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A Study on the Influence Path of Corporate ESG Disclosure Quality and Sustainability Performance Based on Bayesian Network Modeling

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ABSTRACT
Corporate ESG disclosure quality is a key condition to optimize industrial structure and a realistic path to reach sustainability performance. Based on the theoretical knowledge of Bayesian network model, the research program of corporate ESG disclosure quality and sustainability performance influence path is designed. According to the current status of enterprise development, 11 research variables are set, which contain explanatory variables, interpreted variables, and control variables. Mathematical statistics and Bayesian network modeling are adopted to parse the mutual influence mechanism between the two. In the forward Bayesian inference, the probability of enterprise sustainability performance being in a good state is 49.3%, and the probability of the explanatory variables being in a good state is increased to 58.7% by changing the state probability of other variables. In order to provide a comprehensive overview of the relationship, backward Bayesian inference was also performed, and when the probability of sustainability performance being in a good state was 100%, the probability of the board concurrent position being in a good state was the highest with a value of 72.3%. This study enhances the most effective corporate ESG disclosure quality control program for companies to maximize the possibility of sustainability performance.

Keywords: Bayesian network modeling, ESG disclosure quality, sustainability performance, impact mechanism

1. Introduction

In the current global context, environmental issues, social responsibility and good governance have become key elements of corporate sustainable development, with far-reaching impacts on business performance and long-term competitiveness. Environmental, social and governance factors have been unified and comprehensively called ESG, which has become an important indicator for enterprises to evaluate their sustainable development performance [1-4].ESG performance is closely related to

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corporate performance. Environmental performance can improve corporate image and brand value, increase business opportunities and market share. Social performance can improve employee motivation and productivity, and increase consumer loyalty [5-8]. Good governance can improve trust and operational efficiency, reduce risks and avoid losses. Therefore, enterprises should integrate ESG performance into their strategic and business decision-making processes and take sustainable development as a strategic advantage for long-term competitiveness [9-12].

With the deepening of global economic integration, enterprises are facing increasingly severe market competition and regulatory pressure. In order to improve the competitiveness and sustainable development ability of enterprises, more and more enterprises begin to ESG disclosure quality [13-15].ESG disclosure quality as an important means of enterprises to investors and the public to convey the business situation and values of the enterprise, to enhance the enterprise's reputation, to attract investors, and to reduce the risk of important significance [16-18]. However, there are still many problems in ESG disclosure of enterprises, such as incomplete disclosure content, disclosure standards are not standardized disclosure quality is not high, these problems not only affect the sustainable development of the enterprise, but also constrain the effective operation of the market, and Bayesian network modeling can cope with these problems [19-22].

Literature [23] examined the impact of corporate ESG disclosure on EES sustainability performance. It reveals that the economic value and the social value created by enterprises are interdependent. And disclosure of ESG information to all stakeholders is an important factor in improving corporate sustainability performance. Literature [24] used several econometric models to estimate the impact of ESG disclosure and FRQ on investment efficiency using UAE as a sample. It is emphasized that ESG disclosure, FRQ and investment efficiency are positively correlated and ESG disclosure facilitates investment efficiency. Literature [25] explored the relationship between the quantity and quality of sustainability disclosure of ESG performance reports and surplus quality. Getting the quality of disclosure strengthens the positive correlation between the quality of surplus and the quantity of disclosable and mitigates the negative correlation between the quality of discretionary surplus and the quantity of disclosure. Literature [26] aims to discuss the impact of ESG disclosure on firm performance. The positive correlation between ESG disclosure and firm performance is revealed and this result helps groups such as stakeholders of the firm to improve their understanding of the impact of ESG disclosure on firm performance. Literature [27] used a scoring method to assess the relevance and completeness of environmental kpi. It revealed that the average score of disclosure quality of firms in the current market is very low, while the industrial goods and telecommunication sectors have the highest and lowest disclosure quality respectively. Literature [28] explored the value relevance of corporate ESG performance based on exploring the impact of ESG disclosure quality on corporate sustainability performance. The results indicate that investors value corporate ESG performance and the quality of ESG disclosure. Literature [29] investigated the impact of ESG disclosure on the quality of financial reporting in non-financial companies. Using panel data analysis, companies that adopt a robust ESG reporting framework are able to improve financial transparency and stakeholder trust in the business environment. Literature [30] investigated the impact of ESG disclosure on corporate financial performance. Using a sample of non-financial listed companies, the staggered difference-in-differences method was used to eliminate the endogeneity problem. It is indicated that ESG disclosure can positively affect corporate financial performance.

It is not difficult to see that the quality of corporate ESG disclosure has a positive impact on the sustainable development of enterprises, but in all the research results, the objects of their research are listed enterprises or large enterprises, and the quality of ESG disclosure for small and medium-sized enterprises has not yet been reflected, so it cannot have comprehensive applicability. In addition, the related research and application based on Bayesian network modeling in corporate ESG disclosure quality and sustainability performance has not yet been emphasized.

Under the definition of Bayesian network, a study on the impact of corporate ESG disclosure quality and sustainability performance under the Bayesian network framework is proposed. Corporate ESG disclosure quality is set as an explanatory variable, sustainability performance as an explanatory variable, and profitability (ROA), gearing ratio (LEV), firm size (SIZE), management shareholding (MH), age of the firm (AGE), free cash flow ratio (FCF), return on equity (RET), proportion of fixed assets (PPE), and concurrent board membership (DU) as control variables. The A-share listed companies from 2014-2023 were used as the research object, and the main data were obtained from Python crawling data. Pooled research data, mathematical statistics, and Bayesian networks are used to deeply explore the relationship between ESG disclosure quality and sustainability performance role.

2. Bayesian network theory and realization techniques

2.1. Definition of Bayesian Networks

Bayesian networks (BN), also known as directed acyclic graphs, or confidence networks, belong to the category of probabilistic graphical models (probabilistic graphical models are mainly composed of two main categories: Bayesian networks and Markov networks), which are used to model the uncertainty of causal relationships among different factors in the human reasoning process [31-32]. Probabilistic graphical models usually represent the probabilistic correlations between different variables with graphs, which is an organic combination of knowledge of graph theory and probability theory, and is essentially the use of graphical models to represent the joint probability densities of the variables related to the model.

2.2. Construction of Bayesian Networks

Assuming that two existing variables or nodes with a causal relationship, H and H, are connected by a one-way arrow, pointing from E to H, then E is the cause $(parents)$ and H is the effect $(children)$, and the conditional probability of the variables E to H is shown in Fig. 1, then a connection is usually established between the two variables, which has a certain conditional probability value. Denote by (E,H) the directed arc of E pointing to H, and the strength of the connection between the two is represented by the conditional probability $P(H|E)$. And for a research system containing multiple random variables, the network formed by plotting them in a directed graph according to whether the two satisfy the conditional independence between them is a Bayesian network.

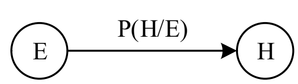


Fig. 1. Conditional probability of variables E to H

The above definition is relatively simple and abstract, and a more concrete definition for Bayesian networks is to assume that there exists a directed acyclic graph, denoted by $G=(I,C)$, where I denotes the set of all nodes in the network, C denotes the set of line segments connecting all the nodes, and then denotes by X_i, $(i\in I)$ the random variable represented by one of the nodes in the set of nodes I, and if the joint probability density of X_i can be expressed as:

$$p(x)=\prod_{i\in I} p\left(x_i \mid x_{po(i)}\right) \tag{1}$$

Then $X=\{X_i\}$ is a Bayesian network with respect to the directed acyclic graph G, where $pa(i)$ is called the "parents" of node i, and the joint probability density of any random variable can be obtained by the product of all its local conditional probabilities:

$$p\left(x_1,\cdots,x_k\right)=p\left(x_k \mid x_1,\cdots,x_{k-1}\right)\cdots p\left(x_2 \mid x_1\right)p\left(x_1\right) \tag{2}$$

2.3. Bayesian network inference

Essentially, the inference process of Bayesian networks is the process of calculating the conditional and joint probabilities described above [33-34]. The advantage of Bayesian networks over the calculation of probability statistics in traditional mathematics lies in the fact that the joint probability distribution can be represented visually by a series of conditional probabilities and graphical structures, and then the probability distribution of partial variables or single variables can be calculated using the elimination method. Based on the known values of the partial variables, the conditional probability distribution of the set of nodal variables closely related to the target can be reasoned and calculated. Built on the basis of conditional probability calculation, Bayesian network has three inference methods, namely, supportive inference, diagnostic inference, causal inference, based on the research direction of this paper, this study adopts causal inference. The detailed description is as follows:

Causal reasoning represents a method of positive reasoning that allows for the prediction of the conditional probability of the occurrence of costs for urban grid projects in the context of specific influencing factors, and thus determines the magnitude of the likelihood of the occurrence of costs for construction projects. In this case, the formula for the above conditional probability changes to:

$$P\left(S=Z \mid X_e\right)=P\left(S=Z \mid X_1=x_1,\cdots,X_n=x_n\right) \tag{3}$$

In the above equation, n denotes the number of nodes and both states N and Z exist for a single node, where N denotes that the event represented by the node does not occur and Z denotes that the event represented by the point occurs, i.e., the cost of the urban grid project must occur.

2.4. Mathematical modeling

Through the above analysis, it can be seen that there are three main steps in the modeling process of Bayesian networks in general, namely, node selection and assignment, determination of network structure, and determination of conditional probability distribution of each node.

1) Node selection and assignment. In the Bayesian network, each node corresponds to each factor in the research problem, for example, for the study of corporate ESG disclosure quality and sustainability performance, the nodes of the Bayesian network correspond to the factors affecting costs. All the nodes in the Bayesian network can be categorized into three types, which are cause nodes, goal nodes and intermediate nodes. Cause nodes are the known conditions of the model, representing the factors that have been determined in advance, and are the premise and basis for realizing inference in a Bayesian network. The target node is the solution goal of the Bayesian network model, which needs to be reasoned according to the cause node to obtain its posterior probability distribution, usually as a reference and basis for subsequent decision-making; the intermediate node plays an intermediary role between the cause node and the target node, and needs to be assigned to each node based on the completion of all the nodes selected in the Bayesian network model.

2) Network structure determination. On the basis of selecting nodes and node assignment, to establish a Bayesian network model, it is necessary to further determine the association relationship between individual nodes. In the face of complex Bayesian networks with large-scale nodes, common network structure determination methods are categorized into two types: determination methods based on the a priori knowledge of domain experts and determination methods based on data learning methods. Determination methods based on data learning methods are mainly based on the idea of data learning, collecting a large number of sample data, and then learning a large number of times to get more accurate results. The determination method based on the prior knowledge of domain experts is based on the existing data samples, which is a way to integrate the existing data samples with the prior

knowledge of experts to establish the correlation between different node variables, so as to determine the network structure of the Bayesian network. Specifically, the process of this method is to first construct a prototype of the network structure according to the expert's a priori knowledge, and then, based on this, utilize the data learning for model refinement, and finally obtain the most accurate network structure. Therefore, for Bayesian networks with large-scale nodes, the more popular method of structure determination is by combining a priori knowledge with data learning, which can effectively compress the initial space of the algorithm as well as avoid excessive expert subjectivity, making the results converge rapidly.

3) Determination of conditional probability distribution of each node. After the network structure between the nodes is determined, that is, after the correlation between the nodes is determined, the conditional probability distribution between the two can be determined. The calculation method of the conditional probability between the nodes has been described in the previous section, and will not be repeated here.

3. Study design

3.1. Variable settings

3.1.1. Interpreted quantities.From a shared-value perspective, sustainable performance takes into account economic, social and environmental aspects, generating profitability for the organization without harming the environment and society, and ultimately leading to a substantial and lasting competitive advantage. Considering stakeholders defines sustainable performance as “performance that encompasses all aspects of society, the environment, the organization and all stakeholders”. Sustainable performance is considered to be more flexible because it takes into account both upstream stakeholders (customers) and downstream stakeholders (suppliers, subcontractors), etc., and corporate sustainable performance can be understood as “progress that integrates environmental, economic and social dimensions”. Currently, one of the most representative and widely accepted frameworks for sustainable business performance is the three dimensions of economic, social, and environmental performance, which aims to emphasize the concept of balanced development of enterprises in the economic, social, and environmental dimensions. The economic dimension of performance is mainly realized by improving the effectiveness and efficiency of services and products as well as economic development; the social dimension of performance is realized through the social behaviors of enterprises, which mainly include enhancing social welfare, facilitating communication between external and internal communities, and improving the health and safety of the society. And the main way to realize the performance of the environmental dimension is to carry out environmental management through cooperation, so as to achieve the purpose of improving the ecological environment. In summary, given that the impacts of frugal innovation for firms explored in this paper are not only the improvement of economic performance, but also encompass the impacts on society and the environment. Therefore, this paper finally determines to use the three dimensions of economy, society and environment to comprehensively evaluate the sustainable performance of SMEs, and for the purpose of experimental analysis and statistics, SP is used to denote the sustainable performance of SMEs.

3.1.2. Explanatory variables. ESG disclosure scoring data is used as an indicator to measure the quality of corporate ESG disclosure. Unlike other third-party rating agencies in China, such as CSI, Runling, Thomson Reuters, etc., B is the only organization that scores the quality of corporate ESG disclosure, thus avoiding the rating divergence faced on ESG performance (performance).B continuously monitors the ESG disclosure of more than 13,000 companies, with a wide range of data sources covering annual reports, sustainability reports, third-party studies, direct contacts, press releases and media news, and other public channels to assess corporate environmental responsibility and corporate governance issues every year. Development reports, third-party research, direct contacts, press releases and media news from public sources, and annually assesses companies on ESG issues. That is, it measures the amount of ESG information, not the company's ESG performance or performance. BSociety B meticulously evaluates each company's ESG disclosure by taking into account a series of quantitative and qualitative indicators in a comprehensive manner and gives a comprehensive ESG score accordingly. These scores cover not only environmental indicators such as greenhouse gas emissions, waste disposal, pollution control and renewable energy, but also in-depth consideration of social aspects such as diversity, community relations, political participation and human rights guarantees, as well as key factors such as executive compensation, the proportion of independent directors, the size of the board of directors, and even the rate of employee turnover at the governance level. These scores visually reflect the quality of ESG disclosure and the level of transparency of the companies.

3.1.3. Control variables. To ensure the accuracy of the data analysis and model regression results, this paper refers to the methodology of relevant references and controls for the following variables: profitability (ROA), gearing ratio (LEV), firm size (SIZE), management shareholding (MH), age of the firm (AGE), free cash flow ratio (FCF), return on equity (RET), fixed asset ratio (PPE), and board concurrent positions (DU).

3.2. Sample Selection and Data Sources

This paper takes A-share listed companies from 2014-2023 as the research sample, annual reports are sourced from Juchao Information Network, annual report disclosure quality is obtained by Python processing, ESG rating data is sourced from Bloomberg, corporate foreign sales percentage is sourced from Wind database, corporate reputation is sourced from manual collection, and the rest of the data is sourced from CNRDS database. In order to ensure the validity of the selected data and the accuracy of the results, this paper processes the selected samples as follows: (1) Delete the samples from which the quality of disclosure cannot be extracted due to the format of the annual report. (2) Delete the companies that had been specially treated ST and ST* during the sample period. (3) Remove financial companies such as banks and insurance. (4) Remove samples with missing relevant data. Eventually, 5320 observations are obtained, and the distribution of sample year is shown in Table 1 respectively. In order to avoid the influence of outliers, this paper winsorize all continuous variables by 1% up and down.

Table 1. Sample distribution

A given year	Sample size	Sample size
2014	415	7.80%
2015	419	7.88%
2016	421	7.91%
2017	450	8.46%
2018	473	8.89%
2019	489	9.19%
2020	565	10.62%
2021	603	11.33%
2022	706	13.27%
2023	779	14.64%
Total	5320	100.00%

4. Example Analysis of ESG Disclosure Quality and Sustainability Performance

4.1. Empirical analysis

After determining the data sources and research samples, the knowledge of mathematical statistics is used to carry out empirical analysis of the explanatory variables, interpreted variables and control variables set above, and the content of empirical analysis includes descriptive analysis, correlation analysis and interaction analysis. The detailed analysis process is shown below:

4.1.1. Descriptive statistical analysis. With the help of mathematical statistics knowledge, the data collected for the study variables were analyzed with descriptive statistics and the results of descriptive statistical analysis of the study variables are shown in Table 2. From the data performance in Table 2, it can be seen that the mean value of the explanatory variable ESG disclosure quality is 0.274, the maximum value is 1.747, the minimum value is -1.296, and the standard deviation is 0.094, i.e., it indicates that there is a large gap in the quality of ESG disclosure, and that the main responsibility of ESG has not yet been thoroughly compressed. And the overall data mean of the explanatory variable sustainability performance (SP) is 0.358, standard deviation is 0.084, and the minimum and maximum values are -1.176 and 1.747, respectively, which indicates that the current distribution of the level of sustainability performance of the enterprise is within a reasonable range. The remaining nine items are control variables whose data distribution meets the standard requirements of this research and can be analyzed for subsequent research.

Table 2. Descriptive statistical results of variables

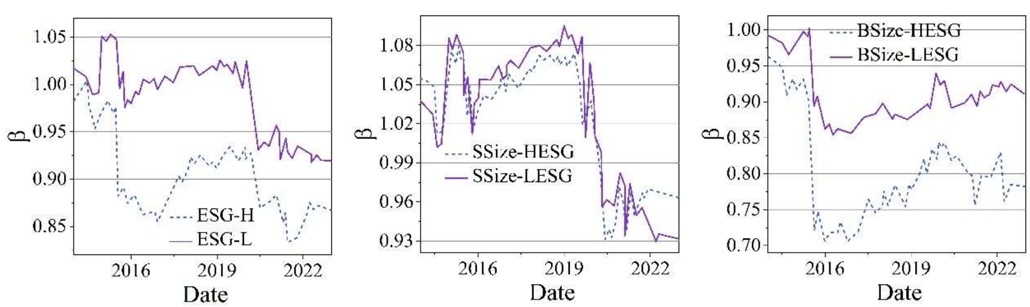
Variable name	Number of samples	Mean value	Standard deviation	Minimum value	Maximum value
SP	5320	0.358	0.084	-1.176	2.287
ESG	5320	0.274	0.094	-1.296	1.747
ROA	5320	4.495	0.989	0.995	7.245
LEV	5320	0.034	0.044	0.005	0.289
SIZE	5320	-0.248	0.286	-0.825	0.447
MH	5320	0.008	0.018	-0.007	0.027
AGE	5320	0.049	0.017	0.019	0.136
FCF	5320	0.469	0.188	0.041	0.916
RET	5320	0.056	0.066	-0.267	0.247
PPE	5320	2.875	0.337	1.378	3.605
DU	5320	-0.029	0.256	-1.937	1.286

4.1.2. Correlation analysis. After the descriptive statistical analysis of the research variables set above, the correlation analysis of the relationship of the variables is carried out next with the help of Pearson's correlation coefficient and the results of the correlation analysis of the research variables are shown in Table 3, where the CPP value denotes the Pearson's correlation coefficient, the N value denotes the sample size and the P denotes the significance value. The data show that the Pearson correlation coefficients of the explanatory variables ESG disclosure quality on sustainability performance (SP), profitability (ROA), gearing ratio (LEV), firm size (SIZE), management shareholding (MH), age of the firm (AGE), free cash flow ratio (FCF), return on equity (RET), proportion of fixed assets (PPE), and concurrent board of directors (DU) have Pearson's correlation coefficients of 0.582, 0.624, 0.655, 0.677, 0.635, 0.306, 0.383, 0.639, 0.341, and 0.67 in that order, and the corresponding P (significance value) is <0.05, which summarizes that the explanatory variables are significantly correlated with each variable.

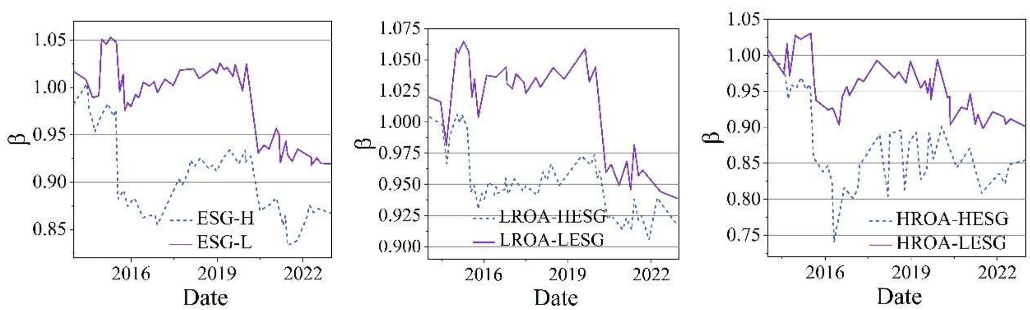
Table 3. The results of correlation analysis of variables were studied

Index		SP	ESG	ROA	LEV	SIZE	MH	AGE	FCF	RET	PPE	DU
	N	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320
SP	PCC	1	0.582	0.624	0.655	0.677	0.635	0.306	0.383	0.639	0.341	0.67
	P		0.041	0.033	0.035	0.001	0.03	0.016	0.03	0.05	0.024	0.001
	N	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320
ESG	PCC	0.582	1	0.354	0.78	0.664	0.4	0.754	0.58	0.449	0.568	0.36
	P	0.041		0.002	0.035	0.021	0.018	0.047	0.012	0.017	0.009	0.015
	N	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320
ROA	PCC	0.624	0.354	1	0.36	0.773	0.79	0.732	0.687	0.698	0.469	0.38
	P	0.033	0.002		0.01	0.026	0.039	0.031	0.031	0.032	0.012	0.035
	N	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320
LEV	PCC	0.655	0.78	0.36	1	0.329	0.639	0.731	0.728	0.683	0.319	0.307
	P	0.035	0.035	0.01		0.04	0.013	0.044	0.03	0.039	0.004	0.025
	N	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320
SIZE	PCC	0.677	0.664	0.773	0.329	1	0.329	0.639	0.731	0.728	0.683	0.319
	P	0.001	0.021	0.026	0.04		0.008	0.034	0.023	0.018	0.01	0.022
	N	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320
MH	PCC	0.635	0.4	0.79	0.639	0.329	1	0.307	0.686	0.635	0.566	0.326
	P	0.03	0.018	0.039	0.013	0.008		0.035	0.036	0.022	0.045	0.011
	N	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320
AGE	PCC	0.306	0.754	0.732	0.731	0.639	0.307	1	0.512	0.71	0.431	0.456
	P	0.016	0.047	0.031	0.044	0.034	0.035		0.034	0.03	0.015	0.003
	N	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320
FCF	PCC	0.383	0.58	0.687	0.728	0.731	0.686	0.512	1	0.512	0.71	0.431
	P	0.03	0.012	0.031	0.03	0.023	0.036	0.034		0.037	0.011	0.048
	N	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320
RET	PCC	0.639	0.449	0.698	0.683	0.728	0.635	0.71	0.512	1	0.573	0.377
	P	0.05	0.017	0.032	0.039	0.018	0.022	0.03	0.012		0.032	0.006
	N	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320
PPE	PCC	0.341	0.568	0.469	0.319	0.683	0.566	0.431	0.71	0.573	1	0.561
	P	0.024	0.009	0.012	0.004	0.01	0.045	0.015	0.71	0.032		0.039
	N	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320	5320
DU	PCC	0.67	0.36	0.38	0.307	0.319	0.326	0.456	0.431	0.377	0.561	1
	P	0.001	0.015	0.035	0.025	0.022	0.011	0.003	0.048	0.006	0.039	

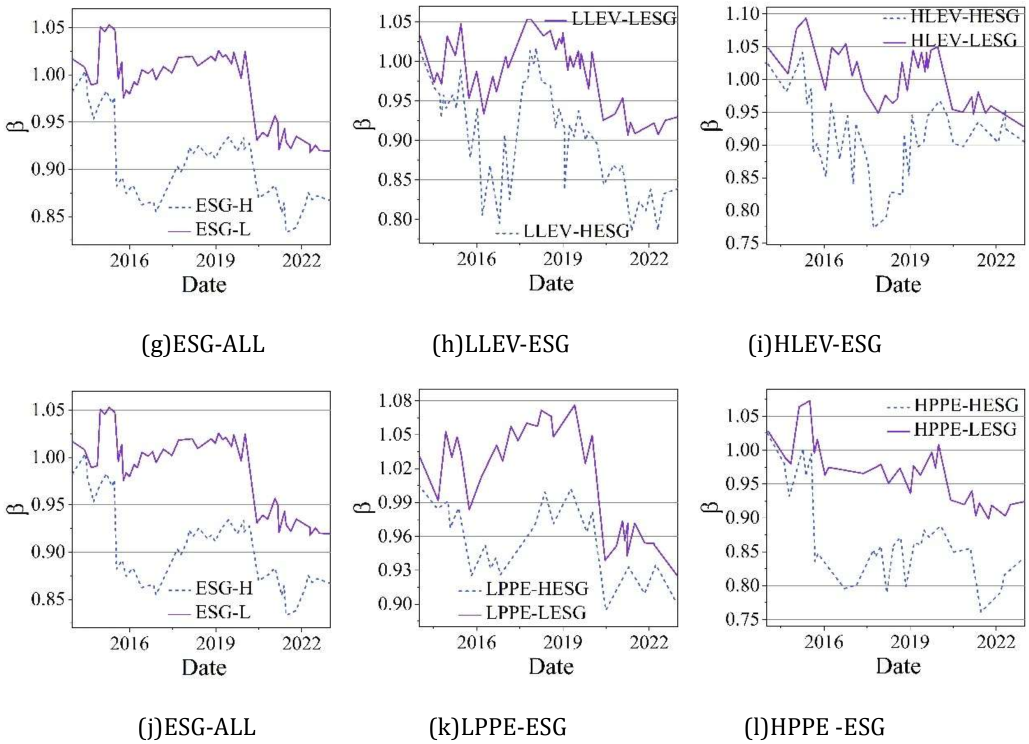
4.1.3. Interaction analysis. In this subsection, four control variables are selected from the nine control variables, namely, firm size (Size), profitability (ROA), gearing ratio (LEV), and proportion of fixed assets (PPE), to explore the effects of the control variables together with the explanatory variables on the explained variables. Figure 2 demonstrates the characteristics of the impact of ESG disclosure quality on sustainability performance, where (a) to (l) denote ESG -ALL, SSIZE -ESG, BSIZE -ESG, ESG -ALL, SSIZE -ESG, BSIZE -ESG, ESG -ALL, LLEV -ESG, HLEV -ESG, LPPE -ESG, respectively, HPPE -ESG, and Figure β indicates the estimated quantities. Thus, to observe the impact of ESG disclosure quality on sustainability performance, the first row reports the moderating effect of firm size (Size) on the impact of ESG disclosure quality on sustainability performance, and the three subfigures correspond to the impact of ESG disclosure quality on sustainability performance under the full-sample group, the small firms group, and the large firms group, respectively. As shown by the results in the first row, overall, the sustainability performance of ESG disclosure quality is lower in the large firms than in the small firms group, which is consistent with the previous analysis. In addition, the difference in sustainability performance between high and low ESG disclosure quality is not significant in the small firms group, while the difference in sustainability performance between high and low ESG disclosure quality is significant in the large firms group group, i.e., the sustainability performance of high ESG disclosure quality is less than that of low ESG disclosure quality. The possible explanation for this result is that since small firms are more cyclical and less liquid, which leads to higher cost of capital and greater bankruptcy risk for small and small firms, so at this point in time, in the small firm group group, investors pay more attention to predictable fundamental risks such as liquidity risk and bankruptcy risk, and the focus on firms' sustainability performance will be weaker. The second, third, and fourth rows report the interaction effects of ESG disclosure quality and profitability (ROA), gearing ratio (LEV), and proportion of fixed assets (PPE) on sustainable performance, respectively, and the main result is similar to that of the first row, in that the difference between the sustainable performance of high and low ESG disclosure quality is only revealed when the underlying data is low. This result suggests that the sustainable performance of low ESG disclosure quality is still greater than the sustainable performance of high ESG disclosure quality after the interaction analysis, which indicates that ESG disclosure quality can represent certain potential sustainable performance crises related to policy risk, environmental risk, social risk, and stakeholders.



(a)ESG-ALL (b)SSIZE-ESG (c)BSIZE-ESG



(d)ESG-ALL (e)LROA-ESG (f)HROA-ESG



(g)ESG-ALL (h)LLEV-ESG (i)HLEV-ESG

(j)ESG-ALL (k)LPPE-ESG (l)HPPE -ESG

Fig. 2. The impact of ESG disclosure quality on sustainability performance

4.2. Bayesian analysis

In the previous section, the relationship between corporate ESG disclosure quality and sustainability performance was empirically analyzed with the help of mathematical statistics knowledge. In this section, Bayesian network will be used to achieve forward prediction and backward diagnosis to comprehensively analyze the influential relationship between corporate ESG disclosure quality and sustainability performance.

4.2.1. Modified Bayesian networks. Bayesian networks are constructed by focusing on observable variables, i.e., manifest variables, and predicting probability distributions at future times from available data. For a complex system, the true state of the system cannot be determined and it is not possible to observe all aspects of the system, so for certain unobservable variables, i.e. latent variables, structural equation modeling can be measured by explicit variables that can be directly observed, so that it is easy to construct a clear and universally correct relationship between the variables of the model, which allows for a more comprehensive and fuller understanding of the concepts in an environment of uncertainty. The nodes created in a Bayesian network are all observable variables, and it constructs a path diagram through the causal relationships between the nodes, and calculates the joint probability of all nodes based on the prior probability distribution of the root node and the conditional probability distribution of the non-root nodes in the Bayesian network. There is only one type of node in the Bayesian network model i.e. chance nodes, which are observable variables. It denotes preorder nodes and successor nodes depending on the direction of the directed arcs between the nodes.

The model of the impact of corporate ESG disclosure quality on sustainability performance is shown in Fig. 3.This subsection combines the results of the above empirical analysis and establishes a Bayesian network model of the relationship between corporate ESG disclosure quality and sustainability performance, and this model represents the relationship between the impact of corporate ESG disclosure quality and sustainability performance.

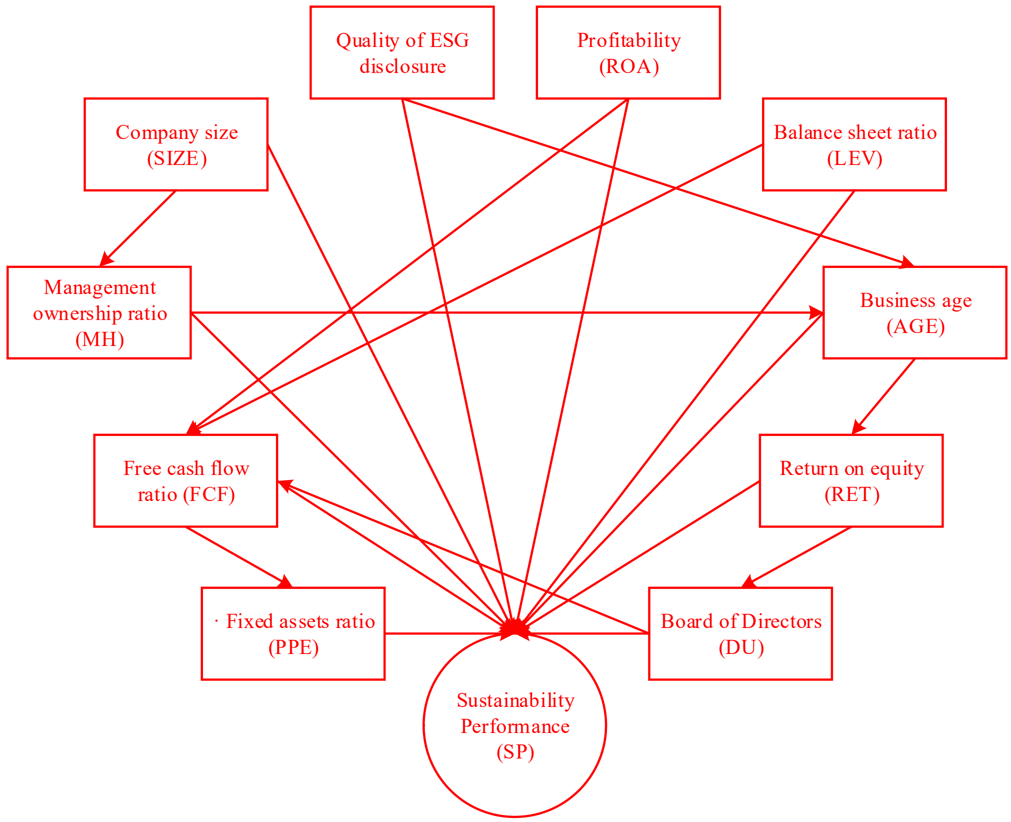


Fig. 3. The impact of corporate ESG disclosure quality on sustainability performance

4.2.2. Constructing conditional probability tables. The data results of corporate ESG disclosure quality and sustainability performance obtained from data collection are averaged and rounded, and the results are used as scores for each item of corporate ESG disclosure quality and sustainability performance, which have the same weights, and the average of their scores is calculated and then rounded, which is the value of the variable. Each item of data is categorized into three states: Poor, Average, and Good. The Bayesian relationship between variables can be quantified by conditional probabilities, which are also known as beliefs on relationships, usually denoted by CPT. The processed data are imported into the Bayesian network model in Netica software, and the conditional probabilities of each node are obtained directly through case study, and Table 4 shows the conditional probability table. For example, the parent nodes of enterprise age (AGE) are management shareholding ratio (MH) and ESG disclosure quality, and management shareholding ratio (MH) and ESG disclosure quality all have three states, so they can be combined into nine cases.

Table 4. Conditional probability

MH	ESG	Poor	Average	Good
Poor	Poor	81.629	15.514	2.857
Poor	Average	59.803	35.681	4.516
Poor	Good	15	70	15
Average	Poor	37.732	56.846	5.422
Average	Average	40.781	36.604	22.615
Average	Good	5.131	25.605	69.264
Good	Poor	32.666	49.279	18.055
Good	Average	6.421	21.225	72.354
Good	Good	0.435	6.851	92.714

4.2.3. Probability assessment. Based on the conditional probability table, a Bayesian network graph of the relationship between the quality of corporate ESG disclosure and the impact of sustainability performance was generated in Netica software, and Figure 4 shows the Bayesian network. The sum of the three states of each node of the survey data is 100%, and the analysis of each node of the Bayesian network shows that the age of the enterprise (AGE) evaluates the variables better, and the percentage of those who think that the level of each variable is good is more than 49%, and among them, 63.5% think that the level of the balance sheet ratio (LEV) is good, 16.7% think that it is average, and 19.8% think that it is poor. This shows that the quality of corporate ESG disclosure and sustainability performance is more important among investors, but only 49.3% think that the sustainability performance is in a good state, so this also means that there is still a lot of room for improvement in corporate sustainability performance.

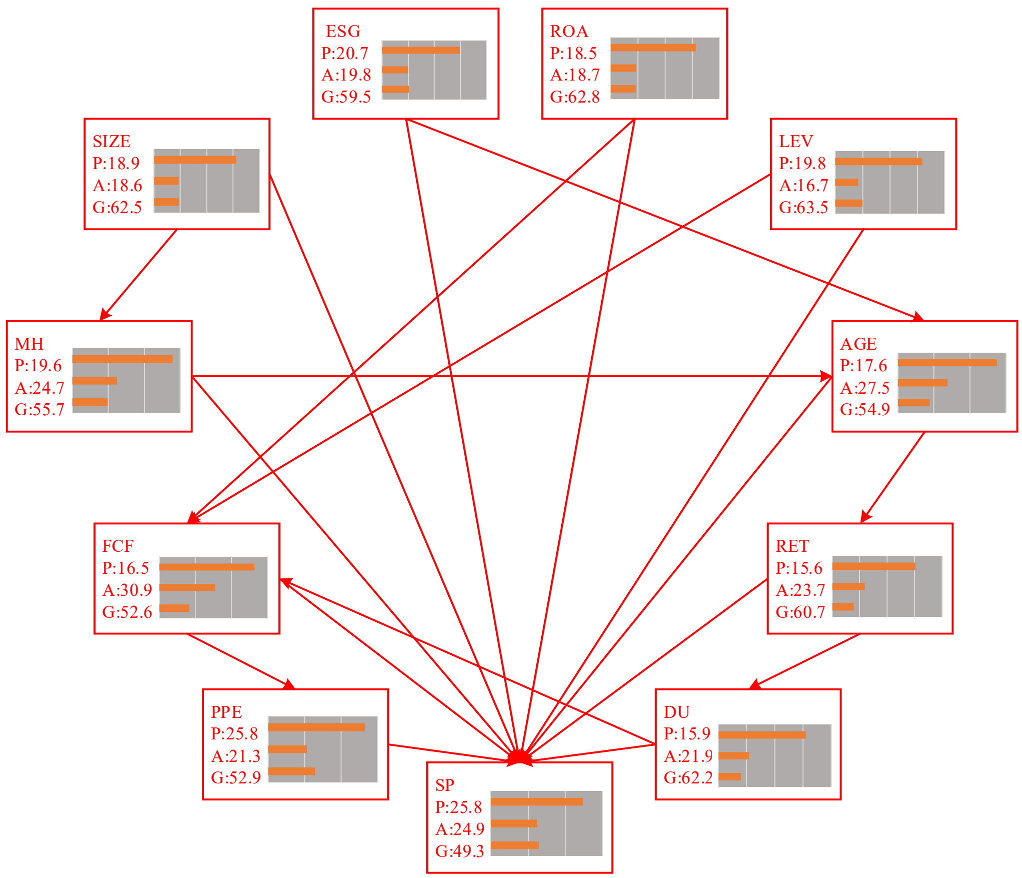


Fig. 4. Bayesian network

4.2.4. Bayesian reasoning. The relationship of corporate ESG disclosure quality on sustainability performance is analyzed through the established Bayesian network, and effective corporate ESG disclosure quality is searched through the prediction and diagnosis of the Bayesian network. Predictive inference refers to projecting the probability of a query variable by using the variable states of the nodes in the Bayesian network, and this is often referred to as forward inference.

1) A simple strategy for a single leading factor change. The change state of the quality node of enterprise ESG disclosure in the tree-enhanced naïve Bayes network can predict the probability distribution of other nodes related to it. By changing the states of the explanatory variables and control variables, the probability of the corresponding quality nodes of corporate ESG disclosure and the probability of sustainability performance nodes in different states can be predicted, and different corporate ESG disclosure quality control strategies can be formulated according to the evaluation

results to identify the best choice. Table 5 shows that when the probability of improving the quality of corporate ESG disclosure is 100%, and the probability of other variables remaining unchanged, the probability of improving the quality of corporate ESG disclosure has the greatest degree of improvement on sustainability performance, and the probability of sustainability performance being in a good state is 58.7%.

Table 5. The impact probability of ESG disclosure quality on sustainability performance

Change node	SP initial value			SP node probability		
	Poor	Average	Good	Poor	Average	Good
FCF	25.8	24.9	49.3	20.6	20.7	58.7
ROA				24.6	24.7	50.7
ESG				22.7	22.8	54.5
RET				21.8	21.9	56.3
PPE				20.7	20.8	58.5
DU				21.9	21.9	56.2
MH				21.9	21.9	56.2
AGE				20.9	20.9	58.2
SIZE				22.6	22.7	54.7
LEV				22.8	22.9	54.3

2) Backward reasoning. Backward reasoning is the process of analyzing and reasoning about a node from the outcome to the cause, and predicting the probability distribution of the cause by changing the outcome of the node, which is the process of backward reasoning, also known as diagnosis. When the probability of sustainability performance being in a good state is 100%, the probability of each state of the variable is shown in Table 6. When the probability of sustainability performance being in a good state is 100%, the probability of board concurrent office (DU) being in a good state is the highest, with 72.3% probability of being in a good state, and the specific probability data are all over 60%.

Table 6. The probability of each state of a variable

Variable	State	Probability(%)
Free cash flow ratio (FCF)	Poor	11.4
	Average	23.6
	Good	65
Profitability (ROA)	Poor	15.7
	Average	17.6
	Good	66.7
Quality of ESG disclosure	Poor	14.6
	Average	15.9
	Good	69.5
Return on equity (RET)	Poor	10.8
	Average	18.4
	Good	70.8
Fixed assets ratio (PPE)	Poor	18.7
	Average	17.6
	Good	63.7
Position on the Board of Directors (DU)	Poor	10.9
	Average	16.8
	Good	72.3
Management ownership ratio (MH)	Poor	13.6
	Average	21.6
	Good	64.8
Business AGE (AGE)	Poor	11.9
	Average	21.6
	Good	66.5
Company SIZE (SIZE)	Poor	12.9
	Average	14.9
	Good	72.2
Balance sheet ratio (LEV)	Poor	13.8
	Average	14.7
	Good	71.5

5. Conclusion

This paper combines relevant references and selects the explanatory variables, explanatory variables, and control variables, a total of 11 variables to form the research variables. The research sample and data sources are identified, and the mathematical and statistical theory and Bayesian network theory are synthesized to jointly explore the interaction between corporate ESG disclosure quality and sustainability performance. In the process of analyzing the interaction between the two under the condition of the control variable (firm size), the sustainability performance generated by low ESG disclosure quality is superior to the sustainability performance generated by high ESG disclosure quality. In addition, the other three control variables (profitability, gearing ratio fixed asset ratio) show the same phenomenon. Then, with the help of Bayesian network to achieve forward prediction and backward diagnosis, the relationship between the two influences is investigated in all aspects, and it is concluded that 49.3% of the investors believe that the sustainability performance is in the good rank level, and the probability of sustainability performance being in a good state is increased to 58.7% by changing the state of the explanatory variables and the control variables. Assuming that the probability of sustainability performance being in a good status is 100%, the board concurrent appointment (DU) has the highest probability of being located in a good status, as demonstrated by the specific data of 72.3%. This study provides a fresher perception of the mechanism of corporate ESG disclosure quality and sustainability performance role for high quality sustainable development.

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