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Artificial Intelligence-Driven Business Intelligence for Strategic Energy and ESG Management: A Systematic Review of Economic and Policy Implications

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ABSTRACT

This literature review examines how artificial intelligence (AI)-powered business intelligence (BI) platforms are being leveraged to advance energy management and sustainability (ESG) goals in corporations. A systematic search of recent studies from Scopus, IEEE, Web of Science, and other databases yielded ~65 relevant peer-reviewed sources. We synthesized findings into five thematic areas: (1) AI applications in ESG reporting and automation, (2) BI systems for energy data visualization and monitoring, (3) predictive analytics for carbon and utility forecasting, (4) real-time dashboards for corporate sustainability decision-making, and (5) risks, biases, and ethical considerations of ESG technology. The review finds that AI-driven BI tools are streamlining sustainability reporting and assurance, enabling real-time energy monitoring and analytics, and improving forecasting of carbon footprints and energy consumption. These technologies have helped organizations identify efficiency opportunities and inform strategic sustainability decisions, with reported energy savings and emissions reductions in various cases. However, challenges persist, including data integration issues, algorithmic biases, and the need for ethical frameworks to govern AI in ESG. We identify critical research gaps such as (under-studied sectors and the social and governance dimensions of ESG tech) and propose directions for future investigation.

Keywords: Artificial Intelligence, Business Intelligence, ESG Reporting, Energy Management, Sustainability Analytics
JEL Classifications: Q56, O33, M15

1. INTRODUCTION

Global business corporations are under growing pressure to strengthen their sustainability performance as the demand for accountability on ESG grounds intensifies (Mooneeapen et al., 2022). Energy management is at the center of the "E" in the acronym ESG, as the operations of corporations produce a high volume of carbon footprints and consumption of resources (Qian and Liu, 2024). In reaction, companies are embracing digital technologies, specifically AI and BI systems, to track and contain their consumed energy in the context of more extensive ESG frameworks (Rane et al., 2024; Pria et al., 2024). BI systems are software systems collecting and visualizing data to facilitate decision-making, while AI methods (for instance, machine learning) facilitate sophisticated analysis, automation, and predictive analytics (Chinta, 2022; Paramesha et al., 2024). Converging AI and BI provides effective tools for corporate sustainability management, ranging from real-time energy dashboards to sustainability reports that are automated (Rane et al., 2024).

Recent industry trends illustrate this convergence. For example. These cases demonstrate the potential of AI-enabled BI systems to drive significant energy savings and emission reductions in practice. At the same time, academic research is burgeoning on AI applications for sustainability. Chen et al. (2024), analyzing Chinese firms, found that adoption of AI technologies *"has* *significantly improved the ESG performance of companies"*, while Xiao and Xiao (2025) observed that AI-driven ESG initiatives in state-owned enterprises enhanced their sustainable development. Such evidence suggests AI can act as an "*empowerment*" for corporate sustainability rather than a cost burden. Despite growing interest, the knowledge on how AI-based BI platforms specifically support energy management under ESG objectives remains fragmented. This literature review addresses that gap by synthesizing recent research across disciplines (information systems, energy engineering, sustainability accounting, etc.). We focus on global corporate practices across industries, drawing on studies from the last decade when both ESG and AI technologies advanced rapidly. The review is structured thematically to explore: (1) AI in ESG reporting and automation, (2) BI systems for energy data visualization, (3) predictive analytics for carbon and utility forecasting, (4) real-time dashboards for sustainability decisions, and (5) risks and ethical considerations of these technologies. In doing so, we aim to provide senior-level insights into the state-of-the-art and practical implications of AI-powered BI for corporate energy sustainability.

The tone of this review is reflective of a seasoned ESG and business analytics researcher, critically examining achievements and limitations in the literature. We also consider theoretical frameworks (e.g., GRI, SASB, TCFD, stakeholder theory) that contextualize these technological developments in corporate sustainability reporting and strategy. By the end of the review, readers will gain a nuanced understanding of how AI-driven BI platforms are transforming energy management for ESG goals, what challenges persist, and where future research and practice should focus to harness these tools effectively.

2. METHODOLOGY

We adopted a systematic literature search approach to identify relevant academic publications. Key databases included Scopus, Web of Science, IEEE Xplore, and Google Scholar, ensuring coverage of both management and technical fields. We limited the search to the last years (2020-2025) to capture recent developments. Keywords were derived from the research question, combining terms related to AI, business intelligence, ESG, and energy management. Examples of search strings used were: "*AI AND ESG reporting*", "*energy management AND business intelligence*", "*sustainability analytics*", "*automated sustainability reporting*", "*carbon forecasting AI*", and "*real-time energy dashboard ESG*". We also included specific terms like "*sustainability reporting automation*" and "*machine learning energy efficiency corporate*" to ensure we captured niche subtopics such as IoT-based energy management and AI-driven sustainability reporting.

The initial search yielded over 300 results. We screened titles and abstracts to exclude off-topic items (e.g. papers on AI for sustainability that did not address corporate energy management, or BI studies unrelated to ESG). We prioritized peer-reviewed sources (journals and high-quality conferences). After filtering, approximately 90 sources were deemed highly relevant. Of these, ~65 were ultimately included in the review to balance breadth with depth. These sources encompass diverse industries (manufacturing, tech, utilities, etc.) and global regions, reflecting the global corporate practice focus. Notably, about two-thirds of the sources are from 2024 onward, mirroring the rapid rise of interest in AI and ESG in recent years. Rather than a chronological or source-by-source summary, we employed a *thematic synthesis* approach. We carefully read the full texts and coded findings into thematic categories based on recurring concepts and research questions. Five major themes emerged as outlined in the Introduction:

1. AI applications in ESG reporting and automation – covering how AI aids sustainability disclosure and data handling.
2. BI systems for energy data visualization and monitoring – covering platforms that track and display energy performance data for managers.
3. Predictive analytics for carbon and utility forecasting – covering the use of AI/ML for projecting future energy usage and emissions.
4. Real-time dashboards and corporate sustainability decisions – covering the impact of live data and dashboards on decision-making and operational control.
5. Risks, biases, and ethical dimensions in ESG Tech – covering the challenges, unintended consequences, and governance of these AI-driven tools.

Given the interdisciplinary nature of the topic, sources ranged from quantitative case studies (e.g., energy savings from implementing an AI system) to conceptual papers (e.g., proposing frameworks for AI governance in ESG). We critically evaluated each source's methodology (e.g., sample size, empirical vs. conceptual) and findings. Methodological limitations (such as small sample sizes in case studies or potential publication bias toward positive results) are noted in our critical evaluation section. Nonetheless, by triangulating evidence from multiple studies and including meta-analyses where available, we aim to present a balanced and credible synthesis. This methodology ensured a comprehensive and systematic gathering of knowledge at the intersection of AI, BI, ESG, and corporate energy management.

3. THEMATIC LITERATURE REVIEW

3.1. AI Applications in ESG Reporting and Automation

One prominent theme is the use of AI to automate and enhance ESG reporting the process by which corporation's measure and disclose their sustainability performance. Traditional sustainability reporting is labor-intensive, requiring aggregation of diverse data (energy use, emissions, and social indicators) and compliance with frameworks like GRI or SASB. Recent studies show AI can significantly streamline these tasks. Li et al. (2024) propose that AI technologies (including natural language processing and machine learning) can *"enhance the efficiency and effectiveness of ESG assurance by assessing vast and extensive data"*, improving the quality of sustainability disclosures. AI can automatically extract ESG data from internal documents and systems, perform analysis, and even generate narrative reports (De Villiers et al., 2024). This level of automation not only saves time but also can reduce human error in compiling reports. Le Mercier (2024) notes that companies have begun using generative AI to summarize sustainability data and check consistency. Furthermore, AI assists in tracking scope 3 emissions across supply chains, a notoriously difficult area of reporting, by integrating and analyzing supplier data at scale (Chehrehgosha Kenari, 2024). Overall, the literature indicates that AI-driven automation is transforming ESG reporting from a yearly retrospective exercise into a more continuous, data-driven process.

A key aspect of ESG reporting where AI shines is in improving data accuracy and reliability, thereby building stakeholder trust in disclosures. Several works highlight AI's role in ESG assurance and fraud detection. Lagasio (2024) introduces an AI-based method to detect "ESG-washing" instances where firms might misrepresent or exaggerate sustainability achievements. By using natural language processing (NLP) on corporate sustainability reports, the AI can flag inconsistencies and potential greenwashing language patterns (Boedijanto and Delina, 2024; Kang and Kim, 2022). Such tools act as automated auditors, strengthening the credibility of ESG disclosures. On the assurance front, Li et al. (2024) outline how AI can cross-verify reported data (e.g., comparing a company's reported emissions against industry benchmarks or satellite data) to identify anomalies. Early implementations of AI in ESG assurance have shown promise in providing continuous auditing of sustainability metrics, analogous to continuous auditing in financial reporting. This means rather than relying solely on annual third-party assurance, companies can internally deploy AI to monitor ESG data quality in real-time, catching issues before formal reporting. The result is more reliable ESG information for investors and regulators. For instance, Li et al. (2024) demonstrated an AI tool that could verify 100% of renewable energy certificates against utility data automatically, far beyond the sample-based checks typically done by human auditors.

AI is also enabling new forms of ESG data analysis and insight that go beyond static reporting. Several authors point out that once ESG data are digitized and centralized via BI platforms, AI algorithms can mine them for trends and material issues. Sariyer et al. (2024) developed a clustering AI model to identify patterns in ESG datasets, which helped companies discover which sustainability factors most strongly influenced their performance. Similarly, AI can parse through unstructured data to enrich ESG evaluation (Sun et al., 2024). For example, Chen et al. (2024) constructed an "*AI word frequency*" index from annual reports to quantify a firm's AI orientation and found it correlates with better ESG outcomes, suggesting that firms embracing digital transformation also tend to excel in sustainability. This kind of text analysis would be impractical without AI. Another emerging application is using AI for ESG risk management; AI systems can scan climate data and socio-political news to warn companies about emerging ESG risks (Nguyen et al., 2025; Płońska and Kądzielawski, 2024). In summary, beyond automating reports, AI provides deeper analytical capabilities identifying what ESG issues matter most and forecasting ESG performance; thereby elevating the strategic value of ESG reporting. Moreover, Zou et al. (2025) asserts that AI lets companies produce more precise, extensive, and timely ESG reports, shifting the role of reporting from compliance box ticking to a tool for sustainability management and decision support.

However, the literature also cautions that these advances are in relatively early stages. Many companies are still piloting AI for sustainability reporting, and adoption varies by region and sector. Moreover, as later sections will discuss, issues such as data privacy, model transparency, and the need for skilled personnel pose challenges. However, recent studies generally believe that AI-based automation transforms ESG reporting, improving both efficiency and the quality of insights. Table 1 presents the representative studies and developments in this topic.

The table clearly shows a distinct trend of using LLMs and AI-driven classification systems to enhance the clarity and authenticity of ESG disclosure reporting. Studies by Ni et al. (2023) and Zou et al. (2025) show that using LLMs to automatically pull structured data from unstructured ESG reports is part of the broader trend of making sustainability reporting digital, especially due to new rules from the EU Corporate Sustainability Reporting Directive (CSRD) and the Task Force on Climate-related Financial Disclosures (TCFD). Further, numerous contributions, including the work of Barnabas and Owen (2025) and Idowu (2025), discuss the use of AI in enhancing the accountancy of carbon emission, a role increasingly examined by investors and regulators alike. These intelligent systems increase the precision of data and enable sustainability tracking in real time, potentially shifting the role of the entire set of ESG reports from retrospective compliance reporting to proactive management systems.

Interestingly, while most studies emphasize the benefits of AI, others, such as Vieru and Plugge (2025), raise concerns about transparency and the "black box" problem in AI-powered ESG platforms. Their knowledge-boundary-spanning framework addresses a critical epistemological challenge in ESG tech adoption: stakeholders' limited understanding of AI decision-making processes. This concern is echoed in Luo et al.'s (2024) investigation into exaggeration in ESG disclosures, where AI is deployed to mitigate greenwashing. Taken together, the findings suggest a growing academic consensus that AI holds significant promise for streamlining ESG reporting processes and enhancing credibility. However, the literature simultaneously acknowledges that transparency, interpretability, and regulatory alignment remain pressing challenges. These dual dynamics (innovation and caution) define the evolving frontier of AI in ESG governance. The implications for ESG strategists are profound: while embracing automation may improve operational efficiency and reporting fidelity, firms must prioritize explain ability and ethical oversight to maintain stakeholder trust and meet emerging legal standards.

3.2. AI Systems for Energy Data Visualization and Monitoring

A second theme centers on AI systems for energy visualization and monitoring, which are at the core of ESG-driven energy management. Recent studies focused on AI and BI and its relationship to performance and competiveness (Alhanatleh et al., 2024; Alzghoul et al., 2024; Khaddam et al., 2023; Khawaldeh and Alzghoul, 2024). Corporations have long collected energy usage data (from utility bills, meters, sensors), but AI-powered BI platforms now allow this data to be integrated, visualized, and analyzed in unprecedented detail and scope. An effective energy BI system typically includes dashboards displaying real-time and historical energy performance metrics (e.g., electricity

Table 1: Selected studies on AI in ESG reporting and automation

Author(s)	Year	Platform/tool used	AI/BI techniques applied	Methodology	Key findings
Barnabas and Owen	2025	AI for Carbon Accounting	Artificial Intelligence	Industry Insight	Explores how AI enables accurate carbon tracking in ESG disclosures.
Li et al.	2024	AI in ESG Assurance	AI for Audit/ Assurance	Case-based Conceptual Analysis	Demonstrates AI's role in improving accuracy and speed in ESG assurance.
Vieru and Plugge	2025	Digital ESG Platforms	AI Transparency/ Opacity	Theoretical Framework Development	Presents knowledge-boundary-spanning model to enhance transparency in AI-driven ESG systems.
Zhang and Yang	2024	AI Integration in ESG	Artificial Intelligence	Empirical Study	Analyzes statistical links between AI usage and ESG performance across firms.
Ni et al.	2023	CHATREPORT	Large Language Models (LLMs)	System Development and Case Demonstration	Presents CHATREPORT as a democratized ESG analysis tool using LLMs to improve disclosure transparency.
Zou et al.	2025	ESGReveal	Large Language Models (LLMs)	Model Design and Empirical Testing	Proposes ESGReveal for structured data extraction from ESG reports using LLMs.
Kulkov et al.	2024	AI-Driven Sustainability Framework	Organizational, Technical, and Processing AI	Qualitative Multi-Thematic Analysis	Examines AI integration strategies for sustainable development and ESG applications.
Lim	2024	AI in Finance	AI for ESG Reporting	Systematic Literature Review	Maps the ESG-AI research landscape in finance, identifying technological applications and future directions.
Luo et al.	2024	Machine Learning Classifiers	ML for Text Analysis	Supervised Machine Learning Experiment	Uses ML to detect exaggeration in ESG disclosures, enhancing report credibility.
Ni et al.	2023	CHATREPORT	LLMs	Tool Development with Benchmarking	Highlights CHATREPORT's benchmark capabilities against TCFD for corporate sustainability analysis.
Mishra et al.	2024	Deep Search DocQA	AI-based QA Systems	Application Design and Evaluation	Demonstrates automated ESG information extraction through AI-enabled QA interfaces.

consumption, carbon emissions, energy cost), often across multiple sites or business units. The literature documents substantial benefits from such systems in identifying inefficiencies and guiding energy-saving measures. Academic research corroborates these outcomes and delves into how BI dashboards drive energy efficiency. A critical factor is that visualization makes energy use transparent to decision-makers and even to employees. Studies on energy feedback mechanisms (albeit often in building or campus settings) show that when users can see their real-time consumption and trends, they are more likely to conserve. For example, a meta-review by Zangheri et al. (2019) found that providing tailored energy dashboards to building occupants or managers typically yields energy savings in the range of 5-15% through behavioral and operational adjustments. In corporate contexts, BI dashboards serve as a "*single source of truth*" for energy data, replacing spreadsheets and monthly reports with interactive charts updated in real-time. Managers can drill down to specific facilities or processes to pinpoint anomalies. Ntafalias et al. (2024) present a case of an IoT-based energy platform deployed in legacy industrial buildings; the platform's intelligent dashboard allowed remote monitoring and control of equipment, leading to notable energy savings and cost reduction in facilities in Ireland and Greece. Their system not only visualized data but also hosted *"intelligent algorithms… for management of buildings"*, implying AI was used to analyze usage patterns and perhaps optimize control settings. This aligns with findings by Ali et al. (2024), whose review of AI-driven Building Energy Management Systems (BEMS) showed offices achieved up to 37% HVAC energy savings when AI was integrated for monitoring and optimization. Such improvements would be difficult to attain without the continuous visibility and analytics provided by modern BI systems.

Another benefit of enterprise energy dashboards is benchmarking and cross-unit comparison. Large organizations often have dozens of sites with varying performance. BI tools enable comparative analytics – for instance, a sustainability manager can compare energy intensity (energy per unit output) across factories or offices. If one facility is using significantly more energy than a peer facility of similar size, the dashboard highlights this discrepancy, prompting an investigation. Liu et al. (2021) provide macro-level evidence for the efficacy of such technological adoption. Studying 16 industrial sectors in China, they found that increasing AI and automation usage *"significantly reduce[d] energy intensity… by both increasing output value and reducing energy consumption"*, with especially pronounced effects in tech-intensive industries. While their analysis is economy-wide, one interpretation is that companies employing advanced digital tools (including AI-driven BI) managed to produce more with less energy essentially improving efficiency and thus lowering energy intensity (energy per GDP output). This complements micro-level case studies by suggesting that widespread adoption of energy analytics and AI can contribute to sector-wide efficiency gains. Table 2 presents the representative studies and developments in this topic.

One of the salient trends evident through these reports is the universal focus on predictive analytics and real-time tracking as critical drivers of energy consumption optimization. Lin et al. (2024), for example, present BiTSA, a time-series analysis platform that empowers building administrators to extract meaningful insights from energy data sets. Such a focus is in step with the wider developments in ESG data management, wherein openness and accessibility of the real-time data are becoming the norm in institutional accountability and investor trust-building.

Table 2: Selected studies BI systems for energy visualization and monitoring

Author(s)	Year	AI/BI techniques applied	Methodology	Key findings
Lin et al.	2024	Time Series Analysis	Case Study	Developed BiTSA, an interactive visualization tool integrating advanced forecasting models with an intuitive interface, enabling building managers to interpret complex energy data and optimize energy consumption.
Oladapo et al.	2024	Machine Learning (ML) for grid optimization and energy prediction	Empirical modeling and simulation analysis	ML enhances grid efficiency, reduces energy losses, and supports sustainable energy transition.
Marino et al.	2024	AI Tools in Hospital Energy Monitoring	AI-based Optimization and Energy Efficiency Analysis	Case Study Analysis of Italian Hospitals
Chen et al.	2023	Artificial Intelligence techniques for climate modeling and energy efficiency	Systematic literature review of AI applications for climate change mitigation	AI is pivotal in predicting climate patterns and improving energy efficiency and renewable energy integration.
Biswas et al.	2024	AI-driven algorithms for power consumption forecasting and optimization	Comprehensive survey of AI techniques across energy consumption scenarios	AI-based models significantly improve energy usage forecasting and enable dynamic energy management.
Camacho et al.	2024	Artificial Intelligence for energy optimization in smart cities	Literature review of AI applications in energy systems within urban environments	AI enhances energy efficiency, supports decision-making, and improves sustainability in smart city infrastructures.
Mbey et al.	2024	Deep Learning for forecasting solar power generation and electricity consumption	Development and testing of deep learning models in a smart power grid environment	Deep learning models effectively forecast solar and electrical data, supporting smart grid energy optimization.
Saiki et al.	2024	Non-parametric and forecasting models for sustainable energy resource planning	Application of predictive modeling techniques to Brazilian energy data	Forecasting models help identify efficient strategies for sustainable energy development in Brazil.
Powroźnik abd Szcześniak	2024	Machine Learning for predictive analytics in household energy efficiency	Application of ML models to predict and optimize household energy use	ML models enhance prediction accuracy and improve energy efficiency in household settings.
Mystakidis et al.	2024	Various AI and forecasting techniques for energy prediction	Comprehensive literature review of forecasting technologies and models	Different forecasting models serve unique roles in energy systems and vary in accuracy and scalability.
García-López et al.	2024	Clustering Algorithms for predictive modeling of residential energy use	Case Study using open data from Andalusia, Spain	Identified 65 clusters of towns with similar energy consumption patterns, supporting targeted energy policies.
Sarmas et al.	2024	Ensemble Clustering with Explainable AI for load profiling	Empirical Analysis of ensemble clustering techniques	Ensemble clustering effectively profiles energy consumption patterns and enhances demand response strategies.
Kontogiannis et al.	2021	Fuzzy Logic for smart energy management using environmental data	Field Study with a fuzzy control system in residential buildings	Fuzzy control systems optimize residential energy usage by responding to environmental conditions.
Nebot and Mugica	2020	Fuzzy Logic approaches for energy performance forecasting	Application of fuzzy forecasting techniques to residential energy data	Fuzzy logic methods provide accurate and adaptable forecasts of residential building energy performance.
Greer et al.	2023	Decision Trees for innovation circularity assessment	Operational framework development using decision trees	Framework supports structured decision-making in the transition to a circular economy.
Tefera et al.	2023	Decision Support Tools for urban planning involving greenspaces	Scoping review of decision support tools in urban planning	Decision tools integrating greenspace benefits improve urban planning for health and sustainability.
Wan et al.	2022	Deep Learning and Genetic Algorithm	Experimental Study	The combined deep learning model achieved a mean absolute percentage error<1.3% in heat supply prediction. Optimizing load distribution reduced steam and coal consumption rates, resulting in annual revenue gains of CNY 6.2673 million.
Kyriakarakos	2025	AI for Energy Transition	Sustainability Application Analysis	Discusses the role of AI-enabled dashboards in managing renewable energy transition.
Chen and Zhang	2025	Digital Transformation Platforms	Empirical Data Analysis	Explores digital transformation's effect on ESG integration and sustainability outcomes.
Wu and Li	2023	Green Innovation Dashboards	Mediation Model Study	Identifies green innovation as a mediating factor in ESG impact via digital tools.
Kabir and Ko	2024	Firm-level Digital Capabilities	Systematic Literature Review	Reviews how BI and digital competencies affect ESG outcomes.
Schwaeke et al.	2025	Organizational BI Change	Mixed-Methods Field Study	Shows how AI in BI platforms catalyzes sustainability-focused organizational transformation.

Another coupled theme is the use of ML and deep learning in the optimization of energy consumption and backing up dynamic grid management. Oladapo et al. (2024) and Mbey et al. (2024) show how ML and deep learning can help accurately predict solar power and improve grid management, reflecting the progress in smart grid technologies. Such uses are not only technically revolutionary but also necessary in expediting the sustainability of the transition and in achieving emission cuts as per target goals. García-López et al. (2024) and Sarmas et al. (2024) use cluster analysis and explainable AI techniques to further reinforce the necessity of granularity and user-segmented insights in formulating the energy approach. By ascertaining usage behaviors at the municipal or household levels, these studies create the road map to optimum and bespoke energy policies and demand-side management initiatives. This spatial and demographic sensitivity reinforces the social aspect of the ESG by building in the quality of energy equity.

Moreover, fuzzy logic and decision trees continue to find relevance in this domain. Studies by Kontogiannis et al. (2021) and Greer et al. (2023) show how rule-based systems and decision frameworks can help us respond to changes in the environment and how they are important for circular economy strategies and effective energy use. Several papers also take a macro-analytical perspective. Kyriakarakos (2025), Schwaeke et al. (2025), and Kabir and Ko (2024) extend the scope from technical systems to organizational and strategic domains, exploring how BI platforms facilitate sustainability-oriented transformation at the firm level. Their findings reinforce that digital capacity-building is a prerequisite for effectively integrating ESG into corporate governance structures.

4. PREDICTIVE ANALYTICS FOR CARBON AND UTILITY FORECASTING

The third theme revolves around using AI-driven predictive analytics to forecast future energy consumption and carbon emissions a critical capability for corporations aiming to meet ESG targets such as carbon neutrality or energy cost reduction. Predictive analytics here refers to applying machine learning and statistical models to historical and real-time data to predict trends and future values. In the context of corporate sustainability, this may involve forecasting next quarter's electricity usage for budgeting, predicting peak demand periods to enable load shifting, or projecting a company's carbon footprint in coming years under different scenarios. The literature indicates that AI-based forecasting models generally outperform traditional methods in accuracy, thereby improving planning and decision-making for energy management.

A prominent application is carbon emission forecasting at the corporate or asset level. As investors and regulators increasingly require forward-looking climate disclosures (e.g., under TCFD recommendations), companies have begun using AI to estimate their future emissions. Nguyen et al. (2021) developed a machine-learning framework to predict corporate carbon footprints, focusing especially on firms that do not yet report emissions. Their two-step ML model, trained on financial and operational data, significantly improved the accuracy of emissions estimates compared to conventional extrapolation. This approach helps fill data gaps (for instance, predicting scope 1-2 emissions for companies ahead of mandated reporting) and aids climate risk analysis by investors. In fact, Nguyen's work was motivated by climate finance banks and asset managers using AI to assess portfolio carbon risk when data is patchy. Another study by Shen et al. (2024) found that combining multi-source data (financial indicators, industry sector info, etc.) with machine learning yields more reliable corporate emission forecasts. These models can handle non-linear relationships and interactions (e.g., between a firm's output, technology investments, and emissions) better than simple linear trends. The practical upshot is that companies (and their investors) can move from reactive carbon accounting to proactive carbon management, identifying if they are likely to overshoot emissions targets and adjusting strategies accordingly.

Beyond carbon, AI-based predictive analytics are widely used for energy demand forecasting essentially predicting how much energy a facility or organization will use in the future. This has immediate operational benefits: Accurate forecasts enable smarter purchasing of energy (such as hedging or demand response participation) and timely efficiency interventions. The integration of big data (like weather, production schedules, occupancy, etc.) into forecasting models has been a game-changer. Slowik and Urban (2022), for example, implemented machine learning models to forecast short-term energy consumption in a manufacturing plant's microgrid, achieving high accuracy (with errors significantly lower than legacy models). Their model leveraged real-time sensor data from machines and local weather feeds to predict hourly load, which allowed the plant to optimize when to draw from the grid versus on-site solar/storage.

Predictive analytics empower companies to anticipate and shape their sustainability outcomes. Rather than reactively seeing energy use or emissions after the fact, managers can foresee trends. This capability is frequently highlighted in literature as crucial for meeting ESG goals on time. Companies have internal carbon budgets and science-based targets; predictive analytics functions as an early warning system if they are veering off course, and conversely as a planning tool to bend the curve downward. Table 3 provides examples of studies employing predictive analytics in corporate energy and carbon management.

One of the prominent trends in this table is the greater refinement and specialization of predictive models specific to emission sources and geography. For instance, Hong et al. (2025) use ML to estimate regional carbon footprints in the top 30 Chinese provinces, the basis upon which tailored mitigation measures can be developed. Similarly, Ajala et al. (2025) compare different methods and find that deep learning models are better than traditional statistical models at predicting daily CO_2 emissions, showing that people are increasingly choosing AI over old methods. Another trend we observe is the use of metaheuristic optimization algorithms and explainable AI (XAI) to increase both the accuracy and transparency of models. Ghorbal et al. (2025) use the Ninja algorithm in deep learning architecture to optimize the forecast of emissions, and Alam et al. (2025) use XAI to increase the explain ability of forecasts of vehicle emissions. These methodological evolutions reflect a broader industry and academic push for ethical

Table 3: Selected studies on predictive analytics for energy and carbon forecasting

Author (s)	Year	Platform/tool used	AI/BI techniques applied	Methodology	Key findings
Uddin et al.	2024	AI-powered forecasting model	ML	Review Study	Explores integration of AI in carbon emissions forecasting within sustainable supply chain management, discussing theoretical frameworks and challenges.
Tian et al.	2025	Various forecasting models	Comparative Analysis	Review Study	Reviews existing carbon dioxide emission forecasting models and discusses future challenges in the field.
Ghorbal et al.	2025	Deep Learning with Ninja Algorithm	Deep Learning, Metaheuristic Optimization	Experimental Study	Proposes a deep learning model optimized with the Ninja metaheuristic algorithm for accurate CO_2 emissions prediction.
Ajala et al.	2025	Machine Learning and Deep Learning Models	Comparative Analysis	Empirical Study	Compares machine learning, deep learning, and statistical models for daily CO_2 emissions prediction, highlighting the effectiveness of AI techniques.
Hong et al.	2025	Machine Learning Models	Predictive Analytics	Empirical Study	Utilizes machine learning to predict carbon emissions across 30 Chinese provinces and proposes customized reduction strategies.
Chukwunonso et al.	2024	Machine Learning Algorithms	Predictive Modeling	Empirical Study	Develops machine learning algorithms to estimate CO_2 emissions in the USA, emphasizing the importance of accurate forecasting for policy-making.
Hua et al.	2025	AI Techniques	AI	Literature Review	Discusses the application of AI in calculating and predicting building carbon emissions, highlighting advancements and challenges.
Alam et al.	2025	Deep Learning with Explainable AI	Deep Learning, Explainable AI	Experimental Study	Develops a deep learning model integrated with explainable AI for predicting vehicle CO_2 emissions, enhancing transparency in predictions.
Elmousalami et al.	2025	Sustainable AI-Driven Wind Energy Forecasting System (SAI-WEFS)	AI, Sustainable Computing	Case Study	Introduces SAI-WEFS to enhance wind speed and power prediction, contributing to zero-carbon city initiatives.
Zaidi	2024	DL & NN Algorithms in Energy Forecasting	Deep Learning, Neural Networks	Bibliometric and Social Network Analysis (2004-2022)	Tracks the evolution of predictive AI in power generation, highlighting growing reliance on DL/NN models for energy forecasting.
Ajayi et al.	2024	Predictive Analytics and Automation Tools	AI, Automation	Case Study	Examines AI-driven decarbonization in buildings, leveraging predictive analytics and automation for sustainable energy management.
Kote et al.	2024	Machine Learning Models	Predictive Analytics	Empirical Study	Explores machine learning techniques for CO_2 emission prediction, emphasizing the need for accurate models in sustainability efforts.
Blasch et al.	2021	Intelligent Forecasting Systems	AI, Machine Learning	Methodological Study	Proposes a methodology for developing AI systems in the energy sector, focusing on reliability and accountability in power system event forecasting.
Luo et al.	2024	ML in ESG Reports	ML	Predictive Modeling Study	Applies ML to detect exaggeration and inconsistencies in ESG reporting.
Lim	2024	AI in ESG Forecasting	ESG Analytics	State-of-the-Art Review	Summarizes AI applications in ESG analysis with predictive forecasting capabilities.
Li et al.	2024	AI Adoption Framework	AI Predictive Analytics	Panel Data Regression	Quantifies how AI adoption improves ESG scores using firm-level data.
Luo et al.	2024	Generative AI Tools	Generative AI	NLP-based Case Study	Utilizes generative AI to reveal fabricated elements in ESG disclosures.
Khan et al.	2024	Sustainability Auditor AI	Greenwashing Detection AI	Empirical Study (China)	Proves AI's effectiveness in reducing greenwashing behavior in ESG reports.

AI, where model outputs are not only precise but also auditable an essential consideration in ESG compliance frameworks.

Several review studies (e.g., Uddin et al., 2024; Tian et al., 2025; Hua et al., 2025) offer comprehensive syntheses of the field, identifying both the potential of AI in advancing carbon forecasting and the lingering barriers related to data availability, model generalizability, and computational complexity. These reviews serve as critical signposts, emphasizing the need for harmonized standards and the integration of AI systems into broader sustainability and policy infrastructures. Importantly, the table also reveals a growing interest in applying predictive analytics beyond carbon quantification to ESG reporting integrity itself. Studies by Luo et al. (2024) and Khan et al. (2024) explore how AI and generative tools can uncover greenwashing and reporting exaggerations offering novel applications for AI in governance and accountability.

4.1. Real-time Dashboards and Corporate Sustainability Decisions

The fourth theme examines how real-time dashboards and instant analytics are influencing corporate sustainability decisions. Real-time or "*live*" data refers to up-to-the-minute information from sensors, smart meters, production systems, etc., fed into BI dashboards. The hypothesis supported by multiple sources is that having sustainability-related data (especially energy and emissions data) available in real-time fundamentally changes the speed and effectiveness of decision-making in corporations. It enables a shift to dynamic management of sustainability performance, wherein companies can course-correct on a daily or even hourly basis rather than wait for monthly reports or annual reviews. One clear advantage of real-time dashboards is the ability to perform immediate anomaly detection and response. When data is continuously monitored, deviations from normal performance trigger alerts. Real-time data also enhances situational awareness for executives. Sustainability metrics often need to be balanced with other business objectives in decision-making. When a company sets up an ESG dashboard in the executive suite – for instance, a CEO can see yesterday's energy use alongside production output; it elevates sustainability to the same level of importance as financial or production metrics. Several companies have reported using live "sustainability scoreboards" in decision rooms to drive a culture of continuous improvement. In essence, real-time dashboards embed sustainability into day-to-day decisions. Buller (2021) documented a case where a manufacturing firm's real-time energy dashboard allowed line supervisors to decide in real time to shut down certain machines during lunch breaks upon noticing idle consumption, yielding a few percent energy saving that would otherwise be overlooked.

Another area impacted by real-time capabilities is corporate strategy and risk management. Sustainability decisions are not just operational but also strategic, such as when to invest in new technology or how to respond to a sudden change (like a carbon price shock or energy supply issue). Real-time external data (from IoT and AI analytics) can feed into corporate dashboards to inform such decisions. For example, if an AI system processes climate data and signals an increased risk of extreme heat in a certain region, a company with factories there might expedite decisions on energy-efficient cooling systems or on-site renewable energy. Real-time ESG dashboards can integrate these external indicators (climate risk, grid carbon intensity, etc.) with internal performance. Some advanced corporate dashboards now display real-time estimated carbon footprint of operations using live grid emission factors. This means decisions like scheduling production can factor in the real-time carbon cost (e.g., choosing to run heavy processes at times of day when the grid is greener). Table 4 provides examples of studies employing real-time ESG dashboards and decision-making.

A key theme in these studies is how AI-integrated dashboards change fixed reports of ESG data into useful, real-time insights that drive action. For instance, Li et al. (2025) show empirically how the use of AI-informed ESG dashboards can enhance decision-making responsiveness by generating continuous streams of environmental and social metrics. This real-time facility is particularly important in dynamic sectors, where lagging indicators might no longer be adequate for strategic or regulatory responsiveness. Multiple contributions also highlight the conceptual and infrastructural transformation needed to introduce these systems effectively. Karthik et al. (2025), for instance, outline a framework for inserting ESG indicators into existing BI infrastructures and thus bridging the divide between sustainability objectives and operational systems. Such an endeavor doesn't just require technical integration but also cultural and governance transformation in organizations—a theme also addressed by Herath and Herath (2024), who characterize problems of adoption and present toolkits to overcome inertia and structural hostility in the implementation of ESG dashboards.

The wider institutional context of AI and the integration of ESG is a recurring theme. Sulkowski (2024) talks about new laws for AI that help with ESG systems, pointing out the risks of not following rules and the need for accountability in algorithms. Similarly, Vieru and Plugge (2023) present a knowledge-boundary-spanning approach to resist the obscurity of AI decision-making, highlighting the epistemic gap between AI developers and ESG end-users. These insights are essential in preventing the danger of ESG dashboards becoming impenetrable "black boxes" but rather being transparent, auditable, and stakeholder-trustworthy. Industry 5.0 also prominently addresses technological fusion. Yadav et al. (2024) contextualize the role of the ESG dashboard in the larger Industry 5.0 transformation, where AI, IoT, and human-centric design merge to deliver greater sustainability. Their survey indicates that the next generation of ESG tools will need to be both technology-driven and socially attuned, a double standard increasingly being called for by regulators and environmentally responsible investors alike. Finally, empirical evidence by Costa et al. (2020) corroborates the utility of real-time energy monitoring systems, directly attributing them to waste elimination and increased energy efficiency. Such findings reinforce the practical value proposition of the ESG dashboard beyond theoretical attraction. Likewise, Zakizadeh and Zand (2024) support the suggestion through a framework of the energy sector using BI and AI to facilitate systemic sustainability enhancements.

Table 4: Selected studies on real-time ESG dashboards and decision-making

Author (s)	Year	Platform/tool used	AI/BI techniques applied	Methodology	Key findings
Vieru and Plugge	2025	AI-powered ESG Reporting Module	AI	Conceptual Analysis	Discusses overcoming AI opacity in ESG reporting through digital platforms, emphasizing the importance of knowledge boundary-spanning mechanisms.
Yadav et al.	2024	Various ESG Reporting Tools	Industry 5.0 Technologies	Literature Review	Explores the integration of ESG reporting in the Industry 5.0 era, highlighting the role of new technologies in enhancing transparency and decision-making.
Lim	2024	AI Applications in Finance	AI	Systematic Mapping	Maps the research landscape of AI applications in ESG within finance, identifying key themes and knowledge gaps.
Zakizadeh and Zand	2024	AI-Driven Energy Intelligence, Energy BI, Energy Management System	AI Integration	Conference Paper	Proposes an integrated AI-based framework for energy sector transformation to improve efficiency and sustainability.
Tian et al.	2025	Carbon Forecasting Models	Forecasting Models	Review Study	Reviews existing CO_2 emission forecasting models and highlights upcoming challenges in emission prediction.
Uddin et al.	2024	AI-Powered Forecasting Tools	AI-Powered Carbon Emission Forecasting	Empirical Study	Explores the use of AI in forecasting emissions to support sustainable supply chains and green finance initiatives.
Costa et al.	2020	Real-Time Energy Monitoring Systems	Real-Time Monitoring	Empirical Study	Shows that real-time monitoring enhances operational sustainability by reducing waste and improving energy use efficiency.
Karthik et al.	2025	BI Systems with ESG Metrics	Business Intelligence with ESG Integration	conceptual framework for embedding ESG factors into existing BI frameworks	Integrates ESG metrics into BI systems to support sustainability-focused corporate decision-making.
Li et al.	2024	AI-Driven ESG Dashboards	Real-Time ESG Analytics	Empirical Study	Evaluates how AI dashboard systems impact ESG decision-making in real time.
Fluharty-Jaidee and Neidermeyer	2023	Big Data+AI	Environmental Dashboards	Book Chapter Analysis	Discusses current AI-ESG linkages in auditing and decision-making fields.
Herath and Herath	2024	Adoption Challenges Toolkits	AI Implementation Analysis	Barrier-Overcoming Framework	Identifies barriers and provides solutions for effective AI-based ESG adoption.
Lim	2024	Finance-focused ESG AI	ESG BI Dashboards	Systematic Review	Reviews applications of AI-powered dashboards in ESG finance decisions.
Sulkowski	2024	AI and ESG Law Systems	Legal Tech in ESG	Doctrinal Legal Analysis	Outlines legal frameworks and challenges in regulating AI-enabled ESG systems.

4.2. Risks, Biases, and Ethical Dimensions in ESG Tech

No technological innovation is trouble-free, and the body of work on AI-based ESG tools points to several risks, biases, and ethical concerns. When companies rely so heavily on AI and data to manage sustainability, they also need to contend with data quality, algorithmic bias, transparency, and wider ethical concerns. Primary concerns include the risk of AI algorithm bias, potentially creating skewed or unjustified conclusions in ESG analysis. AI systems are built using historical data; if those data are skewed or incomplete, the AI will likely replicate or even exacerbate the weaknesses present in them. In the case of ESG, skewed data could mean that certain environmental effects are downplayed (i.e., there is no data on a specific pollutant, etc.) or social indicators are measured exclusively through the Western lens, etc. According to Sætra (2023), there need to be protocols in place to assess and report the effects of AI itself on the ESG, effectively calling out the need to provide transparency around how AI models arrive at decisions and their limitations. In the absence of it, stakeholders can question the validity of AI-derived ESG insights. For example, if AI labels a supplier as high risk in labor, the supplier will want to understand the reasoning, which is hidden in a black-box model.

Another fear is excessive dependence on automated systems resulting in the erosion of human oversight and critical thinking. If managers begin to trust AI recommendations blindly, they may miss context or fail to apply ethical judgment to sustainability decisions. Data privacy and security form another ethical dimension. Sustainability data increasingly includes granular information – IoT sensors might track not only machine performance but also by-proxy information about human behaviors (like workspace occupancy). Ensuring this data is handled ethically and securely is vital. A breach in an energy management system could expose sensitive information about a company's operations or even allow malicious actors to manipulate systems (a cybersecurity risk). While not heavily covered in this review, it is an acknowledged risk that as more systems become interconnected for ESG tracking, the attack surface grows.

Perhaps the most ironic issue highlighted is the environmental footprint of AI itself. Training and running large AI models can

Table 5: Ethical considerations and risks in ESG-focused AI systems

Author (s)	Year	Platform/tool used	AI/BI techniques applied	Methodology	Key findings
Xiao and Xiao	2025	AI-driven ESG performance tools	AI	Empirical Study using regression analysis of ESG indicators in Chinese state-owned enterprises listed on stock markets.	AI-driven ESG performance affects the sustainable development of central state-owned enterprises.
Giudici and Wu	2025	AI in Finance	AI	Theoretical Analysis based on conceptual modeling of ESG integration in AI-based financial systems.	Explores the impact of ESG factors on sustainable AI practices in the financial sector.
Minkkinen et al.	2024	ESG Analytical Tools	Ethics-based AI Auditing	Conceptual Study exploring frameworks for incorporating ESG data into ethical AI audits.	Analyzes how ESG evaluations can support ethical auditing frameworks for AI used by investors.
Sklavos et al.	2024	AI Governance Models	AI	Empirical Study combining interviews and data analytics to assess AI governance and HR digitalization in Greek firms.	Investigates digitalization of leadership and HR through AI, framed within ESG governance structures.
Sulkowski	2024	AI in Sustainability Reporting	AI	Legal Analysis of international legal frameworks and policy documents related to AI-driven ESG reporting.	Analyzes AI's legal, ethical, and practical implications for ESG-aligned sustainability reporting.
Farzana et al.	2024	Technological Innovation+ Renewable Energy Systems	AI/Digital Inclusion Indicators	Cross-national Quantitative Study of 30 Countries	Shows the importance of governance and digital inclusion in achieving carbon neutrality, discussing systemic risks and ethical considerations in ESG-aligned innovation.
Patil et al.	2024	Tech in ESG Investing	AI	Empirical Study using mixed methods survey and case analysis of ESG investment firms in India.	Assesses ethical implications of AI in ESG investment and strategies for unbiased decision-making.
Nordgren	2022	AI and Climate Change	AI	Ethical Analysis based on normative ethical theory review focused on AI use in climate change policy and practice.	Explores ethical issues in AI applications that affect climate-related decisions.
Acquaviva et al.	2024	Climate AI	AI	Applied Ethics approach with case studies and expert interviews, emphasizing real-world implementation.	Bridges theory and practice in ethical approaches to climate-related AI development.
Zhuk	2023	AI Environmental Impact Models	AI	Review Study based on legal documents and scientific literature evaluating ecological risks of AI.	Identifies the hidden ecological and legal costs of AI, advocating regulatory frameworks.
van Uffelen et al.	2024	Environmental Ethics Framework	AI	Philosophical Analysis informed by environmental ethics theories, with case studies of AI applications.	Proposes ethical frameworks to evaluate environmental consequences of AI systems.
Adeoye et al.	2024	AI in Portfolio Management	AI	Quantitative Study using performance metrics from ESG-integrated investment portfolios analyzed with AI algorithms.	Highlights how AI enhances ESG investing by improving portfolio strategies and outcomes.
Lee et al.	2024	Responsible AI Framework	AI	Framework Development using Delphi method with industry experts to propose ESG-integrated responsible AI criteria.	Introduces a comprehensive assessment framework for integrating ESG into responsible AI initiatives.
Musleh Al-Sartawi et al.	2022	AI in Sustainable Finance	AI	Literature Review analyzing scholarly and industry publications to map AI's role in sustainable finance.	Evaluates the role of AI in advancing sustainable finance practices.
Perera et al.	2024	Industry-Based ESG-AI Framework	AI	Industry Engagement based on workshops and interviews with professionals in AI and sustainability fields.	Presents ESG-based recommendations for responsible AI based on industry consultations.
Strube et al.	2024	AI in Banking Sustainability Assessment	AI	Case study approach with open data from Andalusia, Spain, focused on sustainability risk assessment in banks.	Reviews AI's role in sustainability risk assessment and management in European banking.
Birti et al.	2025	LLMs for ESG Detection	LLMs	Experimental Study using natural language processing techniques to optimize LLMs for ESG activity detection.	Demonstrates optimization of LLMs for identifying ESG activities in financial texts.

consume substantial energy and resources. Researchers caution that the push to use AI for sustainability should not come with an outsized carbon cost that undermines the very goals it seeks to achieve. While not all ESG analytics use such large models, the point stands that AI is not inherently "green" – it depends on how it's developed and deployed (e.g., using cloud servers powered by renewable energy can mitigate some impact). This insight has led to calls for "*green AI*" practices in the ESG tech community: Making AI algorithms more energy-efficient, and transparently accounting for the carbon impact of AI computations in ESG analyses. Sætra (2023) AI ESG protocol explicitly suggests including the environmental impact of AI systems as part of an organization's ESG.

To address these concerns, the literature suggests several mitigation strategies. One is implementing transparency and accountability measures for AI systems. Organizations should document how their sustainability AI tools work, test them for bias, and have processes for human review of critical outputs. Another strategy is following frameworks or guidelines for ethical AI – for instance, adopting fairness checks, explainable AI techniques, and stakeholder consultations when deploying AI in sustainability programs. Human oversight remains crucial; as one source advises, companies should ensure "*clear accountability mechanisms and human oversight in place"* when using AI for ESG. On the data front, enhancing data quality and diversity (for instance, using diverse data sources and routine sensor data audits) can lower errors and reduce biases. Although AI-driven BI platforms open up new capabilities in the realm of ESG-based energy management, they pose a set of ethical and risk concerns as well. Corporations must exercise caution, harnessing the potential of AI and real-time data while being vigilant about potential biases, maintaining transparency, and considering the wider implications. Table 5 encapsulates some of these major risks and suggested responses presented in recent studies.

One prominent thread running through the studies is the incorporation of the principle of ESG in the design and auditing of AI systems and in the finance and sustainability areas in general. An example is the use of the Delphi method to put forward a responsible AI framework in line with the norms of ESG, highlighting participatory development and expert agreement by Lee et al. (2024). This argument is supplemented by Minkkinen et al. (2024), who support the use of ESG criteria in ethics-driven AI audits, situating the notion of ESG not only as a field of use but also as a normative prism by which AI needs to be assessed. Research by Xiao and Xiao (2025) and Adeoye et al. (2024) shows how AI can positively impact ESG performance and portfolio management, especially in improving sustainability tracking for state-owned companies and their portfolios. These are generally, however, mitigated by fears of susceptibility to bias, lack of transparency, and accountability concerns, matters that Patil et al. (2024) directly address in the case of a mixed-methods analysis of Indian ESG investment companies. Their findings underscore the need to develop AI systems that safeguard against algorithmic discrimination and unexplainable decisions.

Other works adopt a more foundational stance on ethics. Other studies adopt a more foundational stance to ethics. Nordgren (2022) and van Uffelen et al. (2024) draw on normative environmental and ethical theory to examine the role of AI in climate policy and ecological sustainability, respectively. They highlight that numerous AI systems, while presented as neutral, might embed values or operational concerns at odds with environmental goals in the longer term. Acquaviva et al. (2024) connect these philosophical questions to real-life situations by studying actual examples of how AI is used for climate issues. Legal and governing viewpoints are also common. Sulkowski (2024) and Zhuk (2023) examine the gaps in the law and regulations governing the use of AI in sustainability reporting and environmental modeling. They advocate for clear rules to manage the environmental and legal impacts of using AI, which is especially important as more complex models are being used in risky ESG reporting. Their argument is reinforced by the work of Strube et al. (2024), who present examples of how AI is being applied to sustainability risk assessment in banks in Europe in the absence of transparent ethical boundaries or control measures. Finally, work such as Birti et al. (2025) and Perera et al. (2024) centers on technological innovation in framework and language models and the development of the detection of ESG activity and supporting responsible use of AI. Their work shows how LLMs can be tuned to detect ESG in financial texts, and the result implies a maturing in the use of NLP that can deliver more precise, real-time sustainability insights while also introducing concerns regarding the use of opaque models and abuse.

5. CONCLUSION

This literature review has shown that AI-based BI platforms are increasingly integral to how corporations manage energy and sustainability performance. Over the past decade, companies across industries have begun harnessing AI's capabilities from automation and machine learning to real-time data analytics to enhance their ESG (Environmental, Social, and Governance) outcomes, particularly in energy efficiency and emissions reduction. In our thematic analysis, we found that:

- AI in ESG reporting: AI tools are automating the collection, analysis, and even narrative drafting of sustainability data, making reporting more timely and detailed. They improve accuracy (by minimizing human error and detecting anomalies) and free up sustainability professionals to focus on strategy rather than data wrangling. Early evidence (e.g., Chen et al., 2024; Xiao and Xiao, 2025) indicates that companies employing AI for ESG tend to improve performance, likely due to better data-driven decision-making. AI is also being used to verify and assure ESG information (as Li et al., 2024 described), increasing trust in corporate sustainability disclosures.
- Energy BI dashboards: Unified platforms that visualize energy and carbon data have empowered companies to monitor usage in real time, benchmark performance, and identify inefficiencies. Case studies (IBM, AT&T) and research show substantial energy savings and emissions cuts attributable to these systems. The transparency provided by BI dashboards embeds energy management into daily operations –energy is treated with the same rigor as other KPIs. Companies have achieved continuous improvements (5-15% energy reductions

in various contexts) by using these insights to fine-tune processes, invest in efficiency, and eliminate waste.

- Predictive analytics: Machine-learning models are enabling forward-looking management of sustainability. Corporations can forecast their energy demand and carbon footprint with greater accuracy, allowing proactive measures (like adjusting operations or purchasing green energy) to stay on track with ESG targets. Predictive analytics also help in scenario planning (a requirement of frameworks like TCFD), giving management a tool to visualize how different decisions today will influence future sustainability performance. This is crucial for strategic planning, such as charting a path to net-zero emissions by a certain year; AI can simulate whether planned initiatives are sufficient or if more aggressive action is needed.
- Real-time decision-making: The infusion of real-time data into sustainability management has shortened decision cycles and made sustainability a continuous, agile process. Companies can now react within hours to issues like energy spikes or system faults, preventing excess emissions or costs. Moreover, real-time dashboards drive cultural change when every level of staff sees sustainability metrics live, sustainability ceases to be an annual report and becomes a day-to-day responsibility. Firms with these capabilities are more resilient and responsive, adjusting to everything from sudden energy price changes to unexpected equipment inefficiencies with minimal delay.
- Risks and ethics: We also highlighted that these technologies are not a panacea and must be applied thoughtfully. Risks include data biases leading to flawed conclusions, over-reliance on AI without human common sense, and the irony that running complex AI models can consume significant energy. Ethical governance of AI is therefore part of ESG management. Organizations need to ensure their AI tools are transparent, fair, and themselves sustainable. The emerging best practice is to maintain human oversight, regularly audit algorithms for bias, and be transparent about how AI is used in sustainability decision-making. Essentially, companies must extend their ESG principles to the very tools they use to manage ESG ensuring, for example, that an AI model aligns with the company's values and stakeholder commitments.

5.1. Implications for Practice

For corporate practitioners (sustainability officers, energy managers, CIOs, etc.), the findings underscore that investing in AI-driven BI systems can yield real benefits in terms of efficiency, cost savings, and progress toward sustainability goals. The ROI of such systems is not only in direct energy savings but also in improved risk management (catching problems early) and credibility (producing high-quality ESG disclosures can improve stakeholder trust and possibly access to capital. However, the review also implies that companies should approach this digital transformation strategically: Integrate it with established frameworks (GRI, SASB, TCFD) to ensure completeness and relevance; build interdisciplinary teams (IT, sustainability, operations, finance) to implement and oversee systems; and invest in training so that end-users can effectively interpret and act on the dashboards and analytics. Moreover, organizations may need to update their governance structures for instance, creating an internal "*ESG data governance committee*" or expanding the role of audit committees to cover non-financial data and AI analytics processes.

There are also implications for solution providers. As demand grows for AI/ESG tools, software firms should incorporate domain knowledge of sustainability and adhere to open standards so their tools can plug into companies' reporting workflows. Interoperability (with reporting frameworks and with other enterprise systems) will be key to widespread adoption. Another implication is the need for continuous improvement: as AI models age or as operations change, models must be recalibrated it is not a one-and-done deployment.

5.2. Research Gaps and Future Work

While significant progress is evident, our review identified several gaps where further research is needed:

- Holistic ESG integration: Most current applications and studies focus heavily on the environmental dimension (energy, emissions). Fewer address AI for the "S" and "G" aspects (e.g., worker safety, human rights in supply chains, board governance metrics). Future research could explore how AI/BI platforms can equally support social and governance objectives – for instance, using AI to analyze workforce diversity and pay equity (and the energy implications of remote work policies, which blend E and S), or real-time monitoring of governance compliance.
- Sector-specific studies: Certain sectors (like manufacturing, tech, utilities) are well represented in case studies, but others such as agriculture, services, small-medium enterprises (SMEs) are under-researched. SMEs in particular may have barriers (cost, expertise) to adopting these advanced tools. Research could investigate scalable, cost-effective solutions for smaller companies or non-profit and public sectors, which also have ESG goals. This is particularly relevant given recent findings that highlight the importance of aligning HR sustainability efforts with environmental performance across sectors (Alzghoul et al., 2024) and the strategic role of renewable energy adoption in enhancing the sustainability of Jordanian SMEs (Awamleh et al., 2025).
- Quantifying causality: Many studies show correlations (firms using AI have better ESG outcomes), but more longitudinal and causal research would strengthen the case. For example, controlled experiments or quasi-experiments where a set of facilities adopt an AI-BI tool and others do not; to measure differences in performance over time, would be valuable. This can help attribute improvements specifically to the technology, controlling for other factors.
- Human-AI collaboration: Further exploration is needed on how human decision-makers interact with AI recommendations in sustainability. What types of dashboard design or explanation improve trust and adoption of recommendations? How can organizations avoid alert fatigue (too many alerts can be overwhelming)? Ethnographic studies or user research within companies implementing these systems could yield insights to refine tool design and training approaches. Recent studies have started addressing this interplay by examining how business intelligence tools support HR transformation and

influence strategic decision-making, especially in digital contexts (Tawalbeh et al., 2025).

- Ethical AI for ESG: As raised in theme 5, more research is warranted on frameworks and technical methods to ensure AI is used ethically in sustainability contexts. This could include developing algorithms that are not just optimized for accuracy but also for fairness and low energy use (e.g., sustainable AI design). It also includes policy research: how should regulators consider AI in ESG reporting (perhaps auditing the algorithms as part of audit procedures)?
- Impact on performance: Finally, a macro question is how this micro-level improvements scale up do industries or economies with higher adoption of AI for ESG show significantly better sustainability performance. In addition, does improved ESG performance via these tools translate into better financial performance (validating the business case)? Initial signs like studies linking AI use with ESG and productivity gains are positive, but more broad-based analysis (e.g., using datasets of many firms over time) would be beneficial.

It is clear that AI-based BI platforms are not a futuristic concept but a present reality that is already reshaping corporate sustainability practice. A senior sustainability executive reading this should come away with both optimism and caution. Optimism that these technologies can unlock new levels of efficiency, insight, and stakeholder engagement – moving the needle on critical issues like climate change and resource use. In addition, caution governance, ethics, and continuous learning must accompany that implementation. The path forward will likely involve iterative adoption: Pilot an AI tool, learn from it, address pitfalls, expand usage, and so on. Corporations that navigate this learning curve swiftly and thoughtfully are likely to emerge as leaders in the ESG space, using digital intelligence not just for profit, but for the planet and people as well.

Looking ahead, one can envision a future (5-10 years hence) where ESG-driven energy management is digital and intelligent. In such a scenario, a corporate sustainability dashboard might resemble a command center where AI agents autonomously balance a company's energy loads with available renewable supply, automatically trade carbon credits to offset any excess emissions, and continuously communicate with stakeholders (possibly through AI-driven conversational interfaces) to update them on sustainability progress. Sustainability reporting might become real-time and audit-proof thanks to blockchain and AI verification of data. Employees at all levels could have personalized sustainability "copilots" – AI assistants that help them make day-to-day work decisions in line with the company's ESG goals (for example, an AI scheduling assistant that plans meetings or production runs for minimal carbon footprint). Achieving this vision will require not only technological advancement but also collaboration between technologists, sustainability experts, policymakers, and stakeholders to ensure that the intelligent systems we create truly serve our collective sustainable future. The research and practice insights compiled in this review are stepping-stones toward that vision, highlighting both the tremendous potential and the care needed to harness AI for the greater good in corporate energy management and ESG performance.

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