Transforming Sustainability Reporting through Artificial Intelligence: A Systematic Literature Review (2014–2026)

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Abstract

This study examines the transformation of sustainability reporting and the integration of Artificial Intelligence (AI) in ESG reporting, sustainability disclosure, and greenwashing detection. The review is motivated by the increasing complexity of sustainability reporting standards, the growing volume of ESG-related data, and persistent concerns regarding the credibility of symbolic or inconsistent sustainability disclosures. Using a Systematic Literature Review (SLR), this study analyzes 30 selected articles published between 2014 and 2026. The literature selection process was reconstructed using the PRISMA 2020 flow and supported by inclusion and exclusion criteria, quality appraisal, and thematic narrative synthesis. The findings indicate that sustainability reporting has shifted from voluntary non-financial disclosure toward a more strategic, data-driven, and digitally integrated reporting practice. AI, machine learning, Natural Language Processing (NLP), Large Language Models (LLMs), and data analytics are increasingly used to support ESG data processing, narrative extraction, emissions reporting, financial risk analysis, and greenwashing detection. Nevertheless, AI integration also introduces challenges related to data quality, model transparency, algorithmic bias, assurance, and regulatory readiness. This study contributes to the literature by mapping five synthesis themes and outlining future research directions for responsible AI-based sustainability reporting governance.

Keywords: *Sustainability Reporting, ESG, Artificial Intelligence, Machine Learning, Greenwashing*

INTRODUCTION

Sustainability reporting has emerged as a central component of corporate accountability. Environmental, social, and governance information is no longer positioned merely as a supplement to financial statements, but increasingly serves as an important basis for assessing corporate risk, legitimacy, and long-term business sustainability. The GRI Standards explain that sustainability reporting helps organizations understand and report their impacts on the economy, environment, and society in a credible and comparable manner (Global Reporting Initiative 2021). In the capital market context, the demand for sustainability information has also increased, as IFRS S1 emphasizes the disclosure of sustainability-related risks and opportunities that are useful for users of general-purpose financial reports, while IFRS S2 specifically addresses climate-related risks and opportunities (IFRS Foundation 2023a; IFRS Foundation 2023b). In Indonesia, the implementation of sustainable finance has also been reinforced through POJK No. 51/POJK.03/2017, which requires financial service institutions, issuers, and public companies to strengthen sustainability reporting practices (Otoritas Jasa Keuangan 2017).

As sustainability reporting becomes more institutionalized, its role has expanded beyond regulatory compliance. It has become a strategic mechanism through which companies communicate accountability, risk management, and value creation to stakeholders. Prior research shows that firms with strong sustainability practices tend to

demonstrate better organizational processes and long-term performance (Eccles et al. 2014). Integrated reporting also strengthens this function by connecting financial and non-financial information, thereby allowing corporate reports to present a more comprehensive view of organizational value creation (Dumay et al. 2016; de Villiers et al. 2020). From the perspective of capital markets, ESG information has become increasingly relevant for evaluating corporate risks, opportunities, and firm value (Kotsantonis et al. 2016; Velte 2022).

Despite this development, the increasing volume of sustainability disclosure does not necessarily guarantee higher reporting quality or credibility. Arvidsson and Dumay (2022) argue that the key challenge in ESG reporting lies not only in the quantity of disclosed information, but also in its quality, relevance, and relationship with actual corporate performance. This concern becomes more significant in the context of greenwashing, where companies may disclose sustainability claims that are not fully supported by their actual practices. United Nations (2023) describes greenwashing as a communication practice that may mislead the public regarding an organization's environmental commitments or performance.

The growing complexity of ESG information also creates methodological and practical challenges for sustainability reporting. Sustainability reports often contain extensive textual, numerical, and narrative information, while stakeholders increasingly demand information that is timely, consistent, comparable, and verifiable. Manual reporting and evaluation processes may be insufficient to address this complexity, particularly when companies are required to process large datasets, evaluate supply chain emissions, and identify inconsistencies in sustainability narratives. This condition provides a strong rationale for the use of Artificial Intelligence (AI), machine learning, Natural Language Processing (NLP), Large Language Models (LLMs), and data analytics to support the automation, analysis, and validation of sustainability reporting (Kar et al. 2022; Mustafa et al. 2025; Olivares and Astorga De La Cruz 2026).

Recent studies have examined the application of AI in sustainability reporting from different perspectives. Some studies focus on AI-based reporting automation and narrative extraction, while others examine ESG text analysis, emissions measurement, financial risk prediction, and greenwashing detection (Afzal et al. 2026; Magotra et al. 2026; Kim et al. 2026; Jianfeng and Tiantian 2026). These studies indicate that AI has the potential to enhance the efficiency, analytical capacity, and credibility of ESG reporting. However, the literature remains fragmented, and the integration of AI into sustainability reporting also raises unresolved issues related to data governance, model transparency, algorithmic bias, assurance, and regulatory oversight.

Based on this research gap, this study aims to examine the transformation of sustainability reporting and the integration of AI through a Systematic Literature Review of 30 articles published between 2014 and 2026. This study is guided by three research questions: (1) how has research on sustainability reporting and AI integration developed during the 2014–2026 period; (2) what forms of AI, machine learning, NLP, LLMs, and data analytics are applied in ESG reporting and greenwashing detection; and (3) what challenges, limitations, and future research agendas emerge from the integration of AI into sustainability reporting? This study contributes by developing a thematic synthesis that connects sustainability reporting, ESG disclosure, integrated reporting, AI, and greenwashing literature into a coherent framework relevant to academics, companies, auditors, and regulators.

RESEARCH METHODOLOGY

This study adopts a Systematic Literature Review (SLR) approach to identify,

select, assess, and synthesize prior studies in a structured and transparent manner. The literature selection process was developed by adapting the PRISMA 2020 principles, enabling the stages of identification, screening, eligibility assessment, and inclusion to be presented systematically (Page et al. 2021). The SLR approach was considered appropriate because the topic of sustainability reporting and AI covers diverse types of studies, including empirical research, systematic reviews, scoping reviews, bibliometric reviews, and conceptual papers.

The literature search was conducted through Google Scholar, ScienceDirect or Elsevier, Wiley Online Library, SpringerLink or Nature, Emerald Insight, MDPI, Taylor & Francis or Routledge, and national or local journal portals. The search strategy used combinations of keywords related to sustainability reporting, ESG reporting, ESG disclosure, integrated reporting, non-financial reporting, artificial intelligence, AI, machine learning, NLP, LLMs, generative AI, Scope 3 emissions, greenwashing, external assurance, and financial performance. The main Boolean search string was formulated as follows:

(sustainability reporting OR ESG reporting OR ESG disclosure OR integrated reporting OR non-financial reporting) AND (artificial intelligence OR AI OR machine learning OR natural language processing OR NLP OR large language model OR LLM OR generative AI) AND (greenwashing OR text mining OR Scope 3 emissions OR external assurance OR financial performance).

Inclusion and exclusion criteria were applied to ensure that the selected articles were aligned with the focus and objectives of the review. These criteria covered the publication period, type of publication, language, topic relevance, contribution to the research questions, and completeness of metadata.

Table 1. Inclusion and Exclusion Criteria for Literature Selection

Aspect	Inclusion Criteria	Exclusion Criteria
Period	Articles published between 2014 and 2026.	Articles published outside the specified period.
Publication type	Journal articles, review articles, SLRs, scoping reviews, bibliometric reviews, or relevant academic book chapters.	Blogs, popular news articles, non-academic opinions, promotional technology documents, or sources without an academic review process.
Language	Articles written in English or Indonesian.	Articles in other languages that could not be adequately analyzed.
Topic relevance	Articles discussing sustainability reporting, ESG disclosure, integrated reporting, AI, ML, NLP, LLMs, Scope 3 emissions, greenwashing, assurance, or ESG credibility.	Articles unrelated to sustainability reporting, ESG, AI in reporting, accounting, or corporate accountability.
Research questions	Articles that help answer at least one research question.	Articles that do not contribute to the SLR objectives despite containing similar keywords.
Metadata completeness	Articles with complete author names, year, title, publication source, DOI or official link, and traceable abstract or full text.	Articles with incomplete metadata or insufficient content for verification.

Source: Author's own elaboration based on the literature selection process

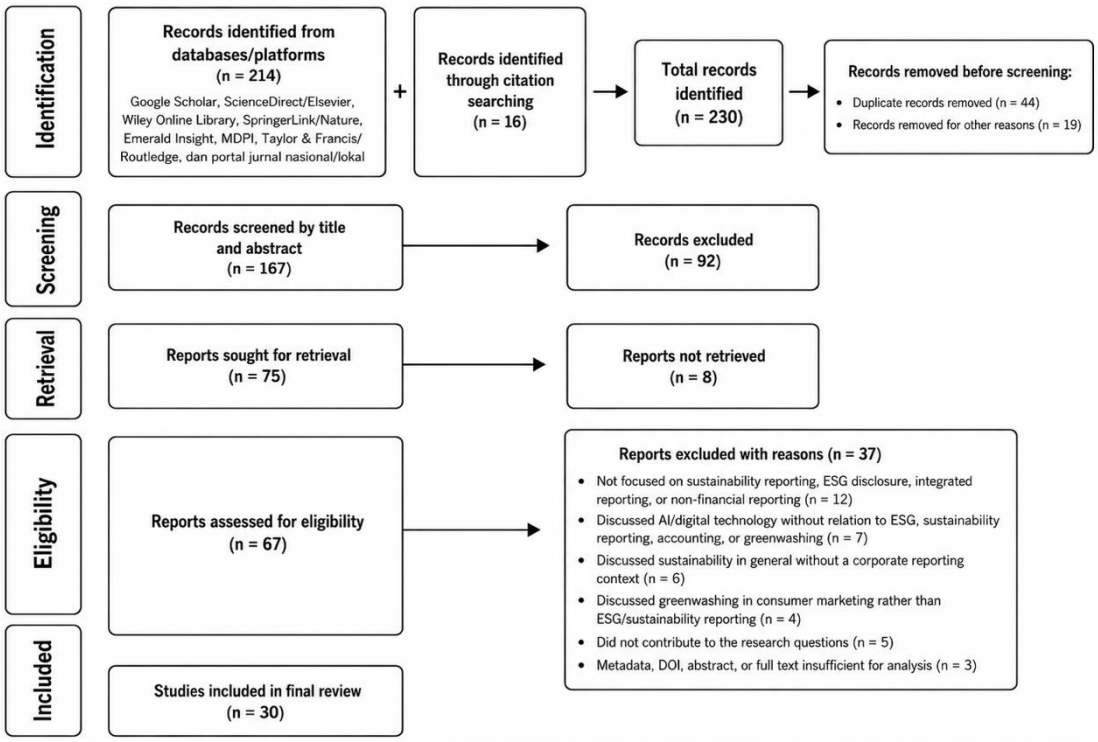
Following the initial selection, the eligible articles were assessed using a quality appraisal checklist adapted from critical appraisal principles. The appraisal covered six aspects: clarity of research objectives, relevance to the SLR focus, clarity of method or analytical framework, verifiability of the source, clarity of findings, and contribution to the research questions. Each aspect was scored from 0 to 2, resulting in a maximum score of 12. Articles scoring 9–12 were categorized as high quality, articles scoring 6–8 as acceptable, and articles scoring below 6 were excluded from the synthesis. All 30 final articles met the minimum eligibility

threshold for further analysis (Critical Appraisal Skills Programme 2024).

Data extracted from each article included the author's name, year, publication source, research objective, method or approach, main findings, and relevance to the research questions. The analytical technique used in this study was thematic narrative synthesis. This technique is suitable for integrating findings from studies with different methodological approaches, contexts, and research focuses without conducting statistical aggregation or meta-analysis. It was selected because the reviewed articles consisted of empirical studies, systematic reviews, scoping reviews, bibliometric reviews, and conceptual papers, making narrative mapping and theme development more appropriate (Popay et al. 2006; Thomas and Harden 2008).

The synthesis process was conducted in three stages. First, open coding was used to identify key concepts from each article, including sustainability reporting, ESG, integrated reporting, AI, machine learning, NLP, LLMs, Scope 3 emissions, greenwashing, and assurance. Second, axial coding was used to connect concepts with similar meanings or analytical focuses, such as the relationship between AI, reporting automation, and ESG analysis. Third, theme formation was conducted to develop synthesis themes based on issue similarity, dominant focus, and each article's contribution to the research questions. The use of open coding and axial coding refers to qualitative coding procedures for systematically developing categories and relationships among concepts (Strauss and Corbin 1998). To avoid overlapping classifications, each article was assigned to one dominant theme. When an article was relevant to more than one theme, its classification was determined based on its main focus and strongest contribution to the research questions.

Figure 1. PRISMA Flow Diagram of the Literature Selection Process



Source: Author's own elaboration adapted from the PRISMA 2020 flow diagram.

RESULTS AND DISCUSSION

The synthesis indicates that research on sustainability reporting and AI has progressed from an early emphasis on reporting quality, integrated reporting, and the relationship between sustainability and corporate performance toward the use of digital technologies for reporting automation, ESG analysis, emissions measurement, and greenwashing detection. Table 2 summarizes the 30 final articles analyzed in this study and their dominant theme classifications.

Table 2. Summary of Articles and Synthesis Theme Classification

No	Article	Main Contribution	Theme
1	Eccles, Ioannou and Serafeim (2014)	Sustainability practices are associated with organizational processes and long-term corporate performance.	Theme 2
2	Frias-Aceituno, Rodriguez-Ariza and Garcia-Sanchez (2014)	Corporate governance influences companies' tendency to issue integrated reports.	Theme 1
3	Dumay, Bernardi, Guthrie and Demartini (2016)	Integrated reporting connects financial and non-financial information to strengthen transparency.	Theme 1
4	Kotsantonis, Pinney and Serafeim (2016)	ESG is an important factor in investment management, risk assessment, and decision-making.	Theme 1
5	de Villiers, Hsiao and Maroun (2020)	Integrated reporting is shaped by organizational context, regulation, and stakeholder information needs.	Theme 1
6	Arvidsson and Dumay (2022)	ESG reporting needs to move beyond information quantity toward quality, relevance, and performance.	Theme 1
7	Velte (2022)	Sustainable corporate governance contributes to materiality disclosure quality in integrated reporting.	Theme 1
8	Kar, Choudhary and Singh (2022)	AI can support sustainability through data processing, prediction, and decision-making capabilities.	Theme 3
9	Chinna (2026)	AI transforms ESG reporting from manual processes into more automated and data-driven reporting.	Theme 3
10	Moodaley and Telukdarie (2023)	The relationship between AI, sustainability reporting, and greenwashing remains underexplored.	Theme 5
11	Qin, Bakoush and McGroarty (2026)	NLP and machine learning extract textual information from sustainability reports to predict financial distress.	Theme 4
12	Mustafa, Smolarski and Elamer (2025)	AI strengthens sustainability reporting but raises regulatory, ethical, and algorithmic bias challenges.	Theme 5
13	Olivares and Astorga De La Cruz (2026)	AI and data analytics accelerate ESG disclosure and improve sustainable financial reporting quality.	Theme 3
14	Hu and Othman (2026)	ESG service capabilities are important for improving the quality and support of ESG reporting.	Theme 2
15	Biancone et al. (2026)	Non-financial reporting in the banking sector has developed due to increasing ESG transparency demands.	Theme 1
16	Almajali (2026)	AI affects environmental performance through the mediating role of ESG reporting.	Theme 3
17	Kilinc, Ince and Badem (2026)	A textual framework based on readability, sentiment, and boilerplate content helps detect potential greenwashing.	Theme 5
18	Magotra et al. (2026)	Machine learning and NLP can analyze ESG and sustainability disclosures on a large scale.	Theme 4
19	Ming, Luan, Bu and Li (2026)	Machine learning can map the relationship between ESG performance and carbon emission reduction pathways.	Theme 4
20	Afzal, Yan, Li and Vasarhelyi (2026)	Generative AI can automatically extract narrative information from corporate reports.	Theme 3

21	Gaybullaev, Miah and Erdei-Gally (2026)	Sustainability practices affect corporate financial performance in the long term.	Theme 2
22	Jhan and Hsieh (2026)	LLM-based ESG summaries and sentiment analysis support sustainability information processing.	Theme 4
23	Hoai (2026)	External assurance enhances ESG report credibility through the mediating role of trust.	Theme 2
24	Kim, Kim, Kum and Vasarhelyi (2026)	Digital platforms support the collection and reporting of Scope 3 emissions data.	Theme 4
25	Pertiwi et al. (2026)	Firm-specific characteristics influence the level of ESG disclosure in Indonesian companies.	Theme 2
26	Belete and Murthy (2026)	AI has the potential to support business sustainability, particularly through strategy and digital reporting.	Theme 3
27	Luo, Xue, Rassiah and Lim (2026)	AI helps reduce mismatches between ESG disclosure and actual ESG practices.	Theme 5
28	Jianfeng and Tiantian (2026)	XGBoost and SHAP can detect ESG greenwashing in a predictive and interpretable manner.	Theme 5
29	Tarigan and Samuel (2014)	Sustainability report disclosure is related to corporate financial performance.	Theme 2
30	Naibaho and Nabilah (2025)	Sustainability reporting and external assurance affect financial performance.	Theme 2

Source: Author's synthesis of the 30 reviewed articles.

The article mapping resulted in five synthesis themes. The first theme explains the development of sustainability reporting, ESG, and integrated reporting. The second theme focuses on determinants, quality, assurance, and the financial impact of ESG reporting. The third theme discusses AI-based automation and digital transformation in sustainability reporting. The fourth theme addresses ESG analysis using machine learning, NLP, LLMs, and emissions measurement. The fifth theme discusses greenwashing detection, smart accountability, and ethical challenges associated with AI.

Table 3. Mapping of Literature Synthesis Themes

Theme	Analytical Focus	Main Articles	Dominant Findings	Research Gap
Development of Sustainability Reporting, ESG, and Integrated Reporting	Evolution of sustainability reporting, ESG disclosure, integrated reporting, and non-financial reporting.	Frias-Aceituno et al. (2014); Dumay et al. (2016); Kotsantonis et al. (2016); de Villiers et al. (2020); Arvidsson and Dumay (2022); Velte (2022); Biancone et al. (2026).	Sustainability reporting has developed from voluntary disclosure into a more integrated accountability mechanism relevant to economic decision-making.	Further research is needed to connect report quality, materiality, regulation, and users' information needs.
Determinants, Quality, Assurance, and Financial Impact of ESG Reporting	Firm-level factors, ESG disclosure quality, external assurance, trust, and financial performance.	Eccles et al. (2014); Tarigan and Samuel (2014); Gaybullaev et al. (2026); Hu and Othman (2026); Hoai (2026); Pertiwi et al. (2026); Naibaho and Nabilah (2025).	ESG reporting quality is influenced by firm characteristics, governance, assurance, and organizational capability in managing sustainability information.	Further testing is needed to examine how digital technology can strengthen ESG assurance and credibility.

AI-Based Automation and Digital Transformation of Sustainability Reporting	Use of AI, generative AI, and data analytics in reporting automation and sustainability information processing.	Kar et al. (2022); Chinna (2026); Afzal et al. (2026); Olivares and Astorga De La Cruz (2026); Almajali (2026); Belete and Murthy (2026).	AI accelerates data collection, narrative extraction, information processing, and the preparation of more efficient ESG reports.	Data governance, organizational readiness, and human oversight are needed to ensure that automation does not reduce report quality.
ESG Analysis Based on Machine Learning, NLP, LLMs, and Emissions Measurement	Text analysis of sustainability reports, sentiment analysis, risk prediction, and carbon emissions measurement.	Qin, Bakoush and McGroarty (2026); Magotra et al. (2026); Ming et al. (2026); Jhan and Hsieh (2026); Kim et al. (2026).	ML, NLP, LLMs, and digital platforms help process large reports, analyze ESG patterns, predict risks, and support Scope 3 reporting.	Model validation, textual data quality, supplier data reliability, and verification of analytical results remain key challenges.
Greenwashing Detection, Smart Accountability, and Ethical Challenges of AI	Use of AI and textual analytics to detect greenwashing, align disclosure with actual practice, and assess ethical risks.	Moodaley and Telukdarie (2023); Mustafa et al. (2025); Kilinc et al. (2026); Luo et al. (2026); Jianfeng and Tiantian (2026).	AI can improve accountability by detecting narrative inconsistencies, exaggerated claims, and mismatches between ESG reports and actual practices.	Major challenges include algorithmic bias, model transparency, interpretability, and regulatory readiness in supervising AI.

Source: Author's thematic synthesis of the reviewed literature.

Development of Sustainability Reporting, ESG, and Integrated Reporting

The first synthesis theme highlights the evolution of sustainability reporting from voluntary disclosure into a more integrated accountability mechanism. Frias-Aceituno et al. (2014) show that governance factors play an important role in encouraging companies to integrate sustainability and financial information. Dumay et al. (2016) further emphasize that integrated reporting functions as a mechanism for connecting financial and non-financial information, allowing corporate reports to become more complete and relevant to stakeholders.

In capital market settings, ESG information has increasingly become part of investment analysis. Kotsantonis et al. (2016) explain that ESG can help investors assess corporate risks and opportunities, while de Villiers et al. (2020) argue that integrated reporting is shaped by institutional pressures, regulatory environments, and the needs of information users. These findings indicate that sustainability reporting is no longer limited to a social responsibility narrative, but has become part of the broader corporate reporting system.

The literature also shows a shift in attention from the quantity of ESG disclosure toward the quality and usefulness of information. Arvidsson and Dumay (2022) argue that the current challenge in ESG reporting is to improve information quality rather than merely increase disclosure volume. Velte (2022) also highlights the importance of materiality disclosure quality in integrated reporting. In the banking sector, Biancone et al. (2026) show that non-financial reporting continues to develop in response to transparency demands and ESG risk management. This theme provides the conceptual basis for understanding why digital technologies, including AI, have become increasingly relevant in sustainability reporting.

Determinants, Quality, Assurance, and Financial Impact of ESG Reporting

The second synthesis theme focuses on the factors that influence ESG reporting quality and its relationship with corporate performance. Eccles et al. (2014) show that firms with strong sustainability practices tend to have better organizational processes and long-term performance. This finding is consistent with Tarigan and Samuel (2014), who identify a relationship between sustainability report disclosure and financial performance. Gaybullaev et al. (2026) also confirm that sustainability practices can influence corporate financial outcomes.

Beyond financial performance, the quality of ESG reporting is shaped by firm characteristics and internal capabilities. Pertiwi et al. (2026) show that firm-specific characteristics can affect the level of ESG disclosure, while Hu and Othman (2026) emphasize the importance of ESG service capabilities in supporting reporting quality. These findings suggest that high-quality ESG reporting depends not only on standards and regulations, but also on organizational readiness to manage sustainability data and reporting processes.

External assurance is another important element in strengthening the credibility of ESG information. Since ESG reports may be exposed to information asymmetry and stakeholder skepticism, assurance can help reduce doubts about the reliability of disclosed information. Hoai (2026) shows that assurance can strengthen ESG report credibility through the mediating role of trust. Naibaho and Nabilah (2025) also show that sustainability reporting and external assurance are associated with financial performance. Therefore, ESG reporting quality requires a combination of governance, reliable data, assurance, and adequate verification mechanisms.

AI-Based Automation and Digital Transformation of Sustainability Reporting

The third synthesis theme shows that AI is reshaping sustainability reporting by shifting the process from manual systems toward faster, more automated, and data-driven practices. Kar et al. (2022) show that AI can support sustainability through data processing, prediction, and decision-making capabilities. Chinna (2026) also emphasizes that AI transforms ESG reporting into a more automated and data-driven process, particularly as companies face increasingly complex reporting requirements.

In corporate reporting, generative AI can support the extraction and preparation of narrative information. Afzal et al. (2026) show that generative AI can automatically extract narrative disclosures from corporate reports. Olivares and Astorga De La Cruz (2026) also explain that AI and data analytics can accelerate sustainable financial reporting and ESG disclosure. These findings suggest that AI functions not only as an administrative tool, but also as an analytical infrastructure for sustainability reporting.

AI is also closely related to environmental performance and sustainability strategy. Almajali (2026) shows that AI technology can influence environmental performance through ESG reporting, while Belete and Murthy (2026) highlight the potential of AI in supporting business sustainability across sectors. Nevertheless, automation cannot be separated from the need for data governance, human validation, and organizational oversight. AI-generated outputs must not only be produced quickly, but also remain accurate, relevant, and trustworthy.

ESG Analysis Based on Machine Learning, NLP, LLMs, and Emissions Measurement

The fourth synthesis theme emphasizes the technical development of ESG analysis through machine learning, NLP, LLMs, and digital platforms. Qin, Bakoush and McGroarty (2026) show that textual information in sustainability reports can be extracted using NLP and incorporated into machine learning models to improve financial distress prediction. This finding indicates that

sustainability reports contain informational value that can be analyzed quantitatively.

Magotra et al. (2026) show that machine learning and NLP can be used to analyze ESG and sustainability disclosures on a large scale. Ming et al. (2026) also apply linear and machine learning approaches to examine ESG performance and carbon emission reduction pathways. Together, these studies demonstrate that analytical technologies can identify patterns that may be difficult to capture through manual analysis.

The development of LLMs creates further opportunities for ESG information processing. Jhan and Hsieh (2026) show that LLM-based ESG summaries and sentiment analysis can help users understand sustainability information more efficiently. Meanwhile, Kim et al. (2026) demonstrate that digital platforms can support the collection of Scope 3 emissions data. However, this theme also highlights several challenges, including textual data quality, supplier data reliability, model validation, and the need to verify AI-generated analytical results.

Greenwashing Detection, Smart Accountability, and Ethical Challenges of AI

The fifth synthesis theme positions AI as a tool for strengthening accountability and detecting greenwashing risks. Moodaley and Telukdarie (2023) show that the relationship between greenwashing, sustainability reporting, and AI remains relatively underexplored, making it an important area for future research. Mustafa et al. (2025) also emphasize that AI can strengthen sustainability reporting, although its application raises ethical, regulatory, and algorithmic bias challenges.

In text-based analysis, Kilinc et al. (2026) develop a multidimensional framework using readability, sentiment, and boilerplate content to detect potential greenwashing in sustainability reporting. Luo et al. (2026) extend this discussion through the concept of smart accountability, which refers to the use of AI to align ESG disclosure with companies' actual ESG practices. Thus, AI can serve as a monitoring mechanism that helps reduce the gap between sustainability narratives and actual corporate actions.

Jianfeng and Tiantian (2026) show that an XGBoost model combined with SHAP can be used to predict ESG greenwashing in an interpretable manner. The use of SHAP is important because it explains the factors that influence prediction results, preventing the model from operating entirely as a black box. However, the main challenges remain model transparency, data quality, developer accountability, and regulatory readiness to ensure that AI is used responsibly in sustainability reporting.

Overall, the synthesis shows that AI plays two major roles in sustainability reporting. First, AI functions as an automation technology that accelerates the collection, extraction, processing, and presentation of ESG information. Second, AI functions as an analytical technology that helps assess information quality, detect inconsistencies, predict risks, measure emissions, and identify greenwashing. These benefits, however, depend on the ability of companies and regulators to strengthen data governance, model transparency, assurance, digital auditing, and algorithmic bias mitigation.

CONCLUSION

Based on a Systematic Literature Review of 30 articles published between 2014 and 2026, this study concludes that sustainability reporting has transformed from informative non-financial disclosure into a strategic, data-driven, and digitally integrated reporting system. Earlier literature emphasizes the importance of sustainability reporting, ESG disclosure, and integrated reporting in strengthening transparency, accountability, and the connection between financial and non-financial information (Dumay et al. 2016; Velte 2022). However, recent developments show that the quantity of

ESG information does not necessarily guarantee report quality and credibility, particularly when greenwashing risks and limitations in sustainability information verification remain present (Arvidsson and Dumay 2022; Moodaley and Telukdarie 2023).

The main contribution of this study is the mapping of the literature into five synthesis themes: the development of sustainability reporting, ESG, and integrated reporting; determinants, quality, assurance, and financial impact of ESG reporting; AI-based automation and digital transformation of sustainability reporting; ESG analysis based on machine learning, NLP, LLMs, and emissions measurement; and greenwashing detection, smart accountability, and ethical challenges of AI. This mapping shows that AI is not only used to accelerate reporting processes, but also to analyze ESG narratives, process sustainability data, measure emissions, predict risks, and detect mismatches between sustainability claims and actual practices (Afzal et al. 2026; Qin et al. 2026; Kim et al. 2026; Luo et al. 2026).

In practical terms, AI integration in sustainability reporting has the potential to improve the efficiency, accuracy, consistency, and credibility of ESG information. However, AI adoption also requires data governance, model transparency, assurance, and regulatory oversight. Future research should therefore focus on explainable AI, algorithmic bias mitigation, AI-based ESG assurance, digital auditing, and regulatory readiness in supervising the use of AI in sustainability reporting.

RECOMMENDATION

Based on the synthesis findings, companies should use AI not only as a tool for report automation, but also as part of sustainability information governance. Companies need to strengthen ESG data quality, reporting system integration, supply chain data validation, and human oversight to ensure that AI-generated analysis remains relevant, reliable, and accountable. Regulators and standard setters should develop guidelines for the use of AI in sustainability reporting, particularly regarding model transparency, bias mitigation, data security, ESG claim verification, and responsibility boundaries when AI is used in reporting processes.

Auditors and assurance providers also need to develop technology-based ESG assurance approaches, including data analytics, NLP, and explainable AI, so that sustainability assurance can respond to the complexity of modern ESG data. Future research is encouraged to empirically examine the effectiveness of AI in improving ESG reporting quality, detecting greenwashing, measuring Scope 3 emissions, and supporting digital audits. Future studies should also examine the readiness of organizations, auditors, and regulators to implement AI ethically, transparently, and accountably within the sustainability reporting ecosystem.

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