ISSN: 3143-8458

Journal of
Artificial Intelligence and Data Analytics

Research Article

Volume: 1 | Isssue: 2 | June 2026 | Pages 01–11

AI-Enhanced Governance for ESG Reporting Integrity: A Sector-Specific Framework Balancing Algorithmic Detection and Human Judgment

Mohsin Khan[1] and Wendy Ashurst[2]*

[1]Financial Reporting Analyst, North American Clinical Associates, United Kingdom
[2]Lecturer, Bangor University, United Kingdom

***Corresponding Author:** Wendy Ashurst, Lecturer, Bangor University, United Kingdom.

Submitted: 28 May 2026 **Accepted:** 03 June 2026 **Published:** 11 June 2026

Citation: Ashurst, W., Khan, M. (2026). AI-Enhanced Governance for ESG Reporting Integrity: A Sector-Specific Framework Balancing Algorithmic Detection and Human Judgment. Journal of Artificial Intelligence and Data Analytics, 1(2), 1-11.
DOI: doi.org/10.67927/JAIDataAnalytics/2026(1)107.

Abstract

Purpose: This paper aims to develop a sector-specific governance framework to understand the application of artificial intelligence in enhancing the quality of ESG reporting, while recognizing the value of human judgement in high-risk disclosure environments.

Design/Methodology/Approach: This conceptual paper uses a theory-driven qualitative approach. It draws on a critical review of the literature and discourse analysis of 120 corporate sustainability reports from the energy, financial services and consumer goods industries.

Findings: Environmental disclosures have the highest verification potential on AI since metrics are more benchmarkable and standardized. It's worth is reduced in social and governance reporting where narrative interpretation and judgement in context are vital. It is also revealed that sectoral conditions have their role as operationally measurable industries would be easier to place under AI-based review as compared to financially oriented narrative reporting.

Originality/Value: The paper re-conceptualizes AI not as a technical solution but as a limited governance mechanism based on legitimacy, stakeholder and agency theory. It offers a workable hybrid approach where algorithmic detection is used to complement, not substitute for, board oversight, assurance and judgement in ESG reporting.

Keywords: Social Media Marketing, Customer Acquisition, Platform Comparison, Engagement Rate, Conversion Rate.

Introduction

Proper environmental, social, and governance (ESG) reporting has emerged as a major issue in the sphere of sustainable finance, as greenwashing may mislead capital distribution and undermine trust in stakeholders [1]. Despite the increased number of ESG disclosure requirements over the past few years, the check of such information is difficult. This is mostly because of information asymmetry, subjectivity of most of the ESG indicators, and differences in reporting standards among firms and sectors [2]. Conventional governance tools such as external assurance and regulatory control are still significant in promoting the credibility of ESG reporting. Nevertheless, the increasing amount and complexity of disclosures on sustainability are increasingly challenging these mechanisms. This has necessitated the need to have supplementary governance instruments that can bring more transparency without eliminating professional judgement.

Artificial intelligence (AI) is also becoming a topic of discussion as a way of enhancing credibility and integrity of ESG reporting. Nevertheless, a significant portion of the current discourse portrays AI primarily as a technical tool, but not as a component of an overall system of governance. Past research has investigated the application of AI in fields like predictive analytics and fraud detection, but fewer have investigated this use of AI through the prism of well-known accounting and finance theories. This gap is significant as the usefulness of AI in ESG governance will not be determined solely by its ability to detect abnormalities, but also by how it will balance with institutional responsibility, oversight at the board of directors, and stakeholder anticipations. In this regard, this paper conceptualizes AI as a limited governance instrument that facilitates but does not substitute human judgement in the process of sustainability assurance.

The current research is based on the perception that legitimacy theory, stakeholder theory, and agency theory can be a valuable starting point to comprehend how AI can be used to mitigate the threat of greenwashing. The legitimacy theory is used to understand the reasons behind the firms reporting ESG information to ensure social acceptance and organizational legitimacy [3]. The stakeholder theory underlines the need to report transparently in response to the interests and expectations of various stakeholder groups [4]. Agency theory, in its turn, brings to the fore the possible conflict that can arise when managers are driven by short-term incentives to the detriment of long-term sustainability goals [5]. Collectively, these theoretical lenses imply that AI could be especially useful in cases where it is employed to identify discrepancies between stated ESG pledges and the visible corporate actions. By doing so, AI can lessen the information asymmetry and reinforce accountability in sustainability reporting.

This paper is methodologically a combination of a critical literature review and a discourse analysis of 120 company sustainability reports of high-risk sectors, such as the energy, financial services, and consumer goods sectors. It is not aimed at asserting real-time algorithmic validation, but it is an attempt to come up with a theory-grounded governance framework based on recurring trends in disclosure practices and the findings of the current studies on ESG reporting and AI. This strategy will allow identifying typical greenwashing tactics and give a foundation to evaluate the added value of AI-aided review in various ESG aspects and industry scenarios.

The article constructs a sector-specific model that makes AI a governance tool to improve the quality of environmental, social, and governance reporting. The analysis shows that AI will probably work best in spheres where disclosures are grounded on standardized, quantifiable, and similar indicators. In comparison, social and governance disclosures tend to be more contextual to interpret, and thus, the level of their evaluation by automated tools is restricted. The suggested framework thus promotes a hybrid approach where AI enhances the quality of the expert review without taking the interpretive role of assurance professionals and governance actors.

The rest of this paper is structured in the following way. Section 2 discusses the literature on the problem of ESG reporting and the application of AI in sustainable finance. Section 3 gives the theoretical framework based on the legitimacy theory, stakeholder theory, and the agency theory. Section 4 describes the research design and methodology, and Section 5 gives the analysis and findings. Section 6 addresses the theoretical and practical implication of the study and Section 7 offers advice to the policymakers, assurance providers and other interested parties.

Literature Review

The use of artificial intelligence in ESG reporting is gaining more attention in scientific literature. The earliest research in this area has been mainly focused on technical aspects of machine learning in predicting ESG rating as neural networks or other algorithms could be used to analyses a large volume of financial and sustainability-related variables [6,7]. But these early attempts did not address the effects of adopting AI on governance dynamics and regarded artificial intelligence as something of a black box.

This has been revisited in recent academic literature on the use of artificial intelligence in greenwashing detection and improving the quality of information. NLP has also proven to be a promising technique to analyze sustainability reports to commit overstatements or inconsistencies, with some studies even proposing dedicated measures to assess the consistency between self-disclosures and external disclosures of firms [8,9]. These techniques of analyzing text can be used to complement traditional financial analysis by determining patterns in narrative reporting that can indicate biased reporting or concealment.

Governance aspect of AI in ESG has become a pivotal point of investigation. A combination of blockchain and AI has been suggested to enhance the transparency of sustainability reporting, and smart contract frameworks aim to automatize compliance monitoring [10,11]. Such technological solutions are intertwined with broader discussions of corporate responsibility, with particular focus on how AI can be used ethically in financial reporting [12]. The ongoing conflict between computational speed and human supervision continues as a central issue, as hybrid frameworks emerge as a compromise solution [13].

Theoretically, there has been a growing concurrent correlation between AI applications and existing accounting and finance models. The legitimacy theory can be used to examine how AI can help companies maintain societal approval through creating more credible ESG reports, and the stakeholder theory to develop AI solutions to meet diverse informational needs [3,4]. The issues of agency theory have led to recommendations to implement AI-based systems of oversight to reduce information asymmetry between managers and investors [5].

Sector-related issues in ESG verification have also been in the limelight. The comparative analysis of manufacturing and financial services industries reveals significant differences in the availability of data and reporting since environmental indicators are generally more aligned with the algorithmic analysis than social indicators or governance [14,15]. These differences highlight the importance of custom-made solutions as opposed to a one-size-fits-all solution. Ethical considerations of artificial intelligence management as part of environmental, social, and governance initiatives have triggered both stringent examinations of potential biases and lack of clarity [16]. Arguments over algorithmic responsibility have seen the introduction of explainable AI systems to sustainability reporting, and arguments as to whether automation or professional judgment should predominate [17,18]. Our study advances these debates by constructing a framework rooted in theory, which situates artificial intelligence as a means of governance instead of just a technological instrument. Even though a variety of uses of artificial intelligence in ESG areas have already been explored, our approach is unique in combining the legitimacy, stakeholders, and agency theories to explain the potential of algorithmic identification to institutional accountability systems. This industry-specific framework addresses a significant gap in the existing literature by offering detailed insights into how AI technologies may be applied across different sectors and ESG dimensions.

Theoretical Foundations: AI, Governance, and ESG Reporting

The use of artificial intelligence in ESG reporting governance needs to be grounded in a robust theoretical framework that goes beyond the technical aspects and connects with institutional accountability. The three related theoretical approaches include legitimacy theory, stakeholder theory and agency theory which underline the understanding of the AI as a governance tool, rather than an analytical tool. All these theories justify the rationale behind organizations revealing ESG information, the way various stakeholders process that disclosure, and what governance loopholes AI could fix in the sustainability reporting ecosystems.

Legitimacy theory sheds light on the motivations behind corporate ESG reporting and the potential for AI to strengthen the trustworthiness of such disclosures. Organizations operate on unspoken contracts with society, and they need to align their activities with the general norms, and ESG reporting is one of the key instruments to maintain the alignment [3]. The voluntary nature of sustainability reporting creates opportunities to engage in superficial disclosure, as opposed to meaningful disclosure, and such a mismatch where artificial intelligence could serve as a solution to enhance credibility. As an illustration, natural language processing techniques can be used to systematically examine the correspondence between the ESG statements of a company and its practices, which can reveal discrepancies that can indicate a gap between what is claimed and what is being done in sustainability. Algorithms analysis can be used to supplement the conventional validation techniques by allowing continuous monitoring as opposed to periodic reviews. This will help minimize the time lag between ESG reporting and identifying possible problems associated with authenticity or consistency.

Stakeholder theory also indicates that AI can enhance the availability of ESG information by transforming technical measures of sustainability into more accessible and comprehensible formats that can be used by various stakeholder groups. This advantage, however, is conditional upon making the outputs of the algorithms transparent, interpretable and not being employed to justify selective or misleading presentation.

The agency theory provides a valuable perspective on governance by considering ESG reporting as a field where there can be conflicts between managers as agents and shareholders or the rest of society as principals [5]. There is motivation to managers to exaggerate sustainability performance or to report adverse effects, especially where executive compensation is linked to ESG performance measures. AI can assist in solving these agency issues in two aspects. To begin with, it can detect abnormal trends in ESG data that can be a sign of manipulation. Second, it can be used together with blockchain technologies to facilitate more resistant and secure reporting systems [10]. These applications are in line with the focus of agency theory on monitoring and alleviating information asymmetry. Simultaneously, they pose new governance issues regarding who owns AI systems and how the outputs of AI systems are to be understood in decision-making.

The correlation between these theoretical viewpoints shows that there are important sector-specific differences in the role of AI in governance. Environmental disclosures, which typically are based on quantifiable metrics like carbon emissions, energy use, or waste generation, are typically well-suited to AI-based analysis. These indicators tend to be more standardized across industries and thus are more suitable for algorithmic verification. In the legitimacy theory view, this can play a role in enhancing greater accountability as firms can Conversely, social and governance disclosures tend to be more narrative, and context-dependent, including the workforce diversity, employee wellbeing, board efficacy, and ethical behavior. These dimensions reveal the shortcomings of AI, particularly in areas where a significant interpretation requires organizational context, professional judgement, and qualitative insights. The stakeholder theory thus justifies a hybrid system of governance where AI is employed to detect possible warning signals, with human professionals in charge of further analysis and ultimate decision making.

The agency theory also implies that the success of AI in ESG governance can be different depending on the incentive structures in the sector. AI monitoring can be applicable in industries where ESG performance is strongly correlated with financial incentives, like renewable energy companies that have sustainability-based executive compensation. In industries where ESG reporting is more reputation-related, e.g. consumer goods companies focusing on ethical sourcing, AI can be more useful in evaluating external sources, e.g. supplier audits, NGO reports and media coverage, to determine whether corporate reporting is aligned with external evidence. Yet, these applications should be strictly regulated to prevent the emergence of new agency issues, including overreliance on the results of algorithms without a clear comprehension of their shortcomings, assumptions, or possible biases.

The UK Corporate Governance Code provides an institutional framework to implement these insights. Its emphasis on the board's stewardship of ESG issues offers a governance context in which AI can be applied to help the board manage sustainability reporting. For example, AI dashboards can help audit committees to identify areas of risk that require further analysis of disclosure, whereas natural language processing can be used to evaluate the sustainability narrative in annual reports.

Research Design and Method

The research uses a qualitative approach that includes theoretical discussion and a structured framework to explore the potential role of artificial intelligence in combating greenwash in ESG disclosures. The framework does not priorities the technical aspects of AI, but the interplay between AI and governance theories. This helps achieve the goal of AI as a governance tool, rather than just a technical tool. These cases embody legitimacy theory by enhancing the link between corporate ESG reporting and ESG performance. Likewise, stakeholder theory supports tailoring AI's outputs to the needs of various governance stakeholders, such as management needing strategic insights and regulators needing to ensure compliance with reporting standards. In all, the framework views artificial intelligence as a limited governance tool that is part of the organizational system and not a standalone solution. This approach depends on the degree to which algorithmic capabilities are aligned with accountability measures influenced by legitimacy, stakeholder and agency perspectives. This will also vary between ESG factors and industries.

Methodological Framework

This paper adopts a critical review method, incorporating legitimacy, stakeholder, and agency theories to explore the phenomenon of greenwashing and how artificial intelligence (AI) can mitigate it. This allows the research to review the evidence and identify gaps in the conceptual understanding of the relationship between AI governance and ESG reporting. The framework is developed in three steps.

First, mapping is applied to explore the interplay between greenwashing typologies, corporate disclosure incentives and AI capabilities. Here, the role of AI approaches is examined in terms of how they may alter the existing relationships in ESG reporting, with a focus on information asymmetry and accountability.

Second, pattern recognition is used to examine case studies of greenwashing across a variety of industries to identify common disclosure techniques such as hedging, gaming metrics, and omission. Such areas are potential avenues for AI support in ESG review. This step also draws upon previous studies of ESG reporting, while not being too technical about the use of AI [2].

Finally, governance integration considers the integration of AI-based greenwashing detection with existing assurance and regulatory frameworks. This involves consideration of constraints such as audit trails, assurance processes and reporting standards.

Data Collection and Analysis

The research uses three primary data sources: corporate sustainability reports, regulatory reports and assurance statements. The sample includes 120 corporate sustainability reports from 2018 to 2023, primarily from vulnerable sectors like energy, financial services and consumer goods. These reports are used for qualitative pattern analysis. They were chosen due to past concerns about greenwashing or significant changes in ESG ratings. ESG claims are then compared with mandatory reporting, such as US Form 10-Ks and EU Taxonomy reports, to compare different reporting standards.

The textual analysis is not based on transformers, but on discourse analysis, focusing on rhetorical elements, including passive voice, imprecise quantifiers and vague environmental claims. Quantitative verification uses ESG indicators to compare them with industry benchmarks.

$$|\Delta_{it} = \frac{|y_{it} - \bar{y}_{jt}|}{\sigma_{jt}} \quad (1)$$

where y_it represents firm i's reported metric at time t, y ̄_jt the sector j median, and σ_jt the cross-sectional standard deviation. Data points with values greater than 2.5σ are identified for qualitative review, as they may be the result of manipulation or reporting errors.

Analytical Approach

The paper takes a comparative case approach to investigate the potential role of AI in tackling greenwashing. The analysis includes a method for overclaiming detection to uncover discrepancies between company narratives and quantitative metrics, as well as benchmark gaming to specifically examine practices particular to certain industries that may skew metrics. Omission analysis also tests if firms withhold reporting of material ESG issues in their reports against industry standards.

The second step in the analysis approach includes a governance component, by considering corporate factors and detection outcomes.

$$G_{score} = \alpha + \beta_1(AI_{flag}) + \beta_2(Board_{ESG}) + \beta_3(Reg_{pressure}) \quad (2)$$

G score is the quality of governance and AI flag is the reporting problems identified by AI-based analysis in this model. Board-ESG is the level of ESG knowledge and expertise on the board level, and Reg-pressure is the level of regulatory scrutiny. The model conceptually connects the AI-based detection to the institutional governance variables that influence the corporate reporting practices.

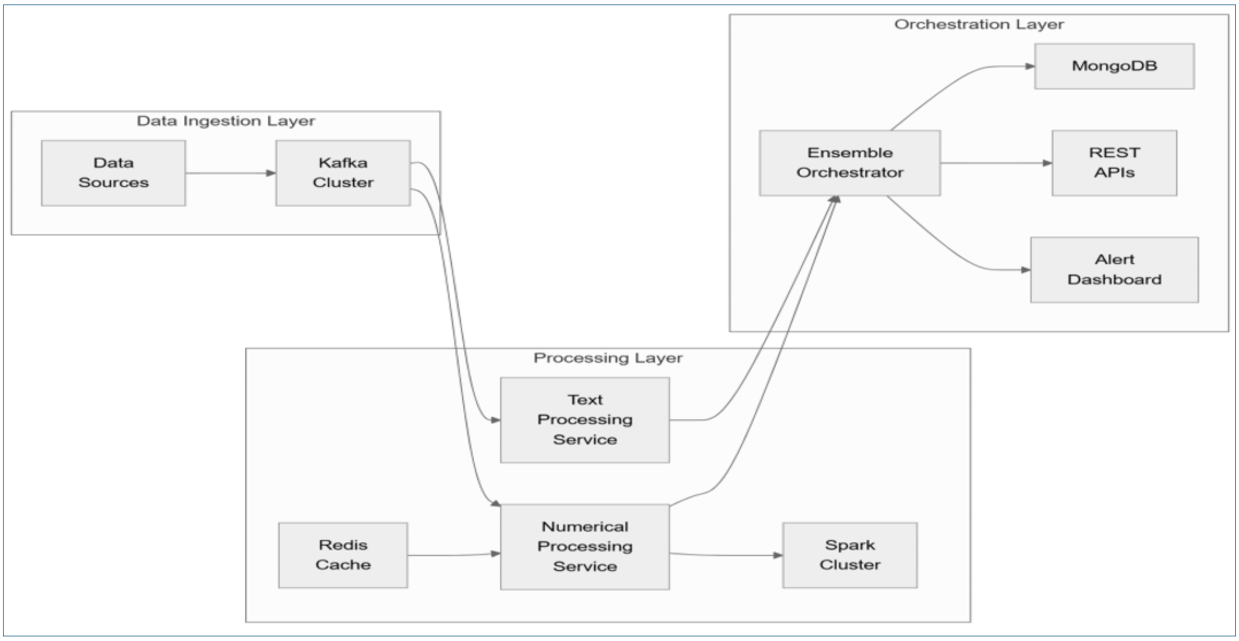

Figure 1: Top-Level System Design of Real-Time ESG Monitoring.

Figure 1 shows the governance layers that enclose the technical aspects of real-time ESG monitoring, with a specific focus on accountability mechanisms, as opposed to the outputs of algorithms in isolation. The system is structured into interdependent functional layers such as data ingestion, transformation and orchestration. This design is indicative of the larger issue of the study in terms of integrating technical competencies into governance-based support systems.

Validity Considerations

The research design ensures validity by triangulating the results with legitimacy theory, stakeholder theory and agency theory. The research uses a variety of data sources, such as voluntary sustainability reports, mandatory regulatory reports and external statements of assurance. Negative case analysis is applied to explore potential challenges in using AI to identify more advanced greenwash, thus providing a more nuanced view of the limitations of algorithms. In conclusion, this research design offers an appropriate approach for accounting studies by preserving its academic rigor and directing research focus from technicalities of AI towards governance related solutions to improve ESG reporting.

Analysis and Results

The research provides insights into the use of AI in the governance of ESG reporting, including variations across ESG and industry segments. It also outlines the key requirements for implementation. The analysis of the qualitative evaluation of corporate disclosures and the relevant theoretical approaches underline the potential and challenges of the use of AI as a governance tool.

Variation in AI's Governance Value Across ESG Dimensions

The analysis shows that the potential of AI as a governance tool is different between environmental, social and governance reporting. Environmental disclosures have the greatest potential for algorithmic verification as indicators like greenhouse-gas emissions and energy use are more easily standardized and benchmarked. Their quantitative nature makes it easier to detect anomalies, and third-party assurance in this area offers further comparisons [19]. While there are some quantitative social metrics (e.g., workforce diversity percentage), they are not as standardized as environmental metrics [20]. Our analysis showed that there were recurrent patterns of narrative framing in the social disclosures where firms highlighted positive actions and de-emphasized negative impacts through textual techniques such as passive voice and conditional statements. These narrative patterns are difficult to be evaluated by AI without much information about workplace and community relations [21]. The interpretive nature of many social performance measures makes it more difficult to assess by algorithms, as the meanings of "fair wages" or "safe working conditions" vary across stakeholders and cultural and regulatory contexts.

The suitability of AI verification is most evident in governance. Hard numbers, such as board composition ratios, are relatively easy to verify by algorithms, especially if compared with industry standards or regulatory requirements [22]. However, the qualitative aspects of governance disclosures, such as descriptions of board oversight of their operations or ethical decision-making frameworks, are difficult for AI to assess. The research found that companies tend to use boilerplate language in their governance reports, making it difficult to distinguish between genuine commitments and compliance [23]. These findings are in line with the expectations of agency theory about the incentives of managers to conceal governance deficiencies and to appear to be compliant with external pressures.

The relative suitability of the environmental aspect for AI verification is reflected in several trends. Environmental measures have less diversity in reporting formats than social and governance measures, which reduces the pre-processing burden on AI. Second, the existence of predetermined conversion measures (e.g., GHG emission ratios) adds to more accurate comparisons between different firms. Third, environmental data is often associated with operational systems, including energy monitoring devices, providing automated streams of data, reducing errors of manual reporting. These attributes establish advantageous circumstances for artificial intelligence systems designed to identify irregularities and analyze patterns.

In the case of social disclosures, the analysis found three main limitations to the value of AI in governance. First, algorithmic benchmarking is complicated by the absence of standardized measurement methods of most social indicators. Second, the differences in cultures and regulations in different jurisdictions pose interpretation problems to uniform AI models. Third, social reporting requires a fine understanding of local environments, which is not easily achieved by current natural language processing techniques due to its strong storytelling nature. These limitations suggest that artificial intelligence may be best used as an initial assessment tool of social disclosures, which can be used to reveal potential issues to be addressed by humans later rather than provide final decisions.

Governance disclosures display distinct mixed attributes where AI holds potential for specific organized components but encounters challenges in assessing qualitative aspects. Algorithms can be useful in analyzing board composition statistics and other quantitative measures, especially in determining whether diversity and independence (or other governance characteristics) are responsive to regulatory standards or industry practices. Analysis, however, revealed that the description of governance processes and cultural characteristics in most cases is based on indefinite terms that do not allow the substantive evaluation of algorithms. This difference suggests that AI will make the most significant contribution to governance in this regard when applied to evaluate verifiable structural factors, as opposed to procedural practices or claims influenced by organizational culture.

These variations in ESG dimensions have important conceptual implications as well. From a legitimacy theory perspective, the greater fit of environmental disclosures for AI-based verification may increase their perceived legitimacy for stakeholders and help to close legitimacy gaps in this dimension. Stakeholder theory, on the other hand, highlights the importance of varying AI applications across ESG dimensions, as different stakeholder groups may prefer different types of information. Agency theory also suggests that the current challenges of AI in evaluating qualitative governance narratives may remain, given the flexibility of managers in narrative disclosures. Overall, these theories help explain the differences in the governance value of AI across ESG dimensions and suggest that implementation strategies should consider these differences. Assurance practitioners evaluating AI systems should understand that environmental data are likely to represent the best investment

in terms of verification by automated means, but that social and governance information might need more human-integrated approaches. Governments designing AI monitoring programs should start by focusing on environmental data, where more uniformity can aid algorithmic processing. Likewise, companies embracing internal AI governance structures should priorities resources across the ESG areas, with environmental data more likely to be automated and social and governance data more likely to require human oversight. These insights flow from the findings of different governance values of AI across ESG.
Sectoral Variations in AI-Driven Verification.

A study of industry-specific reporting shows that artificial intelligence as a governance tool varies between different industries. The manufacturing and industrial sectors seem to provide relatively good opportunities for AI-based verification, while financial services and technology companies are more complex due to variations in reporting formats and materiality. These differences reflect differences in operational features, data collection and reporting, and ESG impacts. **Manufacturing and extractive industries** are well suited to the application of AI for ESG verification. The study highlights several factors that enable the use of AI, including the presence of standardized environmental performance indicators, such as emissions per unit of production, well-established data collection systems, and relatively uniform reporting practices across companies [24]. Such characteristics enable artificial intelligence to perform significant inter-firm analysis and detect anomalies in reported results. As an example, energy intensity measures in automotive production show sufficient standardization to benchmark algorithms, and variations beyond expected values can be a sign of potential reporting issues. The tangible elements of environmental impact in these sectors, such as waste generation or water consumption, also create tangible measures that can be evaluated by artificial intelligence in terms of manufacturing outputs. However, the analysis uncovered sector-specific limitations even within manufacturing. Industries with complex supply chains, e.g. aerospace, or electronics manufacturing, are difficult to monitor in terms of indirect (Scope 3) emissions and other extended responsibility measures [25]. As much as AI can be used to determine inconsistencies in the supplier-reported information, the lack of standardized measurement systems within global supply chains limits the accuracy of verification.

The nature of the **financial sector** makes it difficult for AI to be used in the verification of ESG. The financial sector (banks and insurance) tends to focus more on narrative accounts of ESG strategies than quantitative performance indicators, particularly for social and governance concerns [26]. This lends itself to a story-telling approach that constrains the use of algorithmic verification, which relies on standardized information. Furthermore, some material ESG issues in the financial sector such as ethical lending and financed emissions, relate to indirect impacts that are hard to quantify [27].

Three key challenges to the application of AI in ESG governance emerged from the review of reports in the financial sector. First, the disclosures are often based on cherry-picked case studies that emphasize positive events but do not include detailed performance information. Second, there are no standardized measures to evaluate the ESG quality of financial products and services. Third, the downstream impacts of financial activities are hard to track. These characteristics make it hard to set industry standards or identify significant variations in reported performance. These patterns may be explained because of the incentives associated with financial institutions' desire to highlight sustainability management and minimize reporting of potentially controversial investment activities (agency theory).

The consumer goods and retail sectors have more varied prospects for AI verification. On the one hand, these sectors have improved standard environmental measures, particularly with respect to operational measures such as energy use in retail stores and packaging waste (Kuefeooglu, 2026). Our analysis shows that larger retail companies are beginning to adopt more standardized reporting approaches for these operational indicators, enhancing the prospects for AI-based benchmarking. On the other hand, reporting on social and supply chain matters is very variable; companies report on issues such as labor rights and sustainable sourcing in different ways [28].

The results identify several industry-specific factors that affect the use of AI in businesses that deal directly with consumers. First, the many brand sustainability claims, such as labelling a product as environmentally friendly, pose challenges beyond traditional ESG risk assessment. Diverse supply chains and regulatory regimes make it challenging to gather social information. Further, many disclosures in this industry are targeted at the consumer, which may lead to a more marketing-oriented focus. These considerations suggest that, while AI can be applied to this industry, it may be more effective to focus on operational environmental disclosures and to take a cautious approach to social and supply chain disclosures, particularly in a context-specific context.

Telecommunications and technology industries offer unique opportunities and challenges for AI-based ESG management. There are opportunities to report on relatively specific issues such as energy-efficient data centers and sustainable sourcing, which may enable benchmarking and trend analysis [29]. But these industries also encounter challenges in quantifying and disclosing less visible ESG aspects, such as digital inclusion, privacy, and responsible AI development [30].

The analysis indicates that ESG reports of technology companies tend to emphasize future-oriented aspects, such as innovation and long-term goals, over current performance measures. Although this may be helpful for engaging stakeholders, it presents challenges for AI models that rely on historical performance metrics. Additionally, ESG issues are rapidly shifting in these industries, with increasing focus on issues such as algorithmic bias, data ethics and privacy. These can evolve more rapidly than the development of standardized metrics. Therefore, the governance benefits of employing AI in tech-related industries may be greatest regarding standardized environmental indicators, whereas social and governance issues demand constant evolution and human judgement. There are important conceptual implications of these differences. Legitimacy theory implies that industries with more tangible environmental impacts (such as manufacturing and extractives) may stand to benefit from AI verification in terms of legitimacy because AI can more readily verify the congruence between stated goals and actual impacts. Stakeholder theory also emphasizes the importance of sector-specific AI developments, as different stakeholders will care about different ESG issues. For instance, investors may be more concerned with risk and financed emissions in financial services, while consumers may be more concerned with sustainable sourcing, product sustainability and working conditions in retail.

The agency theory implies that more narrative adaptable disclosures in industries, including financial services, may be able to retain more opportunities to report symbolically, as opposed to substantively, until AI approaches to qualitative evaluation develop. The practical implications of implementing AI governance systems differ significantly across sectors. In the manufacturing sector, companies can focus on automated testing of the operational environmental indicators and create more incremental strategies on the effects of the supply chains. Banks and other financial entities might first have to concentrate on strengthening the numerical bases of their environmental, social, and governance disclosures prior to anticipating substantial benefits from artificial intelligence validation systems. Companies that manufacture consumer products can have benefits with artificial intelligence tools that check compliance between claims regarding individual products and the overall company performance indicators. To monitor the progress of their environmental, social, and governance objectives that are focused on innovation, technology firms can use artificial intelligence tools. These industry-related channels of execution reflect the fundamental differences in the ways sectors approach ESG reporting and where AI can most effectively provide the most governance advantages.

The UK system of corporate governance adds another layer of deliberation on an industry-specific level. The analysis also suggested that industries that have stronger historical ties to reforms of the UK governance, such as the financial services, might have more developed systems of integrating AI verification tools with the existing board oversight processes. By comparison, industries with a lower history of alignment of governance codes might need to do more establishment work to tie AI systems to accountability frameworks. This variation suggests that effective AI oversight of ESG disclosure is likely to differ according to sector-specific characteristics, as well as the governance expectations and regulatory requirements of different jurisdictions.

Overall, the findings on sectoral differences support the flexible approach to using AI in ESG. Rather than taking a one-size-fits-all approach, the study demonstrates the need for sector-specific frameworks that account for differences in reporting protocols, relevant ESG issues and verification requirements. This perspective is in line with the study's overall theoretical approach, which offers AI as a limited governance tool with effectiveness constrained by institutional and operational factors. The following section integrates the dimensional and sectoral insights to present the study's key propositions on how AI can enhance ESG disclosure integrity.

Core Propositions on AI’s Role in ESG Reporting Integrity

The combination of dimensional and industry-level analyses results in three propositions that conceptualize artificial intelligence as a governance control mechanism to enhance the integrity of ESG reporting. These hypotheses are guided by theoretical views as well as trends in corporate disclosures. They offer a systematic foundation of the way AI technologies can be applied in ESG reporting, as well as acknowledge their shortcomings.

Proposition 1: AI can best enhance the integrity of ESG reporting when it is oriented at resolving the legitimacy issues and the agency-related conflicts. The analysis indicates AI governance systems ought to focus on theoretical conflicts in sustainability reporting instead of adopting broad verification methods. When it comes to the legitimacy gaps, the variations between corporate statements and stakeholder expectations, AI tools can make comparisons between narrative disclosures and operational data streams, external news coverage, and regulatory submissions [31]. Natural language analysis methods can be especially useful in identifying rhetorical patterns indicating symbolic and non-actual commitment, including the overuse of future-oriented language to depict the sustainability successes [32].

In the case of agency conflicts, AI applications ought to be directed towards the alignment of managerial incentives with long-term sustainability performance. Calculation methodologies of ESG metrics can be algorithmically monitored to identify possible performance indicator gaming associated with executive compensation [33]. The analysis suggests that manufacturing firms that adopted sustainability-related bonus systems exhibited more rates of changes in environmental metrics approaches, which were detected using artificial intelligence-based longitudinal analysis. These findings support the development of AI governance models that are specific to the principal-agent problems that theoretical models predict, rather than if all ESG data verification fulfills the same function.

Proposition 2: The governance value of AI is predictable in different dimensions of ESG depending on their measurement standardization and situational reliance. The research sets a clear hierarchy of AI verification potential in the disclosures of environmental, social, and governance. Environmental indicators are likely to be the easiest for algorithms to validate as many are quantitative and measured using similar approaches. Social performance measures are somewhere between environmental and governance, since there are quantitative metrics, such as workforce composition, that can be reviewed using AI. But qualitative aspects still require human judgement. Governance indicators are likely to be the least suitable for AI support because they often rely on narrative descriptions of firm processes, culture and board practices [34]. This variation across the dimensions indicates a need for a gradual roll out of AI within ESG governance. While environmental reporting may be conducive to more widespread automated verification, social and governance reporting may benefit more from AI as a tool to detect anomalies, inconsistencies and shifts in reporting. The analysis reveals several linguistic features where AI may contribute to ESG. These include identifying abrupt shifts in disclosure language from one period to another; and the disclosure of metrics without enough detail about how they are calculated. This view aligns with stakeholder theory, which highlights the importance of information quality safeguards that are relevant to the nature of the information disclosed.

Proposition 3: Human judgement and accountability in the context of ESG reporting need to be complemented by governance models that include algorithmic insights. This research therefore suggests against the use of fully automated ESG reporting verification processes and advocates a balance between human judgement and algorithmic processes. The study highlights several scenarios in which AI may be prone to false positives or miss more nuanced approaches to reporting manipulation [35]. For example, in the financial sector, assessing the ESG implications of complex financial products often requires specialized industry knowledge. This form of judgement is more appropriately provided by human experts than by AI systems.

The hybrid model thus sees AI as a means of flagging and prioritizing potential issues for human review, rather than as a means of making final decisions about reporting quality. This is in line with the UK Corporate Governance Code, which enables clear lines of accountability and enhances efficiency with the aid of technology [36]. The debate highlights the need for human judgement in the determination of anomaly materiality, the understanding of narrative disclosures in terms of organizational culture, and the evaluation of management explanations of the anomalies in performance.

The UK governance environment offers some illustrations of the propositions. Companies can employ AI technologies to alert them to anomalies in environmental performance measures for audit committee review and adopt more conservative algorithmic assessments of governance narratives for nomination committee review. This selective AI use reflects the dimensionality of the benefit of AI use and the board focus of the UK governance model. The review also suggests that UK firms with dedicated board sustainability committees are more likely to employ integrated use of technological tools and traditional oversight to support their governance, as proposed by this study.

The three propositions address a crucial gap in existing techniques for using AI in ESG reporting. Current applications tend to focus primarily on technical performance measures (such as accuracy) of the algorithms, rather than the governance factors under which the algorithms are likely to enhance reporting credibility [37]. This research provides a reframing by placing AI tools in the context of well-developed theories in the fields of accounting and finance, including legitimacy theory, stakeholder theory and agency theory. In so doing, it deals with the governance issues that facilitate greenwashing.

The propositions should be applied to practice with consideration of the variations identified. Manufacturing companies may focus on using AI to ensure the credibility of environmental metrics, while putting in place fewer controls over governance-related reporting. Service providers in banking and investment may find value in AI-based checks of the consistency between product-level ESG reporting and corporate-level performance. The combination of AI-based anomaly detection and human ethical auditing in supply chain monitoring can be of the greatest benefit to consumer goods companies. These industry-specific insights maximize the use of scarce resources for AI governance in areas of highest verification and value.

The theoretical ramifications of these propositions go beyond ESG reporting to the wider debate on the governance of technology in accounting systems. The results question technical views of AI through a view of AI as a scarce institutional resource that is effective when it aligns with organizational accountability processes [39]. This view helps to explain why some AI technologies enhance reporting quality, while others are resisted or don't make a difference to decision-making. So, the effectiveness of AI relies not just on the technical aspects, but also on the governance context.

The paper's focus on human-AI interactions also adds to the discussion about judgement in an increasingly automated accounting industry. The study provides evidence that some elements of ESG reporting, especially those that include qualitative judgement or multiple stakeholders, can't be fully automated without sacrificing some of the context [35]. Human judgement is thus still needed, despite the increased role of AI in initial screening and red flagging. The UK corporate governance environment is a perfect place to test these propositions due to its principles-based approach and emphasis on board responsibility. The discussion suggests that UK firms can be at the forefront of establishing blended governance systems in which AI applications complement, but do not replace existing supervisory systems, such as providing audit committees with algorithmic risk assessments that inform, but do not dictate areas of assurance focus. This would be in line with the flexibility of the UK Corporate Governance Code of compliance or explain and respond to the increasing investor expectations of a stronger ESG verification [39].

The propositions eventually place AI as not disruptive but an enhancement of the existing ESG governance systems. AI tools can be applied in organizations that truly enhance the credibility of sustainability reporting by mitigating specific theoretical issues, identifying limitations on the cross-dimensional level, and maintaining human oversight, thus preventing the emergence of excessive claims and the possibility of further governance risks. This moderate position underlines the main thesis of the research: AI becomes most efficient when employed as a limited governance instrument but not as an all-encompassing technical policy to address the issue of ESG reporting.

Theoretical and Practical Implications

The study findings have implications for both the debate and the practice of ESG reporting and assurance. Theoretically, the study adds to the accounting and finance discourse by conceptualizing AI as a governance mechanism rather than just a tool. This approach can link emerging digital technologies to established theories of legitimacy, stakeholder engagement and agency [40-42]. The varying usefulness of AI across the ESG and industry segments also highlights the need for context specificity in its use. This debunks the idea that a "one-size-fits-all" technological approach can be used across all sustainability reporting practices.

The study has practical implications for several parties. Sustainability assurance practitioners can build multi-layered verification schemes that target the use of AI resources based on the type of ESG data being examined. For instance, AI is best suited to reviewing standardized environmental measures, but human judgement is still needed for complex social and governance disclosures. Regulators can also apply these insights to focus on standardization where AI verification is more likely to be effective, such as with Scope 1 greenhouse gas emissions, while still requiring human judgement for complex, unstandardized disclosures. Corporate boards may implement the hybrid model of governance advocated in this study by using AI tools within their committees. For example, computer algorithms can assist audit committees in monitoring data but human oversight is still needed for narrative assessments.

The UK policy framework offers unique opportunities to co-ordinate AI technology-based governance tools with the

Corporate Governance Code's focus on board oversight. The Financial Reporting Council could provide guidance on how AI verification tools could complement the Code's principles while maintaining the UK framework of complying or explaining [43]. This guidance would assist companies to consider the need for efficiency and flexibility against human oversight, particularly in high-impact industries like financial services where ESG disclosure is largely narrative-based.

These insights should be interpreted with caution, given the limitations of the research. While the qualitative critical review method is useful for informing theoretical development, it might not fully reflect all new AI uses in ESG verification. The purposive sample of 120 corporate reports represents high-risk industries, but it may not represent smaller organizations or privately held firms that may have different reporting priorities. Further, the governance aspects are theoretical rather than empirically tested, so the challenges faced in implementation of AI systems may be different to those expected. These factors suggest that although this study offers a solid theoretical framework, more empirical research is required to examine the framework across various organizational settings.

This study can be extended in several ways. Cross country research would help to gauge how different governance paradigms, such as principles-based and rules-based regimes, affect the impact of AI verification systems. Longitudinal studies in firms that implement AI oversight tools would also be valuable to assess whether the anticipated differences across ESG dimensions persist as firms continue to evolve their disclosure practices. Collaborative research between accounting academics and computer scientists is essential to develop natural language processing techniques to analyses qualitative ESG disclosures. Finally, laboratory studies could assess the decision-making processes of various stakeholder groups in response to AI-verified ESG information.

The focus of the study on human-AI collaboration identifies another important research direction: the study of the interaction of assurance professionals with the outputs of algorithms in practice. Ethnographic studies of audit teams utilizing artificial intelligence tools may reveal important insights about cognitive biases, trust relationships, and judgment processes in mixed verification environments. Likewise, a study of the board-level implementation of AI governance systems may help illuminate how directors strike a balance between technological contributions and their fiduciary duties. Such studies would contribute to closing the gap between the theoretical propositions regarding the role of AI in governance and real organizational practices. Another valuable direction of research is the unique challenges of the financial sector in ESG verification. Studies could explore whether custom AI systems trained on disclosures in the financial sector are more effective than generic techniques, and the potential to develop domain-specific natural language processing techniques to evaluate sustainability claims in banking and investment settings. Similarly, studies on the use of AI to monitor financed emissions and other indirect effects may be used to fill the existing gaps in the measurement of financial institutions reporting.

The practical implementation issues found in the study also deserve to be further investigated. A comparison of organizations with different degrees of AI governance implementation can help to find common problems and effective approaches to adapting these systems to the existing audit frameworks. A study of the reskilling requirements of accounting professionals in the context of AI systems would assist educational institutions and professional bodies to design the relevant training programs. Research on the cost-benefit tradeoffs of AI verification systems in organizations of various sizes and industries is also required.

The evolving governance structure in UK offers unique research opportunities in line with the findings of this study. Research into the impact of the 2018 revisions of the Corporate Governance Code on stakeholder engagement on ESG reporting practices may inform the creation of AI tools that are in line with these principles. Comparative studies of UK firms and companies in other jurisdictions with different legal systems may reveal the impact of domestic regulatory standards on the adoption and effectiveness of AI validation systems. Research into the perception of AI-verified ESG data by investors in the UK market may also provide valuable insights to assurance service providers and regulators.

The theoretical framework of the study provides new possibilities in the field of accounting research. Studies could focus on the impact of different combinations of legitimacy, stakeholder, and agency variables on the design and functioning of AI governance systems. The study of the interaction between AI verification and impression management strategies in ESG reporting may provide valuable information regarding technological limitations to symbolic disclosure practices. Research into the ways in which AI tools could transform conventional notions of materiality and assurance in the context of sustainability reporting is also possible. The combination of these fields of research underscores the need to continue scholarly research on how artificial intelligence is transforming environmental, social, and governance management. With the advancement of technological skills and the evolution of reporting standards, the theoretical and practical results of this study provide a foundation to further research and emphasize the timeless role of human judgment in sustainability verification. The context-specific application and mixed governance systems of the framework provide a balanced approach to technological development, considering the complexity of ESG reporting and using the capabilities of AI to enhance integrity.

Conclusion

The conclusion of this paper is that artificial intelligence can play a valuable role in the integrity of ESG reporting when it is perceived as a limited governance tool and not as a technical one. It is most useful in environmental disclosures, where indicators tend to be more standardized, measurable and comparable. In contrast, social and governance disclosures can largely be based on organizational context, interpretation of narratives, and professional judgement which restricts the degree to which such disclosures can be measured by automated systems in isolation. The UK corporate governance environment is particularly significant as it offers a board-based accountability model where AI tools can be used to supplement the current oversight and assurance procedures without substituting human accountability. In this regard, AI can be considered as a complementary tool that enhances monitoring, exposes possible inconsistencies, and enhances the credibility of ESG information, but final judgement remains in the hands of governance actors and assurance professionals. The proposed framework should be empirically tested in various sectors and regulatory settings in future studies. The integration of AI-assisted review into the creation of sustainability reporting practices should also be studied further to ensure that it does not undermine the responsibility of the institution.

Submission Declarations

Funding: There was no external funding for this research.

Conflict of Interest: The author declares that there are no conflicts of interest.

Ethics Statement: The publicly available sources of corporate reports, regulatory filings, and published sources are used in this study. There is no human involvement, no personal data gathering, and no research that involves interventions and needs to be ethically approved.

Data Availability Statement: The study is based on publicly accessible corporate sustainability reports, regulatory documents, and published literature referenced in the manuscript. The author is happy to provide additional information on document selection and framing of the analysis on request.

Acknowledgements: The author would like to acknowledge the informal feedback received from colleagues and reviewers on drafts of the manuscript. Any errors are the authors alone.

References

1. Chopra, S. S., Senadheera, S. S., Dissanayake, P. D., Withana, P. A., Chib, R., et al. (2024). Navigating the challenges of environmental, social, and governance (ESG) reporting: The path to broader sustainable development. Sustainability, 16(2), 606.
2. Tettamanzi, P., Venturini, G., Murgolo, M. (2022). Sustainability and financial accounting: A critical review on the ESG dynamics. Environmental Science and Pollution Research, 29(11), 16758-16761.
3. Dasinapa, M. B. (2024). The integration of sustainability and ESG accounting into corporate reporting practices. Advances in Applied Accounting Research, 2(1), 13-25.
4. Junaedi, J. (2024). Understanding the role of finance in sustainable development: A qualitative study on environmental, social, and governance (ESG) practices. Golden Ratio of Finance Management, 4(2), 113-130.
5. Gherghina, Ș. C. (2024). Corporate finance and environmental, social, and governance (ESG) practices. Journal of Risk and Financial Management, 17(7), 308.
6. Patel, S., Nath, A., Desai, P. (2026). Predicting ESG Scores Using Machine Learning for Data-Driven Sustainable Investment. Analytics, 5(1), 7.
7. 7. D’Amato, V., D’Ecclesia, R., Levantesi, S. (2021). Fundamental ratios as predictors of ESG scores: A machine learning approach. Decisions in Economics and Finance, 44(2), 1087-1110.
8. Luo, Y., Cui, X., Liu, Q., Zhou, Q., Zhang, Y. (2025). Identifying exaggeration in ESG reports using machine learning techniques. Data and Information Management, 9(2), 100084.
9. Davidescu, A. A., Manta, E. M., Bîrlan, I., Miler, A. M., & Niță, S. C. (2026). Detecting greenwashing in ESG disclosure: an NLP-based analysis of central and eastern european firms. Sustainability, 18(3), 1486.
10. Rajput, N., Chopra, K., Lohia, S., & Kumar, K. (2025). Blockchain and AI Integration for Transparent ESG (Environmental, Social, Governance) Reporting in Corporate Finance. In 2025 2nd International Conference on Integration of Computational Intelligent System (ICICIS) (pp. 1-5). IEEE.
11. Baplawat, A., Janardhan, R., Rashmi, M. G., Rafique, J., Mahajan, V., & Kumari, R.M. (2025). Smart Contracts in ESG Reporting: A Fintech-Based Framework for Enhancing Corporate Governance Transparency. Lex Localis, 23(S6), 5339-5348.
12. Saebah, N. (2025). AI-Based ESG Accounting: Transparency and Ethics Challenges in the Digital Era. Accounting and Financial Analysis Journal, 1(2), 33-38.
13. Omar, B., & Habiba, L. K. (2025). Artificial intelligence in sustainable finance: Mapping ESG integration and risk detection frameworks. International Journal of Accounting and Economics Studies, 12(8), 878-886.
14. Xiao, J., Wang, Z., & Yu, Z. (2026). ESG Risk Assessment in Real Estate Development Application of Machine Learning Algorithms in Environmental and Social Impact Prediction. International Journal of Computational Intelligence and Applications, 2650007.
15. Reyes-Sánchez, J.D.J. (2026). Algorithmic Modeling of ESG Contingencies Using Intelligent Analytics and Predictive Parameterization of Corporate Risk. In Data-Driven ESG Strategy Implementation Through Business Intelligence (pp. 141-172). IGI Global Scientific Publishing.
16. Chakrabarti, M., Fabozzi, F.J., Narain, A., & Sood, A. (2025). Ethical AI in Asset Management: Frameworks for Transparency, Compliance, and Trust. Journal of Financial Data Science, 7(1).
17. Peixoto, E. Palumbo, G. Carneiro, D. Alves, V. (2025). ESG Transparency in AI-Driven Value Chains: An Architecture for Monitoring and Reporting Key Indicators. 1-6. 10.1109/ResgenXAI64788.2025.11343994.
18. Li, N., Kim, M., Dai, J., & Vasarhelyi, M.A. (2024). Using artificial intelligence in ESG assurance. Journal of Emerging Technologies in Accounting, 21(2), 83-99.
19. Simpson, S.N.Y., Aboagye-Otchere, F., Ahadzie, R. (2022, April). Assurance of environmental, social and governance disclosures in a developing country: perspectives of regulators and quasi-regulators. In Accounting Forum 46(2), 109-133. Routledge.
20. Mishra, B. (2018). Social Impact Measurement and Investment: Methods, Limitations and Challenges. Transcience, 9(1), 20-47.
21. Tamkin, A., Brundage, M., Clark, J., Ganguli, D. (2021). Understanding the capabilities, limitations, and societal impact of large language models. arXiv preprint arXiv:2102.02503.
22. Khanna, T., Kogan, J., Palepu, K. (2006). Globalization and similarities in corporate governance: A cross-country analysis. Review of Economics and Statistics, 88(1), 69-90.
23. Hasan, A., Sufi, U., Elmarzouky, M., Hussainey, K. (2025). The impact of corporate governance on narrative disclosure tone: a machine learning approach. Journal of Applied Accounting Research, 26(3), 577-602.
24. Thassim, S. (2025). An analysis of industry-specific variations and sectoral differences in sustainability disclosure among Indian companies. Journal of Technology Management and Business, 12(1), 33-45.

25. Halat, K., Childe, S., Golding, N., Summerscales, J. (2023). Scope 3 Carbon Emissions Assessment for Manufacturing SMEs. Corporate Social Responsibility and Environmental Management.
26. Diwan, H., Amarayil Sreeraman, B. (2024). From financial reporting to ESG reporting: a bibliometric analysis of the evolution in corporate sustainability disclosures: H. Diwan, BA Sreeraman. Environment, Development and Sustainability, 26(6), 13769-13805.
27. Dako, O. F., Onalaja, T. A., Nwachukwu, P. S., Bankole, F. A., & Lateefat, T. (2023). Integrating ESG performance metrics into financial reporting frameworks to strengthen sustainable investment decision-making processes. International Journal of Advanced Multidisciplinary Research and Studies, 3(2), 1239-1252.
28. LeBaron, G., Lister, J. (2015). Benchmarking global supply chains: the power of the 'ethical audit' regime. Review of International Studies, 41(5), 905-924.
29. Troshani, I., & Rowbottom, N. (2024). Corporate sustainability reporting and information infrastructure. Accounting, Auditing & Accountability Journal, 37(4), 1209-1237.
30. Ferrari, A., Cini, F., & Castellano, R. (2025). Beyond Traditional Metrics: ESG and Financial Performance in Innovation-Driven Sectors. Journal of Financial Management, Markets & Institutions, 13(1).
31. De Villiers, C., Dimes, R., Molinari, M. (2024). How will AI text generation and processing impact sustainability reporting? Critical analysis, a conceptual framework and avenues for future research. Sustainability Accounting, Management and Policy Journal, 15(1), 96-118.
32. Janik, A., Ryszko, A. (2025). Greenwashing in Sustainability Reporting: A Systematic Literature Review of Strategic Typologies and Content-Analysis-Based Measurement Approaches. Sustainability, 18(1), 17.
33. Usman, A., Yahaya, A. (2024). Executive compensation and ESG performance. International Journal of Sustainable Economics, 10(26), 89-122.
34. Aguilera, R. V., Desender, K. A. (2012). Challenges in the measuring of comparative corporate governance: A review of the main indices. In T. Pedersen & L. Devinney (Eds.), Research methodology in strategy and management. Emerald Group Publishing. 8, 221-254. https://doi.org/10.1108/S1479-8387(2012)0000008014
35. Ali, I., Nguyen, K., Ali, A.M., Cui, T. (2025). Human–AI collaboration in knowledge ecosystems: a multidisciplinary review, integrative framework and future directions. Journal of Knowledge Management, 1-22.
36. Karamatzanis, G., Tilba, A., Nikolopoulos, K. (2026). Corporate Governance Reporting, Disclosures, Monitoring, and Decision-Making: The Role of Big Data Analytics and Technological Tools. Corporate Governance: An International Review, 34(1), 2-17.
37. Sreseli, N., & Kadagishvili, Z. (2023). Use of artificial intelligence for accounting and financial reporting purposes: A review of the key issues. American International Journal of Business Management (AIJBM), 6(8), 72-83.
38. Lehner, O. M., Knoll, C., Leitner-Hanetseder, S., & Eisl, C. (2022). The dynamics of artificial intelligence in accounting organisations: a structuration perspective. In The Routledge Handbook of Accounting Information Systems. Routledge, 121-139.
39. Slack, R. (2022). Capital market perspectives on sustainability accounting and reporting. In Handbook of Accounting and Sustainability. Edward Elgar Publishing, 67-88.
40. Wilmshurst, T.D., Frost, G.R. (2000). Corporate environmental reporting: A test of legitimacy theory. Accounting, Auditing & Accountability Journal, 13(1), 10-26.
41. Lock, I., Seele, P. (2017). Theorizing stakeholders of sustainability in the digital age. Sustainability Science, 12(2), 235-245.
42. Espinosa-Méndez, C., Maquieira, C. P., Arias, J.T. (2023). The impact of ESG performance on the value of family firms: The moderating role of financial constraints and agency problems. Sustainability, 15(7), 6176.
43. Financial Reporting Council. (2024). UK Corporate Governance Code 2024. Financial Reporting Council.
44. Küfeoğlu, S. (2026). Measuring Sustainability: Metrics and Standardisation. In Financing the Green Transition: Principles and Instruments. Cham: Springer Nature Switzerland, 103-159.
45. Sarna, N. J., Rithen, F. A., Jui, U. S., Belal, S., Amin, A., Oishee, T. K., & Islam, A. M. (2025). AI Driven Fraud Detection Models in Financial Networks: A Review. IEEE Access.
46. Zou, Y. (2024). Predicting future ESG performance using past corporate financial information: Application of deep neural networks. In Proceedings of the 5th International Conference on Computer Information and Big Data Applications, 284-289.