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Advancing new energy industry quality via artificial intelligence-driven integration of ESG principles

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This study seeks to investigate the assessment of new energy enterprises' performance by integrating Environmental Social Governance (ESG) using artificial intelligence, aiming to enhance the high-quality development of the new energy industry. Initially, an ESG-centered performance evaluation system is established for new energy enterprises, encompassing four dimensions: financial, environmental, social, and governance performance. Subsequently, multimodal data is gathered, and deep learning (DL) techniques, specifically Word2Vec and the graph convolutional neural network, are applied to extract and consolidate features from text and images related to performance within these enterprises. This facilitates the classification and identification of key performance indicators, leading to the development of a DL-based performance evaluation model for new energy industry incorporating ESG. The empirical analysis reveals superior performance indicators, achieving a classification accuracy of 90.48%, surpassing the Convolutional Neural Network algorithm. A detailed examination of individual dimensions and overall performance demonstrates relatively high financial performance and a stable upward trend in environmental performance. However, social performance scores exhibit significant fluctuations, particularly in areas related to employees and product responsibility. Consequently, the developed performance evaluation system effectively identifies trends in enterprise development. In subsequent phases, it is recommended to continuously enhance corporate governance mechanisms, internal controls, and risk management.

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Introduction

In the 21st century, advanced Artificial Intelligence (AI) technologies, including 5th Generation Mobile Communication Technology (5G), Internet of Things (IoT), deep learning, cloud computing, and blockchain, exert a profound influence on the operations and decision-making processes of enterprises and organizations, enabling them to operate more intelligently and efficiently. Furthermore, these technologies are rapidly reshaping the production factors and competitive landscape across various industries globally (Kim and Kim 2022; Wang et al. 2023b). The new energy industry stands as a pivotal domain in the realm of sustainable development (SD). Fueled by the escalating global demand for renewable energy sources and environmental conservation, the new energy sector enhances the reliability and sustainability of energy provision by curbing carbon emissions, lowering energy costs, and fostering new avenues for employment (Liu et al. 2022b). New energy enterprises assume a central role in propelling the transition toward sustainable energy practices and realizing the objectives of a green economy. Nonetheless, this endeavor is accompanied by a host of challenges, including the demand for technological innovation, intensified market competition, policy and regulatory uncertainties, and the intricate nature of the energy supply chain (Zhironkin and Cehlár 2022). Primarily, the imperative for technological innovation imposes considerable research and development investments, necessitating substantial allocations of talent, equipment, and resources. Facilitating interdisciplinary collaboration, particularly among engineers, scientists, and data scientists, serves to bolster the efficiency of technological advancement initiatives. Secondly, the heightened competition within the market mandates enterprises to strive for differentiation as a means of securing a competitive edge. This underscores the importance for seasoned scholars to concentrate on pioneering innovative technologies and services. Concurrently, the ever-evolving policy landscape introduces a degree of uncertainty, compelling seasoned scholars to adapt to environmental shifts through astute policy interpretation and forecasting, alongside proactive engagement with governmental bodies. Finally, the multifaceted challenges inherent in the energy supply chain underscore the significance of addressing issues such as data management and integration, as well as implementing robust risk management strategies. Faced with rapidly changing markets and technological advancements, traditional financial performance evaluation methods are no longer sufficient to comprehensively reflect a company's long-term value and social responsibility. Therefore, constructing a comprehensive Environmental, Social, and Governance (ESG) performance evaluation system is particularly urgent. Not only can it help companies identify and improve their performance in environmental and social responsibility aspects, but it can also promote the optimization of corporate governance structures.

In this context, ESG covers three aspects: environment, society, and governance, including reducing environmental footprint, maintaining social responsibility, and improving corporate governance standards (Dong et al. 2023; Zhou et al. 2022). The theoretical foundation of the ESG performance evaluation system can be traced back to the concepts of Corporate Social Responsibility (CSR) and SD. This concept is later incorporated into frameworks such as the United Nations Global Compact and the Sustainability Accounting Standards Board (SASB), emphasizing that companies should balance economic, environmental, and social performance. However, upon introducing ESG criteria for evaluating enterprises and organizations, certain limitations persist, including challenges related to information gathering and complex decision-making procedures. By integrating AI technologies, such as big data analysis and deep learning algorithms, into the framework of the new energy industry, significant enhancements in operational efficiency and effectiveness can be achieved. These advancements encompass refining new energy production processes, optimizing energy consumption patterns, monitoring and forecasting the performance of energy systems, and fostering sustainability within the supply chain (Yang et al. 2022). Through data-driven decision-making approaches, enterprises can attain a more precise assessment of their ESG performance and subsequently implement targeted measures to enhance it. Leveraging automation and data analytics capabilities, AI technologies contribute to bolstering transparency and regulatory compliance across internal organizational processes. Notably, the monitoring of financial reporting, internal controls, and the performance of the board of directors stands to mitigate risks, deter instances of malpractice, and fortify corporate governance frameworks (Saura et al. 2023; Tikhonov et al. 2022). Such initiatives not only facilitate the widespread adoption of renewable energy solutions but also contribute to the cultivation of a more sustainable economy and environment.

This study aims to explore the potential advantages of integrating ESG considerations from an AI perspective to promote the high-level development of the new energy industry. It delves into the application of AI techniques, particularly deep learning methods, in constructing a performance evaluation model for new energy enterprises based on ESG principles. Innovatively, this study employs Bidirectional Encoder Representations from Transformers (BERT) and the Graph Convolutional Network (GCN) in the field of deep learning. The goal is to extract and integrate features from multimodal data, including text and visual performance-related information obtained from new energy enterprises, to identify and classify key performance indicators. The overarching objective is to discern and categorize key performance indicators pertinent to these enterprises. Subsequently, a performance evaluation model tailored to the new energy industry, grounded in deep learning principles and incorporating ESG considerations, is formulated. Empirical scrutiny is then applied to this model to furnish pragmatic recommendations aimed at aiding decision-makers and industry leaders in leveraging AI technology to foster the high-caliber progression of the new energy sector while concurrently enhancing ESG standards.

Practical significance and contributions of this study:

(1) Innovative Performance Evaluation Model: This study integrates deep learning techniques to develop a performance evaluation model for new energy enterprises based on ESG principles. Covering four dimensions of financial, environmental, social, and governance, it provides a more comprehensive and precise assessment tool for enterprises.
(2) Advancing ESG Management: By incorporating ESG management into the performance evaluation system, this study facilitates corporate social responsibility fulfillment, enhances governance levels, and promotes SD. In the new energy industry, a robust ESG management framework is crucial for attracting investment and gaining public recognition.
(3) Optimizing Resource Allocation: Through in-depth analysis of performance across different dimensions, enterprises can allocate resources more accurately and maximize the combined economic, social, and environmental benefits.
(4) Industry Leadership: This study offers advanced methodologies to help enterprises strengthen their leadership in the new energy sector. A comprehensive understanding of performance across various dimensions enables enterprises to better adapt to market dynamics, enhance competitiveness, and drive overall technological and managerial advancements in the industry.

The study adheres to a structured framework comprising the "Introduction," "Literature review," "Performance evaluation of ESG applied in the new energy industry under AI technology," "Results and discussion," and "Conclusion" sections. The introductory segment of the initial section underscores the contextual backdrop and rationale underpinning the study, accentuating the importance of integrating ESG evaluation into the assessment of new energy enterprise performance through the prism of AI. A clear delineation of study objectives and significance is provided. Subsequently, the literature review section systematically surveys pertinent research and literature within the domain, encompassing ESG assessment methodologies within the new energy sector, as well as the utilization of AI in corporate performance appraisal. The subsequent section elaborates upon the construction of the ESG framework, multimodal data collection methodologies, and the deployment of deep learning techniques. A blueprint is delineated for the development of a novel performance evaluation model tailored to the new energy industry, harmonizing ESG considerations with deep learning principles. In the ensuing segment, empirical findings are presented, including a comparative analysis of the performance of the model algorithm proposed in this study against the conventional Convolutional Neural Network (CNN) algorithm. A meticulous elucidation of each dimension alongside a comprehensive performance assessment is offered. The concluding section encapsulates the entirety of the study, underscoring its contributions and innovative facets. Limitations inherent in the study are acknowledged, and avenues for future research are posited.

Literature review

Status of ESG utilization in the new energy industry. As an emerging evaluation paradigm, ESG embodies the ethos of SD, a concept that resonates with China's current economic trajectory and national development imperatives. The information encapsulated within ESG frameworks offers a comprehensive portrayal of an enterprise's operational landscape, exerting a profound influence on its trajectory toward sustainable growth. ESG principles advocate for enterprises to prioritize environmental stewardship, social responsibility, and robust corporate governance frameworks. A plethora of scholarly endeavors have delved into the application and implications of ESG. Nitlarp and Kiattisin (2022) employed qualitative research methodologies to systematically collect and analyze data via case studies and expert interviews conducted across multiple energy firms. Their findings underscored the transformative impact of Industry 4.0 technologies on the energy sector, particularly in augmenting energy efficiency, mitigating environmental footprints, and fortifying governance structures. Liu et al. (2022a) conducted a qualitative comparative analysis focusing on Chinese new energy enterprises to ascertain the interplay between ESG performance and financial outcomes. Their investigation revealed a nuanced relationship, wherein elevated ESG performance exhibited potential correlations with improved financial metrics, contingent upon various factors including strategic decision-making and competitive market dynamics. Behl et al. (2022) utilized cross-sectional lagged panel analysis techniques to elucidate the dynamic interrelationship between ESG scores and corporate valuation within the Indian energy landscape. Their study outcomes underscored the dynamic nature of this association, affirming the pivotal role of ESG considerations in informing corporate decision-making processes. Jiang et al. (2023) employed a time-frequency domain connectivity analysis approach to examine shifts in the relationship dynamics among traditional and new energy paradigms, green finance, and ESG considerations before and after the Russo-Ukrainian conflict. Their findings underscored the nuanced impact of international events on the interconnectivity among energy, finance, and sustainability domains. Wang (2023) conducted quantitative analyses utilizing data sourced from renewable energy enterprises to probe the correlation between low-carbon transitions and ESG disclosures. Their investigation revealed a positive nexus between low-carbon transformations and enhanced ESG disclosure practices within the renewable energy sector, indicative of the catalytic role of low-carbon initiatives in fostering heightened ESG consciousness and practices within the industry.

Scholars have also conducted research on the sustainability of energy development. Li et al. (2023a) used a difference-in-difference model to evaluate the impact of China's low-carbon city pilot policy on urban entrepreneurial activities. The results showed that the policy generally had an inhibitory effect on entrepreneurial activities, but the improvement of the green innovation level could alleviate this impact to a certain extent. In addition, the low-carbon policy helps to promote entrepreneurial activities in emerging industries and drive the optimization and upgrading of the industrial structure. Li et al. (2024a) found that climate change significantly suppressed the ESG performance of enterprises, but the continuous elimination of resource misallocation effectively alleviated this negative impact. Their study also pointed out that the ESG performance of enterprises in resource-based cities was instead improved under the influence of climate change, and mature and large enterprises had stronger buffering capabilities. At the same time, external pressure factors such as public attention and analyst supervision can further motivate enterprises to improve their ESG levels. Wang et al. (2024) introduced the use of data platform management to implement the "5W" analysis framework to prevent and control grassroots government corruption, and argued that improving government governance efficiency and transparency also had a positive effect on promoting energy transition and SD. Li et al. (2024b) explored the impact of intellectual property pledge financing on enterprise innovation from the aspects of innovation dimension expansion, dynamic mechanism analysis, and intermediary mechanism refinement. They found that it had an inhibitory effect on innovation quality, but this adverse impact could be alleviated by raising the innovation threshold. In summary, current research on the application of ESG in the new energy industry is relatively rich, showing the key role of policy guidance, enterprise characteristics, external supervision, and other factors in promoting the sustainable development of enterprises.

The impact of AI technology on the new energy industry. Currently, common AI methods applied in ESG evaluation include natural language processing (NLP) and deep learning. NLP techniques, such as BERT, can extract semantic information from textual data, making them suitable for analyzing corporate social responsibility reports, annual reports, and other text-based documents. Deep learning techniques enable the extraction of complex features from both image and text data, facilitating the integration of multimodal data for comprehensive analysis. The integration of various deep learning approaches has enabled the development of performance evaluation models in the new energy sector, enhancing ESG performance analysis and improving evaluation accuracy. This approach has driven a transformative shift in the industry, ultimately improving sustainability measures and ESG performance while creating new opportunities to advance renewable energy initiatives. A corpus of scholarly investigations has been undertaken to elucidate these dynamics. Lyu et al. (2020) proposed a methodology for constructing trustworthy systems within the realm of industrial IoT by scrutinizing the veracity of AI-driven systems. They underscored the pivotal role of AI in fortifying the security and reliability of IoT infrastructures, thereby bolstering the trustworthiness of industrial IoT systems. Sharma et al. (2022) conducted a comprehensive review of machine learning applications in nanofluid heat transfer, underscoring its significance in optimizing renewable energy systems. Their findings underscored the instrumental role of machine learning in augmenting energy system efficiencies, thereby offering valuable insights for enhancing the effectiveness of renewable energy systems. Franki et al. (2023) conducted an exhaustive examination of AI enterprises operating within the power industry, offering detailed insights into their roles and applications to discern the evolving trends of AI within the sector. Their findings furnished valuable insights for stakeholders navigating the landscape of AI integration within the power industry. Wei et al. (2023b) provided a systematic review of the integration, modeling, optimization, and AI application within hybrid renewable energy systems. Their synthesis of existing research elucidated potential avenues for leveraging these systems in advancing renewable energy endeavors, offering a roadmap for future investigations in the domain. Lei et al. (2023) evaluated the ramifications of digital transformation, with a specific emphasis on AI application, on the economic resilience of the energy industry. Their findings underscored the transformative potential of digital transformation and AI in enhancing the industry's resilience and fostering economic sustainability. Ukoba et al. (2023) conducted a comprehensive review of the impact of renewable energy and Industry 4.0 on the African continent, emphasizing their pivotal roles in bolstering energy sustainability and industrial modernization across the region. Their insights offered valuable guidance for policymakers and stakeholders invested in driving SD initiatives in Africa. Yang et al. (2023) devised a collaborative filtering recommendation algorithm that integrated time weighting and reward–penalty factors to enhance recommendation accuracy. Their algorithmic framework, which accounted for temporal dynamics and user feedback, demonstrated notable improvements in recommendation precision and user satisfaction, offering a valuable contribution to recommendation system design.

Additionally, scholars have conducted research on the application of artificial technologies such as blockchain and big data analytics in the new energy industry. Wang et al. (2023a) explored the use of blockchain technology for risk prediction and credibility detection in online public opinion, finding potential applications of blockchain technology in enhancing information transparency and credibility, providing more effective tools for social governance, and indirectly contributing to the achievement of SD goals. Dong et al. (2023) studied the impact of AI-based economic resilience assessments and policies on the low-carbon economy. By assessing the economic resilience of coal resource-based cities, the researchers proposed policy recommendations for achieving a low-carbon economy, promoting energy transition, and SD. Li et al. (2023b) explored the paths for mining projects to develop clean energy in the context of the ecological environment under the drive of big data, as well as related sustainable development issues. The study showed that with economic growth, both wind power installed capacity and carbon dioxide emission reduction had significantly increased. It shows that artificial intelligence technology is injecting new momentum into the transformation, upgrading, and sustainable development of the new energy industry, and its potential and application value are worthy of further exploration and expansion.

Summary. Upon scrutinizing the research contributions of the aforementioned scholars, it becomes evident that they adopted diverse methodologies to investigate the nexus between ESG principles and energy enterprises, thereby furnishing invaluable insights conducive to SD initiatives. Concurrently, the advent of AI technology has heralded transformative prospects for the new energy sector, encompassing advancements such as smart grids, distributed energy management systems, and battery storage technologies, thereby amplifying the industry's capacity for innovation and resilience. Although the application of ESG and AI technologies in the new energy industry has gained increasing attention in recent years, significant research gaps remain. First, most studies focus on a single dimension of ESG, such as environmental performance or social responsibility, lacking a comprehensive framework to evaluate environmental, social, and governance aspects simultaneously. Moreover, while AI technology has made notable progress in the new energy sector, few studies have integrated it with ESG evaluation systems to enhance assessment accuracy and efficiency.

Therefore, this study proposes an AI-based ESG performance evaluation model for new energy enterprises, aiming to address these gaps and comprehensively capture the ESG performance of new energy enterprises. Those results not only provide a new perspective on the integration of ESG and AI in theory but also offer practical guidance for new energy enterprises on how to utilize AI technology for ESG performance evaluation. By filling the gaps in existing research, this study makes an important contribution to the SD of the new energy industry and the advancement of global ESG practices.

Performance evaluation of ESG applied in the new energy industry under AI technology

Analysis of ESG application in the new energy industry. The ESG evaluation system encompasses three dimensions: Environment (E), Society (S), and Corporate Governance (G), incorporating a multitude of influencing factors that interact in a cohesive manner (Garnov et al. 2022). The establishment of an ESG evaluation framework necessitates adherence to four foundational principles: scientific, systematic, applicable, and operable, aimed at ensuring the objectivity, efficacy, and relevance of the evaluation outcomes. Scientificity mandates that evaluation methodologies and standards are grounded in robust scientific principles to uphold objectivity and precision in assessment. Systematicity entails consideration of the interplay among ESG factors, ensuring comprehensive coverage within the evaluation framework to capture potential ramifications. Applicability dictates that evaluation methodologies are tailored to accommodate the diverse needs and circumstances of different industries and organizations. Operability entails streamlining the evaluation process to facilitate ease of execution and comprehension, thereby furnishing actionable insights to inform decision-making and enhancement efforts (He et al. 2023; Roy 2023; Tan and Zhu 2022; Zeng and Jiang 2023). In Fig. 1, the ESG evaluation system delineates the intricate interrelationships among its constituent elements.

Figure 1 illustrates the ESG evaluation system, comprising three primary dimensions: environmental performance, social responsibility, and corporate governance. Environmental performance pertains to the measures undertaken by companies in their production and operational endeavors to mitigate environmental pollution, serving as a yardstick to gauge a company's adherence to its environmental responsibilities. This facet not only embodies a company's commitment to societal welfare but also holds pivotal significance for its long-term sustainability. By adopting environmentally sustainable business practices, companies can ameliorate adverse impacts, bolster sustainability, and align with evolving environmental regulatory frameworks. Social responsibility delineates a company's obligations toward stakeholders

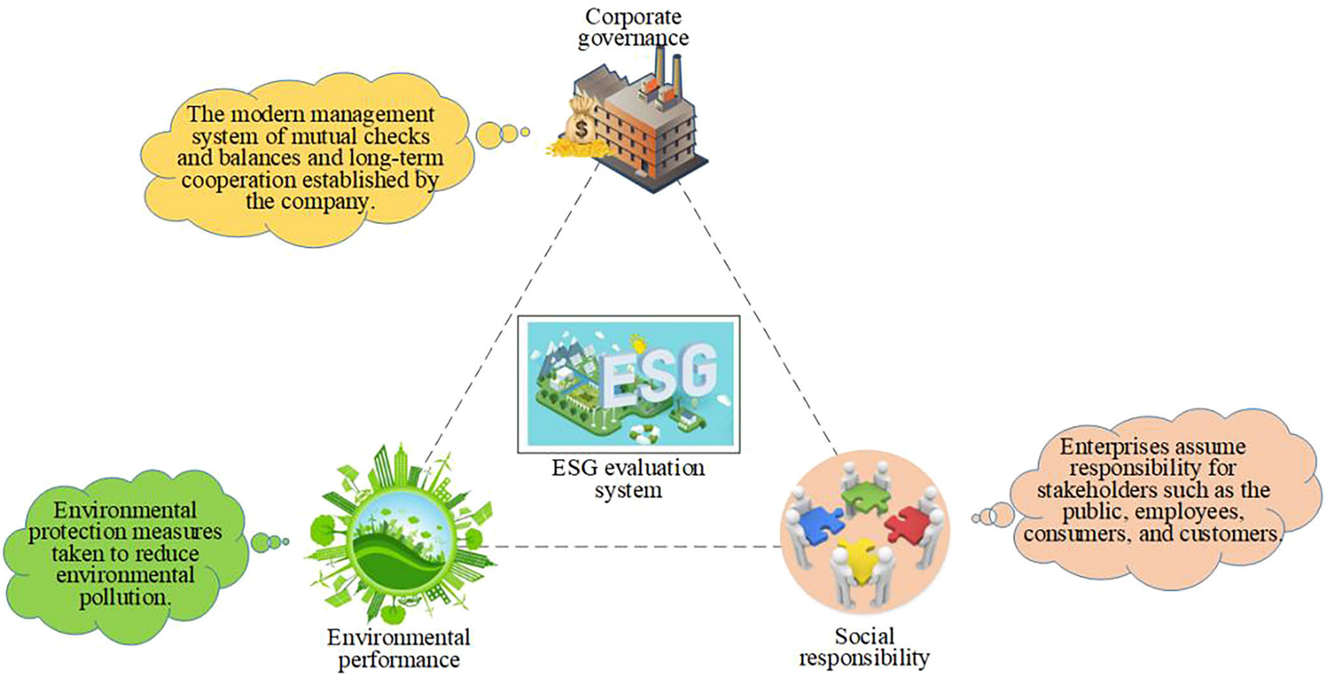

Fig. 1 Diagram of the ESG evaluation system.

such as the general public, employees, consumers, and clients, serving as a fundamental benchmark for assessing ethical standards and brand competitiveness. Actively discharging social responsibilities contributes to cultivating a positive corporate image, engendering employee and consumer loyalty, thereby fostering SD endeavors. Corporate governance underscores the establishment of modern management systems characterized by mutual checks and balances and enduring collaboration among company operators throughout the management continuum. It furnishes the institutional underpinnings for overseeing organizational structures, managing investor relations, enhancing competitiveness, and fostering sustained corporate growth. The efficacy of corporate governance is intricately linked to a company's long-term viability and resilience. Robust corporate governance practices can mitigate operational risks, enhance transparency, and instill shareholder confidence, thereby nurturing the enduring success of the company. The ESG evaluation system furnishes a comprehensive and methodical framework, serving as a potent instrument for facilitating a nuanced understanding and assessment of the performance metrics of new energy enterprises. This framework aids in identifying areas of strength and opportunities for improvement across environmental protection, social responsibility, and managerial governance domains, thereby steering companies toward a trajectory characterized by sustainability and high-quality outcomes.

In conventional enterprise performance evaluation paradigms, performance assessment primarily revolves around financial metrics, which encapsulate parameters such as profitability, operational prowess, debt-servicing capacity, and developmental aptitude (Debbarma et al. 2022). Within this framework, the financial performance of an enterprise stands as a pivotal indicator, offering a direct reflection of its operational health. Research endeavors focusing on financial performance as a primary evaluative metric serve to elucidate the economic robustness and operational efficacy of a company with greater precision. Primarily, the financial well-being of an enterprise serves as the bedrock for SD endeavors. A sound financial footing furnishes a stable reservoir of financial resources, thereby underpinning uninterrupted business operations and facilitating avenues for expansion. Consequently, an assessment of financial performance serves as a direct barometer of an enterprise's capacity for sustained growth. Moreover, financial performance exerts a direct influence on the viability and expansion prospects of a company. Exemplary financial performance signifies adept fund utilization, attainment of profitability, and the capacity to service debts, thereby ensuring consistent access to financial backing and fostering the stable operation and evolution of the enterprise. Conversely, enterprises grappling with subpar financial performance may encounter challenges in securing funding and experience dwindling profitability, thereby risking closure and market disengagement.

Financial performance is intricately intertwined with ESG management, transcending mere economic considerations to encompass the broader realms of social responsibility and governance standards within a company's operational framework. Exceptional financial performance often correlates with robust governance structures and heightened social responsibility awareness, underscoring the symbiotic relationship between financial prowess and ESG management efficacy. Firstly, the symbiosis between social responsibility and financial performance is apparent. Companies exhibiting stellar financial performance are often at the forefront of embracing social responsibilities. Actively discharging social obligations not only burnishes the corporate image but also yields tangible economic benefits. For instance, initiatives aimed at bolstering employee welfare, enhancing product quality, and curbing environmental degradation not only elevate social standing but also attract a wider customer and investor base, consequently enhancing profitability and market competitiveness. Secondly, a sound governance framework serves as a linchpin for ensuring the stable operation and enduring growth of a company. Effective internal controls, transparent information disclosure practices, and independent regulatory mechanisms are hallmarks of a robust governance structure. These elements serve to standardize operational conduct, mitigate risks, and enhance operational efficiency, thereby catalyzing improvements in financial performance. Moreover, a robust governance framework engenders investor confidence, curtails financing costs, and augments long-term

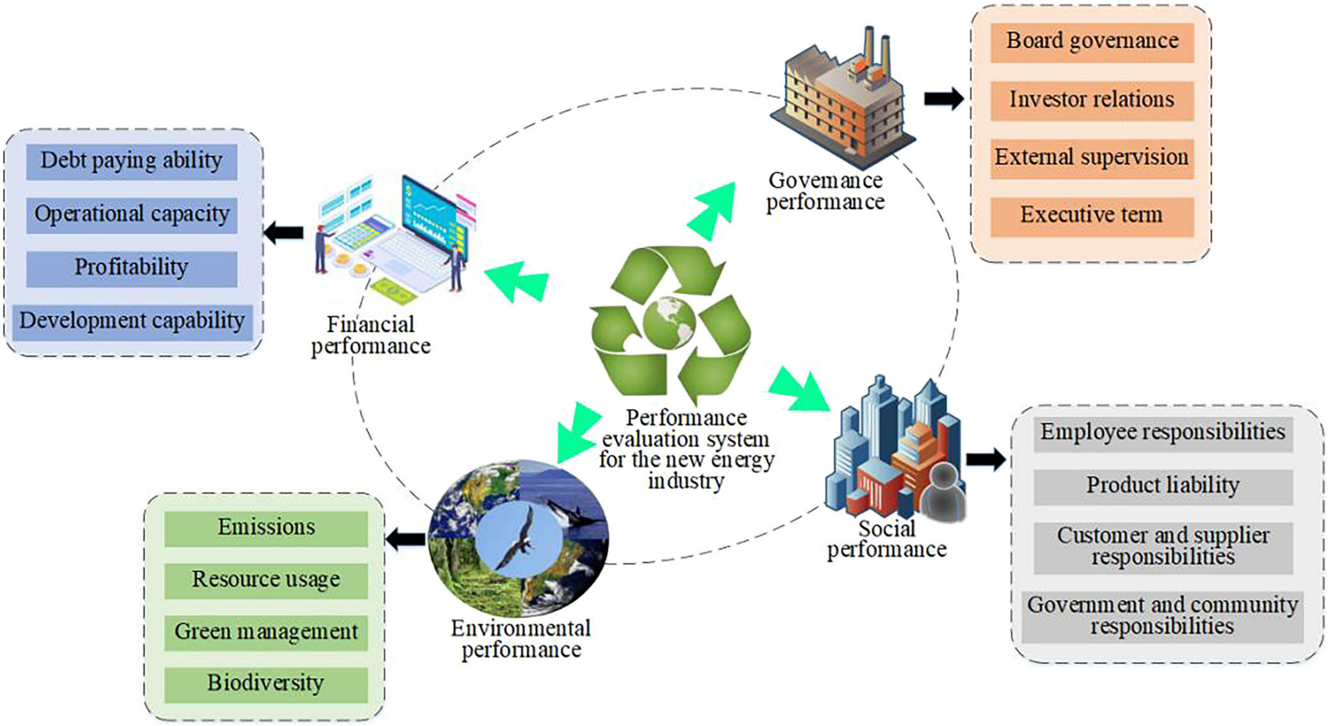

Fig. 2 Diagram of an ESG-based performance evaluation system for new energy enterprises.

competitiveness. Thirdly, ESG management emerges as a pivotal determinant of financial performance. With ESG considerations becoming integral to corporate performance metrics, adept ESG management practices can mitigate risks, bolster brand equity, and fortify market positioning, thereby engendering sustained and stable financial performance. For instance, initiatives aimed at curbing energy consumption, emissions, and fostering collaborative ties within the supply chain yield cost efficiencies, augment operational efficiency, enhance employee satisfaction, and elevate product quality, consequently bolstering market competitiveness. Fourthly, financial performance assumes a dual role as an evaluative metric for both CSR and governance. Given its intrinsic linkages with social responsibility and governance standards, financial performance often serves as a key criterion when appraising a company's CSR endeavors and governance efficacy. The company's performance in social responsibility and governance domains profoundly shapes the trajectory and long-term competitiveness of its financial performance. Consequently, regulatory bodies, investors, and stakeholders frequently leverage financial performance as a barometer to gauge overall corporate performance, thereby informing pertinent decisions and investment strategies. Hence, viewing financial performance as a primary indicator facilitates a holistic evaluation of a company's ESG performance, furnishing a comprehensive assessment framework conducive to the SD aspirations of the enterprise.

Henceforth, as the enterprise performance evaluation system undergoes continual refinement and evolution, the purview of enterprise performance has transcended mere financial metrics to encompass a holistic amalgamation of financial and non-financial indicators. The assessment of financial performance affords a more comprehensive analysis of a company's economic robustness, developmental potential, and capacity for sustainable growth, thereby furnishing a robust foundation for informed management and decision-making endeavors. Concomitant with the iterative enhancement and evolution of the enterprise performance evaluation framework, the ambit of corporate performance has expanded to encompass the fusion of financial metrics with an array of non-financial parameters. This study combines financial indicators with the ESG framework (as delineated in Fig. 2), aiming to construct a new performance evaluation paradigm that meets the needs of new energy enterprises. This integration not only reflects the dynamic evolution of the evaluation system but also demonstrates the response to the requirements of high-quality economic development.

Figure 2 illustrates that the newly developed performance evaluation system for new energy enterprises embodies a multi-faceted and multi-objective framework. Comprising four distinct performance dimensions—finance, environment, society, and governance—the system is underpinned by a primary indicator that undergoes a stepwise decomposition process until quantifiable. Each subsystem encapsulates specific facets or capabilities of enterprise performance, necessitating delineation through subordinate indicators. The relative significance of these indicators varies, contributing to the inherent complexity of the entire system. To ascertain an optimal indicator structure, this study integrates deep learning, an AI technique, aimed at discerning specific tertiary indicators. The integration of deep learning technology serves to refine indicator selection, ensuring alignment with real-world contexts while accounting for interrelationships among diverse indicators. Facilitating the elucidation of latent patterns and correlations, deep learning aids in identifying factors exerting the most pronounced impact on corporate performance. Consequently, the incorporation of deep learning enriches the establishment of the performance evaluation system for new energy enterprises, infusing technological and intelligent dimensions and furnishing robust support for a comprehensive comprehension of corporate performance.

Analysis of indicator feature extraction in AI technology. To ascertain the specific tertiary indicators across diverse facets of the new energy industry, the utilization of deep learning algorithms within AI technology is paramount for classification and recognition purposes. In the context of extracting indicator content features within the new energy domain, the Word2Vec model emerges as a pivotal tool. Through unsupervised learning from extensive corpora and voluminous performance datasets that

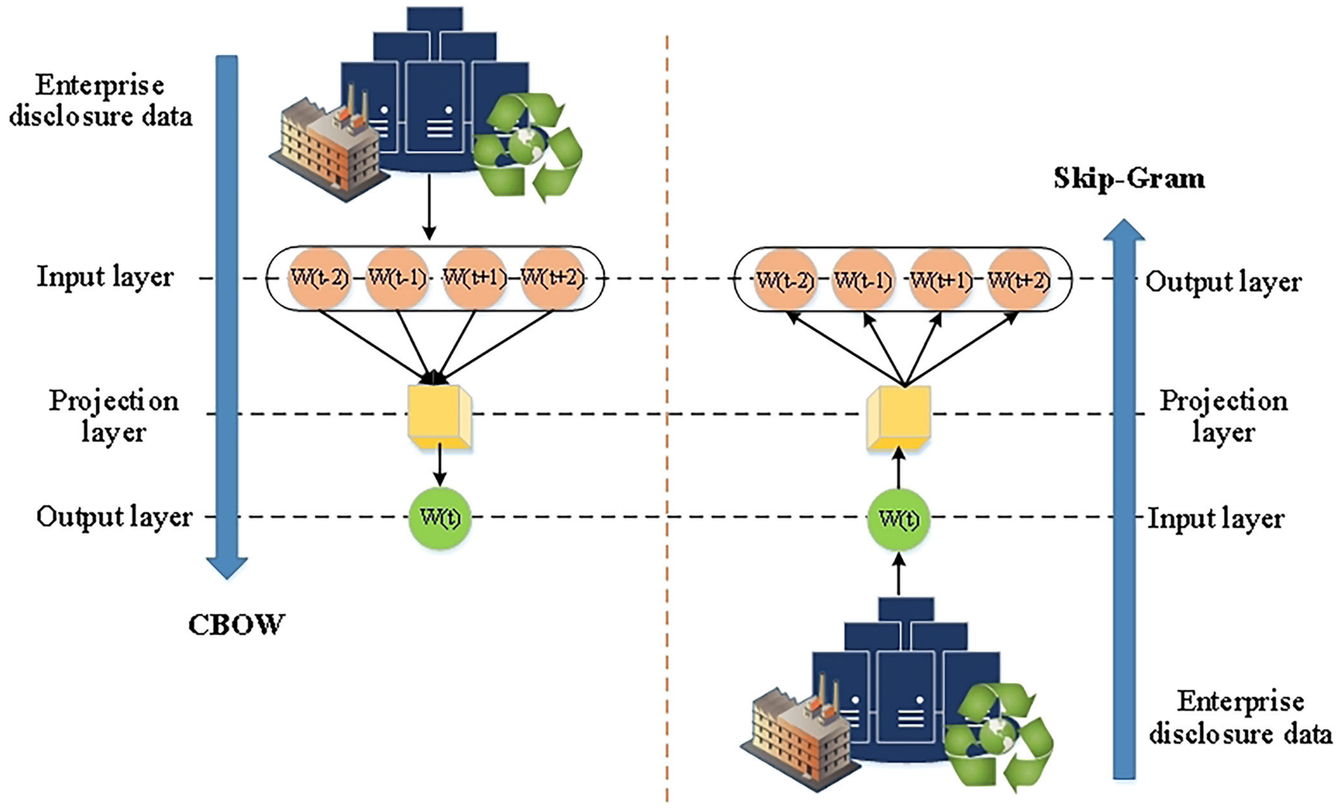

Fig. 3 Schematic diagram of Word2Vec model structure.

meet national data security standards, the Word2Vec model adeptly captures the semantic nuances embedded within textual data (Kurata et al. 2022; Wei et al. 2023a). The structure of the Word2Vec model is delineated in Fig. 3.

Figure 3 illustrates that the Word2Vec model primarily comprises two architectures, Skip-Gram and Continuous Bag of Words (CBOW). Each architecture encompasses an input layer, a projection layer, and an output layer (Yin and Zeng 2023). The projection layer is utilized to transform word vectors into a lower-dimensional space, thereby converting high-dimensional discrete representations (such as one-hot encoding) into lower-dimensional continuous vector representations. In this diagram, *w(t)* represents the performance center word, while $w(t-2)$, $w(t-1)$, $w(t+1)$, and $w(t+2)$ represent the context words. The CBOW model predicts target words from known contexts, while the Skip-Gram model predicts context words from known target words. Although Word2Vec is efficient in generating word vectors, it fails to capture long-distance dependencies and lacks the ability to distinguish polysemous words.

In contrast, the BERT model demonstrates stronger semantic understanding. Employing a Transformer architecture, BERT can simultaneously analyze contextual information before and after a word, making it particularly suitable for processing semantically complex text data. It learns hierarchical semantic information through multi-layer structures and shows excellent task adaptability. This study uses a pre-trained BERT model to convert indicator texts in the new energy industry into vector forms for subsequent analysis (Bedi and Toshniwal 2022; Kumar et al. 2023). The application of the BERT algorithm to represent the textual content of indicators in the new energy industry is illustrated in Fig. 4.

In Fig. 4, in the word vector space, BERT utilizes a word vector matrix to convert the input textual content of indicators in the new energy industry into real-valued vector representations. Assuming the one-hot vector representation for the input sequence x is denoted as $e^t \in R^{N\times|V|}$, the calculation of the word vector E^t is expressed as in Eq. (1):

$$E^t = e^t W^t \tag{1}$$

In Eq. (1), $W^t \in R^{|V|\times d}$ is a word vector matrix obtained by training. $|V|$ represents the size of the vocabulary, and d represents the dimension of the word vector.

Block vectors are used to encode the semantic segments to which each word belongs. Let the input block heat vector be $e^s \in R^{N\times|S|}$, and the calculation method of its real value representation is shown in Eq. (2):

$$E^s = e^s W^s \tag{2}$$

In Eq. (2), E^s refers to the conversion of block encoding to real-valued vectors using the block vector matrix W^s. $W^s \in R^{|S|\times d}$ represents the block vector matrix, and d is the embedding dimension. $|S|$ denotes the number of blocks.

Positional vectors are utilized to encode the absolute position of each word and can be expressed as in Eq. (3):

$$E^p = e^p W^p \tag{3}$$

In Eq. (3), $W^p \in R^{N\times e}$ signifies the positional vector, and N represents the maximum position length.

This study introduces the GCN and integrates the graph attention mechanism into the feature extraction process from indicator images. The GCN algorithm facilitates end-to-end learning on graph-structured data, enabling the capture of both local node relationships and global structures (Ali et al. 2022; Hu et al. 2022). GCN is well-suited for processing graph-structured data and capturing complex intercompany relationships. In ESG evaluation, supply chain connections, market networks, and other corporate interactions can be represented as graph structures, and GCN can effectively extract features from these relationships. Graph attention networks (GAT) possess the capability to dynamically learn attention weights between

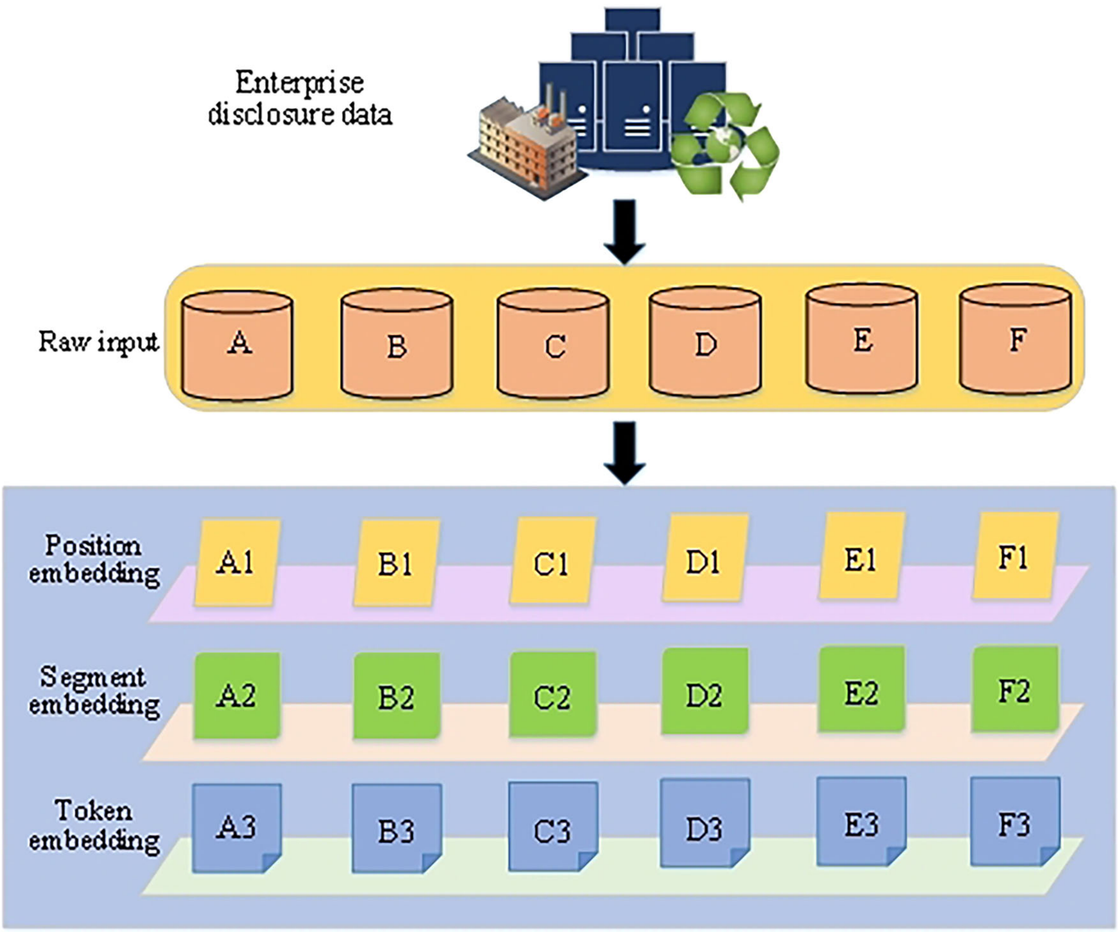

Fig. 4 Schematic representation of the application of the BERT algorithm to the textual content of indicators in the new energy industry.

each node and its neighbors, facilitating feature propagation and aggregation (Dong et al. 2022).

Construction of a performance evaluation model for the new energy industry using DL incorporating ESG. In the field of enterprise performance evaluation, a systematic approach is required to effectively classify and identify performance indicators. This involves leveraging deep learning methods, such as the Word2Vec model, to extract features from performance-related textual content, while utilizing GCN to capture features from image or video data. These technologies are applied to develop a performance evaluation model for new energy enterprises based on ESG principles. Subsequently, an attention mechanism is deployed to analyze and integrate these distinct features. Concurrently, this methodology is applied to the constructed ESG performance evaluation system. Ultimately, a comprehensive model is formulated, comprising a word embedding layer, an image convolutional network layer, an attention layer, and a performance indicator classification layer. This model constitutes a novel framework for performance evaluation within the new energy industry, seamlessly integrating deep learning methodologies with ESG considerations, as depicted in Fig. 5.

Figure 5 delineates the operational framework of the model, wherein the initial step entails preprocessing the disclosed data pertinent to the new energy industry. Subsequently, feature extraction is executed separately through the utilization of the word embedding and graph convolutional layers. The word embedding layer employs the BERT algorithm to encode and extract features from textual data. In comparison to conventional word vector models, BERT excels in capturing semantic nuances and contextual relationships within textual data, thereby enhancing the model's capacity for feature extraction. Consequently, the model gains a comprehensive understanding of the textual information, yielding more precise and informative feature representations for subsequent performance evaluation endeavors.

The graph convolution layer introduces the GCN alongside the integration of a graph attention mechanism. GCN, tailored for processing graph data, adeptly exploits inter-node connections to extract features and propagate information throughout the graph structure. Incorporating a graph attention mechanism into GCN enables the model to autonomously prioritize and accentuate pertinent nodes and edges, thereby enhancing its capacity to capture the structural intricacies and relational dynamics within the graph data. This amalgamation of graph convolution and attention mechanisms facilitates the model's ability to discern critical features within the graph data, consequently bolstering the accuracy and reliability of performance evaluation outcomes. Within the GCN layer, a propagation rule is established, with its calculation delineated in Eq. (4):

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-\frac{1}{2}}\tilde{Q}\tilde{D}^{-\frac{1}{2}}H^{(l)}K^{(l)}\right) \tag{4}$$

$$\tilde{Q} = Q + I_N \tag{5}$$

$$\tilde{D}_{ii} = \sum_j \tilde{Q}_{ij} \tag{6}$$

In Eq. (4), $\tilde{Q}$ refers to the adjacency matrix with the addition of a self-connected undirected graph, represented as in Eq. (5). In Eq. (5), I_N is the identity matrix. $\tilde{D}_{ii}$ can be expressed as in Eq. (6). $K^{(l)}$ indicates the trainable weight matrix for a specific layer,

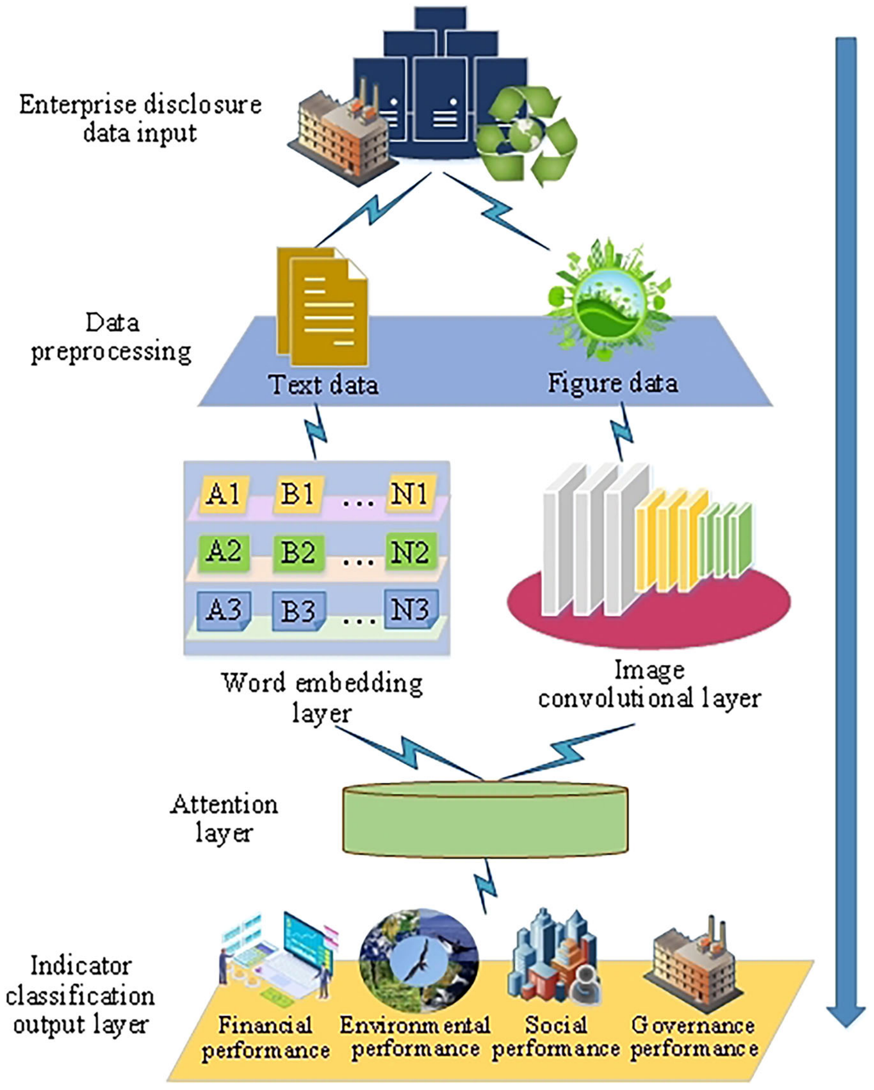

Fig. 5 Diagram of the performance evaluation model for the new energy industry based on DL integrated with ESG.

while $\sigma(\cdot)$ represents the activation matrix. $H^{(l)}$ denotes the activation matrix of the l-th layer, and $H^{(0)} = X$.

The experiment further analyzes the nodes, edges, and model of the GCN layer. Nodes represent feature vectors of each modality input transformed to the same dimension through modality encoders, enabling different modal feature vectors to converge to a common dimension. The output u_i^t, u_i^a, u_i^v are considered as the graph nodes. Edge configuration is crucial for the graph neural network. For a given node of a specific modality, it should be connected to nodes from the same modality, and interactions with nodes from different modalities should be considered differently. Therefore, only nodes from the same modality within a specific segment are interconnected, and nodes from different modalities and different segments are not connected. Similarly, the greater the correlation between two nodes, the higher the weight of the edge between them. To realize the difference in edge weights between nodes, this study adopts angle similarity as the calculation method of edge weights. Specifically, the weight of the edge between two nodes is defined by the cosine similarity of the included angle between their feature vectors, as shown in Eq. (7):

$$sim(u_i^s, u_j^s) = \frac{(u_i^s)^T u_j^s}{\|u_i^s\| \cdot \|u_j^s\|} \tag{7}$$

u_i^s and u_j^s represent the eigenvectors of the i-th and j-th nodes in mode s, respectively. Further, the edge weights between two nodes are shown in Eqs. (8) and (9):

$$E_{ij}^s = 1 - \frac{\arccos(sim(u_i^s, u_j^s))}{\pi} \tag{8}$$

$$E_{ij}^{s \leftrightarrow s'} = \gamma\left(1 - \frac{\arccos(sim(u_i^s, u_i^{s'}))}{\pi}\right) \tag{9}$$

Equation (8) ensures that the closer the features of two nodes are, the closer their edge weights are to 1. On the other hand, the closer it is to 0. For the same node, i.e., $i = j$, there is $sim(u_i^s, u_j^s) = 1$, so that $E_{ij}^s = 1$, i.e., the edge weight between the node and itself is the largest, which accords with the diagonal reinforcement characteristics of the graph product. In Eq. (9), $s, s' \in \{t, a, v\}$, but $s \neq s'$. E_{ij}^s represents edges between nodes of the same modality, and $E_{ij}^{s \leftrightarrow s'}$ denotes edges between nodes of different modalities. $u_\cdot^\cdot$ indicates a node of a specific modality in the graph, and γ represents hyperparameters.

An undirected graph is defined as G_m, and its computation is expressed as in Eq. (10):

$$G_m = (V_m, E_m) \tag{10}$$

In Eq. (10), V_m encompasses all nodes u_i within the network. E_m denotes the representation of edges between nodes, where $(u_i, u_j) \in E$. The feature vector matrix for nodes is $X \in R^{N \times C}$, where N indicates the number of nodes, and C represents the dimension of the feature vectors. The Laplacian matrix L is defined as in Eq. (11).

$$L = I_n - D^{-\frac{1}{2}} Q D^{-\frac{1}{2}} \tag{11}$$

In Eq. (11), the elements in the adjacency matrix Q can be binary-encoded or weighted real numbers. D_{ii} represents the degree matrix, and I is the identity matrix. The iterative computation of the graph neural network for each layer is expressed as in Eq. (12):

$$H^{(l+1)} = \sigma\left(\left((1-\alpha)LH^{(l)} + \alpha H^{(0)}\right)\left(\left(1-\beta^{(l)}\right)I + \beta^{(l)}K^{(l)}\right)\right) \tag{12}$$

$$\beta^{(l)} = \log\left(\frac{1}{\eta} + 1\right) \tag{13}$$

In Eq. (12), α and $\beta^{(l)}$ refer to two hyperparameters. $\beta^{(l)}$ can be represented as in Eq. (13). η is also a hyperparameter. Through this iterative approach, the recognition performance of graph features in the model can be further enhanced.

An attention mechanism is employed to merge these features. By merging the features from the word embedding layer and the graph convolution layer, and incorporating an attention mechanism for feature fusion and enhancement, the model's performance is improved. This mechanism of feature fusion and attention allows the model to better integrate information from textual and graph data, fully leveraging the associative relationships between different data sources. Consequently, the model becomes more suitable for performance evaluation tasks. Through the effective fusion and integration of features from diverse data sources, the model can comprehensively and accurately assess the performance of new energy enterprises, providing stronger support and guidance for business decision-making. This mechanism leverages unsupervised learning to automatically focus on and emphasize the most relevant features, thereby enhancing the understanding and evaluation of performance indicators. This feature fusion and attention mechanism improve the model's performance, making it more suitable for performance evaluation tasks.

Figure 6 presents the pseudocode for this model's algorithm.

Figure 6 harnesses multimodal data and attention mechanisms to facilitate the classification and feature extraction of performance indicators. This approach ensures the comprehensive extraction of informational value from the data, thereby augmenting the accuracy and efficacy of the evaluation model. The holistic utilization of diverse data modalities, including text and images, enables a more thorough comprehension of enterprise performance, furnishing decision-makers with heightened confidence in the reliability of data support. Additionally, regulatory frameworks such as the "ESG Guidelines" issued by the Hong Kong Stock Exchange and the "ISO 26000: Guidelines for Social Responsibility" formulated by the International Organization for Standardization serve as pivotal references. Furthermore, informed by the unique attributes of new energy enterprises, a tertiary indicator structure for the performance evaluation system of such enterprises is meticulously derived, as delineated in Table 1.

As shown in Table 1, this study adopts a systematic approach to classify and identify performance indicators in corporate performance evaluation. Specifically, AI technology plays a key role in two aspects. First, deep learning methods such as Word2Vec and GCN are used to extract features from multimodal data (text and images) and identify the most influential indicators for performance evaluation. This process not only reduces subjective bias from manual intervention but also uncovers hidden correlations that traditional methods may overlook, optimizing the indicator structure. Then, the BERT and GCN models, combined with the attention mechanism, are employed to integrate and classify the extracted features, which significantly improves the accuracy and efficiency of indicator identification. The criteria for assessing the rationality of the indicator structure include: Objectivity: Indicator selection is data-driven, minimizing subjective bias. Relevance: Pearson correlation coefficient analysis is used to eliminate highly correlated indicators, ensuring independence among indicators. Interpretability: Each indicator is derived from publicly available corporate data, such as social responsibility and annual reports, and is validated by experts to ensure its practical significance. Table 1 shows that when selecting specific indicators, this study primarily selects 42 tertiary indicators. Further considering the correlation of various indicators, 34 most representative tertiary indicators are ultimately selected after Pearson correlation coefficient analysis. Among them, eight indicators are excluded because they are strongly correlated with other indicators (with a correlation coefficient greater than 0.8). It is to ensure the scientific validity of the evaluation indicators. In the comprehensive performance calculation, the weight allocation for each dimension (financial, social, governance, and environmental) is determined based on industry practices and expert opinions. Specifically, in this study, the weight for environmental performance (w_1) is 0.35, financial performance (w_2) is 0.30, social performance (w_3) is 0.20, and governance performance (w_4) is 0.15. This distribution reflects the new energy industry's strong emphasis on environmental protection and technological innovation while also considering financial stability and social responsibility. The comprehensive performance can be expressed as Eq. (14):

$$C = w_1 \times C_{ep} + w_2 \times C_{fp} + w_3 \times C_{sp} + w_4 \times C_{gp} \tag{14}$$

C_{ep} represents environmental performance, C_{fp} represents financial performance, C_{sp} represents social performance, and C_{gp} represents governance performance.

Empirical evaluation. To evaluate the effectiveness of the performance assessment model for the new energy industry that integrates deep learning and ESG standards, this study selects Mingyang Intelligent as a case study. As a leading enterprise in China's new energy sector, Mingyang Intelligent has demonstrated significant technological innovation and market influence, particularly in the wind power industry. Its comprehensive ESG disclosure practices effectively reflect the core characteristics of high-quality development in the new energy sector. The primary data sources include Mingyang Intelligent's social responsibility reports, annual reports, and official website. Given the high degree of similarity in business models and governance frameworks among leading enterprises in China's new energy industry, selecting Mingyang Intelligent as a case study allows for a focused analysis of ESG dynamics while ensuring methodological rigor in exploratory model validation. Since Mingyang Intelligent has been publishing social responsibility reports since 2018, this study compiles data from 2018 to 2022. A longitudinal analysis of five years of data enables an in-depth examination of the temporal evolution of ESG performance and reveals the interaction between corporate strategy and SD outcomes. To mitigate the impact of dimensional differences, a dimensionless quantification technique is applied to process the raw data and obtain the relevant data for each indicator. Throughout the data collection

```
Start
Input: Disclosure data of new energy enterprises
Output: Different performance classification indicators
# Create text feature extraction layer
    embedding_layer = Embedding(input_dim=vocabulary_size,
    output_dim=embedding_dim) (text_data)
    text_features = # Process embedding_layer using Word2Vec or other text feature
    extraction methods
# Create image feature extraction layer
    convolution_layer = Conv2D(filters=num_filters, kernel_size=kernel_size)
    (image_data)
    image_features = # Extract features using Graph Convolutional Neural Network
# Feature fusion with attention mechanism
    attention_layer = Attention()([text_features, image_features])
    merged_features = # Fuse text and image features using attention_layer
# Build ESG performance evaluation system
    esg_evaluation_system = # Construct the ESG performance evaluation system
# Define classification layer
    output_layer = Dense(num_classes)(merged_features)
# Make predictions using the model
    predictions = model.predict(x_test)
End
```

Fig. 6 Pseudocode flowchart for applying BERT integrated with GCN in feature extraction for enterprise performance indicators.

Table 1 Tertiary indicator structure for performance evaluation system of new energy enterprises.

Primary indicators	Secondary indicators	Tertiary indicators	Data sources
Financial performance	Debt repayment ability (DR)	Asset-to-liability ratio (%), Current ratio, Interest coverage ratio	The social responsibility report, annual report, and official website of Mingyang Intelligence
	Operating capability (OC)	Accounts receivable turnover (times), Inventory turnover (times)	
	Profitability (PG)	Return on equity (%), Net profit margin (%)	
	Development capability (DC)	Net profit growth rate (%), Total asset growth rate (%), Capital accumulation rate (%)	
Environmental performance	Emissions (EGR)	Greenhouse gas emissions intensity (tons/thousand yuan), Hazardous waste emissions intensity (tons/megawatt)	
	Resource utilization (RU)	Comprehensive energy consumption per 10,000 yuan of revenue (tons of standard coal per 10,000 yuan), Total water consumption density (tons/person)	
	Green management (GM)	Impact of business activities on the environment (10000 tons)	
	Biodiversity (BI)	The distribution quantity of different types of forests, wetlands, and grasslands	
Social performance	Employee responsibility (ER)	Equal employment (%), per capita training hours (h), safety production cost (10,000 yuan)	
	Product liability (PL)	Research and development (R&D) personnel ratio (%), R&D investment ratio (%)	
	Customer and supplier responsibility (CSR)	Customer satisfaction (%), major supplier procurement proportion (%), accounts payable turnover rate (%)	
	Government and community responsibility (GCR)	Total tax payment (10,000 yuan), total public welfare donations (10,000 yuan)	
Governance performance	Board governance (BG)	Director attendance rate (%), proportion of independent directors (%), number of board meetings (times)	
	Investor relations (IR)	Cash dividend ratio (%), Equity balance degree	
	External supervision (ES)	Number of information disclosure announcements, penalty expenses (10,000 yuan)	
	Executive tenure (ET)	Number of years of management tenure (years)	

and utilization process, this study strictly adheres to ethical and privacy protocols and emphasizes confidentiality and sensitivity of enterprise data to ensure lawful data acquisition and usage.

During the model training phase, the data preprocessing steps include text cleaning (removing punctuation, stop words, and special characters), tokenization (using the BERT tokenizer), padding and truncation (fixing text sequences to 512 tokens), and label encoding (converting categorical labels into numerical form). For graph data, a supply chain relationship graph is constructed among enterprises, where nodes represent enterprises and edges denote relationships. Additionally, node features are normalized. Table 2 presents the hyperparameter settings for each module in the model.

For the BERT model, the hidden layer dimension is set to 768, which is the standard configuration for the BERT-base architecture. This allows the model to capture complex semantic information while maintaining computational efficiency. The number of attention heads is set to 12 to ensure the model can fully capture the multidimensional contextual relationships within the text. The learning rate is set to 2e-5, and the Adam optimizer is used. This is a stable choice validated through multiple experiments, providing a balance between convergence speed and avoiding overfitting. The number of training epochs is set to 100 to allow the model to stabilize after multiple training cycles while avoiding excessive training time and preventing overfitting. The batch size is set to 32 to strike a balance between computational efficiency and memory usage. For the GCN model, the number of graph convolution layers is set to 2, balancing the capture of local node relationships and the global graph structure. The output dimension per layer is set to 32 to reduce computational complexity while preserving sufficient feature representation capability. The ReLU activation function is selected due to its widespread application and strong nonlinear representation ability in deep learning. The L2 regularization parameter is set to 1e-5 to control model complexity and prevent overfitting. These hyperparameter choices comprehensively consider model performance, computational efficiency, and practical application requirements, ensuring the model's effectiveness and reliability in ESG evaluation tasks.

The validation process aims to evaluate the generalization ability and practical application value of the model. Data splitting is employed to divide the dataset into a training set (80%) and a test set (20%). k-fold cross-validation ($k = 5$) is used to ensure the stability of model performance across different data subsets.

To evaluate the performance of the proposed model, this study compares it with GCN, CNN, and models proposed by relevant scholars (such as Yang et al. 2023 and Jiang et al. 2023). The evaluation metric used is classification accuracy (Accuracy), which represents the proportion of correctly classified samples to the total number of samples, as shown in Eq. (15):

$$Accuracy = \frac{N_{right}}{N_{all}} \times 100\% \tag{15}$$

N_{right} represents the number of correctly classified samples, and N_{all} represents the total number of samples.

In the comparative study, the proposed model is evaluated against the following models. GCN is a deep learning model designed for graph-structured data, suitable for node classification and link prediction tasks. CNN is a conventional convolutional neural network widely used for image and text classification tasks. The model proposed by Yang et al. (2023) is a collaborative filtering recommendation algorithm incorporating time weight and reward–penalty factor. The model proposed by Jiang et al. (2023) employs time-frequency domain connectivity analysis to explore relationships among energy, green finance, and ESG factors.

To ensure the objectivity of classification results, an annotated dataset is used as the benchmark. Specifically, the true category of each sample is manually labeled by experts based on publicly available ESG reports and financial data of enterprises. The classification results generated by the model are then compared with the annotated data. If they match, the classification is considered correct; otherwise, it is considered incorrect. This approach enables an accurate calculation of the model's classification accuracy.

Next, an evaluation is conducted from the four dimensions of finance, environment, society, governance, and comprehensive performance indicators.

Table 2 Hyperparameter settings for each module in the model.

Parameter		Setting
BERT Module	Hidden Layer Dimension	768
	Number of Attention Heads	12
	Learning Rate	2e-5 (Adam Optimizer)
GCN Module	Hidden Layer Dimension	768
	Number of Graph Convolution Layers	2
	Output Dimension per Layer	32
	Activation Function	ReLU
	Regularization Parameter	L2 Regularization (1e-5)
	Number of Training Epochs	100
	Batch Size	32

Results and discussion

Comparative analysis of model classification and recognition performance. The accuracy of the proposed model is compared with that of the model algorithm GCN, CNN, the model proposed by scholars Yang et al. (2023), and Jiang et al. (2023) in related fields. Figure 7 illustrates the comparison results.

Figure 7 reveals that the recommendation recognition accuracy of the model algorithm proposed reaches 90.48%, which is at least 5.77% higher than other algorithms in terms of accuracy. Moreover, the recommendation accuracy of each algorithm is ranked in descending order: the model algorithm constructed here > the algorithm proposed by Yang et al. (2023) > GCN > CNN. The comparison between the model algorithm proposed in this study and the time-frequency domain connectivity analysis method proposed by Jiang et al. (2023) shows that without using AI algorithms, the identification accuracy is only about 52%, significantly lower than that of the model algorithm proposed in this study. This is because the proposed model can process both text and image data simultaneously. It extracts features using BERT and GCN, respectively, and integrates them through an attention mechanism. This multimodal data fusion approach enables a more comprehensive capture of various aspects of corporate performance. BERT and GCN models demonstrate strong performance in their respective domains, effectively extracting complex features. By combining these two models, the proposed approach achieves superior performance in feature extraction and classification tasks. Additionally, the attention mechanism automatically focuses on the most critical features for classification, further enhancing the model's classification accuracy. Therefore, the model constructed has excellent performance indicator recognition and classification accuracy, ensuring that the obtained indicator information for new energy enterprise data is accurate, reliable, and valuable.

Analysis of the evaluation results of various performance indicators in different years. The proposed performance evaluation system is applied to display the evaluation results of

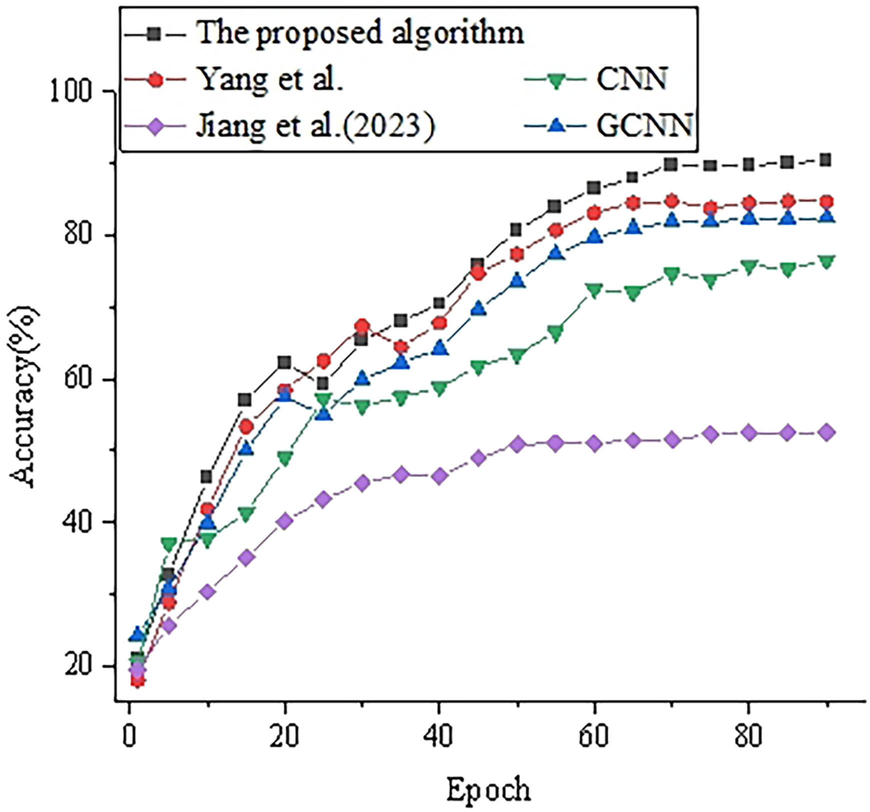

Fig. 7 Accuracy curves under different model algorithms.

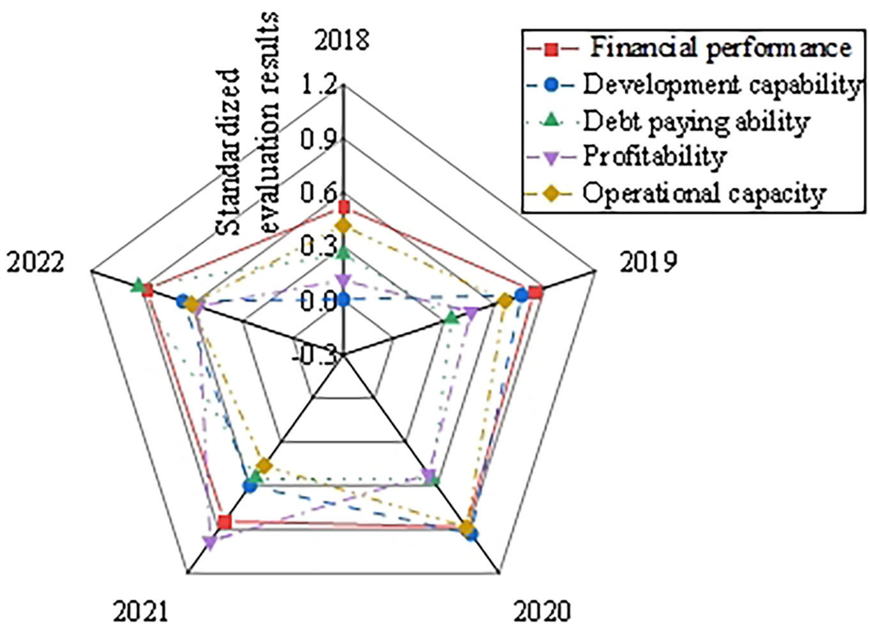

Fig. 8 Evaluation results of financial performance indicators.

financial, enterprise, social, and governance dimensions, and comprehensive performance indicators from 2018 to 2022. The data are standardized and processed. Figures 8–11 show the results.

Figure 8 displays the financial performance indicators of new energy enterprises from 2018 to 2022. These indicators include solvency, operational capability, profitability, and development capability, among others. The financial performance of enterprises peaked in 2020, followed by a slight decline in 2021. This may be due to some challenges faced by companies in debt repayment ability, development capability, and operational efficiency. The data for 2022 shows that financial performance has not significantly improved, indicating that management needs to conduct an in-depth analysis of the reasons and formulate corresponding strategies to optimize the financial structure and enhance economic benefits.

Figure 9 reflects the performance of new energy enterprises in terms of social responsibility, involving employee responsibility,

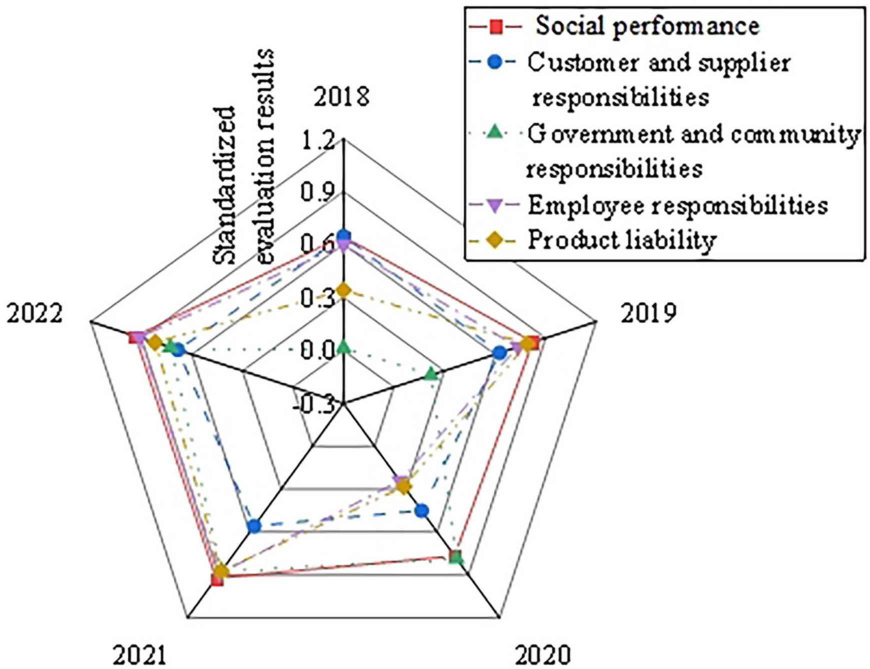

Fig. 9 Evaluation results of social performance indicators.

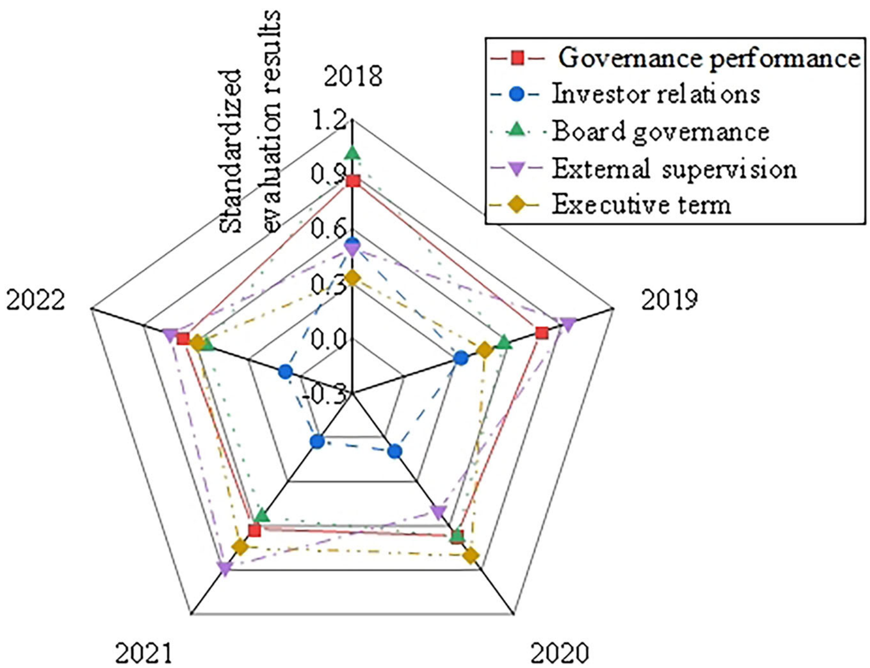

Fig. 10 Evaluation results of governance performance indicators.

product responsibility, responsibility to customers and suppliers, and responsibility to government and communities. In recent years, the social performance of enterprises has shown a fluctuating upward trend. Although there was a slight decrease from 2019 to 2020, it resumed an upward trend in 2021 and 2022. The data indicate that companies have made some progress in fulfilling social responsibilities, but there is still room for improvement in areas such as employee training, product safety and quality, and customer satisfaction.

Figure 10 reveals the assessment results of new energy enterprises in terms of governance performance, including board governance, investor relations, and external supervision. From 2018 to 2021, governance performance showed a slight downward trend, but there was a slight recovery in 2022. This may indicate that companies have made some improvements in governance structure, decision transparency, and risk management. However, overall, there is still a need for improvement in governance performance to ensure the long-term stable development of enterprises.

Figure 11 illustrates the assessment of new energy enterprises in terms of environmental performance, including emissions, resource utilization, green management, and biodiversity. From 2018 to 2021, environmental performance shows a stable upward trend, reflecting the efforts of enterprises in reducing

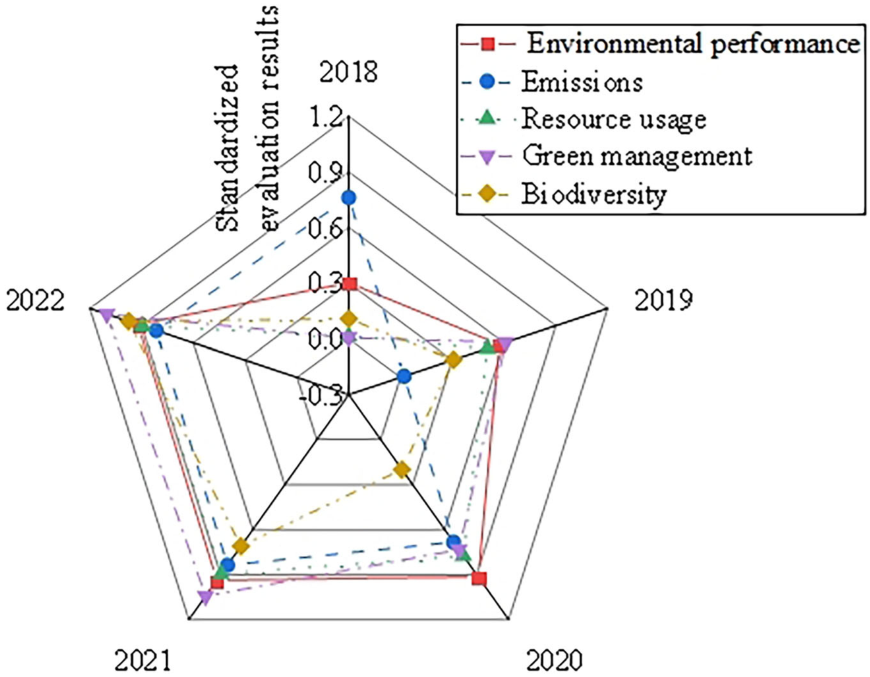

Fig. 11 Evaluation results of environmental performance indicators.

environmental pollution and improving resource efficiency. However, environmental performance in 2022 remains stable, which may be attributed to the fact that companies are not expanding production scale in that year, thereby affecting further improvement in environmental performance.

Figure 12 illustrates the additional evaluation findings pertaining to the comprehensive performance indicators. It is observed that the financial performance score demonstrates a relatively high level, while the environmental performance score exhibits a consistent upward trajectory. Conversely, the social performance score displays notable fluctuations, warranting focused attention toward the fulfillment of employee and product responsibilities. Governance performance scores, on the other hand, generally register at lower levels, highlighting the imperative for ongoing enhancements in corporate governance mechanisms, internal controls, and risk management practices. Such measures are essential to ensure that all business operations adhere to standardized and systematic management protocols, thereby fostering the enterprise's sustained functionality and long-term viability.

Discussion

The precision analysis reveals that the performance evaluation model proposed in this study demonstrates outstanding accuracy in recommendation identification, reaching 90.48%. This represents a significant improvement of 5.77% compared to models based on GCN, CNN, and the algorithm proposed by Yang et al. (2023). This result aligns with the observations made by Liu et al. (2023). The heightened accuracy holds profound practical significance. Firstly, the credibility of the model has substantially increased, instilling greater trust from corporate management in the classification results of performance indicators for new energy enterprises. This result provides decision-makers with a more reliable data foundation, supporting informed and reasoned choices in decision-making, strategic planning, and operational optimization. Secondly, the high accuracy of the model output becomes a robust support for corporate decision-making, offering reliable decision support tools to the management. By gaining deeper insights into performance across different dimensions, companies can allocate resources more accurately, optimize resource distribution, and maximize economic, social, and environmental benefits. Moreover, high accuracy enables companies to better navigate market competition, providing a strong guarantee for gaining a competitive advantage in the market. For stakeholders concerned with CSR and SD, the high accuracy of the model further enhances the credibility of the company's ESG management, elevating overall sustainability and levels of social responsibility. Therefore, the high-precision performance evaluation model constructed in this study holds strategic value in improving decision-making effectiveness, optimizing resource allocation, and strengthening ESG management, providing robust support for sustainable corporate development.

This study conducts an analysis of the four primary indicator dimensions within the performance evaluation system for new energy enterprises. In the financial dimension, from 2018 to 2021, the overall financial performance of the company exhibits an upward trend followed by a decline, reaching its peak in 2020 and slightly decreasing in 2021. This trend is primarily attributed to the company's decreasing solvency, development capability, and operational efficiency after 2020. However, the financial performance in 2022 did not show a significant increase. This trend reflects the economic achievements the company has made in recent years but also signals potential risks and challenges in certain aspects. For the company's management, it is essential to delve into the reasons behind these financial performance trends, especially the declines observed after 2020, in order to formulate effective financial strategies and response measures.

In the social dimension, overall social performance has exhibited a fluctuating upward trend in recent years. Despite a slight decline from 2019 to 2020, there is a steady upward trajectory in both 2021 and 2022. The company demonstrates commendable responsibility to various stakeholders, but special attention is needed for enhancements in employee responsibility and product responsibility. This may reflect the company's efforts in social responsibility, yet it indicates room for improvement in specific areas. By strengthening employee training and product responsibility management, the company can further enhance its social performance and amplify its SD impact at the societal level.

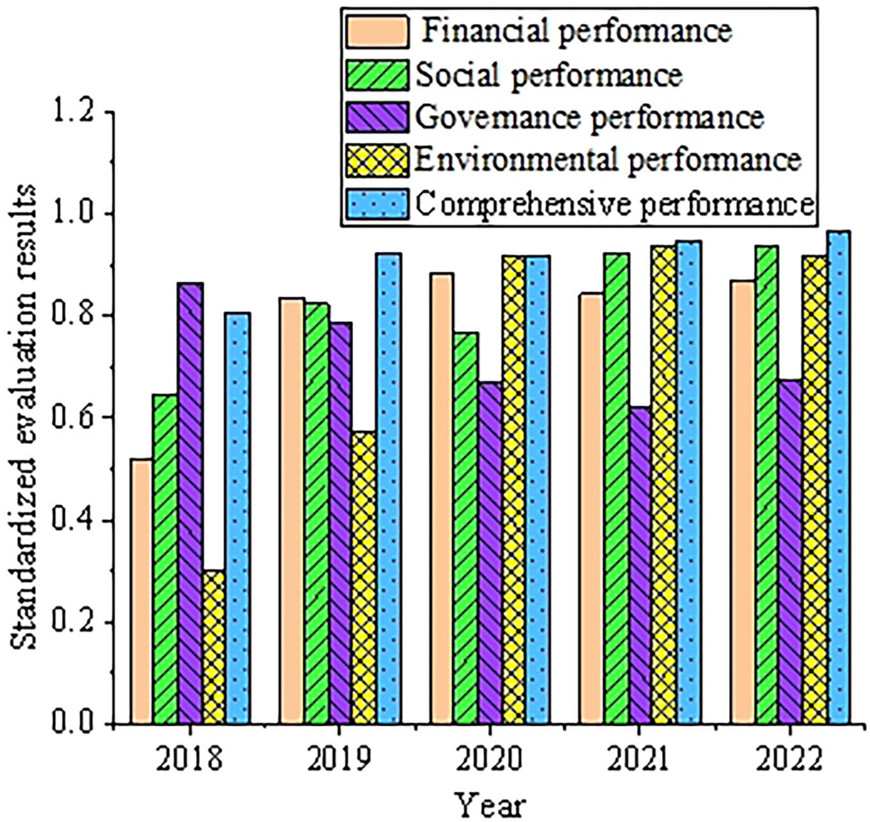

Fig. 12 Evaluation results of comprehensive performance indicators.

In the governance dimension, the company's governance performance from 2018 to 2021 shows a slight fluctuating decline, with a slight increase observed in 2022. This suggests that the company has made certain improvements in governance, particularly in recent years. However, overall governance performance still requires attention, necessitating ongoing enhancements in corporate governance mechanisms, internal controls, and risk management. Improved governance performance contributes to ensuring the normativity and systematic operation of the company, laying a solid foundation for future development.

Within the environmental dimension, the company's environmental performance exhibits an overall upward trend from 2018 to 2021, primarily driven by outstanding performance in emissions, resource utilization, and environmental and natural resource aspects. Environmental performance in 2022 remains relatively stable due to not expanding production scale. This indicates significant achievements in environmental sustainability, yet future efforts may be required to sustain this momentum. By continuing to implement environmental conservation measures, the company can secure its leading position in environmental performance and consistently contribute to SD.

In a comprehensive analysis, the evaluation of composite performance indicators reveals relatively high scores in financial performance and a consistently rising trend in environmental performance. However, social performance scores show significant fluctuations, demanding special attention to fulfill employee and product responsibilities. Governance performance scores are generally lower, necessitating continuous improvement in corporate governance mechanisms, internal controls, and risk management. This aligns with the viewpoints of Kanamura (2022) and Chkareuli et al. (2023). This holistic assessment provides the company with a comprehensive understanding of performance across different dimensions, facilitating the formulation of targeted improvement strategies. The company excels in financial and environmental aspects but requires specific focus on enhancing social and governance dimensions to achieve holistic SD goals.

Firstly, the findings of this study align with those of Nitlarp and Kiattisin (2022), who emphasize the importance of Industry 4.0 technologies in enhancing energy efficiency and environmental governance. Furthermore, through empirical analysis, the study demonstrates the practical application value of AI technology in integrating ESG data and enhancing assessment accuracy. Secondly, concerning the relationship between ESG performance and financial performance, the results of this study are consistent with the qualitative comparative analysis by Liu et al. (2022a), indicating a complex dynamic relationship between ESG performance and financial performance. However, deep learning models offer a more precise assessment method capable of revealing the specific impacts of different ESG dimensions on financial performance, a point not extensively explored in the study by Behl et al. (2022). Additionally, the study expands the understanding of internal decision-making processes within the new energy industry. Analysis of significant performance variations across different years can identify the strengths and weaknesses of companies in specific ESG dimensions, complementing the study by Jiang et al. (2023) on the impact of international events on energy, finance, and sustainability linkages. The results emphasize the need for continuous monitoring and improvement of ESG performance by enterprises to adapt to the evolving market and policy environment. Finally, by proposing an AI-based ESG performance evaluation model, the study offers a new perspective on the SD of the new energy industry. This model not only enhances assessment accuracy but also provides data support for resource allocation and strategic planning, which is considered a key factor in improving the economic resilience of the energy industry, as highlighted in the research by Lei et al. (2023).

This study introduces deep learning and AI technologies to develop a performance evaluation model for the renewable energy industry based on ESG principles. The model leverages advanced techniques such as Word2Vec and GCN to analyze multimodal data, enabling a more accurate assessment of the ESG performance of renewable energy enterprises. The practical significance and value of this research are reflected in several aspects:

(1) Innovative Performance Evaluation Model: This study integrates deep learning techniques to develop a performance evaluation model for renewable energy enterprises. Based on the ESG management framework, the model encompasses multiple dimensions, including financial, environmental, social, and governance indicators, providing a more comprehensive and precise assessment of corporate operations. This innovative model offers enterprises more accurate and trustworthy data support, aiding decision-makers in formulating development strategies and management plans with greater precision.

(2) Promotion of ESG management: Integrating ESG management into the performance evaluation system strengthens the assessment of companies in ESG aspects. This contributes to better fulfillment of social responsibility, improved governance levels, and the promotion of SD. For the new energy industry, possessing a robust ESG management system is a crucial assurance for attracting investments and gaining public recognition.

(3) Optimization of Resource Allocation: Through in-depth analysis of performance in various dimensions, enterprises can allocate resources more accurately, maximizing economic, social, and environmental benefits. For resource-limited enterprises, this translates to more efficient operations and SD.

(4) Leadership Role Fulfillment: The study provides an advanced method for enterprises to better fulfill a leadership role in the new energy industry. By comprehensively understanding performance in different dimensions, companies can adapt to market changes, enhance competitiveness, and contribute to the overall advancement of industry technology and management standards.

This study has significantly impacted the new energy industry by introducing an AI-based ESG performance evaluation model. The model employs deep learning techniques to analyze ESG performance and provides renewable energy enterprises with a more accurate and comprehensive evaluation. Firstly, the model enhances the ability of enterprises to assess and optimize their environmental and social responsibility performance, thereby promoting SD practices across the industry. Secondly, a precise ESG performance assessment allows investors and stakeholders to gain clearer insights into company performance, thereby enhancing market transparency and trust. Additionally, the study highlights the importance of interdisciplinary collaboration in driving technological advancements in the new energy sector, providing new avenues for future technological innovations.

This study introduces a performance evaluation model based on AI and ESG principles, significantly impacting the renewable energy industry. By leveraging deep learning algorithms, the model autonomously extracts features from multimodal data and significantly enhances ESG assessment accuracy and efficiency (achieving a classification accuracy of 90.48%). This provides reliable decision support for management, investors, and regulatory bodies. Additionally, the model establishes a standardized framework for the industry and improves transparency and comparability, which encourages enterprises to disclose ESG reports and attract more financial support for SD. Moreover, this study highlights the potential of applying AI in ESG evaluation. It fosters interdisciplinary collaboration between the renewable energy sector and fields such as data science and environmental science, thus providing a new direction for technological innovation and industry advancement. Overall, the model serves as a scientific and efficient evaluation tool for the renewable energy industry and promotes SD and technological progress in the renewable energy sector.

Model interpretability is crucial for decision transparency and credibility in ESG assessment. This study enhances model interpretability through the integration of attention mechanisms and feature importance analysis. Specifically, the attention mechanism can visualize the key features the model focuses on in classification tasks. For example, in text data, the attention weights can show which words or sentences have the greatest impact on the ESG score. In image data, the attention mechanism can highlight the regions that contribute the most to the classification result. Additionally, feature importance analysis can quantify each feature's contribution to the final prediction and help stakeholders understand how the model derives the ESG score. For instance, in environmental performance evaluation, the model may identify carbon emissions and resource utilization as the most critical features, whereas, in social performance assessment, employee training duration and product safety costs may hold greater significance. By incorporating these techniques, the proposed model not only delivers high-precision predictions but also generates interpretable reports, enabling decision-makers to comprehend the reasoning behind ESG assessments. This enhances its practicality and credibility in ESG evaluation, providing stakeholders with more transparent decision-making support.

Although the performance evaluation model proposed based on AI and ESG principles holds significant potential for application in the renewable energy industry, several challenges remain in its practical implementation. First, potential biases in data sources may affect the model's accuracy. For example, discrepancies in data disclosure standards across different companies' ESG reports could lead to bias in the model's training data. To mitigate this bias, it is recommended that future research establish a unified data disclosure framework and ensure the authenticity and completeness of the data through third-party audits. Next, the challenge of integrating multimodal data (such as text, images, and structured data) lies in the heterogeneity of data formats and semantics, which may impact the effectiveness of feature extraction and fusion. Future studies could explore more advanced multimodal fusion techniques, such as cross-modal attention mechanisms, to better capture the relationships between different data sources. Moreover, assumptions within the model (such as linearity or independence assumptions) may not align with the complex real-world ESG evaluation scenarios, leading to bias in prediction outcomes. Therefore, future research should incorporate more complex nonlinear models and optimize model assumptions with domain knowledge. Lastly, although the "black-box" nature of deep learning models may reduce the transparency of decision-making, integrating explainable AI technologies (such as attention mechanism visualization and feature importance analysis) can enhance model interpretability and help stakeholders understand the reasoning process behind the model. To address the challenge of rapidly evolving technology, it is recommended that the model be regularly reviewed and updated to ensure its technical relevance and evaluation accuracy. Additionally, to reduce the implementation cost for small and medium-sized enterprises, future research could develop lightweight model versions or cloud service platforms to lower technological barriers. Through continued research and technological innovation, these challenges can be addressed, further advancing the application of AI in ESG evaluation within the renewable energy industry.

To remain competitive and maintain market position in the fast-evolving renewable energy sector, companies must adopt a series of strategies to strengthen governance practices and mitigate risks. The AI and ESG-based performance evaluation model proposed offers a valuable tool for companies to assess and improve their ESG performance. Firstly, companies need to enhance board governance by increasing the presence of members with technical and market insights to improve decision-making quality. Secondly, establishing a comprehensive risk management framework and utilizing AI and machine learning technologies to proactively identify and address market, technological, policy, and supply chain risks is essential. Additionally, enhancing transparency in corporate operations by regularly publishing ESG reports to build trust among investors and consumers is vital. Furthermore, continuous investment in technological innovation and research and development, along with collaboration with research institutions, is necessary to translate the latest research findings into practical products. Ensuring the sustainability of the supply chain by collaborating with suppliers to promote environmentally friendly materials and energy-saving technologies is crucial. Providing training for employees in new energy technologies and AI applications to enhance the flexibility and efficiency of the company's response to industry changes is important. Actively participating in policy discussions, establishing communication channels with government agencies, and influencing policy formulation to align with industry interests are essential. Lastly, developing emergency plans and business continuity strategies to enhance the company's ability to respond to unforeseen events is crucial. Through these strategies, companies can maintain stable development in the rapidly changing new energy industry and achieve long-term SD goals.

The significance of interdisciplinary collaboration. Innovation in the renewable energy sector requires the integration of multidisciplinary knowledge, including engineering, physics, computer science, environmental science, and economics. The AI and ESG-based performance evaluation model proposed is a prime example of such interdisciplinary collaboration. Combining data science and deep learning technologies enables a more accurate assessment and prediction of the environmental and social impacts of new energy enterprises while optimizing their governance structures.

Firstly, the integration of engineering and physics. In the development of new energy technologies, engineers and physicists collaborate closely to jointly develop more efficient solar panels and wind turbines. This collaboration has led to a significant improvement in energy conversion efficiency.

Secondly, the application of computer science. Computer scientists play a crucial role in the application of new energy industries, as algorithms and software they develop can optimize energy production processes, enhance automation levels, and reduce operational costs.

Thirdly, the integration of environmental science. The expertise of environmental scientists is crucial for assessing the environmental impacts of new energy projects. They collaborate with engineers to ensure that new energy projects minimize disturbance to ecosystems while providing renewable energy.

Fourthly, the guidance of economics. Economists provide decision support for policymakers by analyzing the economic benefits of new energy projects. Their research helps evaluate the effectiveness of fiscal incentive measures and guides the healthy development of the new energy market.

This study particularly emphasizes the collaboration between data scientists and industry experts. Data scientists utilize advanced technologies such as machine learning and GCN to analyze vast amounts of data generated by new energy enterprises, while industry experts provide an in-depth understanding of this data and industry background knowledge. This interdisciplinary collaboration not only enhances the accuracy of the model but also provides new solutions for the SD of the new energy industry.

Interdisciplinary collaboration enables a more comprehensive understanding of the complexity of the new energy industry and the development of more innovative technical solutions. This not only drives innovation in new energy technologies but also contributes to the long-term development of the industry and the achievement of global SD goals.

Conclusion

Achievements and prospects. This study introduces AI and ESG standards to assess the performance of renewable energy companies, aiming to promote the high-quality development of the renewable energy sector. The choice of Mingyang Intelligent as a single case study focuses on depth rather than breadth, allowing for a detailed analysis of this highly influential company in the industry to explore the practical path of ESG integration. While the sample size may limit the generalizability of the conclusions, Mingyang Intelligent's representativeness in technological innovation and ESG maturity provides key insights for other companies in the sector seeking scalable practices. Firstly, this study establishes a performance evaluation framework for renewable energy companies that covers four dimensions: financial, environmental, social, and governance. Then, by combining Word2-Vec and GCN methods, the work extracts and integrates features from multimodal data, such as text and images, to build a deep learning-based performance evaluation model grounded in ESG principles. In empirical research, the proposed model performs exceptionally well in identifying and classifying performance indicators, achieving an accuracy rate of 90.48%. Meanwhile, the empirical results indicate that financial indicators perform relatively well, while environmental performance shows a continuous upward trend. However, social performance scores exhibit noticeable fluctuations. This study contributes to the development of a more scientific, rigorous, and accurate performance evaluation method for renewable energy companies.

Indeed, it is imperative to acknowledge the presence of certain research limitations and shortcomings. Firstly, the study process may necessitate a broader spectrum of data and a more extensive array of samples to validate the model's applicability across diverse contexts. Moreover, while the study has identified fluctuations in social performance, a comprehensive analysis of the underlying causes of this phenomenon has not been undertaken, indicating a potential avenue for further investigation. Therefore, the model can be improved and expanded in future research to extend it to more diverse contexts, including small and medium-sized enterprises and cross-regional cases, to validate its adaptability and refine industry-specific ESG benchmarks. Additionally, there is an opportunity to delve deeper into the volatility of social performance and propose targeted solutions to mitigate such fluctuations. Ultimately, these efforts are anticipated to furnish new energy enterprises with robust tools to effectively navigate ESG pressures and foster higher-quality development.

Recommendations. To enhance ESG performance and achieve high-quality development in the new energy sector, this study proposes the following recommendations: First, data transparency and disclosure are central to ESG management. Companies should regularly release ESG reports to enhance information transparency and build trust with investors and consumers. Governments should encourage companies to adopt internationally advanced ESG disclosure standards to improve global comparability and consistency. Second, interdisciplinary collaboration is key to driving innovation in the renewable energy sector. The integration of engineering, physics, computer science, environmental science, and economics, particularly the collaboration between data scientists and industry experts, can improve model accuracy and provide innovative solutions for SD. Additionally, companies need to establish a comprehensive risk management framework. They should leverage AI and machine learning technologies to proactively identify and address market, technological, policy, and supply chain risks, while enhancing board governance to improve decision-making quality. Finally, policy support and incentives play a crucial role in promoting ESG practices. Governments should use financial subsidies, tax incentives, and other measures to support corporate investment in ESG areas and encourage international collaboration by introducing global advanced ESG standards and practices. These measures together form a key pathway to advancing ESG development and provide a solid theoretical and practical foundation for the SD of the renewable energy industry.

Data availability

The data that support the findings of this study are available on request from the corresponding author, upon reasonable request.

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Author contributions

XZ: writing–review & editing, conceptualization, methodology, resources; XS: writing–review & editing, conceptualization, data curation, project administration; YP: writing–original draft, conceptualization, methodology; ZW: writing–original draft, data curation, formal analysis; XC: writing–original draft, visualization, formal analysis; JZ: writing–original draft, validation, formal analysis. All authors have read and agreed to the published version of the manuscript.

Competing interests

The authors declare no competing interests.

Ethics approval

Ethical approval was not required as the study did not involve human participants.

Informed consent

Informed consent was not required as the study did not involve human participants.

Additional information

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