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Assessment Methods for ESG Information Disclosure Quality and Investor Behavior in the Renewable Energy Industry

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Abstract. In emerging nations, there's a growing wave of Environmental, Social, and Governance (ESG) reporting. ESG disclosure aimed to meet the informational needs of all stakeholders of the company, with a particular focus on investors. Industries are becoming increasingly engaged in sustainability initiatives as a result of global resource scarcity and inequality. 365 Chinese investors were carefully chosen using the convenient sampling technique. The research study has analyzed the influence of investor behavior on ESG (Environmental, Social, and Governance) information disclosure and also the role of risk tolerance in mediating the relationship between investor behavior and sustainable development within the new energy sector in China. The results were obtained through analyzing Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA) by contributing Python software. The outcomes revealed that ESG factors have a significant effect on Investor's behavior. Also, Risk tolerance as a mediating variable has a significant effect on investor behavior and sustainable development in the new energy industry. The hypothesis with the variables are passed into the DL strategy that involves two classifiers like DCNN and LinkNet. These models classifies that whether the investor is likely to prioritize ESG concern in investment decision or not and determines the sustainable development in the new energy industry.

Key words. ESG, Risk Tolerance, Renewable Energy Industry, Sustainable Development, Legitimacy Theory.

1. Introduction

The incorporation of ESG disclosure in evaluating investment options has emerged as a significant global trend in recent times. This upward trend is anticipated to imply transparency regarding the societal and environmental impacts of corporate actions and governance structures. Additionally, it may prompt adjustments to internal control systems, further enhancing information compliance and reliability. The increasing interest from both domestic and foreign investors, along with the financial risks and opportunities it presents, has fueled the growing demand for enhanced ESG disclosure [1]. ESG factors are progressively becoming integral to investors' decision-making processes.

Three primary groups of investors consider ESG disclosure practices for various reasons. Financial motivations include compliance with regulatory frameworks and risk mitigation, understanding potential factors affecting financial performance, and enhancing long-term returns [2]. Investors driven by ethical and values-based considerations prioritize positive social and environmental impacts, aligning their investments with responsible practices. Factors such as management reputation and societal impact allow investors to promote positive change while maintaining ethical and sustainable reputations [3]. Lastly, strategic and competitive advantages include differentiation from competitors, attracting a broader investor base, and fostering increased investor engagement through transparent ESG disclosures [4].

Sustainable development promotes mutual growth between humans and the environment, with long-term consequences for achieving sustainable goals. In response to the growing demand for ESG investments, the financial services industry has introduced ESG-focused exchange-traded funds (ETFs) and other initiatives [5]. The rapid development of the new energy industry has significantly contributed to efforts aimed at addressing environmental pollution and climate change [6]. As the new energy sector emerges as the future, many nations and regions are vigorously advancing this promising industry to gain a competitive edge in the market (Xu & Lin, 2018). Chinese new energy companies have garnered attention from the capital market, with environmental, social, and corporate governance (ESG) considerations becoming integral to investors' strategies for these companies [7].

Previous empirical research has recommended the assessment of ESG factors as a means of enhancing investment opportunity selection [8], [9]. Nevertheless, while considerable examination has been directed at the application of ESG and its effect on a company's economic performance at a macro level, limited attention has been given to the importance investors attribute to ESG factors while taking investment options. Despite evidence showing that each of the proponents and non-proponents of ESG practices has an optimistic effect on investment outcomes, this research found variations in investor behavior regarding ESG considerations in their investments. To address this gap in the literature, our study focused on examining the influence of investors' behavior toward ESG factors on their investment allocation decisions. Furthermore, the study highlights a direct correlation between achieving sustainable outcomes and an increase in disclosure practices related to ESG. Additionally, it investigates the role of risk tolerance in mediating the relationship between investor behavior and sustainable development within the new energy sector in China. From these objectives, we derived the following research questions:

RQ1: How does investor behavior influence the quality of ESG (Environmental, Social, and Governance) information disclosure?

RQ2: Does risk tolerance mediate the relationship between investor behavior and sustainable development within the new energy industry in China?

The paper follows a structured format, beginning with a literature review in the second section, followed by practical studies and the exposition of the conceptual structure, which leads to the development of hypotheses. The third part delineates the research methodology employed. Subsequently, in the fourth segment, the study's results are presented. Lastly, the fifth segment encompasses the conclusion, along with the limitations and implications of the study.

2. Literature Review

As a vital element of corporate social responsibility disclosure, the environment, society, and governance have garnered increased attention from businesses worldwide and their stakeholders. This focus has facilitated the development of sustainable strategies that are expected to influence future business growth. Zhang et al. [10] suggested that disclosing social and environmental information is crucial for enhancing a company's value, with their study aiming to explore the impact of social responsibility information transparency on firm value. Furthermore, by integrating ESG factors with the green revolution within a combined outline, analyzing their combined effect on firm value, and examining the communication outcome between overall invention and inclusive social accountability on firm value, their research expands upon previous research.

Institutional regulations aimed at bolstering the legitimacy of businesses' disclosure of ESG issues are referred to as ESG reporting guidelines. Darnall et al. [11] investigated whether companies adhering to ESG reporting guidelines disclose more sustainability-related information. These guidelines provide businesses with a clear framework for publicly disclosing sustainability information. According to Romito & Vurro [12], companies that publish sustainability reports but do not adhere to ESG reporting guidelines disclose 39% less sustainability information compared to companies that follow these guidelines. However, compared to Verification centered on content, which is further successful in reassuring process-focused verification, information disclosure is prioritized in the majority of international ESG reporting guidelines. Their findings raise important questions about the preference for verification that is process-focused over the verification that is content-focused among global developers of ESG standards and suggests that companies seeking to differentiate themselves in the sustainability arena through ESG reporting could benefit from advocating for stronger verification methods.

Chouaibi et al. [13] analyzed how board composition influences the quality of integrated reporting among European companies listed in the ESG index. The directors' board's main responsibility is to create tactics to enhance the worth of the company's investors. Research in corporate governance has shown that board independence enhances investment efficiency by reducing tunneling, particularly through high-quality disclosure of information [14]. Their empirical results show that diversity, independence, and board size all have a substantial effect on the eminence of integrated reporting, underscoring the importance of these factors for directors, stakeholders, and officials. Stakeholders must contemplate disclosure correctness when selecting the most effective reporting approach.

Helfaya et al. [8] utilized Hofstede's measurements to examine ESG disclosure practices in Europe, focusing on the effects of the board's corporate social responsibility (CSR) strategy and orientation, GRI (Global Reporting Initiative), and country-cultural dimensions. Employing a quantitative research methodology, by statistically analyzing 7840 observations from European companies, they tested hypotheses and evaluated the connection between macro and micro variables and ESG disclosure. Data for the European dataset was sourced from Bloomberg and Refinitiv Eikon. Their findings indicate that both GRI and the board's CSR approach and positioning significantly impact the complete disclosure of ESG in Europe.

Jiang HAN, [15] has employed deep user sequence data, enhancing LSTM for investment prediction. LSTM was chosen based on user behavior sequences and circular network structure. Model parameters were optimized, and a method integrating behavioral asset price models was proposed for stock market prediction. Empirical analysis and backtesting confirmed the model's efficacy in predicting stock trends and user behavior, showcasing its applicability in multidimensional data analysis. Jingjian Sia et al., [16] has studied the attention on risk spillover within the energy stock market was prominent in energy finance research, assisting investors in managing risks. A fresh forecasting approach was presented, utilizing shared investor concerns to forecast risk spillover among listed energy firms. Outcomes demonstrated enhanced predictive accuracy with the introduced deep neural network employing a tailored loss function.

Nan Jing, et al., [17] has introduced a hybrid model that merged deep learning with sentiment analysis for stock price prediction. Utilizing a Convolutional Neural Network (CNN), we classified investors' hidden sentiments from a major stock forum. This sentiment analysis was combined with technical indicators using the Long Short-Term Memory (LSTM) Network. Moreover, the real-life experiments across industries and time intervals on the Shanghai Stock Exchange validated the model's effectiveness. Results showed superior sentiment classification and stock price prediction contrasted to baseline classifiers and models without sentiment analysis. The findings suggest that regulators and standard-setters should focus on enhancing investors' insights into the importance and accuracy of ESG information when imposing future disclosure requirements.

A. Hypothesis

Hypotheses play a crucial role, serving as a guide for designing experiments and gathering data to support or refute them. Consider five hypothesis like H1, H2, H3, H4 and H5 which represents Environmental Factors have a substantial influence on Investor behavior, Social Factors have a substantial influence on Investor behavior, Governance Factors have a substantial influence on Investor behavior, Investor behavior has a substantial relation to Sustainable development and Risk Tolerance mediates the connection between Investor behavior and Sustainable development, respectively.

B. Proposed Conceptual Framework

The hypothesis like H1, H2, H3, H4 and H5 that indicates Environmental factors, Social factors, Governance factors, Investor behaviour and Risk tolerance, respectively, which are passed into the classifiers such as DCNN and Linknet. The DCNN and Linknet models train these hypothesis and the average result classifies whether the investor is likely to prioritize ESG concern in investment decision or not. Thus, this framework determines that the ESG information disclosure quality and investor behaviour in the new energy industry is sustainable development. The proposed investigation looks into the association between investors' behaviors concerning ESG factors, as depicted in Figure 1.

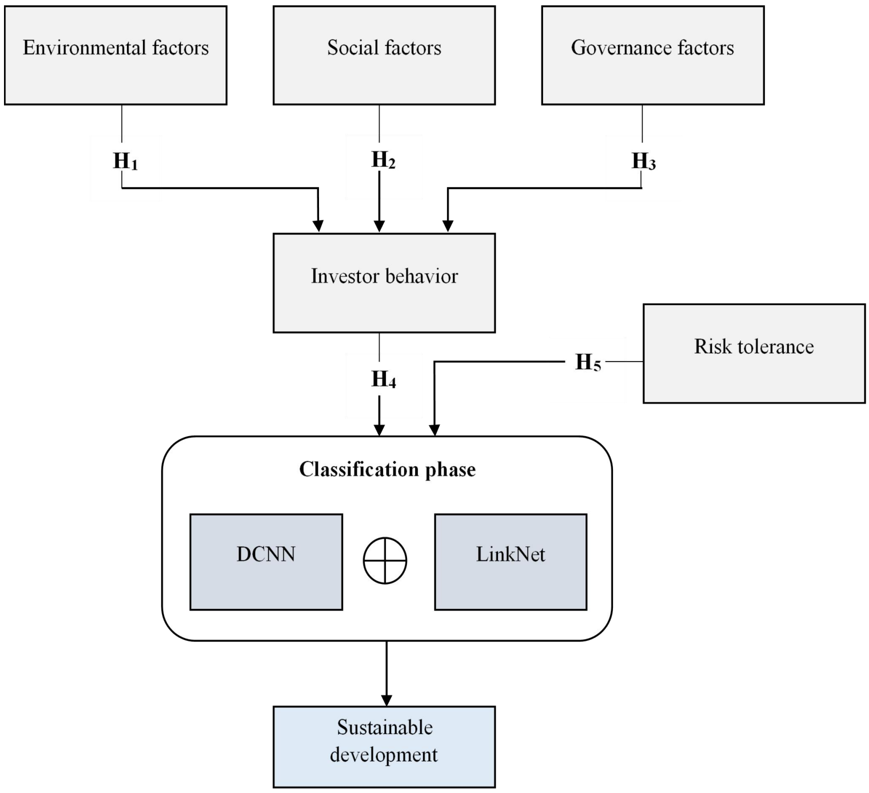


Fig. 1. Hypothesis Background

3. Research Methodology

A. Data Collection

The process of collecting information and sampling for this study involved participants from investors in China's new energy industry. These investors were invited to complete a comprehensive survey covering various aspects of their investment behavior, ESG disclosure practices, risk tolerance, and sustainability perspectives. Utilizing a convenient sampling technique, 420 questionnaires were distributed, resulting in 356 valid responses. Of these, 64 were found to lack essential data. Consequently, the final sample size of 356 participants was established, and rigorous validation measures were applied to settle the validity and reliability of the survey items. This investigation employed a combination of descriptive and quantitative methodologies to analyze the collected data. Specifically, an online survey platform facilitated the selection of 356 investors from Chinese companies listed under the new energy industry sector. The decision to concentrate on Chinese investors was deliberate, driven by the acknowledgment of China's pivotal role as a developing nation in the context of the new energy industry.

B. Variables

Investor behavior plays a crucial role in shaping the landscape of sustainable development, driven by various factors encompassing environmental, social, and governance considerations. Environmental factors (EF) underscore an investor's awareness of climate-related risks (EF1) and inclination towards eco-friendly solutions like solar energy (EF2), alongside a commitment to improving performance, transparency, and accountability in environmental practices (EF3) [18]. Social factors (SF) highlight priorities concerning employee well-being (SF1), consumer health and safety through clean energy production (SF2), and a steadfast belief in upholding fundamental human rights conventions (SF3) [19]. Governance factors (GF) emphasize the advocacy for board independence and accountability (GF1), transparency through financial reporting (GF2), and adherence to information disclosure policies and compliance matters (GF3) [20]. Investor behavior (IB) reflects a growing demand for addressing Environmental, Social, and Governance (ESG) concerns in investment decisions (IB1), prioritizing social or environmental impact in ESG criteria (IB2), and seeking access to comprehensive annual reports for informed investment choices (IB3) [7]. Sustainable development (SD) aspirations are evident through interests in sustainability-linked bonds (SD1), promoting corporate ESG improvement programs (SD2), and advocating for dedicated board-level committees overseeing sustainability in emerging energy sectors (SD3) [18]. Risk tolerance (RT) influences investment strategies, with considerations ranging from business risk assessments (RT1) to acknowledging elevated risks associated with evolving energy policies, prices, and regulations (RT3), while rejecting the notion of risk-free investments (RT2) [21]. Collectively, these variables reflect a nuanced interplay between investor preferences, sustainability imperatives, and risk management strategies, underscoring the evolving landscape of responsible investing.

C. Analysis

Following an initial exploration of features of the population using SPSS, this investigation progressed to evaluate the reliability of measuring items through the application of Cronbach's α coefficient. This crucial stage is expected to confirm the consistency of the gathered data. Upon confirming reliability, the investigation proceeded to Python software for analyzing Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA). Through the utilization of SEM and CFA, the study scrutinized correlations in the hypothesis amid various constructs. A comprehensive understanding of the relations among variables was made possible by this sophisticated rational method, which also offered a nuanced examination of the fundamental aspects prompting the hypothesis in this research. The incorporation of SPSS and Python software into the data analysis method was crucial in carrying out an exhaustive analysis of the objectives of study as well as hypotheses, consequently augmenting the resilience as well as validity of the study outcomes.

D. Classification

As stated before, the classification phase takes input features like Environmental factors, Social factors, Governance factors, Investor behaviour and Risk tolerance; and the above stated variables. The classification phase involves two classifiers like DCNN and Linknet that individually takes the input and train it, as illustrated in Figure 2. Moreover, the weight of the DCNN is optimally tuned via SE-RFO algorithm. The outcome of both classifiers are subjected to take average that predicts whether the investor is likely to prioritize ESG concern in investment decision or not. This can predicts the output as '1', '2', '3', '4', and '5' indicates "Strongly disagree, Disagree, Neutral, Agree and strongly agree", respectively.

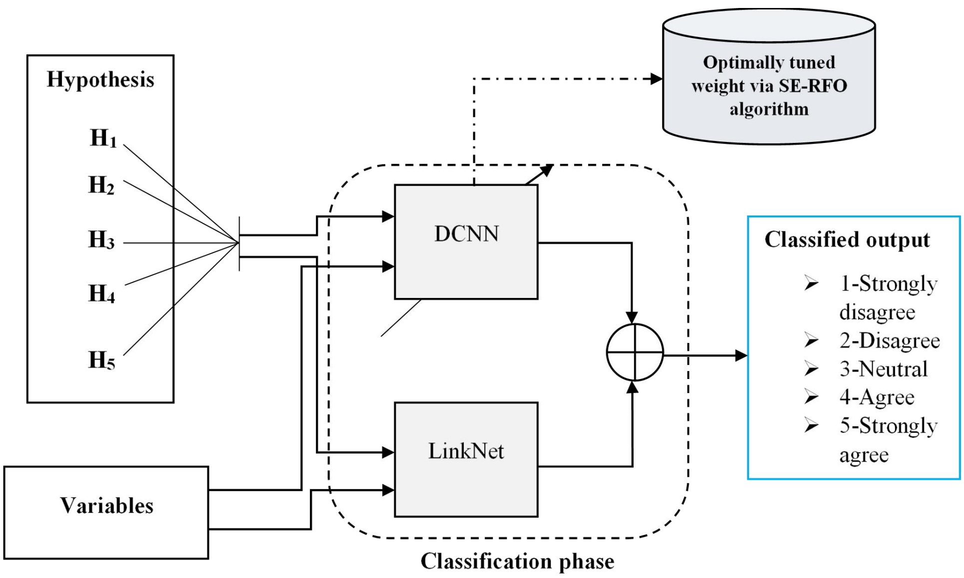


Fig. 2. Flow of Classification Phase

1) DCNN

DCNN stands for Deep Convolutional Neural Network, which is a type of artificial neural network that automatically learn hierarchical representations of hypothesis [22]. The structure of DCNN involves "input layer, convolutional layers, activation function, pooling layers, fully connected layers and output layer". the input layer considers as input and passed the input into convolutional layers. this layer apply a series of learnable kernels to the input. Each filter convolves over the input, extracting local patterns and features. This layer involves the weight parameter that are learned during the training process. Each neuron in the network has associated weights that determine how it responds to the input data. During training, the weights are optimally tuned using SE-RFO algorithms with the factors like time, cost and efficiency. Thus, this network minimizes the difference among the predicted as well as the actual output. By stacking multiple convolutional layers, the network can learn increasingly complex features. Following each convolution operation, an activation function is applied element-wise to introduce non-linearity into the network. Subsequently, pooling layers downsample the feature maps produced by convolutional layers, reducing the spatial dimensions. Further, these feature maps are flattened into a vector. This layer allow the network to learn global patterns and relationships in the data. Finally, the output layer produces the classification based on the learned features.

2) LinkNet

LinkNet is a CNN architecture specifically designed for classification task that involves "encoder, linking layers, decoder, skip connection and output (Final classification)"[23]. LinkNet employs an encoder-decoder architecture, with an encoder section for feature extraction. The encoder typically consists of a pre-trained CNN with its final layers modified or replaced. The encoder processes the input hypothesis and extracts high-level feature representations. Additionally, the LinkNet introduces linking connections between encoder layers and decoder layers to improve feature reuse and information flow. These linking layers connect corresponding feature maps from the encoder to the decoder, helping to preserve spatial information. Conversely, the decoder section of LinkNet is responsible for upsampling the feature maps and generating segmentation masks. It typically involves a sequence of upsampling layers followed by convolutional layers to refine the predictions.

In addition to the linking connections, LinkNet also employs skip connections between the corresponding encoder as well as decoder layers. Skip connections facilitate the flow of low-level and high-resolution information from the encoder to the decoder, aiding in precise localization. At the end of the decoder, a final classification layer gives the classification result. This layer typically consists of a convolutional layer with softmax activation for multi-class semantic calssfiication.

3) Objective Function

The objective function applies for optimal weight tuning of DCNN considers three factors such as time, cost and effciency. The objective function for proposed SE-RFO algorithm is minimization function. Then, the objective function is defined as in Eq. (1). Here, f_1 refers to time, f_2 refers to cost, and f_3 refers to efficiency. Also, W indicates weight such that $\sum_{i=1}^{3} w_i = 1$.

$$ObF = \min\left[w_1 * (f_1) + w_2 * (f_2) + w_3 * (f_3) \right] \tag{1}$$

4) Proposed SE-RFO Algorithm for Optimal Weight Tuning of DCNN

The RFO population comprises individuals occupying established territories as well as those adopting a nomadic lifestyle [24]. A proficient hunter of small animals, whether domestic or wild, the fox seizes every opportunity for sustenance while moving through its territory. It stealthily approaches its prey, patiently closing the distance before launching an effective attack. In oredr to enhance the convergence and speed, this work adopts a new SE-RFO algorithm that optimally tune the weights of DCNN model. The pseudocode of SE-RFO algorithm is shown in Algorithm 1.

Fundamental Principle Guiding the Algorithm: In subsequent iterations, the fox (weight) population remains constant, each fox represented as a point $\overline{R} = (R_1, R_2, \ldots R_{n-1})$. Foxes navigate the solution space using given equations to seek optimal values for the criterion function $f \in \mathbb{R}^n$. The notation $(\overline{R})^{(i)} = \left[(R_0)^{(i)}, (R_1)^{(i)}, \ldots, (R_{n-1})^{(i)} \right]$ represents each point in the space $\langle b, a \rangle^n$ where $b, a \in \mathbb{R}$.

Global Search Stage: In a fox herd, each member plays a crucial role for family survival. When local resources run low or for territorial exploration, members journey to distant areas, sharing gathered knowledge to aid survival. Land exploration prioritizes based on individual fitness. The most fit fox explores and shares findings with the family. Population is sorted by fitness, and the squared Euclidean distance to each individual is calculated for the individual as in Eq. (2) and the individuals in the population are directed towards the optimal solution as in Eq. (3). Here, $\delta \in \left(0, d\left(\overline{R}^i \right)^t, \left(\overline{R}^{Bst} \right)^t \right)$ (i.e. in each iteration, a scaling hyperparameter set is randomly chosen and applied uniformly to all individuals in the population).

$$d\left(\left(\overline{R}^i \right)^t, \left(\overline{R}^{Bst} \right)^t \right) = \sqrt{\left\| \left(\overline{R}^i \right)^t - \left(\overline{R}^{Bst} \right)^t \right\|} \tag{2}$$

$$\left(\overline{R}^i \right)^t = \left(\overline{R}^i \right)^t + \delta sign\left(\overline{R}^{Bst} \right)^t - \left(\overline{R}^i \right)^t \tag{3}$$

Local Search Stage: In the hunting process, when a potential prey is spotted, the fox stealthily approaches without raising suspicion, circling and deceiving the prey to appear uninterested in hunting. However, once at close proximity, the fox swiftly moves to surprise and attack. In the Red Fox Optimization (RFO), observation and deceptive movement during hunting are modeled into a local search phase. To account for the possibility of the fox being noticed while nearing the prey, a random value $\mu \in \langle 0,1 \rangle$ is set once per iteration for all individuals in the population, defining the fox's action as in Eq. (4).To control the population's movement in this iteration, we employ a modified Cochleoid equation to depict the trajectory of each individual with the parameter μ .

$$\begin{cases} Approach\ nearer & if\ \mu > 0.75 \\ \mathrm{Re}\,main\,\&\,conceal & if\ \mu \le 0.75 \end{cases} \tag{4}$$

To characterize the movement of foxes, the observation radius is defined by two factors: $b \in (0, 0.2)$, a scaling parameter set uniformly for all individuals in the population in each iteration to simulate varying distances from the prey during approach, and $\chi_0 \in (0, 2\pi)$, chosen for all individuals at the algorithm's onset to represent the observation angle. These parameters collectively establish the vision radius γ for the hunting foxes as in Eq. (5). Here, φ indicates arbitrary value in the interval 0 and 1. To depict the movement of the population of individuals, we utilize the following system of equations for spatial coordinates are defined as in Eq. (6). Here, every angular value is arbitraries for all points based on $\chi_1, \chi_2, \cdots \chi_{n-1} \in \langle 0, 2\pi \rangle$.

$$\gamma = \begin{cases} b\dfrac{\sin(\chi_0)}{\chi_0} & if\ \chi_0 \ne 0 \\ \varphi & if\ \chi_0 = 0 \end{cases} \tag{5}$$

$$\begin{cases} R_0^{new} = b\gamma.\cos(\chi_1) + R_0^{actual} \\ R_1^{new} = b\gamma.\sin(\chi_1) + b\gamma.\cos(\chi_2) + R_1^{actual} \\ R_2^{new} = b\gamma.\sin(\chi_1) + b\gamma.\sin(\chi_2) + b\gamma.\cos(\chi_3) + R_2^{actual} \\ \cdots \\ R_{n-2}^{new} = b\gamma.\sum_{q=1}^{n-2}\sin(\chi_q) + b\gamma.\cos(\chi_{n-1}) + R_{n-2}^{actual} \\ R_{n-1}^{new} = b\gamma.\sin(\chi_1) + b\gamma.\sin(\chi_2) + \cdots + b\gamma.\sin(\chi_{n-1}) + R_{n-1}^{actual} \end{cases} \tag{6}$$

In Eq. (6), the last two formulation is get added for better performance as in Eq. (7).

$$R_{2n-3}^{new} = b\gamma.\sum_{q=1}^{n-2}\sin(\chi_q) + b\gamma.\sin(\chi_1) + b\gamma.\cos(\chi_{n-1}) + b\gamma.\sin(\chi_2) + R_{n-2}^{actual} + b\gamma.\sin(\chi_{n-1}) + R_{n-1}^{actual} \tag{7}$$

Procreation and Departure from the Group: In nature, red foxes confront various threats, including scarcity of food in their local habitat, prompting the need for migration. Another peril arises from human activity, particularly hunting, especially if there are significant damages to populations of domestic animals. However, not all foxes succumb to these dangers or migrate. Many exhibit intelligence and evade threats, enabling them to reproduce and contribute to the fox population. To maintain a constant population size, these individuals are replaced by new ones, following a model of habitat territory established by the alpha couple. Choose two optimal individuals $\left(\overline{R}^{(1)}\right)^t$ and $\left(\overline{R}^{(2)}\right)^t$ that indicates the alpha couple then evaluate the habitat center for them as in Eq. (8).The habitat is defined by the square of the Euclidean distance among the alpha couple as in Eq. (9). Eq. (10) reveals the transformation in the iteration. Following this, merge two optimal individuals into new one as in Eq. (11). Here, ρ refers to random parameter in the interval 0 and 1.

$$\left(Habt^{(Cent)}\right)^t = \frac{\left(\overline{R}^{(1)}\right)^t + \left(\overline{R}^{(2)}\right)^t}{2} \tag{8}$$

$$\left(Habt^{(Dia)}\right)^t = \sqrt{\left\| \left(\overline{R}^{(1)}\right)^t - \left(\overline{R}^{(2)}\right)^t \right\|} \tag{9}$$

$$\begin{cases} Fresh\ Nomadic\ Individual & if\ \rho \ge 0.45 \\ \mathrm{Pr}\,ocreation\ of\ the\ alpha\ couple & if\ \rho < 0.45 \end{cases} \tag{10}$$

$$\left(\overline{R}^{(reproduced)}\right)^t = \rho\frac{\left(\overline{R}^{(1)}\right)^t + \left(\overline{R}^{(2)}\right)^t}{2} \tag{11}$$

5) Pseudocode of SE-RFO Algorithm

Algorithm 1: Pseudocode of SE-RFO
Begin
Specify parameters: Iteration count T , fitness function f , population size n, search space solution $\langle b, a \rangle$, and observation angle φ .
Produce n foxes at arbitrary within search space.
$t := 0$
while $t \le T$ **do**
Specify iteration coefficients for scaling parameter δ and fox approaching change b.
for each fox in current population **do**
Arrange individuals based on f .

choose $\left(\overline{R}^{Bst}\right)^{t}$
Compute the redistribution of individuals as in Eq. (3)
If the redistribution improves upon the prior position **then**
Shift the fox
Else
Return the fox to prior position
end if
Select value μ to specify hunting fox
If fox is not identified **then**
Evaluate observation radius as in Eq. (5)
Compute redistribution as in Eq. (6)
Improved redistribution as in Eq. (7)
Else
The fox remains at its current position to conceal itself.
end if
end for
Organize the population based on the fitness function.
The least fit foxes depart from the group or are eliminated by hunters.
New foxes are introduced into the population as in Eq. (10), either as nomadic foxes from outside the habitat or through reproduction from the alpha couple within the herd as in Eq. (11).
$t{+}{+}$
end while
Return the fittest for $\left(\overline{R}\right)^{Bst}$
Halt

4. Results and Discussion

A. Experimental Setup

This study was carried out using Python software, with particular emphasis on conducting SEM and CFA analysis. SEM is a powerful statistical method used to test complex theoretical concepts and relations among variables. SEM allows researchers to simultaneously examine the measurement and structural aspects of a model, incorporating both observed and latent variables. SEM helps to measure the validity and reliability of measurement instruments, tests hypothesized dealings between variables and evaluates the overall model fit of the data. Moreover, CFA is a crucial component of SEM and is employed in structural analyses for model validation

B. Correlation Matrix

The correlation matrix provides a comprehensive view of the relationships among the constructs: Environmental Factor (EF), Social Factor (SF), Governance Factor (GF), Investor Behavior (IB), Risk Tolerance (RT), and Sustainable Development (SD). Each value in the matrix (Table 1) represents the strength and direction of the correlation between pairs of constructs, measured using Pearson correlation coefficients (r). Overall, moderate to strong positive correlations are evident among most constructs, indicating significant associations between them. Notably, Investor Behavior (IB) shows strong positive correlations with Environmental Factors, Social Factors, Governance Factors, and Sustainable Development, underscoring the interconnectedness between investor behavior and these dimensions. Additionally, the Governance Factor exhibits strong positive correlations with Social Factors and Risk Tolerance, suggesting intertwined relationships among governance-related aspects, social dynamics, and risk management. These findings highlight the complex and interdependent nature of the constructs, emphasizing the importance of considering their collective influence in understanding the multifaceted aspects of the studied phenomenon.

Table 1. Correlation Matrix

Constructs	EF	SF	GF	IB	RT	SD
EF	0.539					
SF	0.567	0.508				
GF	0.755	0.717	0.649			
IB	0.744	0.776	0.673	0.744		
RT	0.546	0.567	0.597	0.765	0.768	
SD	0.733	0.624	0.649	0.743	0.678	0.778

C. Path Coefficient Test

The path coefficient shows how much of an independent variable (cause) affects a dependent variable. The presented hypotheses and their corresponding results indicate the relationships between different constructs within the research model. Hypothesis H_1, which proposes a path from Environmental Factor (EF) to Investor Behavior (IB), shows a statistically significant positive relationship with a beta coefficient of 0.140 and a p-value of 0.002, thus providing support for the hypothesis. Similarly, Hypothesis H_2, suggesting a path from Social Factor (SF) to IB, demonstrates a significant positive relationship with a beta coefficient of 0.189 and a p-value of 0.000, indicating support for this hypothesis as well. Moreover, Hypothesis H3, proposing a relationship from Governance Factor (GF) to IB, demonstrates a notably significant positive association, with a beta coefficient of 0.768 and a p-value of 0.000, providing support for the hypothesis. These findings (table 2) suggest that environmental, social, and governance factors have notable impacts on investor behavior, underscoring their importance in shaping investment decisions and behaviors.

Table 2. Path Coefficient Test

Hypothesis	Path	β	p-value	Result
H_1	EF → IB	0.140	0.002	Supported
H_2	SF → IB	0.189	0.000	Supported
H_3	GF → IB	0.768	0.000	Supported

The presented hypothesis H_4 in Table 3 explores the relationship between Investor Behavior (IB) and Sustainable Development (SD) within the research model. The results reveal a statistically significant positive correlation between IB and SD, with a beta coefficient of 0.486 and a p-value of 0.000, thereby offering robust support for the hypothesis. This outcome suggests that investor behavior significantly influences sustainable development initiatives. Specifically, as investor behavior aligns with sustainability objectives, it fosters activities and investments that contribute positively to sustainable development goals. Consequently, this supports the notion that investor decisions and actions are essential in advancing sustainable development agendas, emphasizing the reputation of incorporating ESG considerations into investment.

Table 3. Path Coefficient Test

Hypothesis	Path	β	p-value	Result
H_4	IB → SD	0.486	0.000	Supported

D. Classification Analysis

1) Analysis on Positive Metrics

Figure 3 exposes the comparative evaluation of positive metrics for the DCNN+LinkNet method in contrast with DCNN, LinkNet, LSTM, SVM, and CNN. Through this comparative visualization, it becomes apparent how the DCNN+LinkNet method stacks up against these conventional approaches in terms of positive metric evaluation. Absolutely, achieving higher positive metric ratings is essential for ensuring the effective performance of a model. Indeed, the comparison between the DCNN+LinkNet scheme and conventional methodologies underscores the superiority of the DCNN+LinkNet approach, as it consistently yields greater positive metric values. The evaluation of the accuracy metric highlights the superior performance of DCNN+LinkNet method contrasted to conventional strategies. At a training data percentage of 90%, the DCNN+LinkNet method achieved the highest accuracy rate of 0.941. Conversely, conventional approaches yielded lesser accuracy ratings: DCNN=0.827, LinkNet=0.851, LSTM=0.819, SVM=0.835, and CNN=0.847, respectively. Similarly, at a training data percentage of 90%, the DCNN+LinkNet approach achieved a sensitivity score of 0.958, significantly outperforming conventional methodologies. Meanwhile, DCNN, LinkNet, LSTM, SVM, and CNN demonstrated lower sensitivity ratings.

Simultaneously, a comparative analysis of specificity and precision was conducted for both the DCNN+LinkNet and conventional strategies. At a training data percentage of 70%, the DCNN+LinkNet approach achieved a specificity score of 0.785, surpassing that of DCNN, LinkNet, LSTM, SVM, and CNN, which exhibited minimal specificity values. Furthermore, at 90% of training data, the precision achieved by the DCNN+LinkNet scheme significantly outperformed that of DCNN, LinkNet, LSTM, SVM, and CNN. Specifically, the precision of the DCNN+LinkNet scheme reached 0.961, demonstrating its exceptional ability to minimize false positives and accurately classify positive instances. In contrast, the precision values of conventional methods are notably lower, with DCNN at 0.841, LinkNet at 0.856, LSTM at 0.832, SVM at 0.827, and CNN at 0.819, respectively. This demonstrates the DCNN+LinkNet approach's reliability and robustness in practical scenarios, where precise classification of both positive and negative instances is crucial for accurate decision-making.

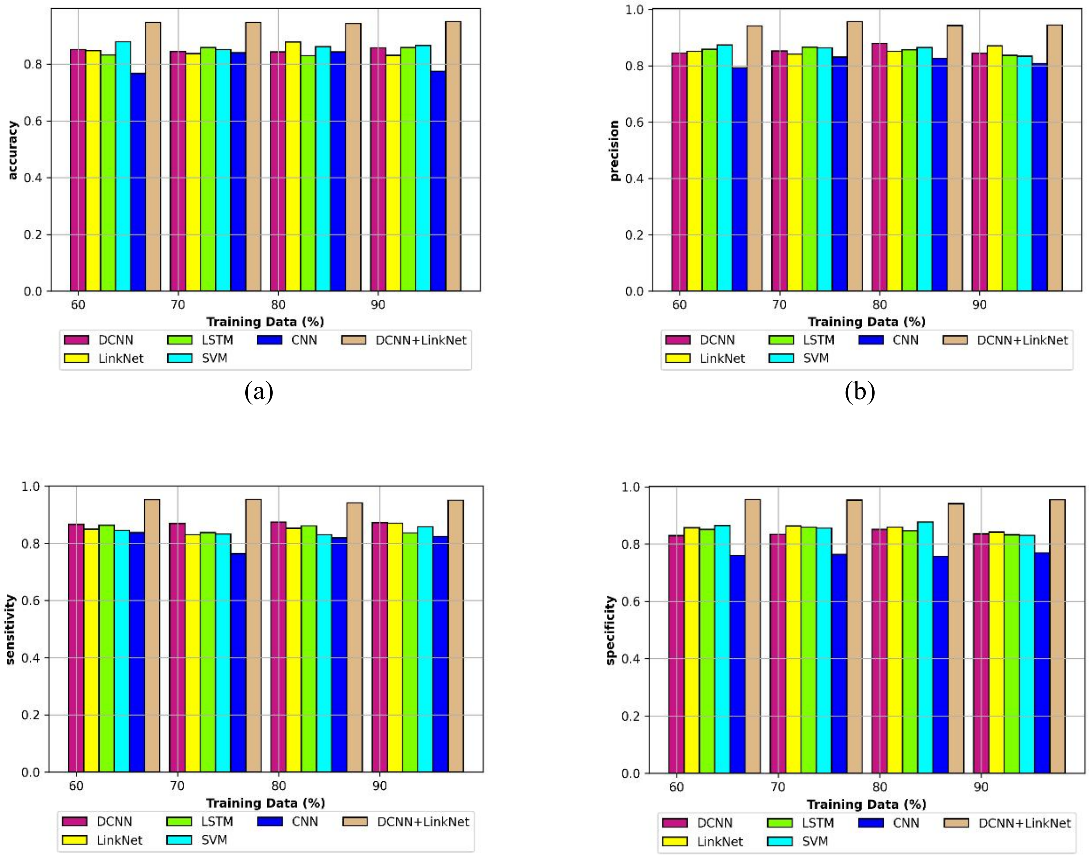
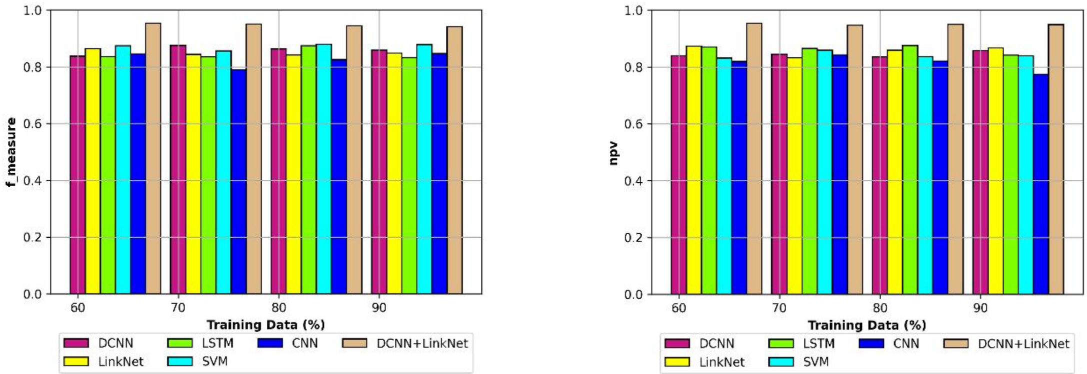


Fig. 3. Comparison of Positive Metric Performance between DCNN+LinkNet and Conventional Strategies

2) Analysis on NPV and F-measure

Figure 4 provides a comprehensive analysis comparing the performance of the DCNN+LinkNet method with conventional methods in terms of two critical metrics: NPV and F-measure. The comparison includes DCNN, LinkNet, LSTM, SVM, and CNN, providing insights into the efficacy of each method. Moreover, it is essential to maximize both the NPV and F-measure for the effective performance of the model. In particular, at the training data percentage of 80%, the F-measure achieved by the DCNN+LinkNet approach stands at 0.946, showcasing its superior performance compared to DCNN, LinkNet, LSTM, SVM, and CNN. These conventional methods exhibited lower F-measure ratings of 0.841, 0.839, 0.852, 0.869, and 0.826, correspondingly. In addition, the NPV scored by DCNN+LinkNet method is 0.937, surpassing that of DCNN, LinkNet, LSTM, SVM, and CNN, which maintained the least NPV ratings. Therefore, the analysis underscores the exceptional performance of the DCNN+LinkNet approach concerning both F-measure and NPV. This performance advantage highlights the potential of the DCNN+LinkNet approach to enhance decision-making processes and deliver superior outcomes.



(a) (b)

Fig. 4 Comparison of NPV and F-measure Metric Performance between DCNN+LinkNet and Conventional Strategies

3) Statistical Examination on Error

Statistical analysis entails evaluating abundant iterations of different models, each executed several times. Analysts calculate crucial statistical measures including the "mean, median, best, worst, and standard deviation." These metrics are then integrated with the iteration results to offer valuable insights into both the performance and changeability of the models. This comprehensive scrutiny enables a deeper comprehension of the efficiency and stability of the assessed models, facilitating notified decisions during model selection and modification. The statistical assessment on DCNN+LinkNet is contradicted with DCNN, LinkNet, LSTM, SVM and CNN is depicted in table 4. Analyzing the best statistical metric across the evaluated methods, it becomes evident that the DCNN+LinkNet method stands out significantly. With a error rate of 0.051, it surpasses all other methods, including DCNN, LinkNet, LSTM, SVM, and CNN. This unequivocal superiority underscores the DCNN+LinkNet method's exceptional capability in error minimization. Conversely, the other methods demonstrate comparatively higher error rates, underscoring their limitations in attaining optimal performance. Comparing the median statistical metric across the evaluated methods reveals distinctive performance trends. The DCNN+LinkNet method emerges as the standout performer, boasting a error value of 0.053, which is notably lower than that of conventional models. Conversely, the conventional models such as DCNN, LinkNet, LSTM, SVM, and CNN exhibit comparatively higher error rates of 0.153, 0.158, 0.155, 0.137 and 0.192, respectively.

Table 4. Statistical Evaluation on Error

Methods	**Best**	**Mean**	**Worst**	**Standard Deviation**	Median
DCNN	0.142	0.151	0.157	0.006	0.153
LinkNet	0.123	0.152	0.169	0.018	0.158
LSTM	0.141	0.155	0.170	0.014	0.155
SVM	0.122	0.136	0.149	0.010	0.137
CNN	0.157	0.194	0.233	0.035	0.192
DCNN+LinkNet	0.051	0.053	0.057	0.002	0.053

4)Performance Analysis on SE-RFO and Conventional methods

The comparative analysis presented in Table 5 highlights the performance disparities between the SE-RFO method and a set of conventional approaches, including RFO, COATI, PSO, MRFO, and SMO, across various performance metrics. Importantly, the SE-RFO method consistently outperforms its conventional methods across all evaluated metrics, providing clear evidence of its superiority. The SE-RFO method shows a remarkably low FNR of 0.047, indicating its effectiveness in accurately identifying positive instances. Conversely, conventional methods display greater FNR values, ranging from 0.090 to 0.141, signifying a comparatively greater tendency to misclassify positive instances as negative. Moreover, the MCC reached by the SE-RFO system is exceptionally high at 0.958, indicating a remarkably strong agreement between predicted and observed classifications. In contrast, the MCC values for the conventional methods show varying degrees of performance: RFO at 0.491, COATI at 0.702, PSO at 0.597, MRFO at 0.650, and SMO at 0.623.

Table 5. Comparative Study on SE-RFO and Conventional Strategies

Metrics	**RFO**	**COATI**	**PSO**	**MRFO**	**SMO**	**SE-RFO**
Accuracy	0.636	0.889	0.762	0.826	0.794	0.947

NPV	0.579	0.735	0.657	0.696	0.676	0.954
FPR	0.310	0.182	0.246	0.214	0.230	0.045
F-Measure	0.641	0.826	0.784	0.855	0.819	0.954
Sensitivity	0.591	0.910	0.751	0.831	0.791	0.953
FNR	0.141	0.090	0.115	0.102	0.109	0.047
Specificity	0.690	0.818	0.754	0.786	0.770	0.955
MCC	0.491	0.702	0.597	0.650	0.623	0.958
Precision	0.701	0.903	0.822	0.882	0.852	0.942

5. Conclusion

A. Conclusion

This study analyzed the influence of investor behavior on ESG (Environmental, Social, and Governance) information disclosure and also the role of risk tolerance in mediating the relationship between investor behavior and sustainable development within the new energy sector. The following conclusions of this investigation are based on the problem formulation, hypothesis, and research findings. The analysis revealed that investor behavior significantly impacts ESG information disclosure practices. When choosing which companies to invest in the Chinese new energy sector, investors typically take social responsibility, environmental sustainability, and sound governance practices into consideration. This emphasizes the importance of taking into account ESG factors in investment decision-making processes and underscores the increasing relevance of sustainable investing. Furthermore, the investigation discovered that risk tolerance mediates the relationship between investor behavior and sustainable development. Investors' willingness to accept risk influences the extent to which their behavior contributes to sustainable development goals within the new energy sector in China. Thus, the results of this study are Environmental, Social, and Governance (ESG) factors significantly influence Investor Behavior. Investor Behavior itself exhibits a significant relationship with Sustainable Development outcomes within the new energy sector. Risk Tolerance is identified as a crucial mediating factor influencing this relationship between Investor Behavior and sustainable growth in the new energy industry. Overall, this study's findings provide valuable information for policymakers, companies, investors, and other stakeholders in the new energy sector in China.

B. Implication

The study underscores the reputation of considering ESG aspects of decision-making progressions for investments. Investors can leverage this knowledge to prioritize sustainable investments that line up with their risk preferences and values. Understanding the mediating role of risk tolerance can also help investors better assess the potential impact of their investment decisions on sustainable development outcomes. Regulatory bodies and policymakers can utilize the study findings to inform policy development and regulatory frameworks aimed at promoting sustainable investment practices. By encouraging transparency and accountability in ESG information disclosure, regulators can foster greater investor confidence and facilitate the flow of capital towards sustainable development. Ultimately, CEOs and directors must participate in ESG contemplations in the overall corporate strategy. Based on this study, every board should set up clear lines of communication practices with officials to discuss strategies for addressing sustainability performance for all parties involved. Allocating funds towards more attractive and sustainable opportunities proposed by ESG initiatives can enhance investment outcomes and confer a competitive edge, leading to increased market share. Proactive engagement with governance, social, and environmental issues is imperative for achieving this. By assessing and addressing these factors, organizations can mitigate risks and gain a competitive advantage in the market. Implementing ESG initiatives is critical in the current landscape, and while numerous frameworks exist, management should begin monitoring and disclosing key market indicators. This process is ongoing, with frameworks and solutions continuously evolving and being developed.

C. Limitations and Future Scope

The primary data collection for examining the influence of investor behavior on ESG information disclosure, as well as how risk tolerance functions as a mediator in the relationship between investor behavior and sustainable development in China's new energy sector, may encounter various limitations. These include potential constraints related to sample size, which could impact the broader generalizability of findings across the investor population in the new energy sector. Additionally, there may be limitations in adequately representing the diversity of investors in terms of demographics, investment preferences, and risk tolerance levels. To enhance objectivity, supplementing primary data with secondary sources could be considered, enabling a more comprehensive assessment of firm and investor effects. The study's scope could also be increased to include comparisons with other developing nations more research into unobserved heterogeneity connected to ESG, and the exploration of additional variables such as investment effectiveness, firm reputation, and stakeholder participation. Updating analysis methods, establishing causal relationships through longitudinal studies or experimental designs, and assessing responses from other information users like suppliers, customers, and NGOs could further enhance understanding of the decision usefulness of ESG information in different contexts. Future studies could explore the longitudinal trends and dynamics of investor behavior and ESG disclosure practices, considering evolving market conditions, regulatory landscapes, and technological advancements.

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