

Artificial Intelligence-Enabled Environmental, Social and Governance (ESG) Carbon Accounting and Reporting in Zimbabwe: Expert Perspectives on Opportunities, Challenges, and Future Directions

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Abstract

This paper examines the role of Artificial Intelligence (AI) in enhancing Environmental, Social, and Governance (ESG) carbon accounting and reporting, focusing on opportunities, challenges, and future directions. As regulatory pressure and stakeholder demand for high-quality climate disclosures increase, organizations face growing complexity in measuring, validating, and reporting carbon emissions across operational and value chain activities. AI technologies offer scalable solutions through automated data capture, anomaly detection, predictive analytics, and integrated reporting systems. The study adopts a qualitative methodology based on expert interviews conducted with sustainability professionals, auditors, financial managers, and regulators in Zimbabwe. A purposive sampling approach and thematic analysis were used to generate insights into current practices and emerging adoption patterns. A sample of 15 participants was used. Findings indicate that AI significantly improves efficiency, data consistency, and analytical capability in carbon accounting processes, particularly through the automation of emissions data aggregation and intelligent estimation models. Experts highlighted the value of AI in scenario modeling and forward-looking carbon forecasting linked to strategic planning. However, the results also reveal important constraints, including model transparency concerns, auditability challenges, skills shortages, data quality risks, and reliance on external technology vendors. Governance and assurance implications emerged as central adoption conditions, with explainable models and documented controls viewed as critical safeguards. The paper contributes empirical-style insight from an emerging market context and shows that AI can strengthen ESG carbon reporting quality when supported by appropriate governance, professional capacity, and regulatory guidance. It recommends phased adoption, explainable AI frameworks, and targeted skills development. Future research should extend mixed-method and cross-country analyses of AI-enabled ESG reporting systems.

Categories: Accounting, Auditing and taxation, Banking and financial services

Keywords: artificial intelligence, esg reporting, carbon accounting, sustainability analytics, climate disclosure

Introduction

With carbon accounting and reporting now playing a major part in sustainability disclosures, environmental, social, and governance (ESG) reporting has developed into a fundamental component of corporate transparency and accountability. The need for precise, fast, and decision-useful carbon emissions data has grown as a result of mounting regulatory

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pressure, investor scrutiny, and exposure to climate risk. Traditional carbon accounting methods, however, are still mostly manual, dispersed across data sources, and prone to estimation error, especially in emerging market situations where there is a disparity in the maturity of digital reporting.

Through automation, advanced analytics, anomaly detection, predictive modeling, and intelligent data integration, artificial intelligence (AI) is becoming more widely acknowledged as a transformative enabler that can improve ESG carbon accounting and reporting (Issa et al., 2016) (Zhao et al., 2023). AI technologies are especially useful for ESG carbon accounting because they can handle huge, varied, and unstructured sustainability datasets from operational systems, supplier records, logistical data, energy meters, and company disclosures. AI models may combine various data streams and use pattern recognition and estimation techniques on a large scale, which is not possible with traditional spreadsheet-based methods. This skill is very crucial for measuring greenhouse gases in Scope 1 and Scope 2 emissions, and even more so for Scope 3 emissions, where data is spread out throughout supply chains and measuring is the hardest. Recent studies indicate that machine learning techniques can substantially enhance the estimation of Scope 3 emissions by integrating supplier data, activity proxies, and predictive modelling methods, thus diminishing dependence on broad industry averages and fixed emission factors (Zhao et al., 2023) (Sharma et al., 2014).

Adoption of AI also brings with it new dangers related to governance, assurance, and ethics. Data governance exposure, algorithmic bias, model opacity, auditability issues, and an excessive dependence on proprietary platforms are a few of these (Berg et al., 2022) (Rai, 2020). In emerging economies like Zimbabwe, where expert knowledge is concentrated among a small number of experts and ESG reporting capacities are still growing, these tensions are especially important.

This study examines the opportunities and risks that come with using AI to improve ESG carbon accounting and reporting, as well as potential future development paths. The study is based on expert interview research that was carried out in Zimbabwe and analyzed in conjunction with current academic literature.

To understand the increasing importance of AI-powered ESG carbon accounting, we need to situate it within the broader framework of increasing sustainability reporting and climate-related disclosure requirements. Globally, over 90% of the world's major firms now publish sustainability reports, up from fewer than 20% two decades ago (KPMG, 2022). At the same time, regulatory activities such as the International Sustainability Standards Board (ISSB) standards and the European Union's Corporate Sustainability Reporting Directive (CSRD) are significantly increasing the requirements for transparent, accurate, and auditable carbon disclosures (IFRS Foundation, 2023) (European Commission, 2023). However, carbon accounting is still very complex, especially when it comes to Scope 3 emissions, which can account for more than 70% of an organization's overall carbon footprint and typically result from fragmented data sources across large supplier chains (World Economic Forum, 2022). Moreover, according to research, ESG data quality, consistency, and comparability remain among one of the top issues for sustainability reporting practitioners and assurance providers (Berg et al., 2022). Increasing pressure from investors, regulators, customers, and other stakeholders on organizations to provide credible climate-related disclosures has created a growing need for technological solutions to help improve the efficiency, accuracy, and credibility of ESG carbon accounting processes. Therefore, how AI might enhance ESG carbon reporting while addressing governance, assurance, and implementation issues has become a critical academic and practical issue.

Table 1 shows the study objectives and the corresponding study questions while Table 2 shows the study focus and analytical scope.

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Study Objective	Study Question
To examine the opportunities of using AI in ESG carbon accounting and reporting	What are the opportunities of using AI in ESG carbon accounting and reporting?
To determine the risks associated with the use of AI in ESG carbon accounting and reporting.	Which are the key risks associated with AI in ESG carbon accounting and reporting?
To propose future directions in the use of AI in ESG carbon accounting and reporting	What are the emerging trends in ESG carbon and reporting?

TABLE 1: Research Objectives and Questions

Source: Authors' creation. AI, Artificial Intelligence; ESG, Environmental, Social, and Governance

Dimension	Coverage in This Study
Core Topic	AI in ESG carbon accounting and reporting
Analytical Lens	Accounting + ESG + AI integration
Evidence Base	Primary expert interviews + recent literature
Study Context	Zimbabwe (as expert practice environment)
Contribution	Practice-informed AI-ESG reporting framework

TABLE 2: Study Focus and Analytical Scope

Source: Authors' own creation. AI, Artificial Intelligence; ESG, Environmental, Social, and Governance

The theories in Table 3 underpin this study.

How to cite this article:

Theory	Brief explanation
Technology Acceptance Model (TAM) (Davis, 1989) (Marikyan and Papagiannidis, 2024)	Focuses on how users adopt new technology based on perceived usefulness and ease of use. Helps explain why companies adopt AI for ESG reporting and what drives acceptance among stakeholders.
Institutional Theory (Meyer and Rowan, 1977) (DiMaggio and Powell, 1983) (Aksom and Tymchenko, 2020)	Looks at how external pressures (regulations, norms, societal expectations) push organizations to adopt certain practices. Useful for exploring how regulatory frameworks and industry standards drive AI adoption in ESG reporting.
Legitimacy Theory (Dowling and Pfeffer, 1975) (Suchman, 1995) (Dare et al., 2021)	Suggests organizations adopt practices to appear legitimate to stakeholders. AI in ESG reporting can be a way for firms to gain credibility and trust with investors, regulators, and the public.

TABLE 3: Theories Underpinning the Study

Source: Authors' own creation. AI, Artificial Intelligence; ESG, Environmental, Social, and Governance

Table 3 above shows the three theoretical underpinnings of this study namely TAM by Davis (Davis, 1989), that explains why people accept or reject new technologies. Davis (Davis, 1989) argues that users are more likely to adopt a technology if they perceive it as useful and easy to use, as these perceptions shape their intention to use the technology and ultimately determine actual usage. Institutional theory argues that organizations do not make decisions based only on efficiency or profit. They also respond to the rules, norms, values, and expectations of the society and environment in which they operate. Organizations adopt accepted practices to gain legitimacy, improve their reputation, and secure resources and support (DiMaggio and Powell, 1983). According to Suchman (Suchman, 1995), legitimacy is a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions.

AI applications in ESG and carbon accounting

AI applications are rapidly expanding across accounting and sustainability reporting functions, according to recent research. More precise carbon measurement is made possible by AI-enabled systems that facilitate automatic data collection from meters, invoices, logistics systems, and satellite feeds (Sharma et al., 2014). When direct measurement is not possible, machine learning algorithms are being utilized more and more to estimate emissions, especially across supply chains (Zhao et al., 2023).

In order to extract sustainability indicators and risk signals from reports and filings, natural language processing is frequently used in ESG disclosures (Berg et al., 2022). These technologies are changing the way that organizations evaluate, analyze, and compare their ESG performance. Table 4 summarizes the AI functional applications in ESG Carbon Reporting.

AI Capability	ESG Carbon Reporting Use
Machine learning	Emissions estimation and forecasting
NLP	ESG disclosure extraction and scoring
Anomaly detection	Carbon data error and fraud flags
Predictive analytics	Carbon scenario modelling
Intelligent automation	Data aggregation and classification

TABLE 4: AI Functional Applications in ESG Carbon Reporting

Source: Authors' own creation. AI, Artificial Intelligence; ESG, Environmental, Social, and Governance; NLP, Natural Language Processing

The comparison in Table 4 above demonstrates that different AI capabilities address distinct but complementary requirements within carbon and ESG reporting. Machine learning and predictive analytics primarily strengthen forward-looking functions through emissions estimation, forecasting and scenario modelling, whereas NLP enhances the extraction and interpretation of largely unstructured ESG disclosures. Anomaly detection contributes to data-quality and control processes by identifying potential errors or irregularities, while intelligent automation improves the efficiency of data aggregation and classification. Collectively, these capabilities indicate that AI extends beyond reporting automation to support a broader carbon-management architecture encompassing measurement, verification, integration, control and forward-looking analysis.

Benefits identified in prior research

According to academic research, AI can increase comparability, decrease manual error, boost reporting efficiency, and facilitate forward-looking carbon analytics (Bolton et al., 2020) (Mustafa et al., 2025) (Telukdarie et al., 2026). The integration of financial and non-financial reporting systems is also facilitated by AI-driven analytics. Table 5 shows the benefits identified in previous research.

Benefit Area	Reported Effect
Efficiency	Faster ESG data processing
Accuracy	Reduced classification errors
Coverage	Better Scope 3 estimation
Insight	Forward-looking climate scenarios
Integration	Cross-system ESG data linkage

TABLE 5: Reported Benefits of AI in ESG Reporting Literature
Source: Authors' own creation. AI, Artificial Intelligence; ESG, Environmental, Social, and Governance

The reported benefits in Table 5 above indicate that AI contributes to ESG reporting across operational, informational and analytical dimensions. Efficiency is reflected in faster ESG data processing, while improved accuracy is associated with reduced classification errors. The enhanced estimation of Scope 3 emissions extends AI’s contribution beyond internal reporting to areas where data complexity and measurement challenges are greater. Similarly, the capacity to generate forward-looking climate scenarios suggests a shift from retrospective disclosure towards more predictive sustainability analysis. Cross-system data integration further strengthens this contribution by enabling ESG information from disparate organisational systems to be consolidated. Collectively, these effects suggest that AI can enhance not only the speed and accuracy of ESG reporting but also its analytical depth, coverage and strategic usefulness.

Governance and assurance concerns

The literature highlights governance issues notwithstanding the advantages. Explainability and auditability are limited by the fact that ESG and AI models frequently operate as "black boxes" (Issa et al., 2016). Divergent ESG ratings have been associated with uneven model assumptions and opaque approaches (Berg et al., 2022). More and more academics are demanding model governance frameworks and explainable AI. Table 6 summarizes the governance and assurance concerns.

Risk Category	Description
Model opacity	Limited explainability
Audit difficulty	Hard-to-verify outputs
Bias	Skewed training data effects
Data risk	Weak input data quality
Vendor dependence	Platform lock-in

TABLE 6: AI Governance Risks in ESG Reporting

Source: Authors' own creation. AI, Artificial Intelligence; ESG, Environmental, Social, and Governance

The identified risk categories in Table 6 above demonstrate that AI-enabled ESG reporting presents interconnected technological, data and governance challenges. Model opacity and audit difficulty primarily affect explainability, transparency and the verifiability of AI-generated outputs, whereas data risk and algorithmic bias may undermine the reliability, accuracy and fairness of reported information. Vendor dependence introduces an organisational dimension by potentially reducing control over proprietary systems and increasing technological switching costs. These risks are interrelated: weaknesses in input data may contribute to unreliable outputs, while limited model transparency can make such deficiencies difficult to identify and audit. Collectively, the findings suggest that the credibility of AI-enabled ESG reporting depends not only on technological functionality but also on the availability of effective data governance, explainability, auditability and organisational oversight mechanisms.

Emerging market adoption constraints

Studies in developing and emerging economies identify limited organisational capabilities, skills and institutional support, inadequate infrastructure, and uneven levels of sustainability-reporting development as important constraints on the adoption and quality of ESG reporting (Tauringana, 2021) (Tilt et al., 2021) (Igwe et al., 2023). This supports the need for context-sensitive methodological investigation using expert insight, which informs the design of this study.

Research gap

The literature on the use of AI for accounting, sustainability reporting and ESG analytics is developing but there are major information gaps in relation to its function in ESG carbon accounting and reporting, especially in the context of emerging markets. Prior studies have primarily explored the technical potential of AI, such as automation, predictive analytics, anomaly detection, and emissions estimation. The bulk of the empirical support comes from developed economies with relatively mature digital infrastructure, well-established sustainability reporting frameworks, and sophisticated regulatory environments (Zhao et al., 2023) (Sharma et al., 2014). While these studies provide insights into the potential benefits of AI-enabled ESG reporting, they provide limited insight into the perceptions, governance, and implementation of such technologies in developing countries with significantly different institutional conditions, professional capabilities, and ESG reporting maturity.

Moreover, prior studies have focused primarily on conceptual aspects, technological applications, and governance issues of AI systems (Berg et al., 2022) (Rai, 2020), with limited attention paid to the lived experiences and views of practitioners directly engaged in ESG reporting, sustainability assurance, carbon accounting, and regulatory oversight. As a result,

there is less empirical evidence on the opportunities, governance issues, assurance implications, and adoption restrictions of AI-enabled ESG carbon reporting in emerging nations. This gap is particularly salient given the increased regulatory attention to climate-related disclosures and the increasing demand for credible carbon accounting systems that can enable sustainable decision making.

This study fills this gap by offering expert-based qualitative information from Zimbabwe, an emerging market environment where ESG reporting practices and AI deployment are still at a developmental stage. The study draws on professional perspectives on opportunities, risks, governance requirements and future directions of AI-enabled ESG carbon accounting and reporting to contribute context-specific insight to the emerging literature on sustainability reporting, accounting innovation and responsible AI governance.

Research Method

In order to investigate how AI might improve ESG carbon accounting and reporting, as well as potential governance and implementation issues, this study used a qualitative research design based on expert interviews. Since AI-enabled ESG reporting is still a relatively new practice area with a relatively small number of experts with extensive technical and institutional knowledge, a qualitative expert approach is required. Expert interviews are preferable to large-sample surveys in Zimbabwe since the country's senior auditors, sustainability officers, finance executives, regulators, and ESG consultants are the main sources of ESG and carbon reporting expertise.

An expert panel was created using a purposive sampling technique. Data saturation was assessed iteratively throughout data collection and analysis rather than being determined solely by sample size. Each interview was transcribed and reviewed before the subsequent interview, with initial coding conducted concurrently to identify emerging codes, categories and recurring patterns. Interviews 1-8 generated the majority of the initial codes, while Interviews 9-12 primarily confirmed and refined the emerging thematic structure. By Interview 13, the principal themes relating to AI-enabled data automation, predictive analytics, data quality, governance, transparency, regulatory compliance and human oversight were consistently recurrent, with no substantially new codes emerging. Interviews 14 and 15 were subsequently conducted as saturation-check interviews. These interviews confirmed and elaborated the existing themes but did not generate substantially new codes, categories, dimensions or interpretations. This assessment reflects the distinction between code saturation and meaning saturation proposed by Hennink ([Hennink et al., 2017](#)).

The decision to conclude data collection after 15 interviews was therefore based on evidence of diminishing informational yield rather than an arbitrary numerical threshold. The specialist composition of the sample also provided substantial information power, given participants' direct professional expertise in auditing, corporate reporting, sustainability, financial regulation and carbon-related services ([Malterud et al., 2016](#)). The final sample comprised 15 specialists from audit firms, listed companies, sustainability consultancies, financial regulatory institutions and carbon consulting services. The absence of substantially new thematic insights in the final two interviews, together with the repeated confirmation and elaboration of existing themes, indicated that the study had achieved sufficient thematic saturation in relation to its research objectives.

Table 7 presents the distribution of respondents according to the sector they represented.

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Category	Frequency
Carbon Consulting	2
Financial Regulators	2
Sustainability Experts	4
Listed companies	3
Audit firms	4

TABLE 7: Study Participants by Sector
Source: Authors' own creation

Participant Code	Sector	Professional Role	Gender	Years of Experience
P1	Audit Firm	External Auditor	Male	22
P2	Audit Firm	Audit Partner	Male	20
P3	Sustainability Consultancy	Sustainability Consultant	Female	12
P4	Audit Firm	ESG Assurance Manager	Female	16
P5	Sustainability Consultancy	ESG Consultant	Male	11
P6	Carbon Consulting Services	Carbon Accounting Consultant	Male	14
P7	Listed Company	Sustainability Manager	Female	9
P8	Listed Company	Financial Manager	Male	15
P9	Audit Firm	Risk and Compliance Specialist	Female	13
P10	Financial Regulator	Financial Regulator	Male	17
P11	Listed Company	ESG Assurance Specialist	Female	10
P12	Financial Regulator	Sustainability Policy Analyst	Female	8
P13	Listed Company	Sustainability Director	Male	18
P14	Carbon Consulting Services	Carbon Strategy Consultant	Male	19
P15	Sustainability Consultancy	Chief Finance Officer	Male	25

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TABLE 8: Respondent Demographics

Source: Authors' own creation. ESG, Environmental, Social, and Governance

The gender composition of the sample in Table 8 above warrants critical consideration because 10 of the 15 participants (66.7%) were male and 5 (33.3%) were female. Although the sample was purposively constructed around professional expertise rather than gender, the imbalance has implications for the breadth of perspectives informing the findings. The predominance of male participants may partly reflect the gender composition of senior and specialist positions in auditing, financial regulation, ESG assurance and corporate sustainability; however, this cannot be established from the sample itself and should not be interpreted as evidence that men and women necessarily perceive AI-enabled ESG reporting differently. More importantly, the imbalance raises the possibility that aspects of AI adoption relating to organisational participation, professional experience, risk perception and governance may not have been fully captured from a gender-diverse perspective. The presence of female participants across several sectors-including sustainability consulting, ESG assurance, listed companies, risk and compliance, and financial regulation-provides important counter-perspectives and prevents the findings from being exclusively male-derived. Nevertheless, because qualitative research values depth and diversity of perspectives rather than statistical representativeness, the issue is less one of numerical gender proportionality than of whether the sample adequately captured potentially relevant variations in professional experience. The study therefore treats gender imbalance as a limitation of interpretive breadth rather than a threat to the validity of the findings. Future research should consider purposive gender-balanced sampling and explicitly examine whether gender intersects with professional position, organisational authority and perceptions of AI governance, explainability, assurance and ESG reporting. This would strengthen understanding of whether the institutional and professional factors identified in this study are broadly experienced or whether they vary across different demographic and occupational groups. Table 8 above shows the respondents' demographics with 66.7% being male and 33.3% being female. All (100%) of the respondents had more than seven years of work experience.

The interview guide was developed based on multiple theoretical frameworks: TAM (Davis, 1989) (Marikyan and Papagiannidis, 2024), Institutional Theory (Meyer and Rowan, 1977) (DiMaggio and Powell, 1983) (Aksom and Tymchenko, 2020), and Legitimacy Theory (Dowling and Pfeffer, 1975), (Suchman, 1995), (Dare et al., 2021). Each question was mapped to a specific theory to ensure that data collection was grounded in established academic literature and to facilitate analysis across multiple perspectives. The interview guide included open-ended questions about AI applications, benefits, challenges, organizational resources, external pressures, stakeholder engagement, and future trends in ESG carbon accounting.

Interviews lasted approximately 45-60 minutes were conducted via video conferencing (Zoom) or in person, depending on participant availability. All interviews were audio-recorded with consent and transcribed verbatim for analysis.

All participants were provided with an information sheet and signed a consent form. Participation was voluntary, and participants could withdraw at any time. Confidentiality was maintained by anonymizing all data and using pseudonyms in any reporting. Data were stored securely on password-protected servers and would be destroyed after the required retention period. Table 9 presents an overview of the methodology design.

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Method Element	Study Design
Research approach	Qualitative exploratory
Primary method	Expert interviews
Sampling strategy	Purposive expert sampling
Sample size	15 experts
Study location	Zimbabwe
Analysis technique	Thematic analysis

TABLE 9: Methodology Design Overview
Source: Authors' own creation

The utilization of AI tools, ESG carbon data procedures, reporting controls, assurance implications, governance risks, and adoption hurdles were all covered using semi-structured interview protocols. Interviews lasted roughly an hour, and they were transcribed in order to be coded. In line with qualitative accounting research practices, thematic analysis used an organized coding procedure that included open coding, category creation, and theme consolidation (Creswell and Creswell, 2018).

Coding workflow

Interview coding was conducted using a systematic thematic analysis process. Following each interview, the audio recordings were transcribed verbatim and reviewed alongside the original recordings to ensure transcription accuracy. The researcher immersed themselves in the data by reading each transcript multiple times to gain a comprehensive understanding of participants' experiences and perspectives regarding the use of AI in ESG carbon accounting and reporting.

The coding process began with open coding, whereby meaningful words, phrases, and segments of text relevant to the research objectives were identified and assigned descriptive labels (codes). These initial codes reflected participants' own language where appropriate and captured ideas such as automated data collection, emissions monitoring, predictive analytics, data quality, transparency, governance, regulatory compliance, ethical concerns, and human oversight.

Once all transcripts had been openly coded, the researcher conducted axial coding by comparing and grouping related codes according to similarities and relationships. During this stage, overlapping codes were merged, redundant codes were removed, and broader categories were developed to represent shared concepts across participants. Constant comparison was applied throughout the analysis, with new codes continually compared against existing ones to ensure consistency and to identify similarities and differences between participants' responses.

The final stage involved selective coding, during which the categories were refined and organized into overarching themes that addressed the study's research questions. These themes represented the key patterns emerging from the dataset and included the opportunities presented by AI in ESG carbon accounting, implementation challenges, governance and ethical considerations, and future directions for AI-enabled sustainability reporting. Throughout the coding process, the researcher maintained a coding framework and analytical notes to document coding decisions, refine

theme development, and enhance the transparency and dependability of the analysis. The iterative nature of coding enabled themes to evolve as additional interviews were analyzed until thematic saturation was reached and no new themes emerged.

The coding procedure was assisted by ongoing evaluation of participant responses for consistency and thematic relevance to the study objectives and the extant literature. Table 10 presents the interview coverage framework.

Topic Block	Focus Area
Current practice	Carbon accounting workflows
Technology use	AI and analytics tools
Benefits	Efficiency and accuracy gains
Risks	Governance and assurance concerns
Controls	Validation and oversight mechanisms
Future outlook	Adoption trajectory

TABLE 10: Interview Coverage Framework

Source: Authors' own creation

Trustworthiness

Several qualitative validation processes were used to increase the trustworthiness of the study. The involvement of expert participants with direct experience in ESG reporting, sustainable management, auditing, and carbon accounting increased credibility. Triangulation was performed through comparison of opinions across diverse professional categories, including regulators, auditors, sustainability consultants, and finance specialists. To enhance reliability, the transcripts of the interviews were re-reviewed during the coding process to establish consistency in the creation and interpretation of themes. An audit trail was created using a coding choice log, theme consolidation, and analytical reflections throughout the investigation. Through pattern matching with established literature themes and role triangulation across expert categories, validity was reinforced (Issa et al., 2016) (Berg et al., 2022). The confirmation of themes was improved by comparison with existing literature and the objectives of the study, and confidentiality and anonymization procedures contributed to the ethical integrity of the study and the free articulation of the participants during the interviews. Informed consent, anonymity, and non-attribution of organizational identity were among the ethical protections incorporated into the design.

Results And Discussion

Five main finding clusters emerged from the thematic analysis of the expert interviews: capability restrictions, governance and assurance tension, predictive carbon intelligence, process automation, and data quality enhancement. Although the emphasis differed depending on the professional background, these principles were common to all expert roles.

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Process automation

Process automation is the subject of the first cluster of findings. AI-enabled solutions dramatically reduce the amount of manual labor required for emissions data collection, classification, and aggregation, according to expert reports. One significant efficiency improvement was found to be automated extraction from supplier submissions, energy systems, fleet records, and invoices. However, some findings suggested that although AI-enabled automation can significantly improve efficiency, it does not eliminate operational effort entirely. Organizations may still need human oversight to verify data accuracy, resolve inconsistencies, and maintain system integrations. Therefore, the benefits of automation may be constrained by data quality, system compatibility, and the resources required for ongoing monitoring and validation. Some responses were as follows:

Participant P3 (Sustainability Consultant, 12 years of experience):

"Prior to the introduction of AI-enabled solutions, our team spent weeks collating emissions data from energy bills, transit logs and supplier reports. Today, much of that effort is automated, allowing us to spend more time on analysis than on data collection."

Participant P8 (Financial Manager, Listed Company, 15 years of experience):

"The biggest advantage has been the reduction of reporting cycle times. AI automates the classification of carbon-related data from various sources, which increases efficiency and consistency."

Participant P12 (Sustainability Policy Analyst, Financial Regulator, 8 years of experience):

"While automation reduces the manual effort involved in emissions data collection, it can also create operational challenges where data sources are inconsistent. Staff still need to validate automated outputs, correct classification errors, and maintain integrations with legacy systems, meaning that the reduction in manual work is not always as substantial as expected."

The participants placed a strong emphasis on better classification consistency and time compression in reporting cycles. Table 11 presents the AI automation use cases that were identified.

Process Area	AI Contribution	Frequency
Energy data capture	Automated meter ingestion	15
Supplier data	Intelligent classification	14
Travel emissions	Automated footprint calculation	15
Activity mapping	Rule-based AI tagging	15
Consolidation	Cross-source aggregation	15

TABLE 11: AI Automation Use Cases Identified

Source: Author's own creation. AI, Artificial Intelligence

Anomaly detection and data quality

The second cluster of findings pertains to anomaly detection and data quality. Experts pointed out that by identifying anomalies and irregularities in emissions activity data, AI systems increase dependability. Participants with an audit focus emphasized the increasing convergence of carbon data testing and AI anomaly detection in financial audit analytics. Some responses were as follows:

Participant P2 (Audit Partner, 20 years of experience):

“AI is increasingly valuable because it detects unusual emission patterns that could be overlooked by human reviewers. It is quite similar to financial audit analytics to identify suspicious transactions.”

Participant P11 (ESG Assurance Specialist, 10 years of experience):

“The quality of the data has increased a lot. The technology flags missing records, duplicate entries or numbers beyond expected ranges, which gives us trust in the presented figures.”

One audit partner noted that AI tools detect:

“Surface carbon activity detects anomalies in the same way transaction monitoring systems flag unusual journal entries,” indicating convergence between financial and sustainability assurance analytics (Issa et al., 2016). Table 12 presents the reported data quality effects.

Quality Dimension	Observed Effect	Frequency
Consistency	Standardised classifications	15
Completeness	Missing data alerts	14
Accuracy	Reduced manual error	13
Timeliness	Faster validation	14
Traceability	Improved data lineage	15

TABLE 12: Reported Data Quality Effects

Source: Authors own creation

Predictive and scenario analysis

Predictive and scenario analytics are part of the third finding cluster. Experts discussed the growing application of AI models to test operational decarbonization scenarios and predict emissions trajectories. Some responses were as follows:

Participant P6 (Carbon Accounting Consultant, 14 years of experience):

“The most exciting thing for me is to be able to move beyond historical reporting. AI enables organisations to model future emissions pathways and assess the likely impact of different decarbonization strategies.”

Participant P13 (Sustainability Director, Listed Company, 18 years of experience):

“Predictive models are being used more and more to support strategic planning. AI enables us to see how shifts in operations today could affect our carbon footprint five to 10 years from now.”

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In line with the literature on climate financing, these methods were connected to capital planning and transition risk assessment (Bolton et al., 2020). Table 13 presents the predictive AI applications in Carbon Reporting.

Application	Decision Use	Frequency
Emissions forecasting	Target setting	12
Scenario modeling	Transition planning	11
Supplier risk scoring	Scope 3 management	13
Carbon trend analysis	Strategy alignment	14

TABLE 13: Predictive AI Applications in Carbon Reporting

Source: Authors own creation. AI, Artificial Intelligence

Governance and assurance concerns

Tensions between assurance and governance are highlighted in the fourth finding cluster. The lack of transparency in proprietary AI ESG technologies for assurance purposes has been a source of worry for numerous experts. Some responses were as follows:

Participant P1 (External Auditor, 22 years of experience):

“Explainability is one of our biggest concerns. It’s quite difficult to give assurance if management can’t adequately explain how an AI model came up with an estimate of emissions.”

Participant P10 (Financial Regulator, 17 years of experience):

“Many commercial AI platforms are black-boxes. Organisations might take decisions based on outputs without fully understanding the assumptions that are built in to the models and that creates governance risks.”

It was said that black-box models were troublesome since the approach could not be thoroughly examined. Table 14 presents the governance and assurance concerns that were identified.

Issue	Expert Concern	Frequency
Model opacity	Limited explainability	9
Vendor models	Hidden assumptions	10
Audit trail gaps	Weak traceability	11
Control mapping	Unclear validation rules	8

TABLE 14: Governance and Assurance Concerns

Source: Authors' own creation

Limitations in infrastructure and capability

The fifth cluster of findings pertains to limitations in infrastructure and capability. According to experts, the main obstacles to adoption, particularly outside of large firms, are a lack of skills, unequal ESG maturity, and financial constraints. Some responses were as follows:

Participant P5 (ESG Consultant, 11 years of experience):

"The technology is not the biggest hurdle. The fundamental problem is a lack of people who understand both what is needed in ESG reporting and how AI may be used."

Participant P15 (Chief Finance Officer, 25 years of experience):

"Smaller organizations find the expenses of AI platforms, data infrastructure and professional skills a challenge. "Without phased implementation approaches, adoption will remain limited."

In line with research on emerging market digitalization, capacity-building and phased adoption were generally advised (Taurigana, 2021). Table 15 presents the adoption constraints that were identified.

Constraint	Description	Frequency
Skills gap	Limited AI-ESG expertise	10
Cost	Platform expense	12
Data readiness	Poor source data	13
Governance maturity	Weak control frameworks	15

TABLE 15: Adoption Constraints Identified

Source: Authors' own creation. AI, Artificial Intelligence; ESG, Environmental, Social, and Governance

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Discussion

The Zimbabwean expert perspective provides vital contextual insights into the existing ESG and AI literature. In established markets, the uptake of AI is frequently driven largely by the technological efficiency in optimization and reporting challenges (Tauringana, 2021) (Moll and Yigitbasoglu, 2019). However, the findings of this study reveal that institutional maturity, regulatory readiness, professional competence, infrastructure quality, and governance capabilities equally impact AI-enabled ESG reporting in emerging economies. Similar results were reported by Tauringana, who posits that institutional preparation and uneven technological capabilities have a substantial influence on sustainability-related digital transformation in underdeveloped nations (Tauringana, 2021). Our findings are also consistent with Kotsantonis and Serafeim, who cite fragmented ESG data systems and inadequate reporting frameworks as ongoing issues in developing countries (Kotsantonis and Serafeim, 2019).

The findings support the Institutional Theory, which proposes that organizational behavior is affected by regulatory forces, professional norms and wider institutional contexts. Regulatory ambiguity, governance expectations, and deficiencies in professional capabilities were often cited by participants as key influencers of AI adoption decisions. The findings are consistent with previous studies indicating that ESG reporting practices are more driven by institutional legitimacy demands and compliance requirements than by technological factors (Cho et al., 2015) (Eccles and Klimenko, 2019). The results further corroborate the TAM, especially the notion that perceived usefulness affects the adoption of technology. In general, the participants considered AI systems to be of high value for improving reporting efficiency, predictive analytics, and data integration, which is in line with the findings of the Sharma et al. (Sharma et al., 2014) and Zhao et al. (Zhao et al., 2023), stating that AI improves operational intelligence and carbon estimation capability. Nevertheless, issues of explainability, technological complexity, governance readiness and auditability point to the importance of organizational trust, professional capability, and institutional support structures in influencing adoption decisions (Issa et al., 2016) (Rai, 2020).

Findings are also consistent with Legitimacy Theory, which posits that organizations' motivation to implement governance and reporting processes is partly driven by the need to preserve credibility and legitimacy among stakeholders. Participants emphasized that AI-powered ESG reporting is increasingly recognized as a way to improve transparency, investor trust, reporting credibility, and sustainability reputation. This is consistent with Friede et al., who suggest that high-quality ESG disclosure increasingly affects investor perception and organizational valuation (Friede et al., 2015). However, the findings also imply that without explainability, supervision, governance, transparency, or assurance integration, legitimacy might be compromised. This supports arguments by Cho et al. that sustainability reporting may lose credibility where governance structures are perceived as weak, symbolic, or inadequately controlled (Cho et al., 2015). Berg et al. also warn that the opacity of ESG techniques and divergent analytical assumptions may erode stakeholder trust and impede comparability across reporting systems (Berg et al., 2022).

The report also contributes to the policy debate on AI governance and ESG regulation. The findings imply that regulators and standard setters may need to provide more detailed guidelines on the use of AI in the process of sustainability reporting and assurance. Potential regulatory areas include AI disclosure rules, model transparency requirements, ESG data governance protocols, auditability demands, cybersecurity measures, and ethical precautions around automated decision systems. Similar comments have been made by Rai, who stresses the need for explainable AI frameworks for accountability and governance in high-impact analytical systems (Rai, 2020). Similarly, Issa et al. emphasize the necessity for AI governance frameworks that are geared towards the audit process and can promote assurance dependability and professional responsibility (Issa et al., 2016). In the absence of such frameworks, businesses may inconsistently implement AI technology, which would increase governance risk, degrade assurance quality, and reduce comparability across ESG disclosures (Berg et al., 2022) (Kotsantonis and Serafeim, 2019).

The principal novel insight of this study lies in demonstrating that the adoption of AI-enabled ESG reporting in an emerging-economy context is not determined by technological capability alone, but by the interaction between technological, institutional and professional conditions. While previous research has largely examined AI and ESG reporting from the perspectives of efficiency, data quality, transparency and technological capability, the Zimbabwean expert evidence indicates that institutional maturity, regulatory readiness, professional competence, infrastructure

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reliability and governance capacity operate as interconnected prerequisites for effective adoption. The study therefore extends existing Institutional Theory and Technology Acceptance Model perspectives by showing that perceived usefulness of AI does not necessarily translate into adoption where the surrounding institutional and professional environment lacks the capacity to support trustworthy implementation. A further novel contribution is the identification of governance readiness as a mediating contextual condition: explainability, auditability, human oversight and assurance integration were not viewed merely as desirable features of AI systems, but as mechanisms necessary to convert technological capability into credible and legitimate ESG reporting. In this respect, the study shifts the discussion from whether AI can improve ESG reporting to the broader question of under what institutional, regulatory and professional conditions AI-enabled ESG reporting can be implemented credibly in emerging economies. This provides a context-specific contribution to the literature by positioning AI-enabled ESG reporting as an institutional transformation challenge, rather than solely a technological adoption challenge. Table 16 shows the literature position and the study results.

Theme	Literature Position	Expert Finding Alignment
Automation value	Strong	Strong confirmation
Data quality gains	Moderate-strong	Strong confirmation
Predictive analytics	Emerging	Clearly observed
Governance risk	High concern	Strong concern
Skills constraint	Emerging markets	Strong confirmation

TABLE 16: Literature vs Study Finding Alignment

Source: Authors' own creation

The combined evidence suggests that AI in ESG carbon accounting should be governed, not merely adopted. Control frameworks, model transparency, and assurance integration are decisive success factors.

This paper has analyzed the potential of AI to improve ESG carbon accounting and reporting by utilizing expert interview data from Zimbabwe, evaluated in conjunction with contemporary scholarly literature. The research illustrates that AI may markedly enhance reporting efficiency, data consistency, anomaly detection, and predictive carbon analytics. These features make both operational reporting and making long-term climate decisions better.

Practitioner recommendations

AI introduces governance and assurance challenges, including model opacity, limitations in auditability, dependence on data quality, and vendor concentration. These factors affect the governance, control, and assurance of AI-enabled ESG reporting and indicate that AI adoption extends beyond a purely technical implementation. The findings indicate that explainability is relevant to transparency in AI-supported ESG reporting because it can provide users, auditors, and other stakeholders with greater insight into how AI-generated outputs are produced. Documentation of model logic, methodologies, assumptions, and data sources also contributes to accountability and supports the review and validation of AI systems.

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Control and assurance considerations are similarly important. Validation procedures can be used to assess the accuracy, consistency, and reliability of AI-generated outputs and to identify potential errors or anomalies before information is incorporated into ESG disclosures. Maintaining traceability between source data, AI processes, and reported ESG information also supports auditability by enabling auditors to examine how reported metrics were generated. The findings further highlight the role of human capabilities in AI-supported ESG reporting and assurance. ESG professionals and auditors require an understanding of AI systems to evaluate outputs and exercise appropriate professional judgment. Training therefore represents an important aspect of organizational readiness for AI adoption.

Finally, the findings indicate that AI implementation can involve a gradual process in which organizations test applications, identify implementation challenges, and develop appropriate governance and control arrangements before expanding their use. This reflects the operational and assurance considerations associated with integrating AI into ESG reporting processes.

Policy and regulatory implications

The findings have several important policy and regulatory implications for organizations, regulators, and standard-setting bodies. First, with respect to ESG standards, there is a growing need to incorporate requirements for the disclosure of AI usage within sustainability reporting processes. Such disclosures would enhance transparency by informing stakeholders about the extent to which AI systems are used in data collection, analysis, reporting, and decision-making related to ESG performance.

In the area of assurance guidance, regulatory and professional frameworks should establish clear procedures for auditing and verifying AI-assisted ESG reporting. Defining AI audit procedures would help assurance providers assess the reliability, accuracy, and integrity of AI-generated outputs, thereby strengthening stakeholder confidence in reported sustainability information.

Model governance also requires greater regulatory attention. Organizations should be required to implement transparency controls that allow stakeholders, auditors, and regulators to understand how AI models operate, what data they use, and how decisions or recommendations are generated. Such controls can reduce risks associated with algorithmic bias, opacity, and accountability gaps.

Finally, data governance frameworks should be strengthened to address the increasing reliance on AI in ESG reporting. This includes establishing stricter rules for data quality, accuracy, security, privacy, and traceability. Robust ESG data governance practices will help ensure that AI systems are trained and operated using reliable information, thereby improving the credibility and trustworthiness of sustainability disclosures.

Future research directions

The findings also highlight several promising directions for future research on the application of AI in ESG reporting and assurance. One important area is empirical testing, where researchers can examine and compare the accuracy, reliability, and quality of ESG reports generated with AI support against those produced through traditional, non-AI methods. Such studies would provide evidence on whether AI contributes to improved reporting outcomes and identify circumstances under which its benefits are most significant.

Another key research avenue relates to assurance practices. As AI becomes increasingly integrated into ESG reporting processes, there is a need to develop and evaluate specialized AI audit methodologies. Future studies can explore approaches for verifying AI-generated outputs, assessing model performance, and establishing assurance procedures that address the unique risks associated with AI-driven reporting systems.

Governance represents an additional area requiring further investigation. Researchers can focus on developing model risk frameworks that help organizations identify, assess, monitor, and mitigate risks associated with AI applications in ESG reporting. Such frameworks would contribute to stronger accountability, transparency, and regulatory compliance while supporting the responsible use of AI technologies.

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Comparative studies across different economic and regulatory environments would also provide valuable insights. In particular, future research could examine how AI adoption, governance practices, and reporting outcomes differ between emerging and developed markets. These comparisons may reveal contextual factors that influence the effectiveness of AI in ESG reporting and help policymakers tailor regulatory approaches to local conditions.

Finally, future studies should consider employing mixed-method research designs that combine quantitative and qualitative approaches. By integrating statistical analysis with interviews, case studies, or stakeholder perspectives, researchers can develop a more comprehensive understanding of the opportunities, challenges, and implications of AI adoption in ESG reporting and assurance. Such methodological diversity would strengthen the evidence base and support more robust theoretical and practical conclusions.

Conclusions

The findings of this study provide practice-based qualitative insights from a relatively small sample of industry experts and should therefore be interpreted as context-specific experiences rather than generalized evidence of AI effectiveness in ESG carbon reporting. Within the scope of the study, participants described AI as having the potential to support aspects of carbon accounting and ESG reporting, particularly through the automation of data collection and processing, analysis of sustainability data, identification of emissions-related patterns, and support for decision-making. However, participants also identified practical challenges associated with data quality, model transparency, algorithmic bias, regulatory requirements, and the consistency of reporting practices. The findings further indicate that the use of AI in the context examined is closely associated with governance arrangements and human oversight, particularly where the accuracy and credibility of ESG information are concerned. Accordingly, AI was generally understood by participants as a decision-support technology rather than a replacement for sustainability expertise.

Within its defined scope, this study contributes practice-based insights into how industry professionals perceive and experience the use of AI in carbon accounting and ESG reporting. The qualitative evidence highlights specific applications identified by participants, including automated data processing, monitoring, analytical support, and decision support, while also drawing attention to implementation issues relating to data quality, explainability, governance, and regulatory compliance. These findings do not establish the effectiveness of AI across organizations or ESG reporting contexts more broadly. Rather, they provide context-specific evidence that can inform further investigation into the practical use of AI in carbon accounting and ESG reporting. Future research could examine these issues across larger samples, different organizational settings, and different ESG reporting environments to determine the extent to which the experiences identified in this study are transferable.

Appendices

Appendix A: Semi-Structured Expert Interview Schedule

Section A: Participant Background

1. Please briefly describe your professional role and experience in ESG reporting, sustainability, finance, auditing, or carbon accounting.
2. What level of involvement do you have in ESG carbon reporting or AI-related reporting systems within your organization or sector?

Section B: Current ESG Carbon Reporting Practices

3. How are ESG carbon accounting and reporting currently conducted within your organization or sector?
4. What major operational challenges are commonly experienced in carbon reporting processes?

Section C: AI Adoption and Applications

5. In what ways is AI currently being used in ESG carbon accounting and reporting activities?

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6. What benefits or improvements have resulted from the use of AI in these processes?

Section D: Governance, Risk and Assurance

7. What governance, assurance, or transparency concerns arise from the use of AI in ESG reporting?

8. How can organizations improve the reliability, explainability, and accountability of AI-generated ESG information?

Section E: Adoption Constraints and Future Outlook

9. What barriers affect the adoption of AI-enabled ESG reporting in Zimbabwe or similar emerging market contexts?

10. What future developments, reforms, or capabilities are necessary for effective AI integration in ESG carbon accounting and reporting?

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Funny Chibwe, Tendai J. Mapanga

Acquisition, analysis, or interpretation of data: Funny Chibwe, Tendai J. Mapanga

Drafting of the manuscript: Funny Chibwe, Tendai J. Mapanga

Critical review of the manuscript for important intellectual content: Funny Chibwe, Tendai J. Mapanga

Supervision: Funny Chibwe, Tendai J. Mapanga

Disclosures

Human subjects: Consent was obtained from all participants in this study.

Animal subjects: All authors have confirmed that this study did not involve animal subjects or tissue.

Conflicts of interest: In compliance with [the ICMJE uniform disclosure form](#), all authors declare the following:

- **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work.
- **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work.
- **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

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