

The Application and Challenges of ESG Intelligent Analytics in Corporate Assessment

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Abstract: With the deepening global adoption of sustainable development, environmental, social, and governance (ESG) assessments have become core indicators for measuring a company's overall value. Traditional ESG assessment methods suffer from limitations such as low data processing efficiency and high subjectivity. The introduction of intelligent analytics technology offers a new approach to addressing these issues. This article explores the core architecture of ESG intelligent analytics technology and analyzes the specific applications of artificial intelligence and big data technologies in corporate ESG data collection, risk assessment, and performance forecasting, including practical case studies using solutions such as the IBM Envizi ESG Suite. The study finds that technologies such as natural language processing and machine learning have significantly improved the efficiency and accuracy of ESG assessments. However, practical challenges remain, such as uneven data quality, inconsistent rating systems, and insufficient model interpretability. To address these issues, this article proposes optimization strategies such as strengthening data standardization, promoting algorithm transparency, and improving regulatory mechanisms. This research aims to provide a reference for corporate ESG management practices and the application of intelligent analytics technology, thereby contributing to the achievement of sustainable development goals.

Keywords: ESG assessment; Intelligent analytics; Artificial intelligence; Machine learning; Corporate sustainability; Risk management.

1. Introduction

Against the backdrop of intensifying global climate change and rising awareness of social responsibility, ESG assessments have evolved from a "nice-to-have" for corporate sustainable development to a crucial component of core competitiveness. Investors, regulators, and the public are increasingly focused on a company's ESG performance, prompting companies to prioritize ESG management and disclosure. However, traditional ESG assessments rely on manual data collection and organization, which suffers from inefficiencies, limited coverage, and significant subjective bias, making them inadequate for meeting complex and ever-changing assessment needs. According to research from Southwestern University of Finance and Economics, there are over 100 ESG rating agencies, but the correlation between their ratings ranges from only -0.12 to 0.67, with some even contradicting each other, severely impacting the credibility of these assessments. The rapid development of intelligent analytical technology offers the potential to overcome these limitations. Technologies such as artificial intelligence, big data, and natural language processing can process massive amounts of multi-source data, identify potential risk patterns, and enable dynamic assessment and prediction, significantly improving the scientific nature and timeliness of ESG assessments. For example, IBM Envizi ESG Suite leverages AI technology to reduce the time it takes to generate corporate sustainability reports from days to hours. HSBC's AI-driven ESG index uses machine learning to dynamically adjust its constituent stocks, providing investors with more accurate decision-making. This article focuses on the application and challenges of ESG intelligent analytics in corporate assessments. It first analyzes the core architecture and supporting technologies of ESG intelligent analytics, then explores its specific applications in data collection and processing, risk assessment, and other areas. It analyzes the

key challenges faced in practice and proposes optimization paths. By integrating academic research with practical enterprise cases, this article aims to reveal the application value of ESG intelligent analytics technology, provide reference for companies to improve ESG management and investors to optimize decision-making, and promote the intelligent upgrade of ESG assessment systems.

2. Core Architecture and Technical Support of ESG Intelligent Analytics Technology

The effective application of ESG intelligent analytics technology requires a three-tiered core architecture and diverse technical support to form an efficient operational system. The core architecture comprises a data layer, an algorithm layer, and an application layer, forming a closed loop of "data collection-analysis-value output." The data layer aggregates and preprocesses heterogeneous data from multiple sources; the algorithm layer uses intelligent models to conduct in-depth data analysis; and the application layer transforms the analysis results into visual reports and decision-making recommendations, adaptable to different assessment scenarios. Big data technology is fundamental to this technical support, efficiently processing structured and unstructured data such as corporate annual reports, regulatory announcements, and social media, relying on distributed storage and parallel computing. For example, the IBM Envizi ESG Suite automatically captures hundreds of data types from isolated data sources and integrates them into a single, financial-grade system of record, breaking the "information silos" problem of traditional assessments and laying the data foundation for comprehensive evaluations. Artificial intelligence is a core driver, encompassing natural language processing (NLP), machine learning, and deep learning. NLP can extract key information from text. For example, the

RepRisk system uses NLP to scan over 80,000 global information sources daily to capture corporate ESG-related events in real time [1]. Machine learning enables autonomous model optimization. For example, the Bloomberg Research team uses a gradient boosting tree model to predict corporate excess returns, achieving a Sharpe ratio of 1.25, significantly outperforming the benchmark. Deep learning uses deep neural networks to model the complex, nonlinear relationships in ESG performance, while reinforcement learning allows models to self-adjust in dynamic environments, adapting to the needs of long-term sustainability assessments. Furthermore, cloud computing provides elastically scalable computing resources to meet the needs of enterprises of varying sizes. The Internet of Things (IoT) uses sensors to collect environmental data in real time. For example, AVIC Optronics has implemented an intelligent energy management system that enables real-time monitoring of energy consumption indicators. The synergy of these multiple technologies builds a comprehensive and efficient ESG intelligent analysis system.

3. Application of Intelligent Technologies in Enterprise ESG Data Collection and Processing

3.1. Intelligent Technologies Drive Multi-Dimensional ESG Data Collection

The accuracy of ESG assessments relies on high-quality data. Intelligent technologies overcome the limitations of traditional manual data collection processes, enabling automated, multi-dimensional data acquisition. Regarding environmental data collection, the Internet of Things (IoT) uses sensor networks to monitor carbon emissions, energy consumption, water use, and other indicators in real time, providing objective, foundational data. For example, Growthpoint Properties Australia uses intelligent systems to manage sustainability data, automatically collecting over 6,500 utility bills worldwide annually, significantly reducing manual calculations. Unstructured data related to social and governance relies on natural language processing (NLP) technology, using sentiment analysis and keyword extraction to uncover key information. JPMorgan Chase, in collaboration with Datamaran, leverages NLP to dynamically integrate internal operational data with external public opinion to accurately identify sustainability issues important to the company and its stakeholders, filling the gaps in potential risks and opportunities not covered by traditional financial reporting. Intelligent technology is also addressing the fragmentation of supply chain ESG data. The IBM Envizi ESG Suite's supplier data management module aggregates supplier and product-level transaction data and automatically calculates emissions. After implementing this system, Downer Group significantly reduced the error rate in Scope 3 data classification. AI now handles tasks that once took months in seconds, significantly improving supply chain data quality [2].

3.2. Intelligent Technology Optimizes ESG Data Processing and Standardization

In the data processing phase, intelligent technology effectively addresses common ESG data quality issues. For missing data, machine learning algorithms (such as multiple imputation and generative adversarial networks (GANs)) can

generate appropriate imputed data, reducing assessment bias caused by incomplete information. Data cleansing technologies improve accuracy through outlier detection and deduplication. Allianz Group's application has improved the accuracy of climate risk forecasts by over 50%. Data standardization is a core challenge in ESG analysis. Intelligent technologies integrate heterogeneous data through semantic mapping and rule engines. To address the varying disclosure standards adopted by companies across industries and regions, intelligent systems can uniformly map data to frameworks such as the GRI and ISSB standards. The "Corporate Sustainability Disclosure Guidelines," jointly issued by the Ministry of Finance and nine other departments, provide policy support. Based on this, intelligent systems develop data conversion rules, ultimately enabling effective ESG comparisons across companies and industries.

4. AI-Based ESG Risk Assessment and Performance Prediction Models

4.1. Practical Applications of AI in ESG Risk Assessment

Artificial intelligence transcends the limitations of traditional static assessments, leveraging technologies such as machine learning to enhance the foresight and accuracy of risk identification. In the area of climate risk, Allianz Group combines machine learning algorithms with geospatial artificial intelligence (GeoAI), integrating global climate data, satellite remote sensing imagery, and historical claims information to accurately predict risks such as floods and hurricanes, reducing insurance claims costs by approximately 15% and providing data support for companies to address climate-related physical risks. Social risk assessments rely on real-time monitoring of multi-source data. RepRisk's ESG rating system uses natural language processing (NLP) technology to scan massive global information sources daily, extracting corporate ESG events from news and NGO reports, and quantifying the severity of negative events. When a company experiences an environmental incident or labor scandal, the system quickly captures and updates the rating, addressing the information lags of traditional assessments and providing timely warnings to stakeholders. Governance risk assessments focus on indicators such as board structure and executive compensation. AI uses anomaly detection algorithms to uncover potential flaws [3]. For example, China CITIC Bank has developed an ESG rating system for corporate clients using AI and blockchain technology. This in-depth analysis of governance data not only covers explicit indicators but also uses correlation analysis to identify hidden risks such as mismatches between executive pay and performance and insufficient board independence.

4.2. Application of AI-Driven ESG Performance Prediction Models

AI performance prediction models help provide insights into ESG trends and support long-term decision-making. In 2019, HSBC launched the world's first AI-driven ESG stock index. This index uses machine learning algorithms to screen stocks of companies worldwide with consistently improving ESG risks. It automatically updates its composition and weightings quarterly, and calculates risk scores based on publicly available ESG data, providing a basis for portfolio adjustments. IEEE research shows that integrating multiple machine learning models can build a fully automated ESG

rating system, significantly improving forecasting accuracy. The Bloomberg research team used a gradient boosting tree model to link ESG indicators with long-term returns, classifying and predicting annual excess returns for stocks, achieving an alpha return of 8.7%. Furthermore, the Bloomberg research team utilized Shapley Additive Explanations technology to analyze the model, identifying key features driving ESG performance. This approach balances accuracy and interpretability, providing guidance for companies to optimize their ESG performance.

5. Typical Challenges in the Practice of Enterprise ESG Intelligent Analysis

5.1. Data Level: Quality Shortcomings and Standards Irregularity

Data issues are the primary obstacle to enterprises applying ESG intelligent analysis. Liu Feng of the Central University of Finance and Economics pointed out that much ESG data is difficult to access directly, and the collection and structuring of underlying data present inherent challenges. Corporate sustainability reports often prioritize form over substance, frequently missing key data such as Scope 3 carbon emissions, which is of concern to financial institutions. This undermines the reliability of ESG assessments. Global ESG rating standards are even more complex, with over 6,000 rating systems currently in use, each with varying indicator definitions, weightings, and assessment methods. Research from Southwestern University of Finance and Economics shows that the correlation between the results of mainstream rating agencies ranges from only -0.12 to 0.67, and some are even contradictory. Some consider corporate lobbying activities, while others do not; some use employee turnover rates as a social indicator, while others prioritize the number of employee lawsuits. This lack of uniformity makes it difficult for companies to determine improvement strategies and creates a dilemma for investors [4].

5.2. Technology and Management: Model Limitations and Implementation Obstacles

Technically, the "black box" problem of AI models is prominent. Springer research indicates that ESG ratings lack transparency. Institutions often use proprietary models, disclosing only the underlying principles and failing to fully explain the calculation process. This impacts corporate acceptance of the results, complicates regulatory oversight, and can conceal model biases and errors. Furthermore, ratings are subject to systemic biases: large and European companies receive higher scores due to their strong disclosure capabilities. Universal models are difficult to adapt to industry specificities, for example, with significant differences between environmental assessments in the manufacturing industry and social contribution assessments in the financial sector. A single standard completely ignores the complexity of corporate operations. At the management level, ESG awareness within companies is insufficient, and cross-departmental collaboration is poor. The head of ESG at a listed company in a traditional industry revealed that other departments are lagging behind in ESG awareness, which directly impacts data collection and reporting. Furthermore, the lack of a robust data collection system and cross-departmental coordination mechanism results in low data collection efficiency and difficulty ensuring quality, further hindering the implementation of intelligent analytics.

5.3. Regulatory Level: Policy Differences and Compliance Challenges

Regulatory lags and policy uncertainty exacerbate implementation challenges. While China has the "Corporate Sustainability Disclosure Guidelines," international disclosure frameworks such as GRI, TCFD, and ISSB differ significantly. Companies expanding overseas face the need to simultaneously meet the requirements of multiple regions, significantly increasing compliance costs. More critically, there's no unified standard for determining "greenwashing." Some companies selectively disclose data and avoid risks, undermining market trust and introducing a significant amount of noise into the training of intelligent analysis models, impacting assessment accuracy.

6. Optimizing ESG Intelligent Analysis Applications and Recommendations

To address the challenges of ESG intelligent analysis practice, a multi-dimensional collaborative approach is needed to build a scientific application system. Solidifying the data foundation is paramount. Companies can establish a comprehensive data collection framework covering environmental, social, and governance dimensions, based on the Ministry of Finance's "Corporate Sustainability Disclosure Guidelines," and clearly define data responsibilities across departments [5]. To address data gaps, solutions such as IBM Envizi ESG Suite can leverage AI to automatically aggregate disparate data, establish a single source of truth, and reduce human error. Furthermore, internal data standardization can be promoted, with unified indicator definitions and calculation methods. Technical optimization should focus on the core pain points of the model. Breaking through the "black box" problem can draw on Bloomberg's Shapley Additive Explanations approach, identifying key drivers of assessment results and making the decision-making process traceable. Model development should prioritize representative training data to avoid scale and regional biases. The risk grading approach of the ESG-AI framework can be referenced, adjusting parameter weights based on industry characteristics and enterprise size. Cross-industry assessment challenges can be addressed through modular design, such as developing dedicated components for carbon emissions accounting in the manufacturing industry and social responsibility assessment in the financial industry, integrating them within a common framework and balancing customization and standardization. Standard improvement requires collaborative efforts between government and enterprises. Regulators should accelerate the standardization of ESG disclosure standards, adhering to Huang Shizhong's principle of "actively learning from others while prioritizing domestic practices," balancing international consistency with local adaptability. Industry associations can lead the development of technical specifications for intelligent analysis, clarifying standards for data interfaces and model evaluation. Enterprises, especially those expanding internationally, should participate in the development of industry standards while adhering to national standards, paying attention to the requirements of their overseas partners' countries, and identifying points of convergence between Chinese and international standards to reduce compliance costs. Optimizing management mechanisms is crucial for the implementation of this technology. Companies should establish ESG management committees led by senior

management to coordinate resources, break down information silos, and ensure the smooth flow of data across departments. To address internal gaps in awareness, ESG training should be strengthened to raise awareness among all employees and make data collection a conscious action. System development can draw on the experience of Quanta Computer and customize ESG information collection systems based on specific needs to enable real-time data monitoring, error detection, and correction, reducing reliance on external systems. Supervision and the market must collaborate to curb greenwashing. Regulators should establish a comprehensive "disclosure-verification-penalty" mechanism to promote the authenticity of ESG reports by third-party institutions [6]. They should also encourage the development of professional ESG data analysis services such as RepRisk to leverage market forces to enhance transparency. Investors should also view ratings rationally, going beyond a single score and integrating a comprehensive assessment based on the company's actual situation and industry characteristics to form an objective understanding of its sustainability capabilities.

7. Conclusion

ESG intelligent analysis technology is reshaping corporate ESG assessment systems, providing a more scientific and efficient approach to measuring sustainability capabilities. This article summarizes its architecture, applications, challenges, and optimization directions, it was discovered that technologies such as artificial intelligence and big data offer significant value in improving assessment efficiency, expanding dimensionality, and enhancing predictive capabilities. Practices at companies like IBM, HSBC, and Allianz have demonstrated that these technologies can effectively integrate multi-source data, enabling real-time monitoring of ESG risks and accurate performance forecasting, providing strong support for corporate decision-making and investor selection. However, the widespread application of ESG intelligent analysis still faces numerous challenges: uneven data quality and inconsistent standards make it difficult to compare assessment results; the "black box" nature of models reduces transparency and credibility; industry differences and regional biases affect model universality; and imperfect internal management mechanisms and lagging regulatory oversight further limit the impact of technology. These issues, at their core, stem from a mismatch between the pace of technological innovation and institutional development and management capabilities, requiring a multi-faceted, coordinated solution. Future optimization efforts must address four key areas: first, strengthening the data

foundation, establishing unified standards and governance mechanisms, and improving data quality and coverage; second, promoting technological innovation, developing explainable AI and adaptive models, and enhancing assessment transparency and industry adaptability; third, improving management mechanisms, building a cross-departmental collaborative system, and enhancing companies' ESG management capabilities; and fourth, strengthening the regulatory framework, standardizing disclosure standards, strengthening third-party assurance, and curbing "greenwashing." Only through the coordinated efforts of technology, systems, and management can its full value be unleashed. ESG intelligent analysis is not only an innovation in assessment methods but also a key driver of corporate sustainable development. It can accurately identify ESG risks and opportunities, direct resources toward sustainable enterprises, and encourage companies to improve their environmental performance, fulfill their social responsibilities, and enhance governance, ultimately achieving unified economic, environmental, and social benefits. As the technology matures and the ecosystem develops, it will play a greater role in global sustainable development and provide a solid foundation for building a responsible business environment.

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