Development of a Model for Predicting CEO Compensation Sensitivity Using Metaheuristic Algorithms: Genetic Algorithm and Particle Swarm Optimization

Saeed Khaljastani[1], Habib Piri[2,*] and Reza Sotoudeh[3]

[1] PhD Student, Department of Accounting, Faculty of Humanities, Zah.C., Islamic Azad University, Zahedan, Iran;
[2] Assistant Professor, Department of Financial and Accounting, Faculty of Humanities, Meybod University, Meybod, Iran;
[3] Assistant Professor, Department of Financial and Accounting, Faculty of Humanities, Meybod University, Meybod, Iran;

* Correspondence: hhpiri1354@gmail.com

Citation: Khaljastani, S. - Piri, H. - Sotoudeh, R. (2025). Development of a Model for Predicting CEO Compensation Sensitivity Using Metaheuristic Algorithms: Genetic Algorithm and Particle Swarm Optimization. *Business, Marketing, and Finance Open*, 2(3), 169-184.

Received: 19 March 2025
Revised: 12 April 2025
Accepted: 29 April 2025
Published: 01 May 2025

Abstract: The aim of this study is to propose a model for predicting CEO compensation sensitivity by employing metaheuristic algorithms, including the genetic algorithm and the particle swarm optimization algorithm. The statistical population of this study consists of all companies listed on the Tehran Stock Exchange during the period from 2011 to 2021. A systematic elimination method was used for sample selection, resulting in a final sample of 110 companies. This research is classified as applied research in terms of its objective and as quasi-experimental in terms of its nature and methodology. Furthermore, it falls within the category of descriptive research of a non-experimental survey type. The required data were collected through document analysis, internet searches, and library studies. In this study, 12 influential variables on CEO compensation sensitivity were selected as input variables for the data mining model. These variables include institutional ownership, family ownership, financial statement comparability, earnings management, conditional conservatism, revenue-expense matching, market value added, corporate acquisition, debt contracts, and cost behavior with three indicators (changes in return on assets, changes in sales revenue, and changes in operating costs). Additionally, CEO compensation sensitivity was considered as the output variable of the data mining model. To analyze the data, three data mining models based on cost behavior parameters were designed, and for comparison purposes, three linear regression models were also utilized. Among the 12 examined parameters, seven variables, including institutional ownership (X1), financial statement comparability (X3), revenue-expense matching (X6), market value added (X7), changes in return on assets (X101), changes in sales revenue (X102), and changes in operating costs (X103), demonstrated a significant relationship with CEO compensation sensitivity. Accordingly, these parameters were selected as input variables for the data mining model. The analysis results indicated that the deep neural network model optimized with the particle swarm optimization algorithm recorded the lowest mean squared error (MSE) of 0.0458 and the highest coefficient of determination (0.9853), highlighting its superior performance compared to other examined methods. The deep neural network model optimized with the genetic algorithm ranked second in predictive performance. Ultimately, the findings demonstrate that the deep neural network model outperforms the linear regression model in terms of the coefficient of determination and error index (MSE).

Keywords: CEO compensation sensitivity, deep learning, genetic algorithm, particle swarm optimization.

1. Introduction

To mitigate agency problems arising from conflicts of interest between managers and shareholders, it is essential to focus on how benefits are shared between these two groups. This approach encourages managers to leverage their skills and competencies in alignment with shareholder interests, thereby increasing their motivation to improve performance [1, 2]. One of the most effective strategies for reducing this conflict is compensating managers through incentive pay, which is widely employed as a tool to align managerial perspectives and performance with the goal of maximizing shareholder wealth. The executive compensation structure of companies typically includes fixed salaries, cash performance bonuses, and non-monetary benefits [3]. Theoretically, it is expected that cash bonuses should be performance-based, meaning that increased alignment of managerial actions with shareholder interests should result in higher bonuses. More detailed examinations indicate that various compensation systems exist, each employing different methods for determining and distributing bonuses, which can influence managerial motivation and performance [4].

In today's world, due to the influential role of media, the compensation of corporate CEOs has become a subject of public scrutiny. One of the fundamental questions in this regard concerns the impact of institutional investors on the design of CEO compensation packages [5, 6]. As companies expand, ownership is often delegated to managers, yet this delegation can lead to agency problems. Agency theory highlights the challenges that arise when principals (owners) transfer control of a company to agents (managers), who may pursue goals divergent from shareholder interests [3]. In this context, CEO power theory suggests that CEOs continuously seek to enhance their influence and control over the board of directors. Meanwhile, CEO compensation serves as both a challenge and a strategic tool in corporate management. Shareholders play a crucial role in monitoring CEO performance, but typically, only major shareholders with significant ownership stakes have the necessary incentives and resources to oversee and control executive actions [7, 8].

With the establishment of joint-stock companies and the persistence of conflicts of interest between owners and managers, developing practical solutions to address this challenge has become imperative. One of the most effective tools for reducing this conflict is the design of executive compensation systems, which in practice follow diverse models. Among the most significant of these models is performance-based compensation, determined using various accounting, economic, financial, and hybrid metrics. Agency theory, as a theoretical framework, plays a critical role in offering practical solutions for managing conflicts of interest. Joint-stock companies are formed through multiple contractual relationships among different stakeholders, including shareholders, managers, employees, and creditors. Among these, the contract between shareholders and managers holds particular significance, as it influences other contractual relationships within the company. To mitigate agency conflicts, executive compensation systems should be designed in a manner that aligns with the value created for shareholders [9-11].

In this regard, implementing appropriate compensation models can incentivize managers to make decisions that align with the interests of shareholders and creditors. The primary goal of compensation systems is to remunerate managerial responsibilities and create incentives for improved performance. The accounting literature presents various models and criteria for determining executive compensation, ultimately aimed at aligning managerial interests with those of shareholders and reducing agency conflicts. Among these approaches, value-based compensation is recognized as an effective method for achieving this objective. A key tool for assessing managerial performance is accounting reports, which provide critical information on management activities and investment decisions. These reports not only serve as performance evaluation tools but also play a crucial role in motivating managers. However, the effectiveness of these tools depends on the accounting methods employed in financial reporting, and managerial choices in the reporting process can significantly influence performance evaluation outcomes [5, 8].

Recent studies on CEO compensation sensitivity and performance-based pay have focused on various methodological and theoretical aspects. Khalajestani et al. (2024) developed a prediction model using metaheuristic algorithms and found that deep neural networks outperformed regression models in terms of the coefficient of determination and MSE. Among the data mining models tested, the cost behavior-based model, particularly changes in operating costs, yielded the best results, whereas the return on assets model showed the weakest performance [5]. Ahadzadeh et al. (2023) designed a model aligning human resource subsystems (recruitment, performance evaluation, career development, and job appraisal) with compensation systems and found a significant relationship ($R^2 = 0.644$) between these components, highlighting the necessity of internal coherence within compensation structures. Osmani et al. (2023) analyzed compensation issues in Iran's banking sector using thematic analysis and identified 14 primary and 87 secondary themes in financial and non-financial compensation systems [12]. Nooti Zehi et al. (2021) developed a compensation framework for municipal employees, categorizing pay into six major dimensions, including base pay, short- and long-term incentives, and managerial benefits [13]. Imani et al. (2020) proposed an interpretive-structural model of public sector compensation, emphasizing internal controls, transparent and documented procedures, and performance-based pay as key dynamic elements [14]. Sepahvand et al. (2019) examined the relationship between political sensitivity and CEO compensation in Iran's governmental ministries, finding that political networking mediated the direct impact of political exposure on executive pay, while institutional pressures moderated this relationship [15]. Naqdi and Arab Mazar Yazdi (2019) combined artificial neural networks, genetic algorithms, and particle swarm optimization to predict earnings per share, enhancing the generalizability of neural networks in financial forecasting [16]. Ghaderi et al. (2018) integrated neural networks with metaheuristic algorithms to measure earnings management, demonstrating the superiority of this approach over traditional regression-based models [17].

The genetic algorithm serves as a powerful tool for optimizing neural network structures, which has increasingly attracted the attention of researchers in recent years seeking to enhance the accuracy of statistical model predictions and identify optimal variables. In this regard, some researchers have developed novel methods, including metaheuristic algorithms (Ghadiri et al., 2018). One such method is particle swarm optimization (PSO), a relatively new heuristic search technique inspired by collective behavior and social interaction observed in biological communities. This method operates similarly to the genetic algorithm (GA), as both are classified as population-based search approaches. Both methods iteratively transfer a set of points (population) to another set while improving the optimization process through deterministic and probabilistic rules. The genetic algorithm and its various advanced iterations have gained significant traction in scientific and industrial applications due to their comprehensibility, ease of implementation, and effectiveness in solving complex nonlinear and combinatorial optimization problems.

Given these considerations, the primary issue addressed in this study is the development of an optimized model for predicting CEO compensation sensitivity using hybrid intelligent methods, particularly metaheuristic algorithms such as genetic algorithms and particle swarm optimization. In other words, this research seeks to answer the key question of whether an efficient model can be developed for predicting CEO compensation sensitivity using these metaheuristic algorithms. To achieve this goal, the study examines three fundamental hypotheses, which are outlined as follows:

1. CEO compensation sensitivity can be predicted using the genetic algorithm.
2. CEO compensation sensitivity can be predicted using the particle swarm optimization algorithm.
3. Predicting CEO compensation sensitivity based on a metaheuristic model (genetic algorithm and particle swarm optimization) is more accurate than using linear regression methods.

2. Methodology

Scientific research is generally classified based on its objective, nature, and method. In terms of its objective, this study falls within the category of applied research. Additionally, it is considered a quasi-experimental study and is classified as a descriptive (non-experimental survey) study. Given that past data were used to calculate the variables in this study, it can be categorized as an ex-post facto research. The required data for this study were collected through various methods, including document analysis of financial data (such as annual reports, dissertations, and domestic and international articles), internet searches using sources such as Codal and the official websites of sample companies, and library studies to gather information related to the theoretical foundations and research background.

The statistical population of this study consists of all companies listed on the Tehran Stock Exchange during the period from 2011 to 2021. A systematic elimination method was used for sample selection, resulting in a final sample of 110 eligible companies. Among all the companies active on the Tehran Stock Exchange, only those meeting the following criteria were selected:

- To ensure comparability, the companies must have a fiscal year ending in March of each year.
- The companies must not have suspended operations or changed their fiscal year during the study period.
- All required data for the study must be available.
- The companies must not be banks or financial institutions (including investment companies, financial intermediaries, holding companies, leasing firms, and insurance companies).
- The companies must have been listed on the stock exchange before 2021.
- The companies must have remained listed on the stock exchange throughout the study period, with their required data accessible.

The financial data and information of the companies were collected from the statistical archives of the Securities and Exchange Organization and the Central Bank. Data classification and variable calculations were performed using Excel, while hypothesis testing was conducted using Python programming language and SPSS software.

The statistical methods and tests used in this research include three main phases: the first phase involves data selection and cleaning, the second phase involves training data mining models based on selected data, and the third phase involves evaluating the performance of these models. One of the critical stages in developing a data mining model based on deep neural networks is collecting appropriate data for training the network. In this study, based on the nature of the research problem and available information from prior studies, ten variables were selected as input data. For comparison purposes, a linear regression model was also employed. Since deep neural networks include a set of variable parameters, metaheuristic algorithms were used to optimize these parameters.

Metaheuristic algorithms utilize similar mechanisms to find optimal solutions. In most of these algorithms, the search process begins by generating a set of random responses within the allowable range of decision variables. This set is referred to as a population, colony, or group, depending on the algorithm, while individual responses are called chromosomes, ants, or particles. A series of operators is then applied to generate new responses, and this process continues until a stopping criterion is met. Since these algorithms operate on a population basis, their combination with deep neural networks produces diverse outcomes due to their inherent structural differences. The goal of this combination is to optimize the training parameters of deep neural networks. Given the population-based nature of these algorithms, the problem must be defined in a way that allows optimization through a population. Initially, the problem is defined so that the chromosome (in the genetic algorithm) or particle (in the particle swarm optimization algorithm) optimizes the training parameters of the deep neural network. Accordingly, the number of genes in each chromosome must be equal to the number of training parameters in the deep neural network. A combination of input patterns is extracted to optimize the factors influencing CEO compensation sensitivity. Ultimately, the best variables are selected based on metrics such as MSE, RMSE, MAE, MAPE, and R^2, and the results are compared with those of the linear regression model.

In this study, twelve key parameters affecting CEO compensation sensitivity were selected as independent variables in the linear regression model. These parameters include institutional ownership (X1), family ownership (X2), financial statement comparability (X3), earnings management (X4), conditional conservatism (X5), revenue-expense matching (X6), market value added (X7), corporate acquisition (X8), debt contracts (X9), and cost behavior (X10), which is further divided into three subcomponents: changes in return on assets (X101), changes in sales revenue (X102), and changes in operating costs (X103). Additionally, CEO compensation sensitivity (Y) was considered the dependent variable in the linear regression model.

Independent Variables (Inputs)

Financial Statement Comparability

One of the independent variables in this study is financial statement comparability, which is measured using the model proposed by De Franco et al. (2011). According to this model, two companies are considered comparable if they provide similar financial reports, such as accounting earnings, in response to identical economic events like stock returns. To measure the degree of comparability between two companies *i* and *j*, the regression model below is estimated for each company and each year using data from the previous four years up to year *t*:

$EARN_{iq} = \alpha_i + \beta_i Ret_{iq} + \varepsilon_{iq}$

where:

$EARN_{iq}$ = net income of company *i* divided by the market value of equity at the beginning of the period,

Ret_{iq} = stock return of company *i*.

Institutional Shareholders

Institutional ownership is calculated as the ratio of shares held by banks, insurance companies, holding firms, investment companies, pension funds, capital investment firms, mutual funds, governmental organizations, and state-owned enterprises to the total outstanding shares of the company.

Institutional Ownership Level = (Total shares held by institutional investors) / (Total shares issued by the company)

Family Ownership

Family ownership in this study is defined as a binary variable, assigned a value of one if present and zero otherwise. Based on an examination of Iranian companies and expert opinions, a company is classified as family-owned if it meets either of the following criteria:

- An individual shareholder holds at least 20% of the company's ordinary shares.

- A board member individually owns at least 5% of the company's ordinary shares, or the combined shares of the individual board member and their family and relatives amount to at least 5% of the total ordinary shares.

Companies that do not meet these conditions are classified as non-family firms.

Earnings Management

In this study, discretionary accruals were calculated using the modified Jones model. This model first calculates total accruals and then estimates the parameters a_1, a_2, and a_3 to determine non-discretionary accruals (NDA). This estimation is performed using the least squares method, and after determining NDA, discretionary accruals (DA) are calculated.

Conditional Conservatism

To measure conditional conservatism, the Khan and Watts (2009) model, based on the study by Foroughi and Fallah (2013), was used.

Revenue-Expense Matching

For strong matching, expenses must exhibit high correlation with related revenues, enabling investors to better predict expected costs and estimate future earnings. Dechow and Tang (2008) and Schatt (2011) proposed a matching measure based on the correlation between revenues and expenses over a five-year period. This study adopts the same measure, using the following regression model:

$\Delta\text{Expense\_i,t} = \alpha_0 + \alpha_1 * \Delta\text{Revenue\_i,t} + \text{e\_i,t}$

where changes in revenue and expenses are examined over an eight-year period to calculate annual variations.

Market Value Added

Market value added is the difference between the "company's market value" at the end of the fiscal year and the "book value of invested capital" at the end of the period.

Dependent Variable (Output)

CEO Compensation

In this study, CEO compensation is measured as the total bonus paid to the CEO. The data were extracted from retained earnings statements, annual general meeting resolutions, and summaries of ordinary general meeting decisions. Since companies typically disclose only an aggregate figure for managerial bonuses without specifying non-monetary components, the reported total amount was used as the CEO compensation figure.

3. Findings and Results

This section presents the results of the linear regression model. For this purpose, 12 factors influencing CEO compensation sensitivity were selected as independent variables in the regression model: institutional ownership (X1), family ownership (X2), financial statement comparability (X3), earnings management (X4), conditional conservatism (X5), revenue-expense matching (X6), market value added (X7), corporate acquisition (X8), debt contracts (X9), and cost behavior (X10), which includes three components: changes in return on assets (X101), changes in sales revenue (X102), and changes in operating costs (X103).

Table 1. Descriptive Statistics of Research Variables

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
y	1210	7.242	0.724	1.791	9.765
X1	1210	0.745	0.182	0.073	0.999
X2	1210	0.035	0.104	0	0.45
X3	1210	0.471	0.933	-0.784	8.594
X4	1210	-0.212	0.286	-0.968	0.670
X5	1210	0.331	0.183	-1.428	2.158
X6	1210	0.394	0.555	-0.996	0.999
X7	1210	1.528	2.589	-0.510	31.702
X8	1210	0.819	0.385	0	1
X9	1210	1.841	2.977	-21.901	27.086
X101	1210	0.046	0.173	-0.619	0.966
X102	1210	0.275	0.391	-0.980	1.941
X103	1210	0.078	0.248	-0.459	1.921

The mean, as the primary measure of central tendency, represents the equilibrium point and centroid of the distribution, making it an appropriate metric for determining data centrality. For instance, the mean value for variable Y is 7.242, reflecting the average level of this variable in the dataset. In addition to central tendency measures, dispersion parameters are used to assess the variability of data points and their deviation from the mean. One of the most important dispersion metrics is the standard deviation, which is 2.977 for X9 and 0.104 for X2. These values indicate that X9 has the highest dispersion, while X2 has the lowest standard deviation among the examined variables.

The Shapiro-Wilk test was used to examine the normality of the research variables. The significance level of the Jarque-Bera normality test for all variables was found to be less than 5 percent. Thus, the data do not follow a normal distribution.

To investigate the presence of unit roots in panel data, the Harris test was employed. The results are presented in Table 2.

Table 2. Harris Stationarity Test for All Research Variables

Variable	Test Statistic	Significance Level	Result
y	-16.785	0.000	Stationary
X1	-17.464	0.000	Stationary
X2	-33.785	0.000	Stationary
X3	-33.098	0.000	Stationary
X4	-24.443	0.000	Stationary
X5	-27.246	0.000	Stationary
X6	-21.264	0.000	Stationary
X7	-14.471	0.000	Stationary
X8	-32.371	0.000	Stationary
X9	-21.645	0.000	Stationary
X101	-32.342	0.000	Stationary
X102	-22.055	0.000	Stationary
X103	-25.049	0.000	Stationary

As shown in Table 2, the significance level of all variables in the stationarity test is below 5 percent, indicating that all variables are stationary.

Table 3. F-Limer (Chow) Test Results

Model	Test Statistic	Significance Level	Result
Model	10.76	0.000	Panel Data

As indicated in Table 3, since the significance level of the F-Limer test is below 5 percent, the panel data approach is preferred over the pooled data approach.

Table 4. Hausman Test Results

Model	Test Statistic	Significance Level	Result
Model	14.86	0.249	Random Effects

As seen in Table 4, the significance level in the Hausman test is greater than 5 percent, indicating that the random effects model is appropriate.

When heteroskedasticity is present, the standard deviation of the intercept becomes excessively large. The standard deviations of slope coefficients also depend on the nature of heteroskedasticity.

Table 5. Heteroskedasticity Test Results

Model Test	Test Statistic	Significance Level	Test Result
Model	1720.59	0.000	Heteroskedasticity Present

The results presented in Table 5 indicate that the significance level of the ARCH test is below 5 percent, confirming the presence of heteroskedasticity in the error terms. This issue was resolved in the final model estimation by applying the GLS (Generalized Least Squares) method.

Table 6. Hypothesis Testing Results

Variable	Symbol	Coefficients	Standard Error	t-Statistic	Significance Level	Multicollinearity
Institutional Ownership	X1	-0.603	0.157	3.82	0.000	2.82
Family Ownership	X2	-0.079	0.195	-0.41	0.684	2.76
Financial Statement Comparability	X3	0.121	0.021	5.66	0.000	2.41
Earnings Management	X4	0.059	0.070	0.85	0.397	2.55
Conditional Conservatism	X5	0.114	0.102	1.12	0.261	1.72
Revenue-Expense Matching	X6	-0.099	0.040	-2.44	0.015	2.07
Market Value Added	X7	-0.054	0.012	-4.23	0.000	1.75
Corporate Acquisition	X8	0.044	0.054	0.81	0.418	2.56
Debt Contracts	X9	-0.002	0.006	-0.45	0.654	1.63
Changes in Return on Assets	X101	-0.684	0.134	-5.09	0.000	2.58
Changes in Sales Revenue	X102	0.504	0.057	8.82	0.000	2.62
Changes in Operating Costs	X103	-0.180	0.086	-2.08	0.037	2.45
Intercept	-	7.610	0.132	57.63	0.000	-

- Wald Statistic: 3662.57
- Wald Significance Level: 0.000
- MSE: 0.0801
- Adjusted R-Squared: 0.9711
- Durbin-Watson: 2.351

The results in Table 6 indicate that variables related to decision-making based on private information, base volume, free float shares, and timely reflection of information in stock prices have a significance level below 5 percent, and their coefficients are positive. Therefore, these variables are confirmed at a 95 percent confidence level.

Conversely, investor confidence, firm size, stock price, price fluctuation range, and trading symbol suspension have a significance level greater than 5 percent and are thus not confirmed at a 95 percent confidence level.

The correlation between input parameters and CEO compensation sensitivity, as the output parameter, is illustrated in Figure 1. Pearson's correlation coefficient was used to compute this correlation. As observed, the correlation varies across different columns; some input variables, such as family ownership, have a low correlation with the output parameter, while others, including institutional ownership, changes in return on assets, and changes in operating costs, exhibit stronger correlations.

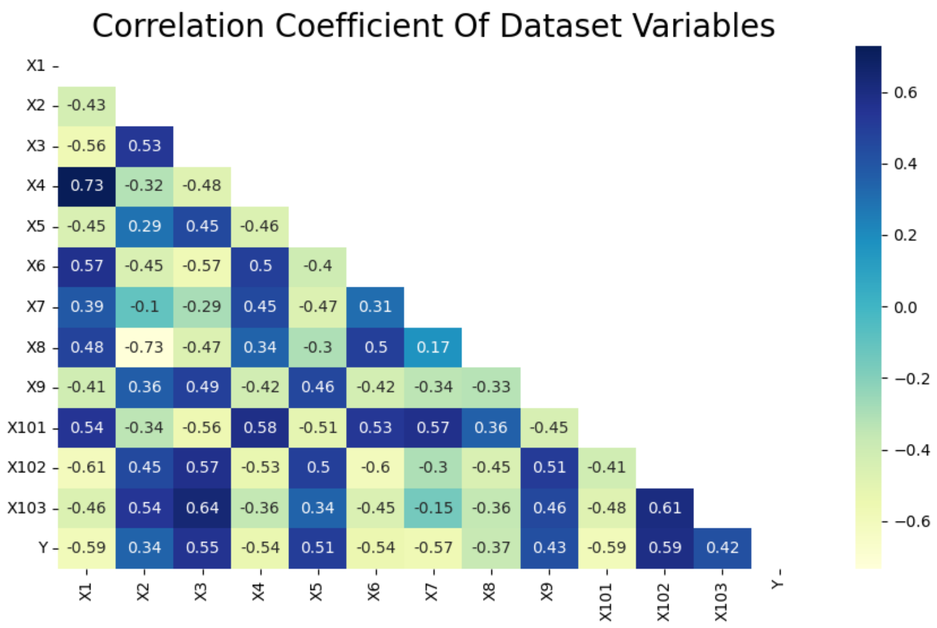

Figure 1. Correlation Between Input and Output Parameters in the Data Mining Model

Next, the dataset used in this research was prepared for training the model. Initially, all dataset rows were examined for missing values, and no issues were detected. The next step involved encoding categorical columns. To achieve this, categorical columns were replaced with numerical values. Thus, all columns became usable for model training. The dataset used in this study did not present any issues in this regard, as all values were already numerical. The final step involved normalizing column values. To this end, column values were normalized between 0 and 1 using Equation 4. In this process, the maximum and minimum values for each column were calculated, and then normalized values for each row were determined based on Equation 4.

Equation 4:

$z = (x - X_{min}) / (X_{max} - X_{min})$

Preprocessing data facilitates easier interpretation and usability. Based on the regression results, five variables, including family ownership (X2), earnings management (X4), conditional conservatism (X5), corporate acquisition (X8), and debt contracts (X9), did not have a significant relationship with CEO compensation sensitivity (Y). Therefore, these variables were removed from the list of input variables in the data mining model.

This section presents the results of the deep neural network algorithm optimized using the genetic algorithm. The data mining model included the following inputs: institutional ownership (X1), financial statement comparability (X3), revenue-expense matching (X6), market value added (X7), changes in return on assets (X101), changes in sales revenue (X102), and changes in operating costs (X103). Additionally, CEO compensation sensitivity (Y) was selected as the output parameter of the data mining model.

Table 7. Adjustable Parameters in the Deep Neural Network Algorithm

Parameter	Possible Values
optimizer	['RMSprop', 'Adam', 'Adamax', 'Nadam']
loss	['mse', 'mae', 'mape', 'msle']
activation	['relu', 'linear']
dropout	[0, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5]
neuron_first_hidden_layer	[64, 128, 256, 512]
neuron_second_hidden_layer	[64, 128, 256, 512]
batch	[8, 16, 32, 64]
epoch	[50, 100, 150, 200]
kernel_initializer	['random_normal', 'uniform', 'random_uniform', 'he_normal']

Table 8. Adjustable Parameters in the Genetic Algorithm

Parameter	Value
Initial Population Size	60
Population Member Dimensions	9
Number of Iterations	100
Crossover Rate	0.95
Mutation Rate	0.05

In this study, the Python programming language was used to train the deep neural network model, particularly leveraging the popular Keras and TensorFlow libraries. The dataset was split into 70 percent for training and 30 percent for testing. Additionally, during model training, the genetic algorithm was utilized to optimize the values of the specified parameters (as shown in Table 8) to determine the optimal values for the deep neural network model.

Table 9. Optimized Parameters for the Deep Neural Network Algorithm with Genetic Algorithm in the Data Mining Model

Model	optimizer	loss	activation	dropout	neuron_1	neuron_2	batch	epoch	kernel_initializer
Data Mining Model	RMSprop	msle	relu	0.05	128	128	8	150	random_normal

Table 10. Performance Evaluation Metrics for the Deep Neural Network Algorithm with Genetic Algorithm in the Data Mining Model

Model	MSE	RMSE	MAE	MAPE	R^2
Data Mining Model	0.0467	0.2160	0.1121	0.0162	0.9835

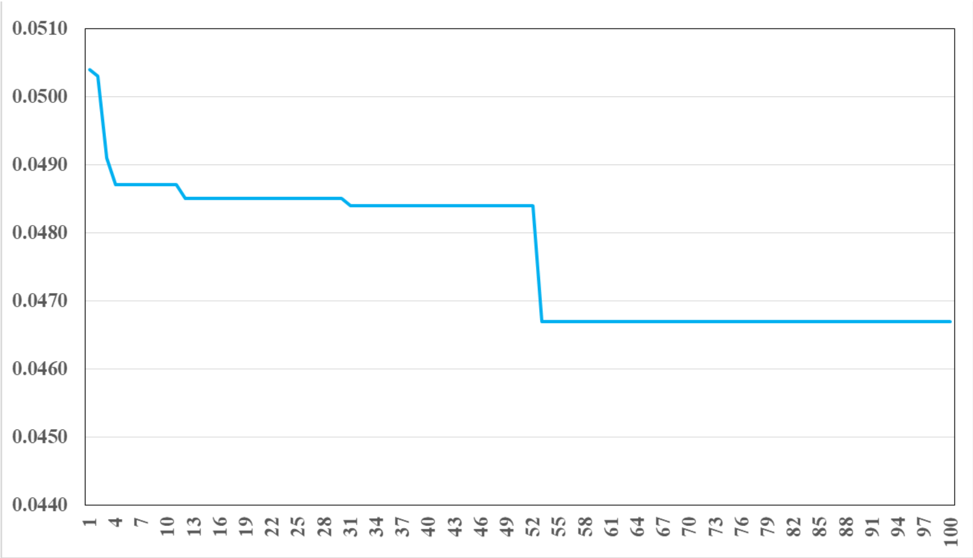

Figure 2. Comparison of Mean Squared Error for the Data Mining Model Under Investigation

Figure 2 illustrates the comparison of the mean squared error (MSE) across different iterations for the investigated data mining model.

This section presents the results of the deep neural network algorithm optimized with the particle swarm optimization (PSO) algorithm. The data mining model included the following inputs: institutional ownership (X1), financial statement comparability (X3), revenue-expense matching (X6), market value added (X7), changes in return on assets (X101), changes in sales revenue (X102), and changes in operating costs (X103). Additionally, CEO compensation sensitivity (Y) was selected as the output parameter of the data mining model.

Table 11. Adjustable Parameters in the Deep Neural Network Algorithm

Parameter	Possible Values
optimizer	['RMSprop', 'Adam', 'Adamax', 'Nadam']
loss	['mse', 'mae', 'mape', 'msle']
activation	['relu', 'linear']
dropout	[0, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5]
neuron_first_hidden_layer	[64, 128, 256, 512]
neuron_second_hidden_layer	[64, 128, 256, 512]
batch	[8, 16, 32, 64]
epoch	[50, 100, 150, 200]
kernel_initializer	['random_normal', 'uniform', 'random_uniform', 'he_normal']

Table 12. Adjustable Parameters in the PSO Algorithm

Parameter	Value
Initial Population Size	60
Population Member Dimensions	9
Number of Iterations	100
C1 Coefficient	1
C2 Coefficient	2
W Coefficient	0.5

In this study, the Python programming language was used to train the deep neural network model, specifically utilizing the Keras and TensorFlow libraries. The dataset was split into 70 percent for training and 30 percent for testing. Additionally, during the model training process, the PSO algorithm was employed to optimize the values of the specified parameters (as outlined in Table 12) to determine the best settings for the deep neural network model. Ultimately, the best values were selected from the list of hyperparameters.

Table 13. Optimized Parameters for the Deep Neural Network Algorithm with PSO for the Data Mining Model

Model	optimizer	loss	activation	dropout	neuron_1	neuron_2	batch	epoch	kernel_initializer
Data Mining Model	Nadam	mae	relu	0.2	128	128	8	150	he_normal

Table 14. Performance Evaluation Metrics for the Deep Neural Network Algorithm with PSO for the Data Mining Model

Model	MSE	RMSE	MAE	MAPE	R^2
Data Mining Model	0.0458	0.2141	0.1116	0.0152	0.9853

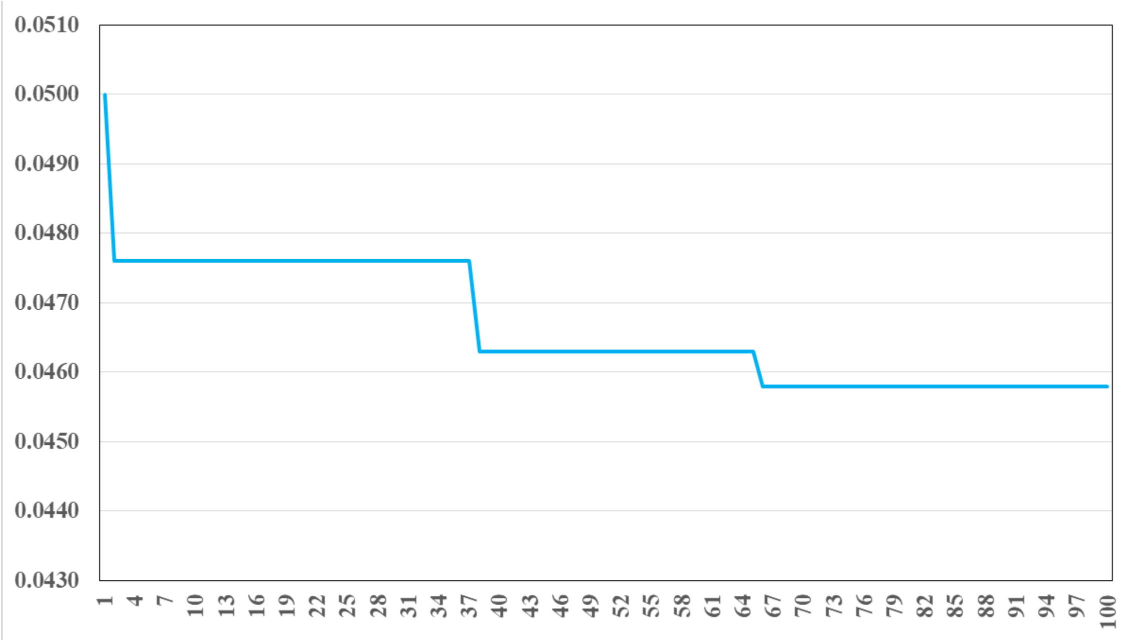

Figure 3. Comparison of Mean Squared Error for the Investigated Data Mining Model

Figure 3 illustrates the comparison of the mean squared error (MSE) across different iterations for the investigated data mining model.

The comparison of results presented in Table 15 highlights the superiority of the deep neural network model in terms of the coefficient of determination and MSE index. This table evaluates the performance of the deep neural network in comparison with two optimization algorithms (genetic algorithm and particle swarm optimization) and the linear regression model. Based on the findings, the deep neural network combined with the particle swarm optimization algorithm achieved the lowest error rate (MSE = 0.0458) and the highest coefficient of determination (R^2 = 0.9853), indicating its superior performance relative to other methods. In contrast, the linear regression model, with an MSE of 0.0801 and an R^2 of 0.9711, exhibited weaker performance compared to the deep neural network model. These results confirm that integrating deep neural networks with optimization algorithms enhances predictive accuracy and reduces error rates.

Table 15. Comparison of the Coefficient of Determination and MSE Between the Deep Neural Network Model and the Linear Regression Model

Algorithm	MSE	Coefficient of Determination (R^2)
Deep Neural Network - Genetic Algorithm	0.0467	0.9835
Deep Neural Network - Particle Swarm Optimization	0.0458	0.9853
Linear Regression	0.0801	0.9711

4. Discussion and Conclusion

The findings of this study indicate that deep neural networks optimized with metaheuristic algorithms outperform linear regression models in predicting CEO compensation sensitivity. The deep neural network model combined with the particle swarm optimization (PSO) algorithm achieved the lowest mean squared error (MSE = 0.0458) and the highest coefficient of determination (R^2 = 0.9853), suggesting a superior predictive capability compared to both the genetic algorithm (GA)-optimized neural network model and the traditional regression approach. This finding is consistent with prior research that has demonstrated the advantages of deep learning models in complex financial forecasting tasks, particularly when integrating metaheuristic optimization techniques (Khalajestani et al., 2024). The superior performance of the PSO-optimized model highlights the effectiveness of evolutionary algorithms in enhancing model training, optimizing hyperparameters, and improving predictive accuracy.

The results further reveal that cost behavior-related variables, particularly changes in operating costs and sales revenue, exhibit the strongest relationship with CEO compensation sensitivity. These findings align with those of Khalajestani et al. (2024), who found that compensation sensitivity is best captured when incorporating cost structure variables [5]. The higher predictive power of models including cost-related variables may be attributed to their ability to reflect managerial decision-making and operational adjustments in response to financial performance. The results also support previous studies demonstrating that cost behavior influences managerial incentives, as firms tend to adjust executive compensation in response to changes in profitability and financial stability (Dai et al., 2024).

Institutional ownership negatively correlated with CEO compensation sensitivity, suggesting that firms with higher institutional investor participation exhibit stricter compensation controls. This finding is in agreement with Liu and Yin (2023), who found that institutional investors with strong monitoring incentives enhance pay-performance sensitivity, thereby curbing excessive executive compensation. The negative impact of institutional ownership implies that when institutional investors exert governance influence, CEOs are less likely to receive compensation that deviates significantly from firm performance metrics. This also aligns with the managerial discipline hypothesis, which posits that institutional investors serve as active monitors, limiting managerial opportunism in compensation decisions [18].

Financial statement comparability emerged as a significant predictor of CEO compensation sensitivity. Firms with comparable financial reports allow investors and boards to assess executive performance more effectively, thereby increasing the alignment between compensation and firm performance. This finding also supports the notion that financial transparency strengthens corporate governance mechanisms and reduces the likelihood of excessive executive pay [4, 12].

Market value added (MVA) exhibited a negative association with CEO compensation sensitivity, suggesting that firms prioritizing value creation over short-term financial metrics may not directly link compensation to immediate performance fluctuations. This aligns with the findings of Nooti Zehi et al. (2021), who reported that firms with long-term value creation strategies design compensation structures that are less sensitive to short-term financial variations [13]. The negative impact of MVA on compensation sensitivity suggests that firms focused on sustainable growth may adopt broader performance evaluation frameworks beyond direct pay-for-performance mechanisms [19].

The findings related to corporate acquisition and debt contracts suggest that these factors do not significantly affect CEO compensation sensitivity. This result contrasts with the findings of Sisari et al. (2016), who reported that post-acquisition compensation structures tend to shift in response to new ownership incentives. One possible explanation for this discrepancy is the contextual differences in corporate governance structures, as acquisition-related compensation adjustments may vary based on firm-specific factors such as ownership concentration and regulatory frameworks [10].

The observed impact of earnings management and conditional conservatism on CEO compensation sensitivity was found to be statistically insignificant. This finding differs from that of Ghaderi et al. (2018), who found that firms engaging in earnings management often adjust compensation schemes to align with reported earnings [17]. The lack of a significant relationship in this study suggests that earnings-based compensation sensitivity may be contingent on industry-specific financial reporting norms or the presence of stricter governance mechanisms that limit the influence of discretionary earnings adjustments on executive pay. The results also align with those of Imani et al. (2020), who reported that transparent financial reporting practices reduce the impact of earnings manipulation on compensation structures [14].

The findings further highlight the role of revenue-expense matching in predicting CEO compensation sensitivity. This result is consistent with prior studies emphasizing the importance of financial alignment in executive pay structures [5, 19]. Firms with stronger revenue-expense matching tend to have compensation policies that are more tightly linked to financial performance, as these firms provide clearer indicators of profitability and efficiency. This suggests that firms with high earnings predictability are more likely to implement performance-based compensation mechanisms, reducing potential distortions in executive pay [10, 12].

Political factors were not explicitly examined in this study, but the findings indirectly support prior research indicating that political sensitivity influences CEO compensation structures. Sepahvand et al. (2019) reported that political networking plays a significant role in shaping executive pay in governmental institutions, where political influence and institutional pressures affect compensation decisions [15]. The absence of political sensitivity variables in this study may explain the divergence in findings related to institutional governance and compensation outcomes.

The comparative analysis between deep learning models and linear regression confirms the limitations of traditional statistical methods in capturing the complexity of executive compensation dynamics. The results support previous studies demonstrating that machine learning techniques, particularly neural networks, outperform regression models in predictive tasks related to financial decision-making [16]. The enhanced performance of neural networks in this study suggests that compensation models incorporating non-linear relationships and data-driven optimization approaches yield more accurate predictions, reinforcing the necessity of adopting advanced analytical techniques in executive pay research.

This study has several limitations that should be acknowledged. First, the analysis relies on publicly available financial data, which may not fully capture all internal compensation determinants, such as boardroom negotiations or informal governance practices. Second, the study focuses on firms listed on the Tehran Stock

Exchange, limiting the generalizability of the findings to other financial markets with different regulatory environments. Third, while the study incorporates advanced machine learning techniques, the results are still dependent on the quality and availability of historical data, and any inaccuracies in financial reporting could impact the model's predictive performance. Additionally, the exclusion of qualitative factors such as leadership style, firm culture, and macroeconomic conditions may limit the explanatory power of the models used.

Future research should explore the role of qualitative factors, such as boardroom dynamics and leadership decision-making, in shaping CEO compensation sensitivity. Investigating the impact of macroeconomic conditions, such as inflation and market volatility, could also provide deeper insights into compensation structures. Expanding the study to include firms from multiple financial markets would enhance the generalizability of the findings and allow for cross-market comparisons. Additionally, future studies could incorporate alternative optimization techniques, such as reinforcement learning, to further improve prediction accuracy. Finally, a longitudinal analysis examining changes in compensation structures over extended periods could provide valuable insights into evolving executive pay trends.

Companies should consider integrating machine learning models into their executive compensation decision-making processes to enhance predictive accuracy and ensure pay-for-performance alignment. Boards of directors should strengthen financial statement comparability and transparency to improve investor confidence and reduce information asymmetry in compensation policies. Institutional investors should actively engage in governance practices to ensure that CEO compensation structures align with firm performance and long-term shareholder value. Firms should also adopt performance metrics beyond short-term financial outcomes, incorporating broader measures of organizational success. Finally, regulatory authorities should consider implementing standardized compensation disclosure frameworks to improve transparency and accountability in executive pay structures.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

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