Optimization Analysis of Corporate Social Responsibility Innovation Paths Based on Bayesian Networks

Yanbin Ni

Yongfu Construction Group, Fujian, 350007, China

niki55555@126.com

Abstract. To optimize corporate social responsibility (CSR) innovation paths, this study utilizes Bayesian networks to construct a dynamic decision-making model, analyzing the long-term effects of different strategies on environmental protection, social impact, and economic performance. The results show that Bayesian networks can effectively address complex uncertainties, enhance the scientific precision of CSR practices, and contribute to the improvement of sustainability and competitiveness.

Keywords: Bayesian networks; corporate social responsibility; path optimization.

1 Introduction

In the practice of corporate social responsibility, companies face complex and variable environments with uncertain challenges, making traditional paths less effective. By leveraging the probabilistic reasoning and causal analysis capabilities of Bayesian networks, dynamic models can be constructed to optimize CSR innovation paths, scientifically predict the long-term effects of different strategies on corporate reputation, economic benefits, and social impact, and provide robust decision-making support. This approach aids companies in achieving sustainable development and enhancing competitiveness while fulfilling their social responsibilities.

2 Importance of Bayesian Networks in CSR Path Optimization

In current research and practice of corporate social responsibility, Bayesian networks offer a new perspective and method with their powerful probabilistic reasoning capabilities. When companies encounter complex CSR issues, they often need to process and analyze large amounts of uncertain information [1]. Bayesian networks can effectively integrate various data sources by constructing causal relationship models, helping companies scientifically predict and evaluate the outcomes of different CSR strategies. Especially in the exploration and optimization of innovative CSR paths, Bayesian networks can simulate various decision scenarios, analyzing the long-term

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impacts of different decision paths on corporate reputation, environmental impact, and economic benefits. This provides companies with decision-making support and drives the continuous improvement and innovation of CSR practices.

3 Constructing the CSR Innovation Path Model Based on Bayesian Networks

3.1 Selection and Definition of Bayesian Network Nodes

When constructing a corporate social responsibility (CSR) innovation path model based on Bayesian networks, the selection and definition of nodes are crucial as they directly impact the model's accuracy and practicality. Key nodes should cover factors such as environmental protection, social impact, economic performance, and stakeholder satisfaction [2]. The environmental protection node measures the company's performance in reducing pollution and resource consumption. The social impact node evaluates the company's contribution to community welfare and social justice. The economic performance node focuses on financial health and returns on social responsibility investments, while the stakeholder satisfaction node reflects public recognition of the company's CSR practices. These nodes are modeled through conditional probability tables (CPTs), dynamically simulating and optimizing CSR strategies, as shown in Table 1.

Table 1. Node Definition Table for CSR Innovation Path Model.

Node Name	Definition
Environmental Protection	Company's performance in reducing environmental pollution and resource usage
Social Impact	Company's contribution to community welfare and social justice
Economic Performance	Company's financial health and returns on social responsibility investments
Stakeholder Satisfaction	Recognition of the company's CSR practices by consumers, employees, and the general public

3.2 Design of Bayesian Network Structure

In the design of the Bayesian network structure, the logical relationships between nodes are key to establishing an effective model. For the CSR Bayesian network model, the relationships between nodes must accurately reflect the causal connections between corporate behavior and its CSR outcomes. The economic performance node serves as the core, directly influencing the environmental protection and social impact nodes, as a company's financial condition determines its investment capacity in CSR activities. Companies with strong economic performance are more likely to invest in environmental technologies and community development projects [3]. Meanwhile, the effectiveness of environmental protection feeds back into economic performance, as good environmental measures can reduce potential fines and litigation costs, enhance corporate image, and attract more consumers and investors. The social impact node is connected to the stakeholder satisfaction node, as active corporate engagement in the community can directly improve public perception and satisfaction.

3.3 Estimation of Bayesian Network Parameters

In the CSR Bayesian network model, the estimation of probabilistic parameters primarily relies on historical data analysis and expert knowledge [4]. It is necessary to collect historical data on environmental protection, social impact, economic performance, and stakeholder satisfaction. This data includes corporate financial reports, CSR reports, environmental records, and market survey results. The parameter estimation process typically involves statistical analysis methods such as Maximum Likelihood Estimation (MLE) and the Expectation-Maximization (EM) algorithm. Through these methods, the parameters in the conditional probability tables (CPTs) can be estimated from the data, representing the conditional probability distribution of a node given the states of its parent nodes. To ensure the accuracy of the estimates, expert judgment can be used to adjust and validate the data analysis results [5]. Experts, drawing on their deep understanding of industry trends and CSR practices, can provide qualitative assessments and adjustment suggestions for the probabilistic parameters, as shown in Table 2.

Table 2. Probability Parameter Settings for CSR Bayesian Network Model.

Node	Condition	Probability Parameter Setting
Environmental Protection	Economic Performance: Good	0.75
Environmental Protection	Economic Performance: Average	0.5
Social Impact	Economic Performance: Good	0.7
Social Impact	Economic Performance: Average	0.45
Stakeholder Satisfaction	Social Impact: High	0.85
Stakeholder Satisfaction	Social Impact: Low	0.55

3.4 Construction of the Bayesian Network Model

After completing node selection, structure design, and parameter estimation, the construction of the Bayesian network model enters a critical phase. This model integrates all the previous steps to form a complete system capable of effectively predicting and optimizing CSR paths [6]. The model represents various CSR activities and decision paths of a company as a Directed Acyclic Graph (DAG), where each node represents a key factor (such as environmental protection, social impact, economic performance), and arrows denote causal relationships between nodes, as illustrated in Figure 1.

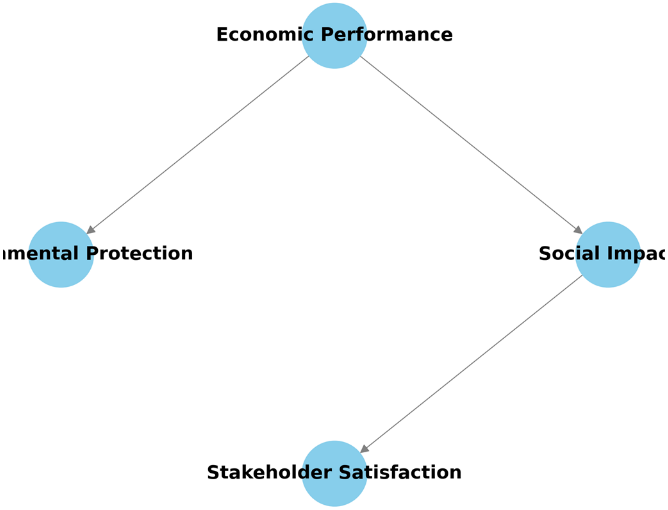

Fig. 1. CSR Bayesian Network Model.

This structure effectively captures the complex causal chain of corporate behavior, ensuring that the model reflects actual business scenarios. Next, the model needs to quantify these causal relationships through probability distributions and conditional probability tables (CPTs). Let there be a node X_i and its parent node $Pa(X_i)$, then the conditional probability of this node is expressed as:

$$P(X_i \mid Pa(X_i)) = \prod_{j=1}^{n} P(X_j \mid X_{Pa(j)}) \tag{1}$$

In this formula, $P(X_i \mid Pa(X_i))$ represents the conditional probability distribution of node $Pa(X_i)$ given the state of the parent node X_i. $P(X_j \mid X_{Pa(j)})$ represents the conditional probability contribution of each parent node to the child node. To further enhance the predictive ability of the model, the model uses a joint probability distribution to represent the joint state of all nodes. The joint probability formula is as follows:

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i \mid Pa(X_i)) \tag{2}$$

The formula generates the overall probability distribution of the network through the product of the conditional probabilities of the nodes, enabling the model to evaluate the overall CSR performance across different paths. The model also uses Bayesian inference for updates and predictions. When new data D is introduced, the model's posterior probability is updated using the Bayesian formula as follows:

$$P(X|D) = \frac{P(D|X) \cdot P(X)}{P(D)} \tag{3}$$

Here, $P(X|D)$ represents the posterior probability of node D given the new data X; $P(D|X)$ is the likelihood function, representing the probability of observing data D under the assumption that X is true. Through these steps, the constructed Bayesian network model can dynamically simulate different strategic paths of corporate social responsibility, analyze their potential impacts, and provide scientific decision support for the enterprise.

4 Experimental Results and Analysis

4.1 Model Validation and Effectiveness Testing

The reliability and accuracy of the Bayesian network model were validated by comparing its predictions with the actual corporate social responsibility (CSR) performance [7]. Data from five companies, representing different industries and sizes, were selected to ensure the breadth and representativeness of the experiment. By analyzing the differences between the model's predictions and actual data across multiple dimensions such as environmental protection, social impact, and economic performance, the applicability of the model was explored in depth. The focus was first placed on the prediction of environmental protection indicators. The comparison of the predicted and actual environmental protection scores in the experiment is shown in Figure 2:

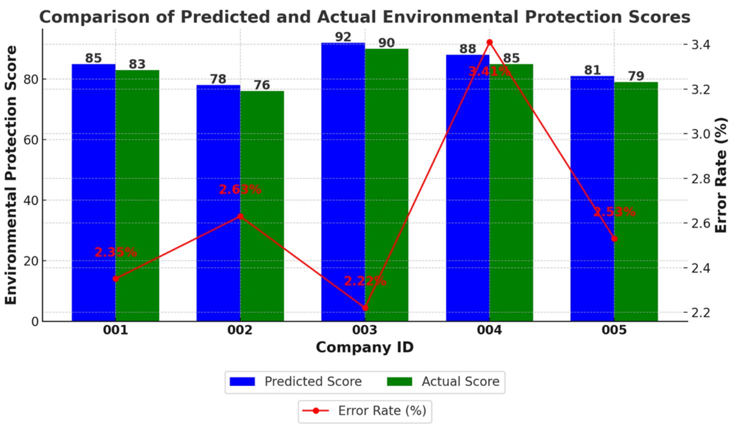

Fig. 2. Model Predictions vs. Actual Environmental Protection Scores.

From the data in Figure 2, it can be observed that the model has a low prediction error rate for environmental protection scores, averaging below 3%. This indicates that the Bayesian network model can predict a company's environmental protection performance quite accurately. Specifically, for Company 001, the actual environmental protection score was 83, while the model predicted a score of 85, resulting in an error rate of 2.35%. This suggests that the model can effectively reflect the company's environmental performance. Similarly, for other companies, the errors between predictions and actual scores also remain within a small range, further validating the model's accuracy in this area. Next, the model's predictions for social impact scores are analyzed, as shown in Figure 3:

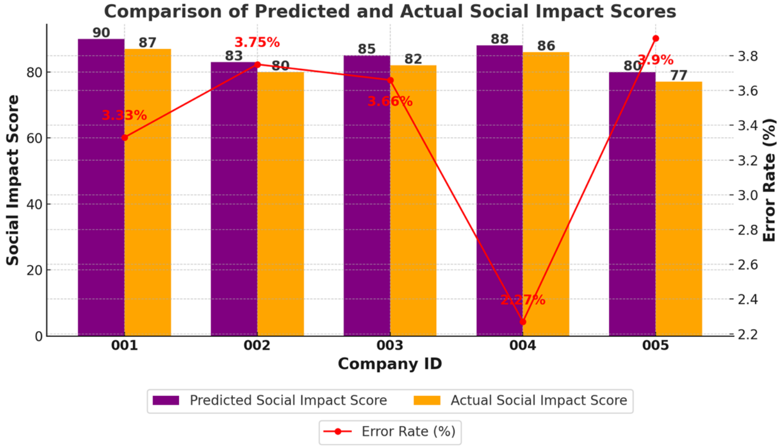

Fig. 3. Model Predictions vs. Actual Social Impact Scores.

The data shown in Figure 3 reveals that the Bayesian network model also demonstrates high accuracy in predicting social impact scores. Although the prediction error rate for social impact is slightly higher compared to environmental protection scores, it remains within 4%. This suggests that the model can accurately capture the main influencing factors when predicting a company's contribution to social impact. For instance, Company 004 had an actual social impact score of 86, while the model predicted a score of 88, resulting in an error rate of just 2.27%. This level of precision is valuable for companies when formulating social responsibility strategies. To further validate the model's comprehensiveness, the relationship between economic performance and stakeholder satisfaction was also analyzed (see Figure 4).

The data in Figure 4 shows that the Bayesian network model demonstrates very high accuracy in predicting economic performance and its impact on stakeholder satisfaction. The error rates are generally below 4%, indicating that the model's predictions are reliable across these two dimensions. For instance, Company 004 had an actual economic performance score of 88, while the model predicted 90, resulting in an error rate of 1.11%. The actual stakeholder satisfaction score was 89, with the model predicting 90, resulting in a similarly low error rate. These results suggest that the model not only effectively predicts a company's economic performance but also accurately reflects the impact of economic performance on stakeholder satisfaction.

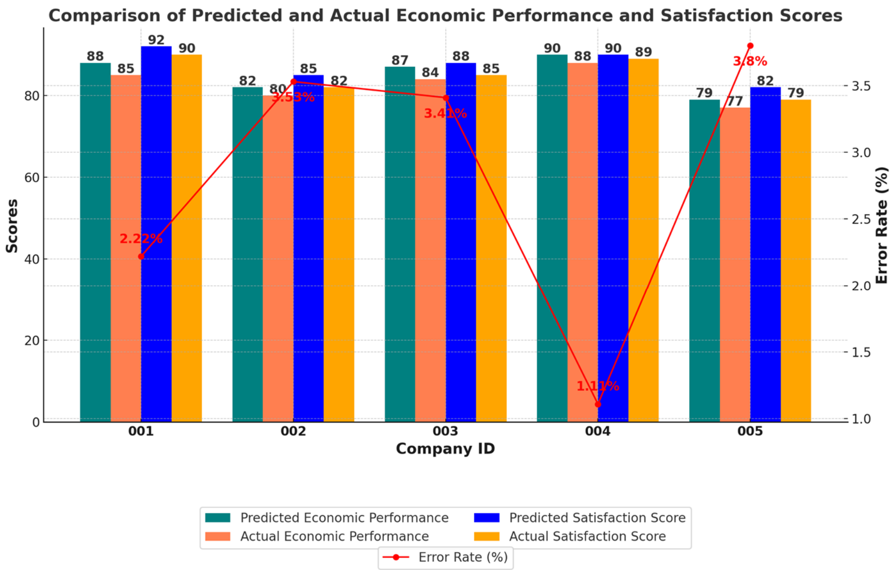

Fig. 4. Model Predictions vs. Actual Economic Performance and Satisfaction Scores.

4.2 Innovation Pathways Identification and Analysis

Through the analysis of the Bayesian network model, three key corporate social responsibility (CSR) innovation pathways were identified: environmental protection priority, social impact enhancement, and economic performance drive [8]. The environmental protection priority pathway enhances the company's image by strengthening environmental measures; the social impact enhancement pathway increases the company's social influence and brand recognition; and the economic performance drive pathway achieves economic benefits through optimizing financial management. Each pathway has its focus, helping companies optimize CSR strategies under different objectives for sustainable development. To further analyze the benefits and feasibility of these pathways, the model simulated the expected performance of five companies under each of the three pathways and compared it with actual data, as shown in Table 3:

Table 3. Comparison of CSR Performance under Different Pathways.

Company No.	Pathway Selection	Environmental Protection Score	Social Impact Score	Economic Performance Score	Stakeholder Satisfaction
1	Environmental Protection Priority Pathway	90	85	78	87

2	Social Impact Enhancement Pathway	80	92	76	90
3	Economic Performance Drive Pathway	75	78	90	83
4	Environmental Protection Priority Pathway	88	80	81	85
5	Social Impact Enhancement Pathway	82	89	79	88
6	Economic Performance Drive Pathway	78	75	88	80

The data analysis from the table shows that different pathways exhibit unique advantages across various dimensions. Companies choosing the "Environmental Protection Priority Pathway" have an average environmental protection score of 89, but lower economic performance, indicating a short-term sacrifice for long-term benefits. The "Social Impact Enhancement Pathway" results in a social image score of 90 but at the expense of economic performance. The "Economic Performance Drive Pathway" excels in economic performance with an average score of 89 but is somewhat lacking in environmental and social impact. This suggests that different pathways should be customized according to the company's actual situation to balance CSR and economic benefits [9].

4.3 Sensitivity Analysis of Innovation Factors

In optimizing CSR innovation pathways, sensitivity analysis of innovation factors is crucial. The model analysis shows (see Table 4) that environmental investment has the greatest impact on the Environmental Protection Priority Pathway; a 10% increase in investment can improve the score by 15%, but economic performance slightly declines [10]. Social public welfare participation significantly affects the Social Impact Enhancement Pathway; a 10% increase can raise the social impact score by 12%, with limited improvement in economic performance. The return on economic investment is most sensitive in the Economic Performance Drive Pathway; a 5% increase can boost economic performance scores by 10% and increase stakeholder satisfaction.

Table 4. Sensitivity Analysis of Innovation Factors.

Innovation Factor	Pathway Selection	Increase (%)	Environmental Protection Score	Social Impact Score	Economic Performance Score	Stakeholder Satisfaction
Environmental Investment	Environmental Protection Priority Pathway	10%	15%	-3%	-5%	2%
Social Public Welfare Participation	Social Impact Enhancement Pathway	10%	3%	12%	1%	8%
Economic Investment Return	Economic Performance Drive Pathway	5%	2%	4%	10%	6%
Stakeholder Satisfaction	Comprehensive Pathway	10%	5%	8%	7%	10%

The data indicates that each key factor has a varying impact on different pathways. Companies should optimize CSR strategies based on these sensitivity analysis results. For example, companies following the Environmental Protection Priority Pathway should balance economic benefits when increasing environmental investment to avoid excessive short-term financial performance sacrifices. For those on the Social Impact Enhancement Pathway, increasing social public welfare participation is an effective way to improve brand image and stakeholder satisfaction, although it should be combined with moderate economic investment strategies. For companies on the Economic Performance Drive Pathway, improving investment returns is crucial, ensuring that economic benefits are achieved while balancing CSR goals and stakeholder needs.

5 Conclusion

The application of Bayesian networks in optimizing CSR pathways demonstrates its effectiveness and accuracy in complex and uncertain environments, especially in balancing environmental protection, social impact, and economic performance. Future work should further explore dynamic data and multi-dimensional factor analysis to enhance the model's support for corporate decision-making and precision, aiding companies in achieving higher levels of innovation and development in CSR practices.

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