reports of companies are a means of communication between company managers and shareholders. Therefore, financial reports should communicate clearly and effectively with the company's stakeholders [9]. In the meantime, the readability of financial reports, which is one of the tools of communication between managers and owners, was also noticed by accounting researchers. Especially,

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the growing complexity of accounting rules and financial reporting language led to concerns about the effectiveness of these reports in communicating information to shareholders [49]. The undesired level of readability of financial reporting is considered a big weakness for an organization. Illegible financial statements reduce the feeling of trust and confidence in investors' decision-making [25]. On the contrary, investors have more trust and confidence in more readable financial statements and make their decisions more easily. Recent research related to the readability of financial reporting has focused on the consequences and characteristics of information disclosure, and the results of researchers show that the readability of financial reports has an effect on market pricing, analysts' behavior, profit continuity, and cost of capital [2,10]. Some other researchers also believe that the readability of financial reports of companies can reduce the cost of representation through the disclosure of company information [41,42]. The findings of Lee et al. [34] indicate that despite the fact that financial reports are very important in supporting the interests of stakeholders, the readability and understanding of these reports are usually complicated. Since the readability of financial reports has important economic consequences, it is very important to identify the factors affecting it [35]. In different countries, capital market regulatory bodies require companies to disclose certain information. In these reports, in addition to quantitative information, a written description is also provided. The way of presenting the written description contained in these reports is subject to the management's request and opinion, and contrary to the information contained in the financial statements, no action has been taken regarding the way of providing written information prescribed by the competent organizations. In comparison with quantitative financial reports, the managers in This area can better pursue their goals by choosing the style of expression or the way of presenting information [25]. Providing written information reveals more detailed and accurate information about the events, and due to the expression of management's views and values, the information asymmetry between the financial report preparers and its users is reduced. Therefore, in Iran, due to the little legal supervision that exists on the disclosure of qualitative information in comparison with quantitative information, with the skillful use of vocabulary, they can show a favorable image of the company and establish a proper relationship with the market participants. The main aim of this research, is to assess the readability of financial reporting and the influence of information presentation time on this readability. This study involves a combination of two main components: a multi-indicator decision-making model and the artificial neural network method. To understand the relationship between these components and the implementation of a robust neural network model, we need to delve into the methodology and results of our research. The study employs a multi-indicator decision-making model to measure the readability of financial reporting. Various financial indicators are used to assess the quality of reporting, and companies listed on the Tehran Stock Exchange during the period of 2010-2020 are evaluated based on these indicators. To carry out this analysis, structural equations and Stata software are employed, emphasizing a traditional econometric approach to assess financial data. In parallel, the study also incorporates machine learning techniques, specifically artificial neural networks, to construct adaptive-robust nonlinear models for financial forecasting. This approach is particularly significant in reducing the risk of model error. We evaluate the relationship between the artificial neural network model and financial forecasting performance, contrasting it with linear regression methodology. The results of our research indicate several key findings: Impact of Information Presentation Time: We observe that the time at which information is provided has a notable impact on the readability of financial reports. This finding underscores the importance of timely disclosure of financial data for investors and shareholders. Relation between Variables and Returns: Our analysis demonstrates a meaningful relationship between certain variables and financial returns. The artificial

neural network model provides valuable insights into these relationships, offering a more accurate and reliable method for financial forecasting compared to traditional linear regression.
Enhanced Forecasting with Neural Networks: The research reveals a significant overall improvement in forecasting accuracy when using the artificial neural network model compared to linear regression. This demonstrates the potential for higher profitability by adopting advanced machine learning techniques in financial analysis. In conclusion, the relationship between the equation model from EViews (used for econometric analysis) and the implementation of a robust neural network model in our research is as follows: EViews is utilized for the econometric analysis of financial data, whereas the neural network model, implemented separately, plays a crucial role in improving the accuracy and reliability of financial forecasting. These two components, though distinct in their application, collectively contribute to a more comprehensive and insightful approach to financial evaluation and forecasting in our research.

2 Theoretical foundations

Annual financial reports of companies are always one of the most important sources of information for decision-making by capital market actors (such as shareholders, creditors, and financial analysts), capital market legislators, and other stakeholders [21]. Therefore, the readability of financial reporting is considered as an important feature of textual information and has been widely investigated in various fields [33, 8]. The value of information contained in the text of financial statements and reports of the board of directors with a high level of readability is understandable for users. Therefore, companies should refrain from publishing complex, long or redundant reports, the purpose of which is to help public companies improve the acceptance of their disclosed information and to help investors better understand the information of the company's financial statements [33, 1]. At the same time, complex and ambiguous information that is considered relevant to meet the needs of users should not be removed from the company's financial statements on the pretext that it is difficult for some users to understand; Rather, such information should be presented as simply as possible [41, 42].

2.1 Artificial Neural Networks

In computer science, artificial neural networks (ANN) are computational models inspired by animals' central nervous systems that are capable of machine learning and pattern recognition. ANN is a non-parametric approach, and it does not consider any assumption about the functional form between inputs and outputs. This technique has the capability to find the relation between the variables and to correlate a set of independent variables with more than one dependent variable [32]. In this paper, a feed forward neural network is used in order to approximate the mapping function between the input parameters and the output parameters as the inputs of the network to the efficiency score as the output parameter of the network. In addition, Back propagation (BP) learning algorithm is applied to update network's weights through minimizing the cost function. Neural networks are one of the entrenched concepts in the world of machine learning, which tries to extract hidden patterns between input and output by creating a structure like a brain. Each neural network is made up of a set of neurons, which is the smallest processing element. Each neuron takes some inputs and, by initial processing, produces outputs, each of which can be the output of another layer or each of which can be the input of another layer of neurons. Each neuron is schematic as follows:

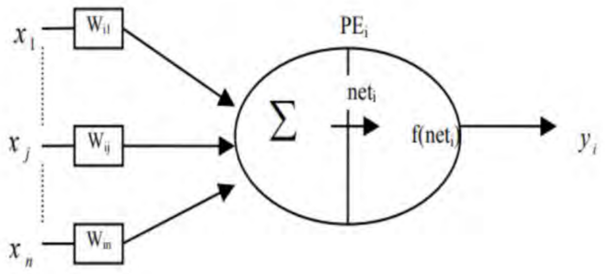

Fig. 1: Schematic structure of a neuron

2.2 Training ANN

The critical step in using ANN is the training step. In training, the weights between different nodes in different layers of the network are set. In this step, the input parameters and the output parameters are used as input of the ANN's input layer and the efficiency score is utilized as the data for the output layer. Therefore, by training the ANN we can find the relation of these factors. We use output parameters as the targets. In training phase ANN tries to close up the outputs to the targets. So in the process of training this relation is estimated. In training of the ANN, the early stopping method is used. This selection is done in order to improve the generality of the neural network. In the early stopping method, data records are divided into the Training set data which is used for computing the gradient and updating weights and biases of the network, Validation set, which is utilized to decrease the error of the validation set, and test set, which is used to compare the performance of different networks after finalizing the training process. In addition, the transfer function for each layer, the learning algorithm, and the number of neurons in hidden layer are optimized by trial and error. These reformations are done in order to find a suitable architecture for the utilized ANN.

2.2.1 Applications of Neural Networks in Financial Forecasting

Financial forecasting plays a pivotal role in the world of finance and investment. Accurate and timely predictions are essential for informed decision-making in areas such as stock market trading, risk management, asset allocation, and portfolio management. Neural networks, a subset of machine learning, have emerged as powerful tools for financial forecasting. This survey delves into their various applications in this domain, highlighting their impact, advantages, and challenges. Stock Price Prediction: Neural networks have been extensively applied to predict stock prices and trends. They can capture complex patterns and dependencies within historical data, making them ideal for time series analysis [52]. Credit Risk Assessment: Neural networks are used to assess the creditworthiness of individuals or companies by analyzing various credit-related features. They can handle large datasets and offer improved risk assessment [53]. Foreign Exchange Rate Forecasting: Neural networks are employed to predict fluctuations in exchange rates, a task critical for forex traders and international investors [54]. Algorithmic Trading: Neural networks are central in developing trading algorithms that can automate buying and selling decisions. They are capable of adapting to market changes in real-time [55]. Portfolio Management: Neural networks are used to optimize portfolio allocation by identifying asset combinations that maximize returns while minimizing risk [56]. Economic Indicators Forecasting: Neural networks are applied to predict economic indicators like GDP, inflation, and unemployment rates. Accurate forecasts help governments and businesses plan more effectively [57]. Risk Management: Neural networks are used to assess and manage financial risks, including market risk, credit risk, and operational risk. They provide an efficient means of quantifying potential losses [58]. Neural networks in financial forecasting are not without challenges. Data quality, overfitting, and model interpretability are some of the ongoing concerns. However, as computational power and data availability increase, neural networks are expected to play an even more significant role in the financial sector. Neural networks have proven to be versatile tools for a wide range of financial forecasting tasks. Their ability to handle complex data and adapt to changing market conditions makes them invaluable for investors, traders, and financial analysts.

2.2.2 Applications of Multi-Criteria Decision Making Models in Financial Forecasting

Multi-Criteria Decision Making (MCDM) models are valuable tools in financial forecasting, enabling decision-makers to consider multiple factors and objectives simultaneously. This survey explores various applications of MCDM in financial contexts and their impact on forecasting accuracy and decision-making. Portfolio Optimization: MCDM models assist in portfolio optimization by considering multiple criteria, including risk, return, liquidity, and diversification. They help investors construct portfolios that align with their financial goals [59]. Credit Scoring and Risk Assessment: MCDM models are used to assess the creditworthiness of individuals and businesses by incorporating various factors, such as credit history, income, and employment status. These models provide more holistic credit risk evaluations [60]. Economic Indicators Forecasting: MCDM models are applied to predict economic indicators such as GDP growth, inflation, and unemployment rates. These models consider multiple indicators to provide more accurate economic forecasts [61]. Financial Performance Evaluation: MCDM models are used to assess the financial performance of companies by considering various financial ratios and indicators. These models provide a comprehensive view of a firm's financial health [62]. Investment Decision-Making: MCDM models assist investors in making informed investment decisions by considering multiple criteria, including risk, return, and liquidity. These models help select investment options that align with an investor's preferences [63]. Exchange Rate Forecasting: MCDM models are applied to predict exchange rate movements by considering multiple factors, such as interest rates, economic indicators, and geopolitical events. These models offer a more comprehensive approach to forex forecasting [64]. While MCDM models offer numerous advantages, challenges include data availability, model complexity, and interpretation. Future research should focus on improving the robustness and transparency of these models in financial forecasting. Multi-Criteria Decision Making (MCDM) models provide a versatile and powerful approach to financial forecasting, enabling decision-makers to consider multiple criteria and objectives simultaneously. They are valuable tools in portfolio management, credit assessment, economic forecasting, financial performance evaluation, and investment decision-making.

2.3 Readability of Financial Reporting

Some accounting experts have considered it as a language (in a general sense) and as business (in a specific sense). Hawes [23] believes that language consists of two parts: symbols and grammatical rules. Therefore, knowing accounting as a language is based on knowing these two components. The two parts that are mentioned as two levels of accounting and related to it can be discussed as follows: First, these symbols or lexical signs of the language are meaningful units or recognizable words in a language. These symbols are linguistic subjects that are used to represent specific concepts [36]. For accounting, the words, numbers, and concepts of debtor and creditor can be defined as accepted and unique symbols, and secondly, the meaning of grammatical rules of a language is the order used in a language to combine words. will be in accounting, the meaning of command rules is a general set of events that are compared to create all the data belonging to the business unit [47]. Readability is determined by the ratio of positive and negative words in the annual reports of the board of directors, which can be an indicator for changing the level of optimism with pessimism in the disclosure of the report. Restripo et al. [44] showed that managers tend to act strategically and use more optimistic readings and less pessimistic readings regarding economic profits. Accounting research in this field shows that the readability of financial reporting can affect the quality of financial statement information; Therefore, the poor readability of financial reporting adds to the organization's problems, including profit management, poor profit stability, the risk of falling stock prices, investors' reaction to the stock market [14, 27, 32]. Measuring the readability of financial reports is one of the research areas of reading studies, which seeks to find the probability of the reader's success in reading and understanding a text, and in this regard, it examines the effective factors in the success of reading and understanding the text [30,29]. Accounting language can be descriptive, which is procedurally significant as it becomes longer and more complex. In addition, descriptive sentences allow annual report preparers to disclose more detailed information and explanations about events. Increasing the importance of accounting descriptions can help reduce the information asymmetry that occurs due to the limitations of current accounting standards [43, 23]. As a result, accounting figures and accounting descriptions can better show the company's fundamental information. The connection between the research hypotheses and the utilization of neural networks in the paper can be elucidated as follows:

While the research hypotheses primarily revolve around the assessment of financial reporting quality using multi-criteria decision-making models and the influence of information presentation time, the role of neural networks becomes evident in the practical implementation of these hypotheses. The neural network, a machine learning technique, is employed to create an intelligent algorithm that enhances the quality and accuracy of financial evaluation. Specifically, it is used to develop adaptive-robust nonlinear models, which are capable of reducing the risk of model error. In the context of the hypotheses, the neural network contributes to the second hypothesis (measuring readability) by providing a powerful tool for processing and analyzing the financial data that underpins the multi-criteria decision-making model. It allows for the comprehensive assessment of various factors affecting the readability of financial reports. Furthermore, the neural network plays a pivotal role in hypothesis testing, particularly the third hypothesis, which explores the effect of information presentation time. The neural network's ability to capture complex relationships in the data allows for a nuanced analysis of how the timing of information disclosure impacts the readability of financial reports. In summary, the research hypotheses provide the theoretical framework for assessing financial reporting quality and information presentation time. The neural network is the practical tool that enables the implementation and evaluation of these hypotheses, ultimately leading to the development of an intelligent algorithm for financial evaluation. It empowers the study to discover meaningful relations, reduce errors, and improve forecasting, reinforcing the arguments and conclusions drawn from the research.

2.4 Multi-Indicator Decision Making Model

Multi-criteria decision-making includes models for choosing the best option based on a number of criteria. This method is abbreviated as MADM and is a branch of MCDM multi-criteria decision making. In these models, choosing an option among the available options is considered. Multi-indicator decision-making models are divided into compensatory and non-compensatory models according to the type of desired indicators. Multi-criteria decision-making methods are usually used with the aim of determining the weights of criteria or prioritizing options. Hierarchical analysis process, network analysis process, best-worst, Swara and entropy methods are used to determine the weights of the criteria. Methods such as SAV, TOPSIS, VIKOR, Electra, Erste and Promethe are also presented with the aim of choosing the best option based on the decision matrix [15].

2.5 The Concept of Disclosure and Transparency

Disclosure refers to sharing vital market information, while transparency is the ease of comprehending a company's activities and economic fundamentals. It signifies management's capacity to offer correct, clear, and timely data, especially audited information in public reports and through various media. It reflects whether investors have an accurate view of a company's internal workings. Thus, disclosure and transparency are intertwined, necessitating accurate, accessible information, often provided by intermediaries such as accountants, auditors, rating agencies, securities analysts, financial journalists, and mass media [46]. Several research studies have revealed valuable insights:

Arianpour and Sahour [3] explored the impact of business strategy and annual report readability on financial reporting quality. Their research, which examined 160 companies on the stock exchange from 2014 to 2020, found that cost leadership strategy, differentiation strategy, and annual report readability positively affected the quality of financial reporting. Alam-el-Din et al. [2] investigated voluntary disclosure and the complexity of financial reporting, considering the role of profit management and profitability in Egyptian non-financial firms during 2010-2018. Their findings suggested that the readability of annual reports decreases with increased voluntary disclosure. This indicates that Egyptian companies with more voluntary disclosure tend to have more complex and less readable annual reports. Additionally, companies with lower profits and practices of earnings management include more voluntary information in their annual reports, negatively affecting readability. Manzoor Hassan and Habib [19] conducted research on the readability of financial reporting, company disclosure, liquidity, and dividend payment politics. They discovered that companies with lower disclosure tend to pay fewer cash dividends and buy fewer shares. Bakarich et al. [5] examined changes in the quality characteristics of annual reports (specifically, readability of financial reporting) during different stages of a company's life cycle. Using data from 24,268 company-years between 2000 and 2014, they found that the readability of financial reports becomes less complex and more optimistic from a company's birth to its maturity stage. In contrast, during a company's decline, reports become associated with less disclosure and more ambiguous information. Habib and Hassan [19] explored the relationship between business strategy and the readability of financial reporting. Their research, covering 38,014 company-years from 1994 to 2013, indicated that aggressive companies present financial reports with lower readability compared to defensive companies. Lim et al. delved into the Australian capital market, revealing that financial reports from offensive companies are less readable compared to defensive ones. Mohammadi et al. [38] focused on the impact of financial reporting readability on stock liquidity, with an emphasis on agency fees in companies on the Tehran Stock Exchange. They found that higher readability in financial reports is positively related to stock liquidity, while negatively associated with agency fees. In a study by Shaygan et al. [50], they examined the effect of auditor style on the relationship between the readability of financial reporting and the synchronicity of stock prices. Their research, covering 108 companies on the Tehran Stock Exchange from 2011 to 2018, found that the auditor's style and the readability of financial reporting negatively affected stock price synchronicity. Nowrozi et al. [42] designed a model to evaluate the moderating role of management ability in the relationship between the readability of financial reporting and agency fees. Their study included 116 companies admitted to the Tehran Stock Exchange from 2011 to 2016. The findings revealed that the readability of financial reporting reduces the cost of representing the company, and management ability moderates and weakens the negative relationship between financial reporting readability and agency fees. Jabarzadeh Kongarloui et al. [24] investigated the impact of profit management and financial constraints on the readability of financial reporting. Their study involved 350 companies from 2010 to 2014. The results showed that profit management negatively affected the readability of financial reporting. Additionally, the company's financial status had a negative impact, while financial constraints had a positive impact on readability. Other variables like company size, company age, agency fees, and company growth also had varying effects on readability, while financial leverage and book value to market value did not significantly affect it. Khani Masoumabadi and Rajab Dari [26] studied the relationship between the readability of financial reports and bold tax policy. Their research, using simultaneous equations and data from 119 companies between 2014 and 2018, revealed a significant two-way relationship between the readability of financial reports and bold tax policies. An increase in readability was associated with a decrease in reckless tax policies, and as the level of bold tax policy increased, the readability of financial reports decreased. Mohseni and Rahnamai Roudpashti [39] explored the financial performance and functions of managing readability in financial reporting. Their research, spanning the years 2008 to 2015, revealed a negative and significant relationship between managing readability and a company's future financial performance. This suggests that managers use text readability management for strategic purposes and to mask a company's weak future performance. Considering the novelty of measuring the readability of a company's financial reporting using a multi-indicator decision-making model and the role of information presentation time, this research aims to:

- ≠ Explain the criteria for measuring financial reporting readability effectively.
- ≠ Measure the readability of financial reporting for companies listed on the Tehran Stock Exchange using a multi-criteria decision-making model.
- ≠ Investigate the impact of information presentation time on financial reporting readability.

No specific hypotheses were proposed for the first two research objectives, as these questions are addressed through the measurement of financial reporting readability. After measuring the readability of financial reporting for companies listed on the Tehran Stock Exchange, the research aims to explore the impact of information presentation time, hypothesizing that the timing of information presentation affects the readability of financial reporting.

3 Research Methodology

The current research is based on the purpose of applied research. Also, in terms of nature and method, it is considered to be a type of descriptive-correlational research. From the point of view of the type of data, it is a qualitative and quantitative research, and in terms of the method of data analysis, it is a research with a mixed method, in which a qualitative method is used in part of the research and a quantitative method is used in another part. Sampling will be done using the snowball method. For this purpose, a list of experts who are firstly a member of the official society of official accountants, secondly a member of the academic faculty of the university and thirdly have at least 10 years of accounting work experience will be prepared to participate in the research. introduced by the experts and the interviews will continue until the received content reaches saturation or in other words, new dimensions and components are not mentioned by the interviewees. The research encompasses companies that were listed on the Tehran Stock Exchange from 2010 to 2020, with their respective financial year-end occurring in March. Also, due to the different economic nature of companies such as investment companies, financial intermediation, holding, bank and leasing from other companies, these companies were excluded from the sample. The final sample of the research included 149 companies after applying the above conditions. In this research, the library method is used to collect data, and the data required for the research is extracted from the information contained in the annual report of the board of directors about the company's activity and general situation. In order to collect and compile the research data, the website of the Tehran Stock Exchange Organization (for calculating readability indicators of financial reports) and Rahavard Novin software (for calculating control variables) will be used. Our research integrates the Artificial Neural Network (ANN) model and the Multi-Indicator Decision Making Model to create a comprehensive framework for financial evaluation and forecasting. The integration is aimed at leveraging the strengths of each model to produce more reliable and understandable results. Here's how this integration was achieved:

Data Preprocessing: We began by collecting financial data from 149 companies listed on the Tehran Stock Exchange from 2010 to 2020. This dataset was used for both the Multi-Indicator Decision Making Model and the ANN.

Multi-Indicator Decision Making Model: This model was employed to assess the readability of financial reporting. It incorporates various financial indicators and decision-making criteria. The model ranks companies based on these indicators, providing a baseline for evaluating the quality of financial reporting.

Artificial Neural Network (ANN): Simultaneously, we implemented an ANN model for financial forecasting. The ANN is a machine learning technique known for its ability to capture complex nonlinear relationships within the data. The ANN was used to predict financial returns based on the same dataset.

Integration of Results: To demonstrate the integration of these models, we compared the ANN's predictions of financial returns with the rankings generated by the Multi-Indicator Decision Making Model. This comparison allowed us to assess the relationship between the financial indicators used for readability and the financial performance, effectively linking the models.

Enhanced Reliability and Understandability: The integration of the Multi-Indicator Decision Making Model and the ANN yielded several benefits:

a. **Enhanced Reliability**: By integrating these models, we could cross-validate the relationships between financial indicators and financial returns. This cross-validation, utilizing both traditional financial indicators and machine learning predictions, enhances the reliability of our findings.

b. **Improved Understandability**: The integration of models provided a clearer perspective on the impact of various indicators on financial performance. By comparing the rankings with the ANN predictions, we could offer a more comprehensive and understandable explanation of how financial reporting quality relates to financial outcomes.

Statistical Analysis: We supported our argument with statistical analyses, including evaluation scales, adjusted R-squared values, and error comparisons, showing that the integrated approach is statistically significant and yields more accurate results compared to using individual models. In conclusion, the integration of the Multi-Indicator Decision Making Model and the ANN in our research paper allows us to not only evaluate the readability of financial reporting but also predict financial performance, providing a holistic view of the relationship between financial reporting quality and outcomes. This integrated approach enhances the reliability of our findings and makes them more understandable by offering a comprehensive analysis of the factors influencing financial performance, thereby contributing to a more informed basis for investment decisions.

3.1 ANN Design

Designed artificial neural network is shown in Fig. 2. For training in network, 70 percent of data was training data and 30 percent for network testing. Results show that for network training data correlation coefficient between aimed data and output data of model is 97.61. Determine coefficient for training data is 0.953. Neural network could predict 95.6 cases correctly with training data. For work test correlation coefficient was 91.71. Determine coefficient for test data was 0.841. Neural network can predict in 84.1 cases correctly.

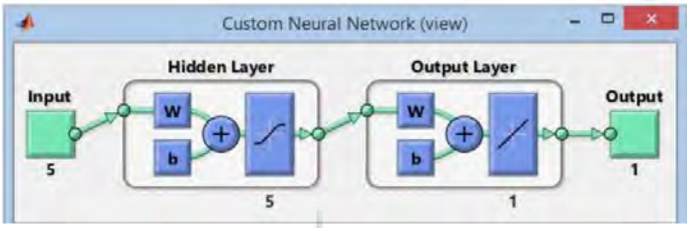

Fig. 2: Structure of the Used ANN

In Fig. 2, the return is calculated regarding the input, output data, and the chosen structure by artificial neural networks. In order to build the associated model, we follow the following steps:

Introduction of Different Models: we present various models employed in our research. Initially, we discuss a single linear regression model used for evaluating financial data. This model serves as a starting point and allows us to establish a baseline for our analysis.

Transition to Artificial Neural Network (ANN): We then introduce the artificial neural network model as a more complex and robust approach for financial forecasting. This transition is gradual and includes a description of the model's architecture, training process, and the rationale behind its application.

Parallel Presentation of Models: While presenting different models, we maintain a parallel structure, ensuring that readers can compare the linear regression model with the ANN. We provide results and insights from each model separately, demonstrating the evolution from a simpler linear model to a more intricate neural network model.

Comparative Analysis: In the conclusion, we synthesize the findings from both models, highlighting the key takeaways. We emphasize that the transition from a linear regression model to the neural network is motivated by the need for more accurate and adaptive financial forecasting.

Enhanced Reliability: We explain how the ANN, with its ability to capture complex nonlinear relationships in financial data, provides more reliable predictions. We discuss the validation of the ANN's performance using evaluation scales and the comparison with adjusted R-squared values, showcasing its superiority in forecasting.

Improved Understandability: We emphasize that the ANN doesn't just improve reliability but also enhances the understandability of results. By capturing intricate relationships within the data, it allows for a more nuanced and comprehensive interpretation of the factors influencing financial outcomes.

Holistic Approach: We conclude by highlighting that the integration of the linear model and the neural network in our research represents a holistic approach to financial evaluation. The combination of traditional financial indicators with advanced machine learning techniques yields a more comprehensive perspective for investors and stakeholders. Designing the structure of an artificial neural network (ANN) for financial forecasting is a crucial step in ensuring the network's effectiveness and relevance to your research objectives. Below, we'll outline the key steps and considerations for designing the ANN structure in the context of our financial forecasting research:

1. Define the Objective: Begin by clearly defining the specific financial forecasting task we want the ANN to address. This could include stock price prediction, credit risk assessment, economic indicator forecasting, or other relevant financial tasks.

2. Data Collection and Preprocessing: Gather the financial data relevant to our research. Ensure the data is clean, well-structured, and adequately preprocessed. Common preprocessing steps include normalization, feature selection, and handling missing data.

3. Input Features: Decide on the input features that the ANN will use for forecasting. These features should be relevant to the financial task at hand. For example, in stock price prediction, input features may include historical stock prices, trading volumes, and relevant economic indicators.

4. Architecture Selection: Choose an appropriate architecture for our ANN. The architecture includes the number of layers, the number of neurons (nodes) in each layer, and the type of layers (e.g., input, hidden, and output layers). For financial forecasting, a feedforward neural network is a common choice.

5. Activation Functions: Select appropriate activation functions for each neuron in the network. Common activation functions include the sigmoid, ReLU (Rectified Linear Unit), and tanh functions. The choice of activation functions depends on the nature of our financial data and the problem we are solving.

6. Loss Function: Define the loss function that quantifies the error between the network's predictions and the actual values in our financial data. Common loss functions for regression tasks include mean squared error (MSE) and mean absolute error (MAE).

7. Training Algorithm: Choose a training algorithm, such as backpropagation with stochastic gradient descent (SGD) or a more advanced optimizer like Adam. The training algorithm is responsible for updating the network's weights during the training process.

8. Hyperparameter Tuning: Optimize hyperparameters such as learning rate, batch size, and the number of epochs through experimentation and cross-validation. This step is crucial for achieving the best performance of our ANN.

9. Model Evaluation: Use appropriate evaluation metrics to assess the performance of our ANN. Common metrics for financial forecasting tasks include Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R2).

10. Regularization Techniques: Consider using regularization techniques like dropout or L1/L2 regularization to prevent overfitting, which is a common concern in financial forecasting due to noisy and complex data.

11. Model Interpretability: In financial forecasting, model interpretability is often important. Utilize techniques like feature importance analysis and SHAP (SHapley Additive exPlanations) values to understand the contribution of each input feature to the model's predictions.

12. Validation and Testing: Split our data into training, validation, and test sets to evaluate the ANN's performance. Ensure that the model generalizes well to unseen data.

13. Fine-Tuning and Iteration: It's often necessary to iteratively fine-tune the ANN's structure and hyperparameters based on the performance on the validation set. Make adjustments as needed to optimize the model.

14. Model Deployment: Once we are satisfied with the performance of your ANN, deploy it for use in our financial forecasting application.

The design of an ANN is not a one-size-fits-all process. It should be tailored to the specific financial forecasting task, data characteristics, and research goals. Additionally, continuous monitoring and refinement may be necessary to adapt to changing financial conditions and data patterns.

3.2 Variables

3.2.1 Dependent Variable

The basic question that is always considered important for investors is how to achieve an index to measure and explain the readability of financial reports. In response to this question, due to the lack of visibility of the readability of financial reports, researchers have provided different criteria to measure the readability of financial reports. By studying the research literature and the local conditions of the country, the data of this research to explain the readability of financial reporting of companies include the following six indicators, which have been used in most of the past domestic and foreign researches to calculate the readability of financial reporting of companies. Since the higher values of the above indices indicate the lower readability of financial reports, each of the calculated indices is multiplied by a negative number of -1 to obtain a direct measure of the readability index of financial reporting. In the following, the method of calculating these six indicators will be presented:

The first index: the total length of the text

The first index of readability of financial reporting is the index of the total length of the text, which is calculated as follows:

$$\text{text length index} = \text{Ln (number of text words)}$$

The relationship between the total text length index and the readability level is as follows:

LENGTH ≥18 means the text cannot be read and is very complicated; Likewise, 18-14 (hard text); 14-12 (appropriate text); 12-10 (acceptable text) and 10-8 (easy text).

Second Index: Flash

The second readability index of financial reporting is the flash index, which is calculated as follows: This method was presented by Rudolph Flesch in order to determine the level of simplicity or difficulty and the simplicity coefficient of financial report texts. This formula is designed based on two linguistic factors, namely the average length of the sentence and the number of syllables. The process and steps of evaluating and determining the level of readability, i.e. the degree of simplicity of the content, are as follows:

1. Random selection of three one-hundred-word samples from the beginning, middle and end of the text of the board of directors' reports
2. Determining the length of words by counting the number of syllables (syllables) in the selected words.
3. Counting the number of sentences in the first, second and third hundred words
4. Determining the average length of sentences by dividing the number of words by the number of complete sentences of each hundred-word text.
5. Calculation of average length of words and average length of sentences of three texts of one hundred words.
6. Multiply the average length of words (number of syllables) by the constant number 0.846
7. The product of paragraph 6 is subtracted from the fixed number 206.835. For localization and validity in Persian language, Diyani [11] suggests a fixed number of 206.835.
8. Multiplying the average sentence length by 1.015
9. Subtracting the product from the remainder of the calculations in paragraph 7
10. We put the obtained number in the table for determining the difficulty or simplicity of the arrow and determine the degree of simplicity or difficulty of the text.

The relationship between flash index and readability level is as follows:

Flesch ≥ 18 means the text is unreadable and very complicated; 18-14 (hard text); 14-12 (appropriate text); 12-10 (acceptable text) and 10-8 (easy text).

Third Index: Fry

The third indicator of the method of determining the level of readability of financial reporting is Frye's index, which can be calculated as follows:

According to Frey, the shorter the sentence, the greater the readability. In this method, three samples of one hundred words are selected and by counting the number of sentences and syllables, the average number of sentences and the average number of syllables in the text are determined. From the intersection of these values in a two-dimensional graph, one dimension of which is the average number of sentences and the other dimension is the average number of syllables, the readability level corresponding to the text is extracted. For Persian texts, Diani [11] suggests to add 56 units to the average number of syllables on the chart. The relationship between the Fry index and the readability level is as follows:

Fry ≥ 18 means the text is unreadable and very complicated; 18-14 (hard text); 14-12 (appropriate text); 12-10 (acceptable text) and 10-8 (easy text).

Fourth Indicator: Gunning Fog

The fourth index of the readability level determination method is the Gunning Fog index, which will be measured as follows: This method was designed by Robert Gunning Fogg with the aim of evaluating and determining the level of readability of the texts of the board of directors' reports; In other words, the main goal of this method is to evaluate and determine the level of texts. The process and method of determining the readability level of writings in the Gunning Fog method is as follows:

1. Choosing a sample of 100 words from the beginning, a sample of 100 words from the middle and a sample of 100 words from the end of the writing randomly.
2. Counting the number of complete sentences of each sample according to four methods (; and? and! and.)
3. Determining the average length of sentences by dividing the number of words by the number of complete sentences of each hundred-word sample

4. Counting the number of three-syllable words and more than three-syllable words in each one-hundred-word text. For the validity of this method in Persian language, it is suggested to calculate the difficult words in Persian words with 4 syllables or more.
5. Summing up the number of difficult words with the average number of words in sentences.
6. Multiplying the sum of the number of difficult and average words in the sentences by a fixed number of 0.4
7. Performing the calculations of clauses 4, 5, 6 for two other samples of one hundred words.
8. Calculate the average results of all three samples by adding and dividing by the number (3).

The number obtained from the above operation in the eighth paragraph specifies the level of readability of the texts or writings. Degrees of the Gunning Fog method are equivalent to the readability levels of financial reporting.

The relationship between the Gunning Fog index and the readability level is as follows:

Gunning Fog ≥18 means the text is unreadable and very complicated; 18-14 (hard text); 14-12 (appropriate text); 12-10 (acceptable text) and 10-8 (easy text).

Fifth indicator: McLaughlin

The fifth method of measuring the readability of financial reporting is the McLaughlin method, which will be measured as follows:

The process and evaluation steps to determine the readability level of this method are as follows:

1. Ten consecutive complete sentences at the beginning, ten consecutive complete sentences in the middle and ten consecutive complete sentences at the end of an article are selected. Considering that a complete sentence is a set of words that ends with a period (.), a question mark (?) or an exclamation mark (!) and a period (;).
2. In this sample of 30 sentences, all difficult words with three syllables and more are counted. For the Persian language, words with 4 syllables or more are considered difficult words.
3. The sum of the number of difficult words (four digits and more) is obtained and then its square root is calculated. If this number does not yield a perfect root, the closest number that has a perfect root should be chosen.
4. We add the number 3 to the root obtained.

McLaughlin states that the obtained number determines the ability of the users (stakeholders) to read the texts in terms of readability level.

We add the number 5 to the root obtained. The resulting number indicates the age that users of financial statements must be to understand the intended text.

The relationship between the McLaughlin index and the readability level is as follows:

Mc Laughlin ≥18 means the text is unreadable and very complicated; 18-14 (hard text); 14-12 (appropriate text); 12-10 (acceptable text) and 10-8 (easy text).

Sixth index: Power, Sumner, Kerl

The sixth readability measurement method is the Power, Sumner, Kerl index, which is measured in the following way:

Random selection of three one-hundred-word samples from the beginning, middle, and end of the text of the board of directors' reports.

Counting the number of sentences in the first, second and third one-hundred-word text.

Determining the average length of sentences by dividing the number of words by the number of sentences in each text.

Counting the number of syllables (syllables) in a hundred words and calculating their average.

Obtaining the text level based on the following formula:
Text level = ((average syllables x 0.0455) – (2.2026)) + (average sentence length x 0.0778)
Obtaining the reading age level through the following formula:
Reading age level = ((average syllables x 0.0455) - (2.7971)) + (average sentence length x 0.0778)
The relationship between Power, Sumner, Curl index and readability level is as follows:
Powers-Sumner-Kearl ≥18 means the text is unreadable and very complicated; 18-14 (hard text); 14-12 (appropriate text); 12-10 (acceptable text) and 10-8 (easy text).
After determining the weight of factors affecting the readability of the company's financial reporting, the answer to the second question of the research, which is to provide a comprehensive model for measuring the readability of the company's financial reporting, is given in the next section.

3.2.2 Independent Variable

Disclosure of information as an independent variable includes the amount of information provided by companies in the text of the basic financial statements or in the accompanying notes to help make decisions. The company is in the annual financial reports. In some cases, this concept is still more limited and means providing information that is not included in the text of financial statements [22]. In order to reduce the gap between the production and public dissemination of information, the Tehran Stock Exchange Organization has calculated the information score of publishers based on their information status in terms of reliability and timeliness of information transmission [18]; In this research, this rating, which is available on the website of the Tehran Stock Exchange Organization, has been used as a criterion for the transparency of financial information.

3.2.3 Control Variables

According to Bakarich's research [5], the following variables are used as control variables of the research. Company size: It is obtained by using the natural logarithm of the total assets of the company.
Financial leverage: It is estimated from the ratio of total liabilities to total assets. Profitability: obtained through the result of the ratio of net profit to the total assets of the company. Several criteria have been proposed to measure the readability of financial reporting in the market. Regarding how we can provide a comprehensive index to measure the readability of financial reporting, the working method has been as follows:
1. Studying the literature and background of domestic and foreign researches on the subject of research and identifying the criteria for measuring the readability of financial reporting of companies that have been used in previous researches and selecting these criteria according to the readability of financial reporting of Iranian companies.
2. Preparation of a questionnaire to solicit opinions from experts about the weight and importance of the considered criteria for measuring the readability of the company's financial reporting with the help of one of the methods of the multi-indicator decision-making model and distributing it among the experts.
3. Collecting the questionnaire distributed among the experts and determining the weight of each of the effective criteria on the readability of the company's financial reporting using Shannon's entropy method.
4. Collecting the data needed to measure each of the criteria affecting the readability of the company's financial reporting through databases and measuring the criteria affecting the readability of financial reporting and standardizing them.

5. Explaining the measurement model of the comprehensive readability index of companies' financial reporting using the criteria that influence it and their weight in a combined way.

To answer the research question, what are the criteria for calculating the readability of companies' financial reporting? By studying the research literature and the local conditions of the country, the data of this research to explain the readability of companies' financial reporting includes six factors: text length index, Flash index, Gunning Fog index, McLaughlin index, Fry index and Power, Sumner and Curl index, which are in most companies. Past domestic and foreign researches used these factors to calculate the readability of companies' financial reporting. The financial data required for the research model were extracted from Rahvard Novin software and the official website of the Stock Exchange Organization. Experts' opinions were used to give weight to the mentioned factors in calculating the readability index of financial reporting. In this way, an electronic questionnaire containing 6 questions, each question including a criterion used in the model, was sent to 36 professional and academic experts, and their opinions were asked regarding the weight of the six effective factors in measuring the readability of financial reporting. Then, all the questionnaires sent to the experts were collected and the weights of the factors were determined using Shannon's entropy technique which is explained in the next part. It should be noted that Cronbach's alpha coefficient of the above questionnaire was equal to 0.783, which indicates its good reliability and validity. Entropy technique implementation steps: To measure the weight and contribution of each of the above six factors, the following basic steps are necessary:

First step: the decision matrix of indicators is determined. Second step: The data obtained from the decision matrix are normalized for analysis and review. The third step: determining the value of Ej in the entropy of the j characteristic. Fourth step: with the help of Ej, the value of di is calculated for each characteristic. The fifth step: the weight of dimensions, criteria and variables wj is obtained as the j feature. According to the above steps, the demographic statistics of the experts and the determined weights are as follows:

Table 1: Research Demographics

Variable	*Sub variable*	*Number*	*Percentage*
Male	gender	32	٪89
	Female	4	٪11
Age	between 30 and 40 years	8	٪22
	between 40 and 50 years	21	٪58
	More than 50 years	7	٪20
The amount of education	doctoral students	6	٪17
	Doctor of specialization	30	83%

Table 2: Degree of importance based on entropy for readability components of financial reporting

Effective factors	**Total text length index**	**Flash indicator**	**Gunning Four index**	**McLaughlin index**	**Fry's index**	**Power, Sumner and Kerl index**
Ej	0.951	0.953	0.960	0.953	0.946	0.966
dj=1-Ej	0.049	0.047	0.040	0.047	0.054	0.034
Wj (weight)	0.117	0.113	0.096	0.112	0.129	0.082

In Table 2, the readability indicators of financial reporting have been segmented based on the most effective indicator and using the two-stage clustering algorithm. In such a way that a set of data is automatically divided into different indicators based on the concept of distance without adding the opinion of experts, and then, during the Shannon entropy process, all indicators are weighted at the same time. After determining the weight of the factors affecting the readability of the company's financial reporting, the answer to the second question of the research, which deals with measuring the readability of the companies' financial reporting using the multi-indicator decision-making model, is given in the next section.

3.3 Simulating the Outputs by Running ANN

Now it is possible to estimate the efficiency scores by preferred alteration in the input and output parameters using obtained ANN from previous step. This method helps managers to decide if input sources are consumed according to desired efficiencies, how much efficiency could be obtained. In this study, 80 percent of data is used for training, 10 percent for validation and 10 percent for test. The used neural network in this study is a two-layer neural network with a single hidden layer. Among different examined ANNs, we used ANN by the architecture that is composed:

≠Early stopping method for improving the generalization
≠Tan-sig transfer function in both layers
≠Resilient Back-propagation (Rprop) training algorithm
≠12 neurons in hidden layer
≠Msereg1 perform function with perform ratio equal to 0.5 in order to compute the error in training

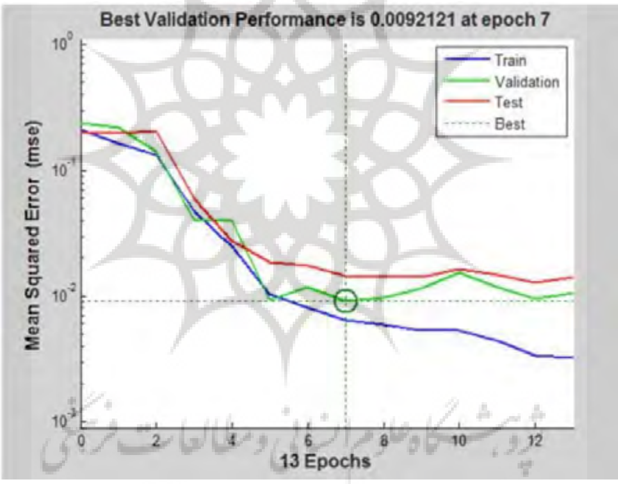

Fig. 3: Error in the training, validation and test process

process and to improve the generalization of the network. [24] Illustrates the error in training, validation and test data sets. Mean Squared Error is used as the error index, and it is calculated for all three datasets: Train, Validation, and Test datasets. As it is clear in the figure, the charts converge to zero after a small number of iterations. [36] Shows the correlation between the outputs and the targets. The correlation is calculated separately for training, validation and test data sets. All the sub images illustrate that the output and the target values follow a similar pattern and the smaller values are corresponded to the smaller values and the bigger values are matched to the bigger ones. It means the model could simulate behavior of the system properly.

In [12], dependency degree between the efficiency value as the output of the system and its target is shown. In average, a correlation equal to 0.8906 shows that the system is simulated correctly.

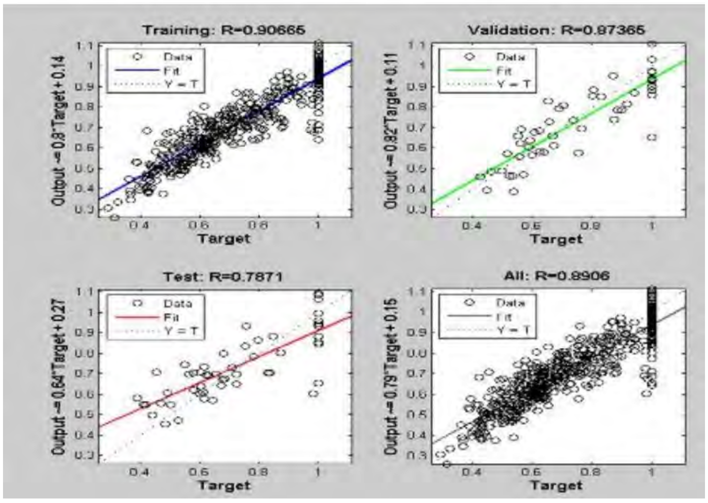

Fig. 4: The R-value in training, validation and test set

In Fig. 5, the return is calculated regarding the input, output data, and the chosen structure by artificial neural networks.

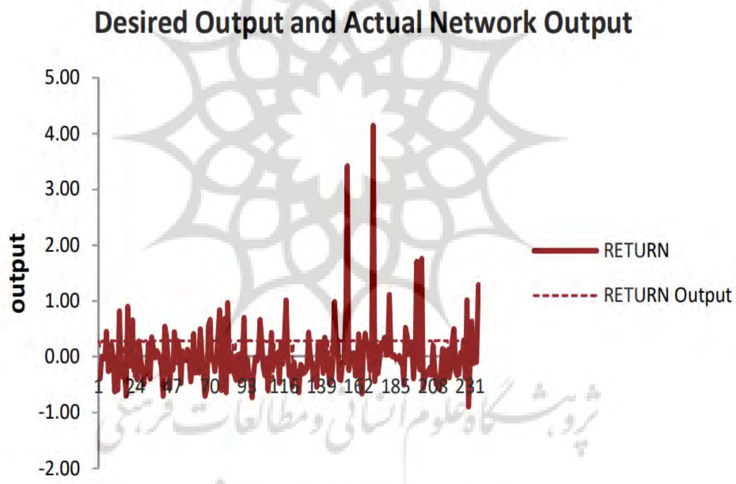

Fig. 5: Simulated return test using ANN

3.2 Multi-Indicator Decision Making Model to Measure the Readability of Financial Reporting

In this research, a balanced composite index is used to measure the readability of financial reporting. To explain the multi-indicator decision making model, it is necessary to consider three basic assumptions. First, to calculate the readability of financial reporting, it accepts the sum ability principle, that is, the readability of financial reporting is equal to the sum of the factors affecting it. In other words, the factors are gathered together with one rule and determine the readability of financial reporting. In addition, the effect of each of these factors on the readability of financial reporting is proportional to their coefficient or weight calculated in the previous section (proportionality). Thirdly, we accept that the influence of each factor on the readability of financial reporting is normalized. This is done because a meaningful floor and ceiling or a minimum and maximum for calculating the readability of financial reporting is determined. According to the above explanations and assumptions, a multi-indicator decision-making model to measure financial readability is presented as follows:

$$FRR_{it} = \sum_{s\in S} W_{s\,it}\,\frac{P_{s\,it}}{\max\limits_{1\le i\le N}\{P_{s\,it}\}} + \sum_{k\in K} W_{k\,it}\,\frac{\max\limits_{1\le i\le N}\{P_{k\,it}\} - P_{k\,it}}{\max\limits_{1\le i\le N}\left\{\max\limits_{1\le i\le N}\{P_{k\,it}\} - P_{k\,it}\right\}}$$

which in this model:

$FRR_{it}$is the financial reporting readability index of company i in year t.

N is the number of companies

S is the index set of factors that are directly related to the readability of financial reporting.

K is the index set of factors that have an inverse relationship with the readability of financial reporting.

W_ (j it) the weight of the j factor of company i in year t.

P_ (j it) value of the j factor of company i in year t.

It is clear that if M is the total number of factors affecting the readability of financial reporting, then M=|S|+|K| where |S| Displays the number of elements of the set S and |K| It displays the number of elements of the set K.

Theorem 1: If for two companies with indices an and b we have:

$$P_{s\,at} \le P_{s\,bt} \quad \forall\, s \in S$$
$$P_{k\,at} \le P_{k\,bt} \quad \forall\, k \in K$$
then
$$FRR_{at} \le FRR_{bt}$$

Theorem 2: Also for the company with index a we have:

$$\frac{P_{s\,bt}}{\max\limits_{1\le i\le N}\{P_{s\,it}\}} \le \frac{P_{s\,at}}{\max\limits_{1\le i\le N}\{P_{s\,it}\}}$$

On the other hand, if P_ (k at) ≤ P_ (k bt); then

$$\max_{1\le i\le N}\{P_{k\,it}\} - P_{k\,at} \le \max_{1\le i\le N}\{P_{k\,it}\} - P_{k\,bt}$$

$$\frac{\max\limits_{1\le i\le N}\{P_{k\,it}\}-P_{k\,bt}}{\max\limits_{1\le i\le N}\left\{\max\limits_{1\le i\le N}\{P_{k\,it}\}-P_{k\,it}\right\}} \le \frac{\max\limits_{1\le i\le N}\{P_{k\,it}\}-P_{k\,at}}{\max\limits_{1\le i\le N}\left\{\max\limits_{1\le i\le N}\{P_{k\,it}\}-P_{k\,it}\right\}}$$

And since W_(j at)≥0 then, $FRR_{at} \le FRR_{bt}$

To prove theorem (2), it is obvious that we have $FRR_{at} \ge 0$ to prove another inequality:

So $P_{s\,at} \le \max\limits_{1\le i\le N}\{P_{s\,it}\} \quad \forall\, s \in S$

$$\text{on the other hand, } \max_{1 \le i \le \mathrm{N}}\{P_{k\,it}\} - P_{k\,at} \le \max_{1 \le i \le \mathrm{N}}\left\{\max_{1 \le i \le \mathrm{N}}\{P_{k\,it}\} - P_{k\,it}\right\}$$

$$\text{So, } \frac{\max_{1 \le i \le \mathrm{N}}\{P_{k\,it}\} - P_{k\,at}}{\max_{1 \le i \le \mathrm{N}}\left\{\max_{1 \le i \le \mathrm{N}}\{P_{k\,it}\} - P_{k\,it}\right\}} \le 1$$

and thus,

$$FRR_{at} = \sum_{s\in S} W_{s\,at}\,\frac{P_{s\,at}}{\max_{1 \le i \le \mathrm{N}}\{P_{s\,it}\}} + \sum_{k\in K} W_{k\,at}\,\frac{\max_{1 \le i \le \mathrm{N}}\{P_{k\,it}\} - P_{k\,at}}{\max_{1 \le i \le \mathrm{N}}\left\{\max_{1 \le i \le \mathrm{N}}\{P_{k\,it}\} - P_{k\,it}\right\}}$$
$$\le \sum_{s\in S} W_{s\,at} + \sum_{k\in K} W_{k\,at}$$

And since {1,2, 3,...,M}= S∪K and also we have $\sum_{1 \le j \le \mathrm{M}} W_{j\,at} = 1$:

$$\sum_{s\in S} W_{s\,at} + \sum_{k\in K} W_{k\,at} = 1$$

$$\text{So, } FRR_{at} \le 1$$

Remarks: Theorem 1 indicates that the readability of financial reporting has the property of uniformity, that is, for each company with ordinal factors, the readability of financial reporting is arranged based on the order of factors. This property justifies the comparability of two companies based on the readability factors of financial reporting. Also, Theorem 2 shows that the readability of financial reporting resulting from the proposed research model is limited and therefore it can be relied upon to evaluate a society including companies.The final model for measuring the readability index of financial reporting:

$$FRR_{it} = 0.117\,V_1 + 0.113\,V_2 + 0.096\,V_3 + 0.112\,V_4 + 0.129\,V_5 + 0.082\,V_6$$

V_i = The standardized factor is the criteria for calculating the readability of financial reporting**.**

3.3 Validation of the Measurement Model

One of the main goals in using structural equation modeling is to know the degree of agreement between experimental data and conceptual and theoretical models. In order to know the degree of agreement between experimental data and the conceptual model, indicators and criteria are used, which are called goodness of fit of the model. The validity of a model is evaluated using goodness of fit criteria. Fig. 6 1 and Table 3 respectively show the modified model for measuring the readability of financial reporting and its related fit indices. Other goodness of fit criteria presented in Table 3 state that the financial reporting readability measurement model has sufficient validity.

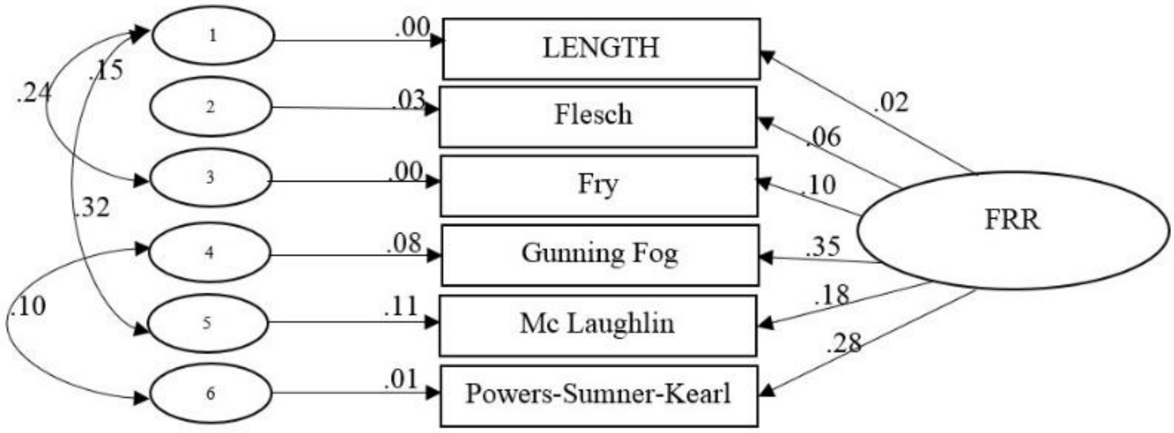

Fig. 6: Financial reporting readability measurement model

Table 3: Goodness of fit criteria for financial reporting readability measurement model

Appropriate criteria of goodness	*index name*	*Abbreviation*	*Modified model*	*Acceptable fit*
Absolute fit indices	goodness of fit index	GFI	0.981	Greater than 90%
	Modified goodness of fit index	AGFI	0.96	Greater than 90%
Comparative fit indices	Unnormalized fit index	NNFI	1.021	Greater than 90%
	Normalized fit index	NFI	0.9	Greater than 90%
	Comparative fit index	CFI	0.905	Greater than 90%
	Incremental fit index	IFI	0.907	Greater than 90%
Indices of parsimonious fit	Normalized parsimonious fit index	PNFI	0.529	Greater than 50%
	The root mean square of the estimation error	RMSEA	0.052	Less than 10 percent
	Chi-square normalized to degrees of freedom	CMIN/df	4.226	Less than 5
Other fit indica-tors	Helter index (0.05)	Hoelter	419	More than 200

In structural equation modeling, different indices are used to ensure the goodness of the model fit. Absolute fit indices are indices that are calculated based on the difference of observed variances and covariance's based on model parameters on the other hand. Comparative fit indices compare the research model with a model in which the variables are independent from each other. In other words, in this case, the conceptual model of the research is compared with a model in which no relationship between the variables is defined. Another group of indices known as parsimonious fit indices helps the researcher to evaluate the effect of his intervention in the model (leaving a parameter free for estimation) to improve the fit indices. According to Table 3, a number of used indicators have also been introduced. In this table, in addition to introducing the indicators, the value of each indicator for an acceptable fit is also given. For example, if the statistic index covered by Chi-Square has a value greater than 5%, the fit of the model is appropriate. Therefore, the goodness of fit criteria presented in Table 3 state that the financial reporting readability measurement model has sufficient validity.

4 Data Analysis

First part: Research findings related to the comprehensive readability index of financial reporting. To provide an overview of the important features of the variables used in measuring the readability of the company's financial reporting, Table 4 presents some concepts of descriptive statistics of these variables, including the number of observations, average, minimum and maximum observations, and standard deviation. The average fog index indicates that the text of the sample companies is not complicated for users. Also, according to the text length index according to its measurement criteria, it indicates easy texts in the text of the board of directors' reports.

Table 4: Descriptive statistics of research variables related to comprehensive readability index of financial reporting

Variable	*Average*	*Middle*	*Min*	*Max*	*standard deviation*
Total text length index	-8/665	-8/191	-8/911	-8/114	1/242
Flash indicator	-5/757	-5/114	-7/810	-4/108	1/519
Gunning fog index	-18/522	-18/882	-24/064	-66/150	2/022
McLaughlin index	-15/668	-15/838	-19/335	-33/114	2/333
Fry's index	-6/882	-6/110	-8/993	-4/507	1/114
Power index, Sumner and Kerl	-7/933	-7/606	-9/515	-5/777	1/966
Disclosure index	33/44	60/42	9/000	97/000	0/609
profitability	0/87	0/33	0/22	2/52	0/81
size of the company	22/9150	22/7134	10/3281	14/9735	0/6681
leverage ratio	0/6433	0/6128	0/3384	1/8512	0/1608

Table 5: Descriptive statistics of financial reporting readability index

Variable	*symbol*	*Average*	*Max*	*Min*	*crookedness*	*standard deviation*	*observations*
Readability of financial reporting	FRR-Index	-11/114	-11/308	-14/424	-0/225	1/646	1341

After checking the validity of the model in the previous section, according to the data collected for each of the readability indicators of financial reporting and the calculated weight of each of these components with the help of entropy technique, Tables 5 and 6 respectively describe the descriptive statistics and the results of measuring the readability of some financial reporting. Companies listed in the Tehran Stock Exchange are shown as examples using the model presented in this research. According to Table 5, which shows the results of the native model of the readability of financial reporting for companies listed on the Tehran Stock Exchange, the obtained average indicates that most of the texts of the board of directors' reports are acceptable. Therefore, it can be stated that the tone of financial reporting in companies admitted to the Tehran Stock Exchange has an acceptable level and is understandable for users. Also, the above table shows that the use of this comprehensive index reduces the skewness caused by the individual use of each of the readability criteria of financial reporting and provides a more accurate criterion for the test.

The results obtained from some companies as examples using the local model of readability of financial reporting based on Iran's environment are given in Table 6. For example, regarding SAIPA company, on average, during the years 2015 to 2018, the level of readability of financial reporting has been at an acceptable level. As other sample companies show, according to the provided native model, the level of the texts of the board of directors' reports is understandable for other users of the financial statements. This means that the texts reported by the companies are presented in a simple and understandable way, which is in accordance with the theoretical concepts of accounting standards , that an important qualitative characteristic of the information included in the financial statements is that it is easy for users to understand.

Table 6: The Readability of Financial Reporting of Companies Calculated by The Proposed Model

Native model of financial reporting readability	$\mathbf{FRR-Index_{it} = 0.117\,P_1 + 0.113\,P_2 + 0.096\,P_3 + 0.112\,P_4 + 0.129\,P_5 + 0.082\,P_6}$			
Company / year	2016	2017	2018	2019
Saipa	-22/077	-22/180	-11/668	-11/933
Pars Petrochemical	-11/899	-11/333	-22/282	-11/665
Khodrosharq Electric	-11/655	-22/079	-22/777	-11/525
Pharmaceutical factories	-11/878	-22/777	-11/689	-11/333
Shahroud Cement	-11/955	-11/694	-11/891	-11/577
Khorasan Steel	-11/181	-11/778	-11/882	-11/656
Mes Shahid Bahonar	-11/442	-11/666	-11/333	-11/938
Baharan oil	-11/992	-11/911	-11/788	-22/666

The second part: Research findings related to research hypothesis testing

Multivariate linear regression models have been used to test research hypotheses. Statistical tests and analyzes have been done with the help of Eviews and Stata software.

Findings of the research hypothesis

The first hypothesis: the time of providing information has an effect on the readability of financial reporting of companies

The time of providing information has no effect on the readability of financial reporting of companies. H0: $\beta 1 = 0$

The time of providing information has an effect on the readability of financial reporting of companies. H1: $\beta 1 \neq 0$

Research Hypothesis Model

The research models to answer the hypotheses are as follows:

$$FRR\text{-}Index_{it} = \beta_0 + \beta_1\, DSCORE_{i,t} + \sum_{j=3}^{n} \beta_j controls + \varepsilon_{it}$$

which in these models:

$FRR - Index_{it}$ represents the readability index of financial reporting of company i in year t.

DSCORE stands for disclosure of company information.

Determining the Estimation Method of the Research Model

In combined data, in order to be able to determine whether the use of panel data method will be efficient in estimating the desired model or not, the F-test of Limer and if the panel data method is used, in order to determine which method (fixed effects or random effects) is more suitable for estimation, Hausman test is used. To detect heterogeneity of variance and serial autocorrelation in the model, modified Wald and Wooldridge tests were used, respectively. The results of these tests are shown in Table 7.

Table 7: Model selection results to estimate the first research model

Test type	The value of the test statistic	observations	Sig
F test	33/966	1670	0/000
Hausmann	33/229	1670	0/008
Modified parent	441/22	1670	0/000
Wooldridge	3/964	1670	0/053

According to the results of Limer's F test, since the significance level of this test is less than 0.05, the heterogeneity of the origin is accepted and it is necessary to use the panel data method in estimating the models. Also, according to the results of the Hausman test, since its significance level is less than 0.05, it is satisfied using the fixed effects method. The significance level of the Wooldridge test is 0.053, indicating the absence of serial autocorrelation in the model. In addition, in order to ensure that there is no collinearity problem between the explanatory variables, the collinearity test was investigated using the Variance Inflation Factor (VIF). The adjusted parent test also shows that there is heterogeneity of variance in the model. Therefore, according to these results, GLS generalized least squares method is used in the final estimation of the model.

In Table 8, the results of the estimation of the research hypothesis are presented. According to the results presented in the table below, the significance level of the F statistic, which indicates the significance of the entire regression, is equal to 0.000 and it indicates that the model is significant at the 95% confidence level. The adjusted coefficient of determination is equal to (0.703) and indicates that approximately 70% of the changes in the dependent variable can be explained by the independent variable of the model. On the other hand, collinearity is a condition that shows that an independent variable is a linear function of other variables. If the collinearity in a regression equation is high, it means that there is a high correlation between the independent variables and the model may not have high validity. According to the last column of Table 6, the VIF value for all independent variables is less than 10 (VIF<10). Therefore, there is no collinearity between the independent variables. Therefore, the fitted model is valid.

Table 8: Research hypothesis test results

$$FRR\text{-}Index_{it} = \beta_0 + \beta_1\, DSCORE_{i,t} + \sum_{j=3}^{n} \beta_j controls + \varepsilon_{it}$$

Dependent variable (native model of financial reporting readability)	*standard deviation*	*t statistic*	*Sig*	*VIF*
Fixed coefficient	0/515	37/222	0/000	---
Time to provide information	0/003	2/142	0/033	1/07
profitability	1/115	3/330	0/0010	1/22
Financial Leverage	0/038	2/474	0/9139	1/38
size of the company	0/077	2/360	0/9189	1/21
Fisher's F statistic (significant level)	Watson camera statistics		2/066	
The coefficient of determination	Adjusted coefficient of determination		0/303	

In order to test the absence of autocorrelation in the model, Durbin-Watson test statistic is used. Based on the findings of Table 8, this statistic is equal to 2.076. If this statistic is in the range of 1.5 to 2.5 (H0), the absence of correlation between the residuals is accepted and otherwise (H0) is rejected. According to the statistics obtained, it can be accepted that there is no positive and negative correlation in this model. Since the probability value of the t statistic for the time of providing information is 2.142, and more than the value of 1.96, it can be stated that the null hypothesis is rejected, and in other words, this coefficient is significant at the 5% error level. Therefore, it can be concluded that there is a significant relationship between the time of providing information and the local readability model of financial reporting. Therefore, the timelier information is provided, the more readable the financial reports will be, and it will improve the financial reports for use by users.

Results of Neural Network Model (ANN)

The error convergence process of MSE for future cash output in neural network model is shown in Fig.1. As can be seen, the neural network algorithm has rapidly converged and from the 52 rd epoch, the value of the target function has remained constant, indicating the power of the algorithm. Fig. 2 shows the trend of mse error in the neural network to its lowest value. As the Diagram shows, the number of replications of this model is 38, and in the marked green area, we see 6 replications without improvement that have stopped the training process

Table 9: Evaluation criteria for neural network model application in the best structure model

Evaluation criteria and parameters	amount of Training data	amount of test data
Mean Squared Error (MSE)	13,04	4,98
Root Mean Squared Error (RMSE)	7,45	4,56
Normalized Mean Squared Standard Error (NMSE)	1,18	0,068
Mean Absolute Error (MAE)	5,32	3,83
Mean Absolute Percentage Error (MAPE)	123	89,9
R Squared(R2)	0,88	0,97
source: Calculations of the research		

The Fig. 5 represents the prediction of the network based on input data, as well as their comparison with real results. The red plot represents the neural network forecast, whereas the blue one shows the real data

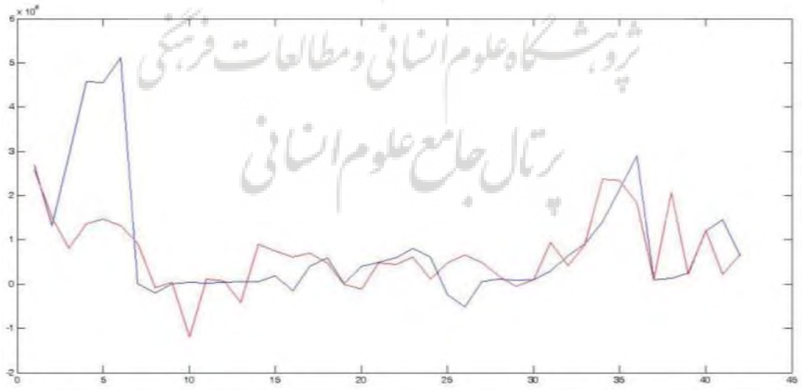

Fig. 7: The Prediction of the Network Based On Input Data in Comparison with Real Data.

5 Conclusion

Annual financial reports of companies are always one of the most important sources of information for decision-making by capital market activists, capital market legislators, and other stakeholders [21]. Therefore, the readability of financial reporting is considered as an important feature of textual information and has been widely investigated in various fields [33]. The value of information contained in the text of financial statements with a high level of readability is understandable for users. From a theoretical point of view, announcing the disclosure of financial statement information such as annual reports of companies are considered a very important communication bridge between management and shareholders in joint-stock companies due to the separation of ownership from management. Minority shareholders and foreign investors can check the company's financial status, financial performance and cash flows through the company's annual reports, and based on this, they can evaluate the company's growth prospects and management competence. Accounting research in this field shows that the readability of financial reporting can affect the quality of financial statement information. Among the most widely used financial reporting readability indicators according to various researches such as Bai et al. [6], Blanco and Dehol [7] and Ertagul et al. and the index of Power, Sumner and Kerl, in this research, in accordance with the first objective of the research, the indicators of calculating the readability of financial reporting of companies were determined using the content analysis method, and then to calculate the comprehensive indicator of the readability of financial reporting in accordance with the second objective of the research, through weighting method Shannon's entropy was used and finally, the readability of financial reporting in companies admitted to the Tehran Stock Exchange was measured using a multi-indicator decision making model. The result obtained in the current research according to the reporting readability model for companies listed in Tehran Stock Exchange shows that most companies use understandable texts for their financial reporting and on the other hand, there is a significant relationship between the time of providing information and the readability of financial reporting. Moreover, the result on the effect of information presentation time can be stated as follows: The timing of information presentation indeed influences the readability of financial reporting. This finding implies a significant connection between the promptness and timeliness of information dissemination and the comprehensibility of financial reports. This observation implies that when companies provide their financial information to shareholders and investors in a timely and well-timed manner, it contributes positively to the readability and understandability of financial reports. In other words, timely information disclosure appears to enhance the quality and accessibility of financial information.

This result holds particular relevance within the context of our study. As the current research is concerned with assessing the readability of financial reports using a multi-indicator decision-making model and an artificial neural network method, this insight contributes to a more comprehensive understanding of the factors that influence financial reporting quality. The significance of timely information presentation in enhancing the readability of financial reports aligns with the overarching theme of our research, where we explore various indicators and techniques to assess and improve the quality of financial reporting. This finding adds to the depth of our analysis by highlighting a practical dimension that can benefit companies, investors, and other stakeholders. In summary, the result pertaining to the effect of information presentation time on the readability of financial reporting is a valuable component of our research findings, as it emphasizes the real-world implications of our work and underscores the importance of timely and well-managed information disclosure for improving financial reporting quality and, by extension, informed decision-making in the financial domain. Moreover, the timelier information is provided, the more readable the financial reports will be, and it will improve the financial reports for use by users.

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