The Impact of Board Diversity on Corporate Performance Based on Neural Network Algorithms

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Abstract. To uncover the specific impact of board diversity on corporate performance, neural network algorithms were utilized to examine the relationship between diversity indicators such as gender, age, and education, and corporate financial metrics. The results indicate that an appropriate configuration of board diversity significantly enhances the company's revenue and net profit, suggesting that companies should consider the diverse characteristics of board members to promote long-term development and market competitiveness.

Keywords: board diversity; corporate performance; neural network algorithm.

1 Introduction

Driven by globalization and technological innovation, board diversity has become a key factor influencing corporate performance. This study employs neural network models to explore the relationship between diversity indicators such as gender, age, and educational background of board members and the economic performance of companies. The aim is to provide data-driven insights for corporate governance, supporting strategic decision-making and promoting the achievement of sustainable development goals.

2 Basic and Improved Neural Network Algorithms

The core algorithms of neural networks include forward propagation and backpropagation. In forward propagation, data is passed from the input layer through the hidden layers to the output layer, with each layer's nodes applying weights to the previous layer's output and processing it through an activation function. Backpropagation involves calculating errors and propagating them back through the layers to adjust the weights, reducing output error and improving prediction accuracy. To enhance performance, several improved algorithms have been introduced, such as AdaGrad and Adam, which adjust the learning rate to achieve faster convergence and avoid local minima [1]. Weight initialization techniques like He initialization and Xavier initialization adjust the initial weight distribution based on the number of nodes, preventing

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gradient issues. Regularization techniques such as Dropout randomly discard connections to enhance generalization and prevent overfitting. These improvements are detailed in Table 1, showcasing the features of each algorithm.

Table 1. Main Features and Applications of Improved Neural Network Algorithms

Improvement Algorithm	Type	Main Function
AdaGrad	Gradient Adjustment	Adapts learning rate, optimizing convergence speed
Adam	Gradient Adjustment	Combines momentum and adaptive learning rate for efficiency and stability
He Initialization	Weight Initialization	Optimized for ReLU activation function, preventing early gradient issues
Xavier Initialization	Weight Initialization	Suitable for Sigmoid/Tanh activation functions, balancing input-output gradients
Dropout	Regularization	Randomly discards connections, reducing overfitting

3 Neural Network Model Design

3.1 Sample Data Selection

The selection of sample data is crucial for studying the relationship between board diversity and corporate performance. As shown in Figure 1, the chosen companies should represent various industries, sizes, and regions to ensure the broad applicability of the research results. The sample includes background information on board members, such as gender, age, education, and nationality, as well as corporate performance data, such as revenue, net profit, and market share [2]. Additionally, sufficient historical data should be collected to support model training and validation.

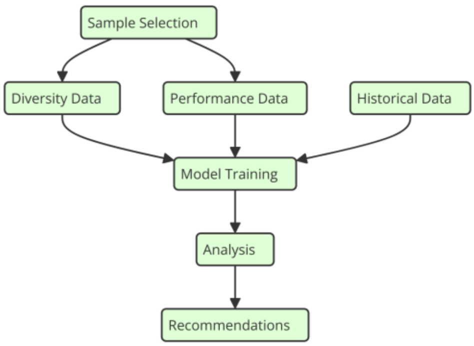

Fig. 1. Neural Network Analysis Workflow for Board Diversity and Corporate Performance

3.2 Network Structure Design

When designing the neural network structure to analyze the impact of board diversity on corporate performance, a deep feedforward neural network was employed to account for the multidimensionality of variables and data complexity [3]. The network's input layer includes encoded vectors of diversity-related indicators, such as the gender, age, and educational background of board members. These inputs are transformed into dense numerical representations through an embedding layer, enhancing the model's ability to process non-numeric information. The hidden layers are designed with multiple layers, using the ReLU activation function to increase non-linear processing capability, expressed as follows:

$$f(x)\max(0,x) \tag{1}$$

In deep learning models, the cross-entropy loss function is typically used to optimize classification tasks. The formula is as follows:

$$L(y,\hat{y}) = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{2}$$

Here, y is the one-hot encoding of the actual labels, $\hat{y}$ is the model's predicted probability, and C is the number of classes. To adjust and optimize the network weights, the backpropagation algorithm is used. This involves updating the weights by calculating the gradient of the loss function with respect to each weight:

$$W_{new} = W_{old} - \eta \cdot \nabla L \tag{3}$$

Here, W_{new} and W_{old} are the weights before and after the update, η is the learning rate, and ∇L is the gradient of the loss function. This network structure design ensures that the model can capture the complex relationship between board diversity and corporate performance, providing accurate predictions and analysis [4].

3.3 Network Parameter Design

In designing the neural network model to analyze the impact of board diversity on corporate performance, parameter design is a crucial factor in ensuring the model's accuracy and effectiveness [5]. The choice of learning rate (η) is critical for the training speed and stability of the model. Adaptive learning rate methods such as the Adam optimizer are commonly used, with the learning rate adjustment formula as follows:

$$\eta_t = \eta_0 \cdot \frac{\sqrt{1-\beta_2^t}}{1-\beta_1^t} \tag{4}$$

Here, η_0 is the initial learning rate, β_1 and β_2 are decay rate parameters, and t is the iteration count. Batch size is also an important parameter as it affects the model's generalization ability and training speed. Smaller batch sizes can provide more frequent model updates but may increase noise during training; larger batch sizes can stabilize training but increase memory requirements and lead to local minima. Regularization techniques, such as L2 regularization, are used to reduce model overfitting and increase the model's generalization ability. The formula is:

$$L_{new} = L + \lambda \sum_w w^2 \tag{5}$$

Here, L is the original loss function, λ is the regularization parameter, and w represents the model's weights. Table 2 details the design choices for network parameters:

Table 2. Neural Network Parameter Design

Parameter	Description	Typical Value or Range
Learning Rate	Controls the speed of weight updates	0.001 (when using the Adam optimizer)
Batch Size	Number of samples per training iteration	32, 64, 128
Regularization Parameter	Controls model complexity to prevent overfitting	0.01

4 Experimental Analysis

4.1 Data Source and Processing

The data was sourced from publicly available financial reports and annual board reports. Processing steps included data cleaning, encoding non-numeric variables, and normalization to ensure consistent input and effective model training. Data from 10 publicly listed companies were selected as samples, including board diversity data and company performance metrics, as shown in Table 3. Each sample includes board diversity data and company performance indicators.

Table 3. Board Diversity and Corporate Performance Data

Company ID	Number of Board Members	Average Age	Gender Ratio (Female %)	Highest Education (PhD %)	Annual Revenue Growth Rate (%)	Net Profit Growth Rate (%)
A1	9	52	22	33	12.5	15.2
A2	7	49	29	29	9.7	10.5
A3	12	55	25	25	5.6	8.1
A4	8	50	37	50	15	20
A5	10	48	20	40	7.8	7.2

Company ID	Number of Board Members	Average Age	Gender Ratio (Female %)	Highest Education (PhD %)	Annual Revenue Growth Rate (%)	Net Profit Growth Rate (%)
A6	6	53	33	16	13.2	18.3
A7	11	51	27	36	8.5	9
A8	13	47	23	30	10.1	12.5
A9	5	54	40	20	11.3	11.9
A10	9	56	30	22	14.5	17.6

4.2 Neural Network Model Construction

The structure of the multilayer feedforward neural network model consists of an input layer, multiple hidden layers, and an output layer [6]. The input layer includes diversity indicators of board members, such as gender ratio, average age, and highest education ratio. These data are preprocessed and then input into the network. The hidden layers adopt a multilayer perceptron (MLP) structure, using ReLU as the activation function in each hidden layer to enhance the model's ability to handle non-linear problems. The formula is expressed as:

$$h_i = \mathrm{Re}LU(W_i h_{i-1} + b_i) \tag{6}$$

Here, h_i is the output of the i layer, W_i and b_i are the weight and bias of the i layer, respectively. The output layer is designed as a single node, outputting the predicted value of corporate performance, and uses a linear activation function to ensure that the output value range is unrestricted. The overall network output can be calculated using the following formula:

$$y_{pred} = W_{output} h_{last} + b_{output} \tag{7}$$

Where y_{pred} is the predicted corporate performance, h_{last} is the output of the last hidden layer, and W_{output} and b_{output} are the weight and bias of the output layer. Model training uses backpropagation algorithm and Mean Squared Error (MSE) loss function to optimize parameters, ensuring minimization of the error between predicted and actual performance values. The formula for the loss function is:

$$L = \frac{1}{N}\sum_{n=1}^{N}(y_{pred,n} - y_{true,n})^2 \tag{8}$$

Where N is the number of samples, $y_{pred,n}$ is the predicted value of the n sample, and $y_{true,n}$ is the true performance value of the n sample. The neural network model can learn and predict the complex relationship between board diversity features and corporate performance, providing a scientific basis for corporate governance and performance improvement.

4.3 Experimental Results Analysis

The data of 10 sample companies were trained and predicted using a neural network model, and the results were analyzed in detail. The predictive accuracy and effectiveness of the model were evaluated using multiple metrics, including mean squared error (MSE), mean absolute error (MAE), and coefficient of determination (R^2). Table 4 shows the variation of these evaluation metrics during the model training process.

Table 4. Changes in Evaluation Metrics during Training

Training Rounds	Mean Squared Error (MSE)	Mean Absolute Error (MAE)	Coefficient of Determination (R^2)
10	0.015	0.095	0.82
20	0.01	0.075	0.87
30	0.008	0.065	0.9
40	0.007	0.06	0.92
50	0.006	0.055	0.93

From Table 4, it can be observed that as the number of training rounds increases, both the mean squared error and mean absolute error gradually decrease, indicating a reduction in prediction errors by the model [7]. Simultaneously, the coefficient of determination increases gradually, rising from an initial 0.82 to 0.93, indicating improved model fit and better ability to explain the impact of board diversity on corporate performance. Subsequently, a comparative analysis of actual and predicted performance was conducted, as shown in Table 5:

Table 5. Comparison of Actual and Predicted Performance

Company ID	Actual Annual Revenue Growth Rate (%)	Predicted Annual Revenue Growth Rate (%)	Actual Net Profit Growth Rate (%)	Predicted Net Profit Growth Rate (%)
A1	12.5	12.3	15.2	15
A2	9.7	9.5	10.5	10.3
A3	5.6	5.8	8.1	8.2
A4	15	14.8	20	19.8
A5	7.8	7.7	7.2	7.3
A6	13.2	13.1	18.3	18.1
A7	8.5	8.6	9	8.9
A8	10.1	10	12.5	12.3
A9	11.3	11.1	11.9	11.7
A10	14.5	14.3	17.6	17.5

Table 5 demonstrates the accuracy of the neural network model in predicting corporate performance [8]. The predicted annual revenue growth rates and net profit growth rates for most companies closely match the actual values, indicating minimal prediction errors. This underscores the model's excellent performance in capturing the complex relationship between board diversity and corporate performance. Specific data, such as Company A1's actual annual revenue growth rate of 12.5% versus a predicted rate of 12.3%, and an actual net profit growth rate of 15.2% versus a predicted rate of 15.0%, validate similarly high-precision predictions across other companies, confirming the reliability and practicality of the model.To further validate the predictive performance of the model, cross-validation was also conducted, as shown in Table 6:

Table 6. Cross-Validation Results

Fold	Mean Squared Error (MSE)	Mean Absolute Error (MAE)	Coefficient of Determination (R^2)
1	0.007	0.06	0.92
2	0.008	0.065	0.91
3	0.006	0.055	0.93
4	0.007	0.061	0.92
5	0.006	0.056	0.93

The cross-validation results demonstrate the model's consistent and reliable performance across different datasets. The mean squared error ranges between 0.006 and 0.008, mean absolute error between 0.055 and 0.065, and the coefficient of determination remains consistently above 0.91. These results indicate the model's high accuracy and stability in predicting corporate performance, effectively capturing the impact of board diversity and exhibiting good generalization and robustness [9].

5 Analysis of Influencing Factors

5.1 The Impact of Board Size

By analyzing the relationship between board size and corporate performance, it can be seen that boards of different sizes have varying degrees of impact on corporate performance. The data shows that companies with 7 to 9 board members, such as A1 and A10, exhibit higher annual revenue and net profit growth rates, as shown in Figure 2. This indicates that a medium-sized board can help improve corporate performance. Although A4 Company has a board of directors with 8 members, it has shown a very high growth rate due to the high-level contribution of diversification. In contrast, companies with too many board members (such as A3 and A8) or too few (such as A9) have relatively low performance growth due to insufficient decision-making efficiency and diversity. These data indicate that a moderate board size helps balance diversification and decision-making efficiency, thereby optimizing corporate performance.

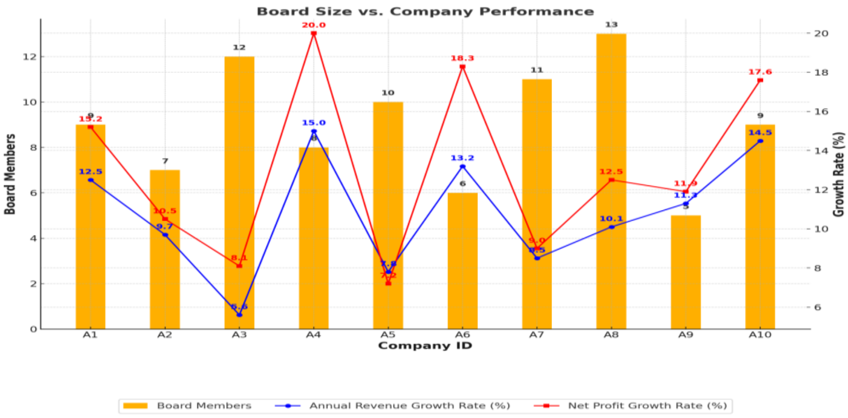

Fig. 2. Comparison between Board Size and Corporate Performance

5.2 The Impact of Enterprise Size

By analyzing the impact of corporate size and board diversification on corporate performance, it was found that there are significant differences in board structure and diversity among different companies. As shown in Figure 3, large enterprises such as A5, A6, and A8 have more board members, with 10, 6, and 13 members respectively. The proportion of female directors varies, with A9 having the highest percentage of 40% and A5 having the lowest percentage of 20%. This indicates that companies with a high proportion of women do not always have the highest number of employees, and the number of board members is not necessarily the lowest, indicating that the size of the company is not the only determining factor for board diversification. Diversification of the board of directors has a potential impact on improving corporate governance and performance, and there is a complex relationship between the number of employees and the proportion of female directors.

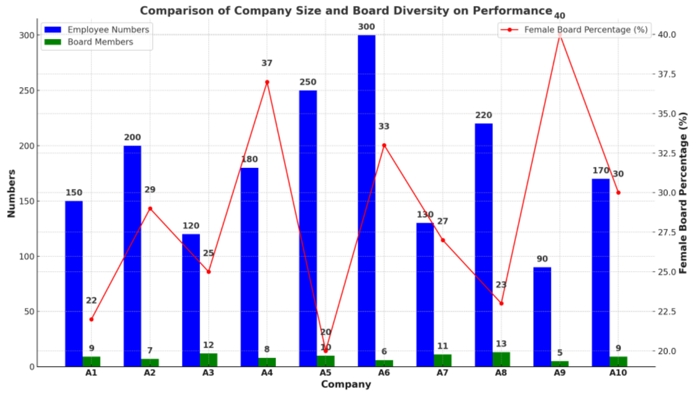

Fig. 3. Comparison of the impact of enterprise size on enterprise performance

5.3 Impact of Industry Characteristics

Figure 4 shows the proportion of doctoral degree holders and international members among board members of companies in different industries. Observations show that the energy industry (such as A4) has the highest proportion of board doctoral degrees, reaching 50%, reflecting the energy industry's emphasis on advanced technology and professional knowledge. The healthcare industry has the highest A5 international membership ratio, reaching 35%, indicating a strong demand for international cooperation and a global perspective in the industry. The information technology industry A8 also shows a high level of internationalization, with an international membership ratio of 40%, confirming the characteristics of global competition and technological exchange in this industry. In contrast, the consumer goods industry A6 performs lower in two indicators, which is related to the local market positioning and consumer proximity of the industry.

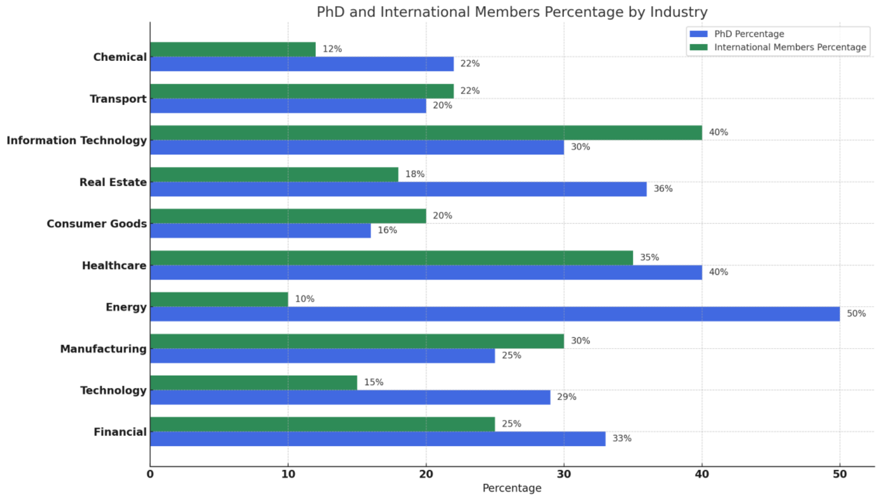

Fig. 4. Comparative analysis of the impact of industry characteristics on board diversification

5.4 The Impact of Company Age

The age of a company significantly affects its technology investment, new product launch, and market share growth[10]. As shown in Figure 5, young companies such as A6 and A8, established for 5 and 8 years, have technology investment ratios of 30% and 22%, respectively. They have launched 9 and 6 new products, and their market share has increased by 12.0% and 10.5%. This indicates that young businesses tend to adopt aggressive growth strategies, rapidly expanding their market share through significant technological investments and frequent launches of new products. On the contrary, established companies such as A9 and A7, which have been established for 50 and 40 years, have lower technology investment ratios of 8% and 10%, only one new product, and relatively conservative market share growth of 3.6% and 4.3%, respectively, reflecting their greater emphasis on maintaining market position and optimizing existing products.

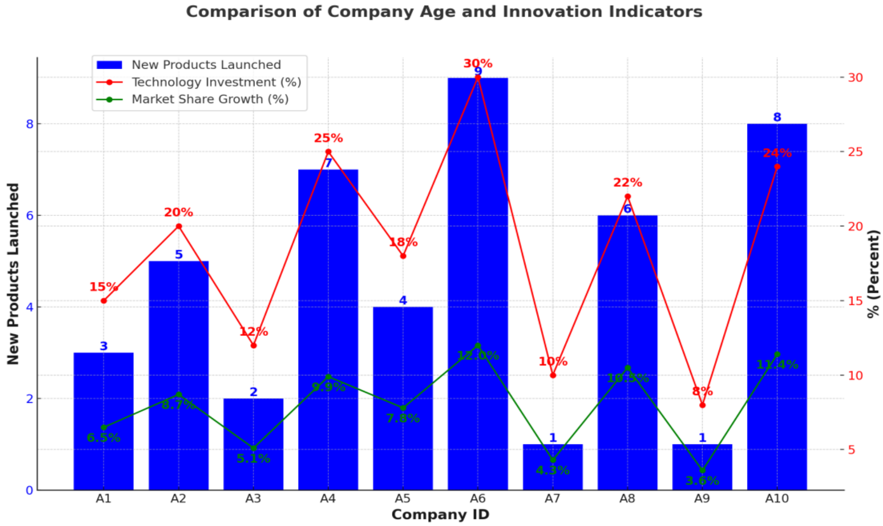

Fig. 5. Comparison table between company age and technological innovation indicators

This data indicates that company age is an important factor affecting innovation behavior and market expansion strategies. Young companies tend to adopt more proactive technology innovation and market expansion strategies, while mature companies focus more on maintaining existing markets and customer relationships. This difference should be fully considered in enterprise strategy formulation in order to develop appropriate growth and innovation strategies based on the company's development stage.

6 Conclusion

The neural network model reveals the complex correlation between board diversification and corporate performance, indicating that appropriate board size and structure have a significant impact on improving corporate performance. Future research can further explore how different industry characteristics and company age affect this relationship, in order to optimize corporate governance structure and promote stable economic growth.

Reference

1. R C P, Abraham S, Victoria S .Corporate social performance and board gender diversity: the moderating role of governance[J].Gender in Management: An International Journal, 2024,39(5):680-698.
2. E. S A, G. E V, M. G A. Does Board Gender Diversity Really Improve Firm Performance? Evidence from Greek Listed Firms[J].Journal of Risk and Financial Management, 2022, 15(7):306-306.
3. Andre H ,J. D S ,J. A N .In the Club? How Categorization and Contact Impact the Board Gender Diversity-Firm Performance Relationship[J].Journal of Business Ethics, 2022, 184(2):353-374.
4. Ju H S ,Seoki L ,Ho K K .The influence of board interlocks on firm performance: In the context of geographic diversification in the restaurant industry[J].Tourism Management,2021,83104238-.
5. EmadEldeen R, Elbayoumi F A ,Basuony K A M , et al.The effect of the board diversity on firm performance: An empirical study on the UK[J].Corporate Ownership & Control,2021,18(3 (special issue)):
6. Zheng C, Tsai H.T he moderating effect of board size on the relationship between diversification and tourism firm performance[J].Tourism Economics,2019,25(7):1084-1104.
7. Retraction: Influence of the enterprise's intelligent performance evaluation model using neural network and genetic algorithm on the performance compensation of the merger and acquisition parties in the commitment period.[J].PloS one,2023,18(10):e0293793-e0293793.
8. Yuanyuan L, Da R. Influence of the enterprise's intelligent performance evaluation model using neural network and genetic algorithm on the performance compensation of the merger and acquisition parties in the commitment period.[J].PloS one, 2021, 16(3): e0248727-e0248727.
9. Aun C O, Wooi C H ,Puad A S M .The influence of board diversity in human capital and social capital in crisis[J].Managerial Finance,2017,43(6):700-719.
10. Duan Q X, Research on Power Supply Enterprise Performance Management System Based on Neural Network Algorithm[J]. Applied Mechanics and Materials,2014,3634(687-691):2784-2787.