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A Paradigmatic Model for the Use of Artificial Intelligence in Sustainability Reporting Using a Grounded Theory Approach

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Abstract

The present study aimed to develop a paradigmatic model for the use of artificial intelligence in sustainability reporting, with an emphasis on stakeholder trust, using a grounded theory approach. Philosophically, the study was grounded in the pragmatist paradigm, and its participants consisted of 12 experts, including university professors, senior auditors, financial and sustainability managers, and information technology specialists, who were selected through purposive and snowball sampling. Data were collected through semi-structured interviews and analyzed in three stages of open, axial, and selective coding. The credibility of the data was confirmed using Lincoln and Guba's criteria and Cohen's kappa coefficient (0.678). Data analysis resulted in the extraction of 62 initial codes, which were organized into five main themes: the role of artificial intelligence in the sustainability reporting process (13 codes—causal conditions), challenges and barriers to artificial intelligence implementation (10 codes—contextual conditions), stakeholder perceptions and trust (9 codes—consequences), mediating variables and mechanisms affecting trust (10 codes—intervening conditions), and strategies and an applied model (20 codes—strategies). The final paradigmatic model indicated that stakeholder trust in AI-generated sustainability reports is a multifaceted phenomenon influenced by a chain of causal, contextual, and intervening factors. Within this framework, explainable artificial intelligence (XAI), as the most important mediating mechanism, plays a decisive role in transforming the technical capabilities of machines into stakeholders' psychological acceptance. The findings indicate that the mere use of artificial intelligence does not guarantee stakeholder trust; rather, transparency, explainability, and data quality constitute the bridge through which trust is established. Accordingly, it is recommended that organizations enhance stakeholder trust by implementing explainable AI systems, strengthening the role of internal auditors, improving the quality of input data, and developing ethical frameworks and national standards.

Keywords: sustainability reporting, explainable artificial intelligence (XAI), stakeholder trust, grounded theory, paradigmatic model.

1. Introduction

Sustainability reporting has become an increasingly important component of corporate accountability, strategic communication, and stakeholder engagement as organizations face intensifying expectations to disclose their economic, environmental, social, and governance impacts. The evolution of sustainability reporting reflects a broader transformation in corporate reporting, in which traditional financial statements are no longer considered sufficient for evaluating long-term

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organizational performance, resilience, legitimacy, and value creation. Earlier discussions on the development of sustainability reporting standards emphasized the need for more coherent, comparable, and institutionally accepted frameworks capable of integrating environmental and social considerations into corporate disclosure systems (Aras & Crowther, 2008). Over time, sustainability reporting has progressed from largely voluntary and narrative disclosures toward more structured reporting practices that are increasingly associated with strategic management, accountability, stakeholder relations, and sustainable value creation. At the same time, the diversity of sustainability indicators, the complexity of environmental, social, and governance (ESG) data, and the need to process large volumes of heterogeneous information have created substantial technical and managerial challenges for organizations.

The growing significance of ESG disclosure has further intensified attention to the quality, usefulness, and credibility of sustainability reporting. ESG information is increasingly incorporated into investors' assessments, corporate risk analyses, lending decisions, stakeholder evaluations, and broader judgments concerning organizational legitimacy. However, the usefulness of sustainability disclosures depends not only on the amount of information provided but also on its relevance, reliability, comparability, timeliness, and decision usefulness. Corporate characteristics and organizational maturity can influence the extent to which ESG disclosures are value relevant and meaningful to external users (Islam, 2025). In addition, sustainability reporting practices are shaped by broader organizational strategies, institutional pressures, internal capabilities, and approaches to responsible corporate behavior. From the perspective of green corporate citizenship, the appropriateness of sustainability reporting practices is linked to organizational strategies and the extent to which firms integrate sustainability principles into managerial and reporting processes (Mobaraki et al., 2024). These developments indicate that sustainability reporting should not be regarded merely as a disclosure exercise; rather, it is an information-processing system that connects organizational activities, data infrastructures, governance mechanisms, and stakeholder expectations.

Despite these advances, sustainability reporting continues to face significant limitations. Sustainability information is often dispersed across organizational units, generated through different systems, and expressed in both quantitative and qualitative forms. Environmental data may originate from production systems, sensors, energy-management platforms, or supply-chain databases, whereas social and governance information may be extracted from human resource systems, compliance records, surveys, and narrative documents. Integrating such heterogeneous data into a coherent and reliable sustainability report requires considerable human effort and is vulnerable to inconsistency, incompleteness, delay, and error. Furthermore, concerns regarding greenwashing have raised questions about whether organizations selectively disclose favorable sustainability information while obscuring unfavorable impacts. The relationship among greenwashing, sustainability reporting, and emerging artificial intelligence applications has therefore become a significant area of scholarly attention, particularly because technological tools may simultaneously enhance reporting quality and create new risks related to opacity and manipulation (Moodaley & Telukdarie, 2023).

Against this background, artificial intelligence (AI) has emerged as a potentially transformative technology for sustainability reporting. AI refers broadly to computational systems capable of performing tasks that traditionally require human intelligence, including pattern recognition, prediction, classification, language processing, anomaly detection, and automated decision support. In sustainability reporting, AI can contribute to data collection, data cleaning, information integration, analysis, forecasting, report generation, assurance, and monitoring. Recent systematic evidence shows a rapid convergence between artificial intelligence and sustainability reporting, with AI increasingly being applied to automate complex reporting tasks, improve data accuracy, support real-time monitoring, and enhance the analytical value of ESG information (Mustafa et al., 2025). These developments suggest that AI has the potential to shift sustainability reporting from a predominantly periodic and retrospective process toward a more continuous, data-driven, and analytically sophisticated reporting system.

The potential contribution of AI is particularly important in the early stages of the sustainability reporting process. AI-enabled systems can support the automated extraction of information from multiple organizational databases, identify missing or inconsistent records, detect anomalies, classify unstructured information, and integrate data from different sources. The use of machine learning, big data analytics, and Internet of Things technologies can further increase the speed and scope of ESG information processing by connecting operational systems with reporting platforms (Rane et al., 2024). In financial services and investment contexts, the integration of AI and business intelligence can strengthen ESG strategy formulation by providing more timely and analytically rich information for decision makers (Rane et al., 2024). Similarly, AI-supported ESG

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applications are increasingly associated with corporate efficiency, information processing, and improvements in sustainability performance (Yu et al., 2025). Such capabilities are especially relevant for sustainability reporting because ESG performance is multidimensional and depends on the analysis of complex relationships among environmental, social, operational, and financial variables.

Artificial intelligence may also improve the quality of sustainability reporting through enhanced analytical accuracy and predictive capability. Generative AI and advanced data analytics can assist organizations in converting large volumes of accounting and sustainability data into structured reporting outputs. Evidence suggests that the use of generative artificial intelligence in accounting data analysis can enhance the quality of digital sustainability reporting, particularly when supported by effective internal green sustainability control systems (Saghafi & Parsapour, 2025). In addition, AI can strengthen the consistency of disclosures by identifying discrepancies, reducing repetitive manual processes, and supporting the standardization of reporting procedures. From a sustainability financing perspective, AI has also been identified as an important enabler of the development and implementation of sustainability reporting standards by improving the processing and use of relevant financial and non-financial information (Khodayari-Siar, 2023).

The significance of AI is not limited to internal reporting processes but also extends to ESG performance and organizational sustainability outcomes. Recent studies have shown that AI adoption can influence corporate ESG performance through improvements in operational efficiency, information utilization, and responsiveness to external environmental conditions (Yu et al., 2025). Evidence from state-owned enterprises similarly indicates that AI-driven ESG performance can contribute to sustainable organizational development (Xiao & Xiao, 2025). The broader integration of AI into organizational functions, including human resource management, has also been associated with stronger ESG integration and the development of more sustainable business strategies (Zulkarnaini et al., 2025). These findings suggest that AI is increasingly becoming embedded not only in sustainability reporting systems but also in the organizational processes that generate the underlying ESG performance being reported.

Another important area concerns the integration of AI with complementary digital technologies. AI and blockchain can jointly strengthen accounting systems, ESG performance, risk management, and the reliability of sustainability-related information flows (Nguyen et al., 2026). Blockchain can contribute to traceability and immutability, whereas AI can provide analytical and predictive capabilities, creating the possibility of more transparent and verifiable reporting ecosystems. The integration of AI with digital infrastructures can therefore enhance not only data processing but also the governance architecture of sustainability reporting. However, the effectiveness of such systems depends on organizational readiness, data quality, technological infrastructure, and the ability of managers and professionals to interpret and govern algorithmic outputs.

The increasing use of AI in reporting has also expanded the scope of sustainability assurance and auditing. Sustainability reports are increasingly expected to be subject to assurance mechanisms that can improve credibility and reduce information risk. AI can support assurance procedures by identifying unusual patterns, screening large data sets, detecting inconsistencies, and prioritizing high-risk areas for auditor attention. Research on AI in ESG assurance indicates that intelligent systems can improve the efficiency and scope of assurance procedures while supporting more continuous and data-driven verification processes (Li et al., 2024). Similarly, AI-based models can be used to identify audit risks in sustainability reporting and strengthen auditors' ability to focus on areas characterized by higher uncertainty or potential misstatement (Jamali et al., 2025). More advanced approaches based on reinforcement learning have also been proposed for adaptive ESG audit decision-making and anomaly analysis, demonstrating the growing sophistication of AI-supported audit technologies (Wang et al., 2026).

Nevertheless, the implementation of AI in sustainability reporting is accompanied by significant challenges. AI systems require high-quality input data, reliable infrastructure, skilled personnel, effective governance mechanisms, and appropriate organizational controls. Poor-quality, incomplete, biased, or outdated data can generate misleading outputs regardless of the sophistication of the algorithm. Furthermore, AI systems may introduce new forms of operational, ethical, legal, and reputational risk. The literature highlights concerns related to algorithmic bias, cybersecurity, data privacy, explainability, organizational resistance, implementation costs, and the shortage of professionals capable of simultaneously understanding sustainability reporting and AI technologies (Mustafa et al., 2025). In financial and ESG applications, researchers have

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similarly identified the need to balance the analytical benefits of AI with concerns regarding transparency, accountability, and appropriate governance (Lim, 2024).

One of the most critical challenges is the opacity of AI-based decisions. Many advanced machine-learning models operate as "black boxes," meaning that users may observe the output without clearly understanding how the system arrived at a particular conclusion. In sustainability reporting, such opacity may be especially problematic because stakeholders increasingly expect companies to explain not only what they report but also how sustainability information has been collected, processed, analyzed, and validated. Artificial intelligence disclosures in sustainability reports are therefore becoming an important element of corporate transparency, and the development of dedicated AI reporting frameworks has been proposed to improve accountability regarding the use of intelligent systems (Bonsón & Bednárová, 2022). This issue becomes particularly important when AI-generated outputs directly influence reported ESG metrics, risk assessments, forecasts, or narrative explanations.

The concept of explainable artificial intelligence (XAI) is therefore central to the trustworthy use of AI in sustainability reporting. Explainability refers to the extent to which the logic, basis, or reasoning underlying an AI output can be made understandable to relevant users. In the context of sustainability reporting, explainability can help stakeholders understand why a system identified a particular trend, classified an ESG issue in a certain way, or generated a specific estimate. Explainability may also facilitate auditor review, management oversight, regulatory scrutiny, and stakeholder acceptance. Without adequate explainability, AI may improve technical efficiency while simultaneously reducing perceived transparency. This contradiction is particularly important because trust is not generated solely by technical accuracy; it also depends on stakeholders' perceptions of fairness, controllability, transparency, and accountability.

Stakeholder trust is therefore a fundamental outcome in the relationship between AI and sustainability reporting. Sustainability reports are designed for multiple stakeholder groups, including investors, employees, regulators, customers, communities, auditors, and civil society organizations. These groups may differ in their information needs, technological familiarity, risk perceptions, and expectations regarding transparency. The interaction among ESG reporting, artificial intelligence, stakeholders, innovation performance, sustainability culture, and climate resilience demonstrates that technology and stakeholder engagement are increasingly interconnected in contemporary sustainability practices (Riyath & Jariya, 2024). If stakeholders perceive AI-generated reports as more accurate, timely, complete, and independently verifiable, AI may strengthen confidence in sustainability disclosures. Conversely, if AI is perceived as opaque, uncontrolled, biased, or difficult to verify, the use of technology may undermine rather than enhance trust.

This issue is also evident in sector-specific applications of AI-supported ESG reporting. Research in the European fashion industry has illustrated how AI can be leveraged to support ESG reporting while simultaneously revealing practical challenges associated with implementation, organizational adaptation, and reporting processes (Strazzullo, 2025). Such findings suggest that the benefits of AI are not automatic but depend on the organizational environment in which the technology is introduced. The actual value of AI in sustainability reporting may therefore be contingent on variables such as data quality, assurance mechanisms, management support, regulatory expectations, technological maturity, and organizational culture.

From a broader financial perspective, the use of AI in ESG-related activities is reshaping how organizations and markets evaluate sustainability information. AI applications in finance increasingly support ESG analysis, investment evaluation, risk assessment, and sustainability-oriented decision-making (Lim, 2024). This growing reliance on algorithmic systems means that the credibility of AI-generated sustainability information may have implications beyond internal reporting, potentially influencing capital allocation and investor behavior. Consequently, the relationship between AI and stakeholder trust cannot be understood exclusively as a technical issue; it is also an organizational, behavioral, governance, and institutional phenomenon.

The literature further indicates that AI adoption must be accompanied by mechanisms capable of reducing information risk and strengthening accountability. AI-based sustainability reporting requires effective internal controls, oversight by senior management, independent assurance, appropriate audit procedures, ethical frameworks, and clear responsibilities for algorithmic decisions. The relationship between AI and sustainability reporting thus involves a socio-technical system in which technical capabilities interact with human judgment, organizational routines, regulatory structures, and stakeholder perceptions.

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This perspective is especially important because a technically accurate system may still fail to generate trust if stakeholders do not understand its outputs or do not believe that the underlying process is adequately governed.

Although the existing literature has advanced understanding of AI applications in sustainability reporting, several important gaps remain. A considerable proportion of prior research has focused on technical capabilities, ESG performance, digital transformation, assurance, or the general opportunities and risks associated with AI (Bonsón & Bednárová, 2022; Moodaley & Telukdarie, 2023; Mustafa et al., 2025). Other studies have examined specific relationships involving AI, sustainability performance, accounting systems, audit risk, or ESG assurance (Jamali et al., 2025; Li et al., 2024; Nguyen et al., 2026; Wang et al., 2026; Xiao & Xiao, 2025). However, the mechanisms through which AI-supported sustainability reporting generates or undermines stakeholder trust remain insufficiently integrated within a comprehensive explanatory framework. In particular, there is a need to understand how causal factors, contextual barriers, intervening mechanisms, organizational strategies, and resulting stakeholder perceptions interact within the AI-enabled sustainability reporting process.

The fragmented nature of current knowledge also creates a methodological gap. Much of the existing literature relies on conceptual analysis, systematic reviews, quantitative modeling, or application-specific investigations. Although these approaches provide valuable evidence, they may not fully capture the perceptions, experiences, and interpretations of professionals directly involved in sustainability reporting, auditing, financial management, and AI implementation. A grounded theory approach is therefore particularly suitable for identifying the underlying categories and relationships emerging from expert experience and for developing an integrated paradigmatic model. Such an approach can clarify not only what factors influence AI-enabled sustainability reporting but also how these factors interact to shape stakeholder trust, implementation strategies, and organizational outcomes.

Accordingly, the aim of the present study is to develop a paradigmatic model of the use of artificial intelligence in sustainability reporting, with particular emphasis on the causal, contextual, intervening, strategic, and consequential mechanisms through which AI influences stakeholder trust.

2. Methods and Materials

From a philosophical perspective, the present study is grounded in the pragmatist paradigm. Pragmatism, as a middle-ground philosophy, holds that truth and knowledge acquire meaning through practice and the applicability of results, and that researchers may employ quantitative, qualitative, or mixed methods according to the nature of the research problem (Tashakkori & Teddlie, 2010). This paradigm was selected because the research problem encompasses both subjective aspects, including experts' perceptions, experiences, and interpretations, and objective aspects, including measurable variables; therefore, neither a purely qualitative nor a purely quantitative approach can provide a complete response. Nevertheless, given the primary objective of the article—namely, to develop a paradigmatic model for the use of artificial intelligence in sustainability reporting—a qualitative approach, and specifically grounded theory, was selected as the principal research method. Grounded theory is a systematic method for discovering and developing theory from data and is particularly appropriate for emerging fields that lack a coherent theoretical framework (Strauss & Corbin, 1998).

The target population in the qualitative phase consisted of experts and specialists possessing sufficient knowledge, experience, and expertise in areas related to the research, including sustainability reporting, artificial intelligence in accounting, trust assessment, and financial information technology. Given the qualitative nature and exploratory purpose of the study, purposive sampling combined with a snowball sampling approach was employed to recruit qualified experts capable of providing the richest and most in-depth information.

The participant inclusion criteria comprised four groups: (1) university faculty members holding the academic rank of associate professor or higher, or assistant professors with at least 5 years of teaching and research experience, in accounting, financial management, or information technology management, with at least 3 peer-reviewed scientific articles in the fields of sustainability reporting, artificial intelligence, or organizational trust; (2) senior auditors with at least 10 years of professional experience in reputable auditing firms and experience in auditing sustainability reports; (3) financial and sustainability managers of companies listed on the Tehran Stock Exchange that had published at least one sustainability report during the previous 2 years; and (4) senior information technology specialists holding a master's degree or higher and having at least 7

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years of professional experience in projects involving the implementation of artificial intelligence systems in finance and accounting.

The number of participants was determined based on the principle of theoretical saturation. Evidence from similar studies suggests that theoretical saturation is generally achieved within the range of 12 to 18 interviews. In the present study, after conducting 12 semi-structured interviews with experts, including 10 individuals with diverse demographic characteristics in terms of gender, education, and age, the newly collected data no longer added new information to the previous findings, and the concepts and categories reached saturation.

The data collection instrument in this study was a semi-structured interview guide developed by the researcher in consultation with the academic supervisor and advisor. Semi-structured interviews were selected because of their flexibility. On the one hand, they contain predetermined questions based on the theoretical foundations, thereby providing overall direction to the interview and preventing excessive digression; on the other hand, they allow the researcher to ask follow-up and explanatory questions based on participants' responses in order to achieve greater depth in the collected data (Flick, 2018).

The interview guide was designed around five principal domains: (1) understanding and defining AI explainability in sustainability reporting; (2) components and dimensions of stakeholder trust in sustainability reports; (3) the role of mediating variables, including procedural understanding and perceived control; (4) moderating factors, including demographic and contextual characteristics; and (5) barriers to and strategies for implementing XAI in Iran. Each interview lasted between 45 and 90 minutes and was conducted at a time and location convenient for the participant, including the workplace, university, or online. All interviews were audio-recorded after obtaining written permission from the participants and subsequently transcribed verbatim. Field notes, including observations, tone of voice, and participants' nonverbal behaviors, were also recorded to enrich the analysis.

Qualitative data were analyzed using thematic analysis with MAXQDA qualitative data analysis software, version 2022 or later. The analysis process was conducted in three stages of open, axial, and selective coding based on the paradigmatic approach of Strauss and Corbin (1998):

Stage One: Open Coding: At this stage, the researcher carefully and repeatedly reviewed the interview transcripts and identified meaningful sentences, expressions, and paragraphs, assigning conceptual labels, or initial codes, to them. Open coding was conducted inductively and without strong preconceived assumptions to ensure that all possible concepts could emerge from the data. Ultimately, 62 initial codes were extracted from the interviews, reflecting the richness of the data and the diversity of participants' perspectives.

Stage Two: Axial Coding: At this stage, the open codes were organized into principal categories and subcategories based on similarities, differences, and causal and contextual relationships. Following the paradigmatic approach of Strauss and Corbin, the researcher explained the relationships among the extracted categories by identifying causal conditions, the central phenomenon, contextual conditions, intervening conditions, strategies, and consequences. Ultimately, the 62 initial codes were organized into five main themes: (1) the role of artificial intelligence in the sustainability reporting process (13 codes); (2) challenges and barriers to artificial intelligence implementation (10 codes); (3) stakeholder perceptions and trust (9 codes); (4) mediating variables and mechanisms affecting trust (10 codes); and (5) strategies and an applied model (20 codes).

Stage Three: Selective Coding: At this stage, the principal categories were reduced to one or more core categories capable of coherently encompassing all of the data and addressing the research questions. In the present study, "stakeholder trust in AI-generated sustainability reports" was selected as the core category. Subsequently, each of the five main themes was assigned to one component of the coding paradigm: causal conditions (Theme 1), contextual conditions (Theme 2), intervening conditions (Theme 4), strategies (Theme 5), and consequences (Theme 3). Finally, the study's final paradigmatic model was graphically presented by depicting causal, contextual, mediating, and moderating relationships.

3. Findings and Results

During the open coding stage, the researcher carefully and repeatedly reviewed the interview transcripts, identified meaningful sentences, expressions, and paragraphs, and assigned conceptual labels, or initial codes, to them. Open coding was performed inductively and was informed by the grounded theory method so that all possible concepts could be extracted from the data. To enhance the credibility of the coding process, coding was performed twice at different points in time, and the

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results were compared. Cohen's kappa coefficient was also used to assess reliability, yielding a value of 0.678, which indicates a satisfactory level of agreement between the two coding rounds.

Ultimately, 62 initial codes were extracted from interviews with 12 experts in the fields of sustainability reporting and artificial intelligence, reflecting the richness of the data and the diversity of participants' perspectives. On the one hand, these codes address the technical and operational dimensions of artificial intelligence within the sustainability reporting process, while on the other hand, they concern the perceptual and behavioral dimensions of stakeholders. Some codes, such as "experience in sustainability reporting" and "familiarity with artificial intelligence," function as contextual and cognitive codes indicating participants' levels of preparedness and knowledge. Other codes, such as "impact on data collection," "impact on data cleaning," "impact on data analysis," and "impact on report generation," directly address the operational functions of artificial intelligence at different stages of the reporting process.

Furthermore, codes such as "key benefits of artificial intelligence" and "implementation challenges" reflect participants' dual perspectives toward this technology. While some interviewees emphasized increased accuracy, greater speed, and reduced human error as key benefits, others identified high costs, technical complexities, and organizational resistance as major implementation barriers. Codes related to stakeholder trust, including "stakeholder expectations," "increased stakeholder trust," "risk of lack of transparency," and "the role of transparency in trust," demonstrate that stakeholder trust is a multidimensional concept influenced by multiple factors. One participant stated: "The greatest risk of using artificial intelligence is the black-box problem. If we cannot explain to stakeholders why the algorithm reached a particular conclusion, their trust will decline dramatically" (Participant P11).

Codes related to mediating variables, such as "the role of explainability," "quality of input data," "the role of independent assurance," and "cultural and organizational factors," indicate the complexity of the relationships between artificial intelligence use and stakeholder trust. One participant stated: "Data quality is the most important factor in the success of artificial intelligence. If the data are incomplete, outdated, or inaccurate, no algorithm can produce reliable outputs" (Participant P2). Finally, codes concerning strategies and the applied model, such as "implementation strategies for increasing acceptance," "the role of regulatory bodies," "the need for standardization," and "the need for an ethical framework," demonstrate participants' attention to the operational and policy-making dimensions of this field.

Table 1 presents a summary of the extracted initial codes together with examples of participants' quotations.

Table 1. Sample Open Coding

No.	Initial Code	Sample Interview Quotation
1	Experience in sustainability reporting	"I have been working in sustainability and ESG reporting for more than 12 years... I have always regarded the main challenge as collecting dispersed data from different organizational units" (P1).
2	Familiarity with artificial intelligence	"I have completed a specialized course on the application of machine learning in financial reporting... this technology can revolutionize sustainability data analysis" (P8).
3	Impact on data collection	"Our greatest challenge is obtaining real-time data from production lines. Artificial intelligence can solve this problem by connecting to sensors and SCADA systems" (P3).
4	Impact on data cleaning	"The algorithm was able to identify more than 2,000 human errors in energy-consumption data, which was truly remarkable" (P4).
5	Impact on data analysis	"By simultaneously analyzing hundreds of variables, artificial intelligence can provide more accurate predictions of the company's future ESG performance" (P5).
6	Impact on report generation	"Automated text-generation tools can prepare the initial draft of the report, but the final quality depends on human oversight" (P6).
7	Key benefits of artificial intelligence	"The most important advantage of artificial intelligence is increased accuracy and reduced human error. Even a small error in calculating carbon emissions can undermine the credibility of the entire report" (P7).
8	Implementation challenges	"Our main challenges are implementation costs and the shortage of skilled personnel. Resistance among long-serving employees is also a major cultural barrier" (P8).
9	Stakeholder expectations	"Investors seek reliable and comparable data" (P9).
10	Increased stakeholder trust	"If artificial intelligence can provide complete documentation and a data verification trail, trust will certainly increase" (P10).
11	Risk of lack of transparency	"The greatest risk of using artificial intelligence is the black-box problem... this issue is particularly critical in the financial industry" (P11).
12	Role of transparency in trust	"Transparency in artificial intelligence processes is the cornerstone of trust" (P12).
13	Role of explainability	"Explainability means the ability to provide a parallel report showing how each figure was calculated" (P1).
14	Quality of input data	"If the data are incomplete, outdated, or inaccurate, no algorithm can produce reliable outputs" (P2).

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15	Role of independent assurance	"Internal and third-party auditing of reports generated by artificial intelligence is essential" (P3).
16	Cultural and organizational factors	"Resistance to change is one of the greatest cultural barriers. Many senior managers still trust traditional methods" (P4).
17	Implementation strategies for acceptance	"Developing national standards for the use of artificial intelligence in sustainability reporting is essential" (P5).
18	Role of regulatory bodies	"Regulatory bodies such as the Securities and Exchange Organization should develop a framework for the use of artificial intelligence in reporting" (P6).
19	Existing research gaps	"The most important research gap is the shortage of empirical studies on the actual impact of artificial intelligence on stakeholder trust" (P7).
20	Suggestions for future research	"Future research should focus on developing artificial intelligence models with high levels of explainability" (P8).

During the axial coding stage, the open codes were organized into principal categories and subcategories based on similarities, differences, and causal and contextual relationships. The axial coding process was conducted using the paradigmatic approach of Strauss and Corbin (1998). According to this approach, the researcher explained the relationships among the extracted categories by identifying causal conditions, the central phenomenon, contextual conditions, intervening conditions, strategies, and consequences. Ultimately, the 62 initial codes were organized into five main themes:

Theme One: The Role of Artificial Intelligence in the Sustainability Reporting Process (13 Codes—Causal Conditions). This theme represents the capacities and capabilities of artificial intelligence to enhance the sustainability reporting process. Codes such as familiarity with artificial intelligence, impact on data collection, impact on data cleaning, impact on data analysis, impact on report generation, key benefits of artificial intelligence, the proposed conceptual model, technical infrastructure challenges, the need for skilled personnel, cost-related challenges, the role of complementary technologies, the role of the Internet of Things, and the impact on the future of the accounting profession were included in this theme. Data analysis indicates that participants believed artificial intelligence could influence all stages of the reporting process, from data collection to report generation, and that this influence is primarily manifested in increased accuracy and speed and reduced human error.

Theme Two: Challenges and Barriers to Artificial Intelligence Implementation (10 Codes—Contextual Conditions). This theme represents the barriers and limitations organizations encounter when implementing artificial intelligence. Codes such as implementation challenges, cultural and individual factors, ethical challenges, qualitative data challenges, legal challenges, social acceptance challenges, historical data challenges, data security challenges, cultural challenges in Iran, and scalability challenges were included in this theme. The findings indicate that barriers to the implementation of artificial intelligence in sustainability reporting extend beyond purely technical issues and also encompass cultural, organizational, legal, and ethical dimensions. One participant stated: "In Iran, cultural resistance to technological change is greater than in developed countries. Many managers still trust traditional methods" (P6).

Theme Three: Stakeholder Perceptions and Trust (9 Codes—Consequences). This theme represents the perceptions, attitudes, and trust of different stakeholder groups toward sustainability reports generated using artificial intelligence. Codes such as stakeholder expectations, increased stakeholder trust, risk of lack of transparency, the role of transparency in trust, impact on investor decision-making, impact on stakeholder relationships, importance of stakeholder education, impact on brand value, and the role of media were included in this theme. Data analysis indicates that stakeholder trust is a multidimensional and complex concept influenced by numerous factors. Conversely, the risk of lack of transparency and the "black-box" problem can reduce stakeholder trust, further emphasizing the necessity of attending to algorithmic explainability.

Theme Four: Mediating Variables and Mechanisms Affecting Trust (10 Codes—Intervening Conditions). This theme represents factors that can moderate or mediate the relationship between artificial intelligence use and stakeholder trust. Codes such as experience in sustainability reporting, the role of explainability, quality of input data, the role of independent assurance, the role of a culture of accountability, impact on organizational transparency, importance of up-to-date data, the role of internal auditors, impact on algorithmic transparency, and data interpretation challenges were included in this theme. The findings indicate that the quality of input data was identified as the most important mediating factor. Explainability and algorithmic transparency were also identified as other key factors capable of enhancing stakeholder trust.

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Theme Five: Strategies and the Applied Model (20 Codes—Strategies). This theme encompasses a set of operational, policy-related, educational, and technical strategies that can contribute to increasing the acceptance and successful use of artificial intelligence in sustainability reporting. Codes such as implementation strategies, the role of regulatory bodies, research gaps, suggestions for the future, prioritization of factors, competitive advantage, the need for standardization, the role of senior management, ethical framework, data integration, social responsibility, sharing platforms, stakeholder feedback, gradual implementation, key indicators, regulators' decision-making, cost transparency, stakeholder participation, the role of universities, and synthesis of challenges were included in this theme. The findings indicate that participants emphasized the importance of a gradual and phased approach to artificial intelligence implementation and identified beginning with pilot projects as an effective strategy.

Table 2. Axial Coding: Five Main Themes

Theme	Paradigm Component	Number of Codes	Examples of Initial Codes
Role of artificial intelligence in the sustainability reporting process	Causal conditions	13	Familiarity with artificial intelligence, impact on data collection, key benefits, role of complementary technologies
Challenges and barriers to artificial intelligence implementation	Contextual conditions	10	Implementation challenges, cultural factors, ethical challenges, legal challenges
Stakeholder perceptions and trust	Consequences	9	Stakeholder expectations, increased trust, risk of lack of transparency, role of transparency in trust
Mediating variables and mechanisms affecting trust	Intervening conditions	10	Role of explainability, data quality, role of independent assurance, algorithmic transparency
Strategies and the applied model	Strategies	20	Implementation strategies, role of regulatory bodies, standardization, ethical framework

During the selective coding stage, the principal categories were reduced to one or more core categories capable of coherently encompassing all of the data and addressing the research questions. In the present study, following a careful review of the interviews and analysis of the relationships among the axial categories, "stakeholder trust in AI-generated sustainability reports" was selected as the core category. This category was considered highly frequent and important because it emerged throughout all interviews as the ultimate objective and principal outcome of the artificial intelligence utilization process. One participant stated in support of this point: "Transparency in artificial intelligence processes is the cornerstone of trust. If reports show where the data originated, how they were processed, and what logic underlies the analyses, stakeholders will use them with greater confidence" (P12).

After identification of the core category, each of the five main themes was assigned to one of the coding paradigm components. According to the paradigmatic approach of Strauss and Corbin (1998), the paradigmatic model consists of six principal components: causal conditions, the central phenomenon, contextual conditions, intervening conditions, strategies, and consequences. In the present study, the identified axial categories were positioned within these components as follows:

Causal Conditions: Theme One, namely the role of artificial intelligence in the sustainability reporting process, functions as the factors that create and facilitate the central phenomenon. These conditions include familiarity with artificial intelligence; its impact on the four stages of reporting—collection, cleaning, analysis, and generation; the key benefits of artificial intelligence; technical infrastructure challenges; the need for skilled personnel; cost-related challenges; the role of complementary technologies such as blockchain and the Internet of Things; and the impact on the future of the accounting profession.

Central Phenomenon: "The application of artificial intelligence in sustainability reporting" encompasses the four stages of data collection, data cleaning, data analysis, and report generation. This phenomenon represents the focal point of the model around which the other categories are organized.

Contextual Conditions: Theme Two, namely challenges and barriers to artificial intelligence implementation, describes the context and environment within which the central phenomenon occurs. These conditions include implementation challenges, cultural and individual factors, ethical challenges, qualitative data challenges, legal challenges, social acceptance challenges, historical data challenges, data security challenges, cultural challenges in Iran, and scalability challenges.

Intervening Conditions: Theme Four, namely mediating variables and mechanisms affecting trust, represents factors that can strengthen or weaken the relationship between the central phenomenon and its consequences. These conditions include experience in sustainability reporting, the role of explainability, quality of input data, the role of independent assurance, the

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role of a culture of accountability, impact on organizational transparency, the importance of up-to-date data, the role of internal auditors, impact on algorithmic transparency, and data interpretation challenges. The quality of input data was identified as the most important intervening factor.

Strategies: Theme Five, namely strategies and the applied model, represents the set of actions and responses adopted in response to causal, contextual, and intervening conditions. These strategies include implementation strategies, the role of regulatory bodies, research gaps, suggestions for the future, prioritization of factors, competitive advantage, standardization, the role of senior management, ethical frameworks, data integration, social responsibility, sharing platforms, stakeholder feedback, gradual implementation, key indicators, regulators' decision-making, cost transparency, stakeholder participation, the role of universities, and synthesis of challenges.

Consequences: Theme Three, namely stakeholder perceptions and trust, represents the final results and outcomes arising from the implementation of the strategies. These consequences include stakeholder expectations, increased stakeholder trust, risk of lack of transparency, the role of transparency in trust, impact on investor decision-making, impact on stakeholder relationships, stakeholder education, impact on brand value, and the role of media. The study findings indicate that the use of artificial intelligence can increase stakeholder trust; however, failure to address risks such as lack of transparency and ethical concerns may also undermine trust.

Table 3. Final Paradigmatic Model of the Study

Paradigm Component	Theme	Number of Codes	Brief Description
Causal conditions	Role of artificial intelligence in the sustainability reporting process	13	Familiarity with artificial intelligence, impact on the four reporting stages, key benefits, technical challenges, need for skilled personnel, cost challenges, role of complementary technologies, impact on the future of accounting
Central phenomenon	Application of artificial intelligence in sustainability reporting	—	Four stages: collection, cleaning, analysis, and report generation
Contextual conditions	Challenges and barriers to artificial intelligence implementation	10	Implementation challenges, cultural and individual factors, ethical challenges, qualitative data challenges, legal challenges, social acceptance challenges, historical data challenges, data security challenges, cultural challenges in Iran, scalability challenges
Intervening conditions	Mediating variables and mechanisms affecting trust	10	Reporting experience, role of explainability, data quality, role of independent assurance, culture of accountability, organizational transparency, up-to-date data, role of internal auditors, algorithmic transparency, data interpretation challenges
Strategies	Strategies and the applied model	20	Implementation strategies, role of regulatory bodies, research gaps, suggestions for the future, prioritization of factors, competitive advantage, standardization, role of senior management, ethical framework, data integration, social responsibility, sharing platform, stakeholder feedback, gradual implementation, key indicators, regulators' decision-making, cost transparency, stakeholder participation, role of universities, synthesis of challenges
Consequences	Stakeholder perceptions and trust	9	Stakeholder expectations, increased trust, risk of lack of transparency, role of transparency, impact on investor decision-making, impact on stakeholder relationships, stakeholder education, impact on brand value, role of media

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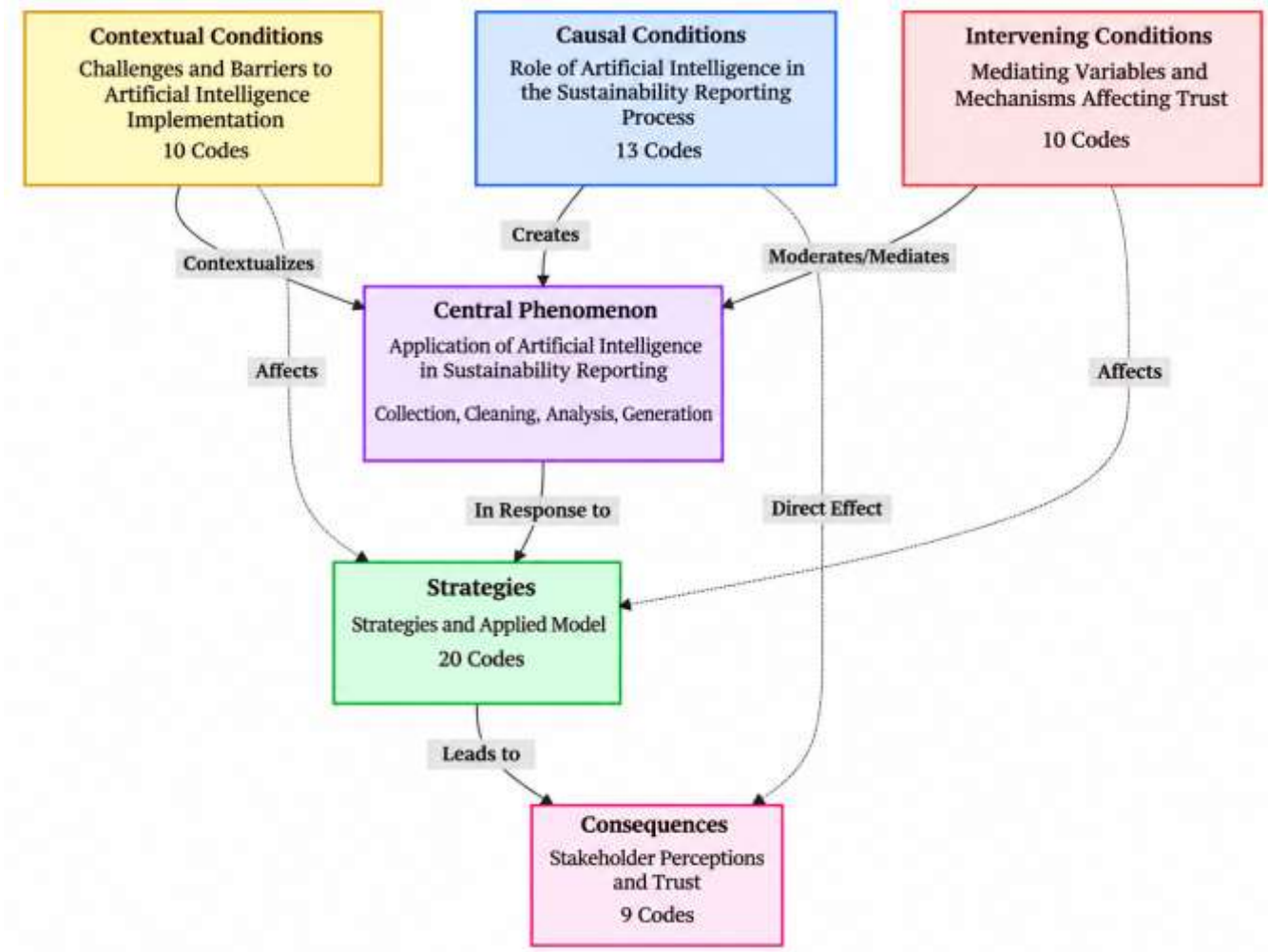

Figure 1. Final Paradigmatic Model

The final paradigmatic model (Figure 1) indicates that stakeholder trust in AI-generated sustainability reports is a complex and multifaceted phenomenon influenced by a set of causal factors, including the role and capabilities of artificial intelligence; contextual factors, including existing challenges and barriers; and intervening factors, including mediating and facilitating variables. In response to these conditions, organizations can adopt various strategies at operational, educational, technical, and policy-making levels, ultimately leading to positive consequences, such as increased trust, or negative consequences, such as reduced trust. This model can serve as a theoretical and operational framework for policymakers, managers, researchers, and other stakeholders.

4. Discussion and Conclusion

The present study developed a paradigmatic model for the use of artificial intelligence in sustainability reporting with particular emphasis on stakeholder trust. The findings showed that stakeholder trust in AI-generated sustainability reports is not produced merely through the adoption of artificial intelligence but rather emerges from the interaction among causal conditions, contextual conditions, intervening mechanisms, organizational strategies, and resulting stakeholder perceptions. The qualitative analysis yielded 62 initial codes organized into five main themes: the role of artificial intelligence in the sustainability reporting process, challenges and barriers to AI implementation, stakeholder perceptions and trust, mediating variables and mechanisms affecting trust, and strategies and an applied model. Selective coding further demonstrated that the application of artificial intelligence in sustainability reporting constitutes the central phenomenon, whereas stakeholder trust represents a critical outcome shaped by the quality and governance of the AI-enabled reporting process. This overall pattern is consistent with the growing literature suggesting that artificial intelligence can substantially transform sustainability reporting

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but that its value depends on governance, transparency, data quality, and organizational readiness (Moodaley & Telukdarie, 2023; Mustafa et al., 2025).

The first major finding concerned the role of artificial intelligence as a causal condition affecting sustainability reporting. Participants emphasized that AI can influence all major stages of the reporting process, including data collection, data cleaning, data analysis, and report generation. These functions were associated with higher speed, improved accuracy, reduced human error, and enhanced capacity to process large and heterogeneous ESG datasets. This finding is aligned with research indicating that artificial intelligence increasingly supports the automation and analytical enhancement of sustainability reporting systems (Mustafa et al., 2025). It also supports the argument that generative AI can improve the quality of digital sustainability reporting by strengthening the analysis of accounting and non-financial data, particularly when effective internal control mechanisms are present (Saghafi & Parsapour, 2025). The present findings further suggest that artificial intelligence should be understood not as a single technological application but as a set of interconnected capabilities that can operate across the sustainability reporting value chain.

The identified role of AI in data analysis and report generation also corresponds with studies examining the contribution of artificial intelligence to ESG performance and sustainable organizational development. AI can enhance corporate efficiency, support faster processing of complex information, and improve the identification of relationships among environmental, social, and governance variables (Yu et al., 2025). Similarly, AI-driven ESG performance has been shown to contribute to the sustainable development of large organizations by strengthening information processing and managerial responsiveness (Xiao & Xiao, 2025). The present study extends this perspective by demonstrating that such analytical capacities are directly relevant to the reporting process itself. In other words, AI does not merely influence underlying ESG performance; it also changes how that performance is captured, analyzed, interpreted, and communicated to stakeholders.

The findings also highlighted the role of complementary technologies such as the Internet of Things and blockchain. Participants viewed such technologies as important infrastructures that can strengthen the effectiveness of AI-enabled sustainability reporting. This interpretation is consistent with research showing that the combination of AI, big data analytics, and the Internet of Things can significantly improve ESG-related data collection and decision support (Rane et al., 2024). Likewise, the integration of AI and blockchain in accounting systems has been shown to contribute to stronger ESG performance through improved risk management, transparency, and information reliability (Nguyen et al., 2026). These findings indicate that AI-enabled sustainability reporting is likely to evolve within a broader digital ecosystem in which multiple technologies operate together rather than independently.

The second major theme concerned implementation challenges and contextual barriers. Participants emphasized technical infrastructure limitations, high implementation costs, shortages of specialized personnel, organizational resistance, cultural barriers, legal uncertainty, ethical concerns, data security risks, and scalability problems. These findings strongly support previous research showing that the adoption of artificial intelligence in sustainability reporting is constrained by both technical and non-technical factors (Mustafa et al., 2025). The literature on artificial intelligence in ESG and finance similarly emphasizes the importance of governance, transparency, data quality, cybersecurity, organizational capabilities, and regulatory development (Lim, 2024). Therefore, the results of the present study reinforce the argument that successful AI adoption cannot be achieved through technological investment alone. Instead, implementation requires organizational, institutional, human, and regulatory conditions that support the responsible use of AI.

The cultural and organizational barriers identified in the interviews are particularly important. Participants noted that resistance to technological change and persistent reliance on traditional reporting practices may reduce organizational willingness to adopt AI-based systems. This finding can also be interpreted through the broader literature on ESG integration, which suggests that the implementation of sustainability-oriented technologies depends on changes in organizational processes, employee capabilities, and strategic priorities (Zulkarnaini et al., 2025). The transition to AI-supported sustainability reporting therefore requires not only software and technical infrastructure but also organizational learning, workforce development, and a supportive managerial culture.

The third major finding involved stakeholder perceptions and trust as consequences of AI-enabled sustainability reporting. Participants emphasized that stakeholders seek sustainability information that is reliable, comparable, transparent,

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understandable, and verifiable. The use of AI was perceived as potentially increasing stakeholder trust when it improves accuracy, documentation, traceability, and consistency. However, AI was also considered capable of undermining trust when algorithms are opaque or when stakeholders cannot understand how reported outputs have been generated. This finding is consistent with the broader conceptualization of sustainability reporting as a mechanism of accountability and stakeholder communication. Earlier work on sustainability reporting standards emphasized that reporting quality depends on the development of credible and consistent disclosure frameworks capable of meeting stakeholder expectations (Aras & Crowther, 2008). More recent evidence likewise indicates that the usefulness and value relevance of ESG disclosures depend on organizational maturity and the quality of the reporting environment (Islam, 2025).

The relationship between AI and stakeholder trust is also supported by research examining the interaction among ESG reporting, artificial intelligence, stakeholders, and sustainability outcomes. The integration of AI into ESG reporting can contribute to sustainability culture and climate resilience when technological applications are aligned with stakeholder expectations and innovation capabilities (Riyath & Jariya, 2024). The findings of the present study add an important explanatory dimension to this literature by showing that trust is not a direct or automatic consequence of AI adoption. Instead, trust is shaped by several intervening mechanisms, including explainability, data quality, independent assurance, organizational transparency, and the presence of effective internal audit functions.

Among the most significant findings was the role of explainability. Participants repeatedly emphasized that the "black-box" nature of AI constitutes a major risk to stakeholder trust. If stakeholders cannot understand how AI reaches particular conclusions or generates sustainability indicators, the credibility of the resulting reports may be weakened. This finding is closely aligned with the literature emphasizing the need for greater transparency in corporate AI disclosures. The development of specific frameworks for reporting the use of artificial intelligence has been proposed as a means of strengthening organizational accountability and increasing the transparency of AI-related practices (Bonsón & Bednárová, 2022). The present study suggests that explainability should be treated not merely as a technical property of AI systems but as a central trust-building mechanism in sustainability reporting.

The role of explainability is also closely related to the broader issue of greenwashing. Although AI can enhance the analytical quality of sustainability reports, opaque AI systems may create new opportunities for selective presentation, untraceable calculations, or automated narratives that stakeholders cannot independently evaluate. Previous research has highlighted the complex relationship among artificial intelligence, sustainability reporting, and greenwashing, showing that AI may both reduce and reproduce reporting risks depending on how it is governed (Moodaley & Telukdarie, 2023). The present findings reinforce this concern by demonstrating that transparency and explainability are necessary conditions for preventing technology from becoming an additional layer of opacity in sustainability disclosure.

Another critical intervening factor was the quality of input data. Participants identified data quality as one of the most important determinants of reliable AI-generated sustainability information. This finding is theoretically important because even highly advanced algorithms cannot compensate for incomplete, inaccurate, outdated, or biased data. The observed importance of data quality is consistent with research showing that AI-supported ESG and sustainability systems depend on reliable and integrated information infrastructures (Nguyen et al., 2026; Rane et al., 2024). It also supports findings showing that AI-based improvements in sustainability reporting are more effective when internal control systems ensure the integrity of the underlying accounting and ESG data (Saghafi & Parsapour, 2025). Thus, the effectiveness of AI in sustainability reporting depends fundamentally on the quality of the data environment within which the algorithms operate.

Independent assurance and internal auditing were also identified as important mechanisms affecting trust. Participants suggested that AI-generated sustainability reports should be subject to internal and external review to ensure that automated outputs remain reliable and accountable. This result is aligned with emerging research on the use of AI in ESG assurance, which indicates that intelligent systems can increase the scope and efficiency of assurance procedures while requiring appropriate professional judgment and oversight (Li et al., 2024). It is also consistent with grounded-theory research on AI-based audit risk modeling in sustainability reporting, which highlights the importance of artificial intelligence for identifying reporting risks and supporting auditor decision-making (Jamali et al., 2025). More advanced approaches using reinforcement learning have likewise been proposed to improve adaptive ESG audit decision-making and anomaly detection (Wang et al.,

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2026). Collectively, these studies support the finding that assurance should not be separated from AI adoption but rather embedded within the architecture of AI-enabled sustainability reporting.

The fifth major theme concerned strategies and the applied model. Participants emphasized the importance of standardization, ethical frameworks, regulatory guidance, gradual implementation, pilot projects, management support, data integration, stakeholder participation, education, cost transparency, and collaboration with universities. These strategies suggest that the transition to AI-enabled sustainability reporting should occur through a structured and incremental process. This finding is supported by research emphasizing the need for systematic governance and policy development around artificial intelligence and sustainability disclosure (Bonsón & Bednárová, 2022; Mustafa et al., 2025). It is also consistent with arguments that AI can contribute to the development of sustainability reporting standards and sustainable financing when appropriate institutional and regulatory frameworks are established (Khodayari-Siar, 2023).

The emphasis on standardization and regulatory guidance also reflects the broader evolution of sustainability reporting itself. The development of credible sustainability reporting has historically required greater standardization, consistency, and comparability (Aras & Crowther, 2008). The findings of this study indicate that the same need now applies to AI-assisted reporting. Organizations require clear expectations regarding acceptable AI applications, documentation requirements, auditability, transparency, model governance, and responsibility for algorithmic decisions. Without such standards, differences in implementation may reduce comparability and increase stakeholder uncertainty.

The importance of gradual implementation through pilot projects was another noteworthy result. Participants suggested that organizations should begin with limited AI applications before expanding to full-scale sustainability reporting systems. This approach can reduce implementation risk, allow organizations to evaluate data quality and algorithmic performance, and provide employees and stakeholders with time to become familiar with the technology. Sector-specific research similarly shows that AI implementation in ESG reporting depends heavily on organizational context, technological readiness, and the ability to adapt existing reporting processes (Strazzullo, 2025). A gradual implementation strategy may therefore help organizations identify practical barriers before committing substantial resources to large-scale transformation.

Overall, the paradigmatic model developed in this study suggests that stakeholder trust is the result of a socio-technical process rather than a simple technological effect. AI capabilities create opportunities for improving sustainability reporting, but these opportunities are shaped by contextual barriers and mediated through data quality, explainability, assurance, organizational transparency, and accountability mechanisms. Appropriate strategies can strengthen these relationships and produce positive stakeholder outcomes, whereas weak governance or inadequate attention to transparency may lead to reduced trust. This interpretation is consistent with the emerging literature showing that AI can improve ESG reporting, assurance, and performance, but that its effectiveness depends on the broader organizational and institutional environment in which it is applied (Lim, 2024; Mustafa et al., 2025; Riyath & Jariya, 2024). The contribution of the present study lies in integrating these previously fragmented factors within a grounded paradigmatic framework and explicitly positioning stakeholder trust as a central outcome of AI-enabled sustainability reporting.

The present study has several limitations. First, the findings were based on interviews with 12 experts and therefore reflect the experiences and interpretations of a relatively small qualitative sample. Although theoretical saturation was achieved, the transferability of the findings to all industries, organizational sizes, and institutional environments should be approached cautiously. Second, the participants represented professional and academic groups involved in sustainability reporting, accounting, auditing, finance, and information technology, but other stakeholder groups such as investors, regulators, employees, customers, and civil society representatives were not directly interviewed. Third, the study focused on perceptions and expert judgments rather than observing actual organizational implementation of AI-enabled sustainability reporting systems. Fourth, because AI technologies and sustainability reporting standards are evolving rapidly, some of the identified challenges and strategies may change as technological and regulatory environments develop.

Future research can extend the present findings by quantitatively testing the relationships proposed in the paradigmatic model using larger and more diverse samples. Researchers may develop measurement instruments for the identified constructs and examine direct, mediating, and moderating effects using structural equation modeling. Comparative studies across industries, countries, and institutional environments could clarify whether the importance of explainability, data quality, assurance, and regulatory support varies across contexts. Future studies may also examine the perspectives of investors,

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regulators, employees, and other external stakeholders and compare them with those of managers and reporting professionals. Longitudinal studies could evaluate how stakeholder trust changes before and after the implementation of AI-enabled sustainability reporting systems. Experimental research may also compare stakeholder reactions to conventional reports, AI-generated reports, and AI-generated reports accompanied by different levels of explainability and independent assurance.

From a practical perspective, organizations should approach AI-enabled sustainability reporting as a governance and trust-building initiative rather than merely as a technology project. Managers should first strengthen data governance, improve the quality and integration of ESG data, and establish clear responsibilities for AI-generated outputs. Explainable AI systems should be prioritized, particularly for high-impact sustainability indicators and disclosures that directly affect investor and stakeholder decisions. Internal auditors and independent assurance providers should be involved from the early stages of system design and implementation. Organizations should adopt pilot-based and phased implementation strategies, provide specialized training for accounting, sustainability, audit, and IT personnel, and create mechanisms for obtaining stakeholder feedback. Regulatory institutions should develop clear standards for transparency, documentation, accountability, auditability, and ethical AI use in sustainability reporting, while universities and professional bodies should contribute through interdisciplinary education and the development of specialized competencies in AI, accounting, auditing, and sustainability.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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