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The Convergence of Artificial Intelligence and Sustainability Reporting: A Systematic Review of Applications, Challenges and Future Directions

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ABSTRACT

This research examines the potential of artificial intelligence (AI) to improve sustainability reporting, particularly in relation to environmental, social and governance (ESG) issues. Despite growing interest in the field, the integration of AI in sustainability remains underexplored, especially in terms of its impact on data accuracy, transparency and sustainability reporting effectiveness. This study conducts a systematic literature review (SLR) of 135 peer-reviewed articles to identify significant research gaps and presents a comprehensive framework that integrates AI technologies, such as machine learning, Industry 4.0 innovations and decision support systems (DSS), with sustainability reporting practices. The findings support the need for stronger theoretical and practical frameworks to effectively leverage AI's capabilities in sustainability reporting. The originality of this study is found in its innovative approach to connecting AI technologies with sustainability reporting, a field characterised by fragmentation and underdevelopment in research. This study introduces a broad framework and takes a critical look at the unintended externalities of AI, such as increased inequality and environmental costs. It does this by challenging existing sustainability frameworks, like the GRI and SASB, to change with the times and keep up with new technologies. The emphasis on both the advantages and possible drawbacks of AI in sustainability reporting substantiates the study's publication, providing fresh insights into AI's role in enhancing ethical, transparent and effective ESG disclosures. The study offers recommendations for managers and policymakers aimed at improving the accuracy, transparency and credibility of ESG disclosures via AI-driven solutions, thereby promoting more effective sustainability practices. This paper provides a framework for future research and practical application of AI in sustainability reporting, with the goal of enhancing academic knowledge and real-world practices in the pursuit of sustainable development.

1 | Introduction

Sustainability has evolved from a theoretical construct into a global imperative, deeply woven into both policy frameworks and corporate strategies (de Villiers et al. 2021). Anchored by the principle of meeting present needs without jeopardising the ability of future generations to do the same, sustainability has been formally institutionalised through the United Nations Sustainable Development Goals (SDGs), which offer a blueprint for organisations to integrate economic, social and environmental issues into their long-term strategies (Mustafa, Lodh, et al. 2022; United Nations 2015). While the SDGs have gained considerable traction, many organisations continue to disproportionately prioritise the economic dimension, often sidelining the environmental and social pillars (de Villiers et al. 2021). This unbalanced focus has become increasingly untenable as businesses face growing pressure from regulators, investors and civil society to act more responsibly and adopt more holistic sustainability practices (KPMG 2020; Truby 2020).

Despite theoretical advancements in the field, organisations face considerable practical challenges in aligning their operations with sustainability frameworks. The credibility of environmental, social and governance (ESG) reporting constitutes a significant obstacle to the efficacy of corporate social responsibility (CSR) disclosures. Furthermore, high-profile cases of greenwashing—where businesses purposefully misrepresent their ecological performance—have eroded public trust in their sustainability reporting (Li et al. 2024; Tsang et al. 2023).

Sustainability reporting offers stakeholders insight into a company's commitment to economic, environmental and social performance. Frameworks such as the Global Reporting Initiative (GRI) and the recently established International Sustainability Standards Board (ISSB) under the IFRS Foundation have been instrumental in harmonising these reporting practices (Kazemi et al. 2023). However, many businesses continue to struggle with fragmented and inconsistent reporting approaches, often failing to capture the full spectrum of their sustainability impacts (Cheng et al. 2023; Moloi and Obeid 2024).

Amidst these pressures, AI has emerged as a transformative solution, offering the potential to significantly enhance decision-making and operational efficiency across different industries (Di Vaio et al. 2020; Oppioli et al. 2023; Nishant et al. 2020; Singh et al. 2024). AI, defined as a collection of technologies designed to simulate human intelligence and autonomously perform complex tasks, has already begun reshaping the business landscape (Hoehndorf and Queralt-Rosinach 2017; Moloi and Obeid 2024).

In a sustainability context, AI-driven predictive analytics have significantly enhanced supply chain management by minimising inefficiencies and forecasting disruptions, resulting in annual savings of billions for companies (Helo and Hao 2022; Kumar, Mangla, et al. 2021; Joardar and Sarkis 2021; Naz et al. 2022). Machine learning (ML) algorithms have similarly optimised energy consumption in manufacturing, allowing industries to reduce energy costs (Kapp et al. 2023; Mhlanga 2023). AI also is involved in environmental sustainability contexts, including climate change mitigation, smart cities and resource optimisation (De Guimarães et al. 2020; Di Vaio et al. 2020). AI-driven solutions, such as autonomous drones for real-time environmental monitoring, AI-assisted renewable energy forecasting and precision agriculture, have significantly improved sustainability goals (Getahun et al. 2024; Truby 2020).

Although AI has been acknowledged for its ability to enhance sustainability, especially in the precise processing of large and complex datasets, its integration into sustainability reporting remains fragmented and insufficiently underexplored. Di Vaio et al. (2020) offer a quantitative analysis of AI's role in sustainable business models, emphasising its effects on production and sustainable consumption as well as the enhancement of knowledge management systems. Simultaneously, literature has expressed growing apprehension regarding the ethical implications of unregulated AI implementation by leading technology companies, especially in developing countries (Truby 2020). Concerns include insufficient transparency, algorithmic bias and data misuse, all of which jeopardise advancements in critical SDGs, including financial inclusion and poverty reduction.

Regona et al. (2024) studied the AI applications throughout construction project phases, aligning their results with various SDGs. Their work identified challenges in adoption, ethical considerations and the potential for AI to enhance sustainability in the construction sector. Other studies emphasise the increasing acknowledgement of AI's potential for sustainable development while demonstrating a clear gap in the literature regarding its systematic application in sustainability reporting. Even though there is an increasing complexity of ESG data, there is still an absence of comprehensive frameworks that incorporate AI technologies and themes, such as decision support systems and innovation, into sustainability reporting, ensuring transparency, credibility and alignment with the SDGs (Kazemi et al. 2023).

To address this gap, the current study conducts a systematic literature review (SLR) to map the intersection of AI and sustainability reporting, identifying key trends, thematic areas and directions for future research. This review responds to many scholars who have highlighted the fragmented nature of existing research at this intersection and the need for a more structured synthesis of knowledge (Kazemi et al. 2023; Regona et al. 2024; Tiwari and Khan 2020; Mustafa, Mordi, et al. 2024). Thus, this study aims to answer the following research questions, each of which responds to specific calls in the literature:

What are the primary trends in AI and sustainability reporting research, including geographical areas, yearly publications, research methods and theoretical frameworks?

Many studies have pointed to the predominance of conceptual over empirical work, and the need for a wider understanding of the gaps in literature to have a coherent theoretical underpinning in AI–sustainability reporting studies (e.g., Di Vaio et al. 2020; Kazemi et al. 2023; Mustafa, Mordi, et al. 2024). This question helps to map these patterns systematically and provides a foundation for key trends that will lead future researchers based on a strong understanding of the existing work.

What are the major themes investigated in AI and sustainability reporting within the research context?

Thematic fragmentation has been widely noted in prior research and analyses, with scholars calling for a more integrative estimation of the focus areas and topics of digitalisation, AI and sustainability reporting (e.g., Kazemi et al. 2023; Palmaccio et al. 2021; Mahran and Elamer 2024; Mustafa, Lodh, et al., 2022). Addressing this question helps clarify which areas have received the most scholarly attention and which remain underexplored.

What gaps and limitations exist in the current body of literature, and how can future research address these gaps?

Several studies have clearly noted the lack of inclusive reviews that identify and synthesise the limitations and blind spots in current literature, including areas to be covered, methodological constraints, or insufficient cross-disciplinary dialogue (Di Vaio et al. 2020; Kazemi et al. 2023; Mustafa, Lodh, et al., 2022). Therefore, the third question aims to consolidate these observations and suggest directions for future research in the field.

To address these questions, this study utilises an SLR and bibliometric analysis to investigate the potential of AI in improving sustainability reporting. A total of 135 peer-reviewed journal articles were picked from Scopus and Web of Science, employing stringent screening criteria based on journal quality (ABS 3, 4, 4* and SJR Q1 scores). These articles encompass the domains of business, accounting, management, finance and economics, identified using a thorough keyword approach guided by professional insights and established methodologies like PRISMA and SPAR-4-SLR. This methodological approach ensures openness, reliability and replicability, thereby establishing a solid foundation for the integrated framework and the practical insights presented in the study.

This research study has four interrelated objectives. First, it aims to identify and synthesise key trends in the academic literature on AI and sustainability reporting, including geographic distribution, changes in patterns in publication years, applied methodological approaches and used theoretical frameworks. Second, it focuses on mapping the thematic structure of the field by uncovering the main themes and research clusters of scholarly focus. Lastly, we endeavour to critically evaluate the limitations and gaps in the current body of knowledge where research remains underdeveloped. As a result, we propose an integrated framework for AI applications in sustainability reporting and outline future research directions and practical implications for academics, practitioners and policymakers that can be applied across various stages of AI applications for sustainability reporting.

The remainder of this paper is structured as follows: Section 2 details the methodology used for the literature review. Section 3 presents the findings of the review, focusing on identified trends, themes and gaps. Section 4 discusses future research directions and practical implications. Finally, Section 5 concludes the paper with a summary of key findings and contributions.

2 | Theoretical Framework

Sustainability reporting has significantly transformed over recent decades, transitioning from voluntary corporate social responsibility (CSR) disclosures to established and regulated systems that align with global development objectives. Initial sustainability reporting was predominantly narrative-driven and exhibited inconsistency across various businesses and nations (Damaceno et al. 2025). Over time, frameworks such as the GRI, Integrated Reporting and the more recent International Sustainability Standards Board (ISSB) have aimed to standardise sustainability disclosures and improve their comparability, reliability and materiality (Kazemi et al. 2023).

The growing institutionalisation of sustainability reporting has produced extensive amounts of structured and unstructured data, hence fostering an environment conducive to the use of AI technology. AI presents prospective solutions to the intricacies, subjectivity and scalability issues inherent in conventional sustainability reporting, especially concerning ESG performance evaluation, real-time monitoring and compliance with various reporting standards (Alshahrani et al. 2022; Kazemi et al. 2023). The incorporation of AI into sustainability reporting signifies a merging of technological advancement and strategic management.

The resource-based view (RBV) theory asserts that an organisation's enduring competitive advantage stems from its capacity to obtain and efficiently utilise resources that are valuable, rare, inimitable and non-substitutable (VRIN) (J. Barney 1991). The potential of AI as a strategic resource is evident in its capacity to enhance operational efficiency, improve decision-making and bolster the credibility of sustainability disclosures (De Villiers et al. 2024). Machine learning algorithms can efficiently process extensive ESG data, recognise patterns and produce actionable insights more rapidly and accurately than conventional approaches (Zhang and Zhang 2024). These capabilities allow firms to comply with regulatory frameworks and demonstrate leadership in transparency and accountability, thus reinforcing their competitive position in sustainability-conscious markets.

This reconceptualisation is particularly significant in the realm of AI-enhanced sustainability reporting. AI derives value when integrated with company-specific investments, including data infrastructure and stakeholder confidence (De Villiers et al. 2024). The potential of AI depends on stakeholder participation, with stakeholders—including investors, regulators and consumers—acting as providers of strategic resources. However, Acquisti et al. (2015) emphasise that the processes regulating the collecting and dissemination of consumer data frequently lack transparency, resulting in discrepancies between expressed desires and actual behaviours.

Nonetheless, RBV emphasises the necessity of resources to fully leverage the advantages of AI in sustainability reporting (Alkaraan et al. 2024). Thus, organisations need to invest in capabilities including strong data governance systems, technical expertise and ethical frameworks to address risks linked to AI deployment, such as algorithmic biases.

Building on RBV, stakeholder theory offers an additional perspective for understanding how firms can effectively manage relationships with key stakeholders to attain sustainable value creation. The new stakeholder theory (McGahan 2021) posits that stakeholders are essential contributors of strategic resources rather than just external entities. Effective stakeholder management necessitates credible commitments to share value with resource providers, thereby incentivising firm-specific investments that promote long-term value creation (J. B. Barney 2018).

Stakeholders require enhanced accountability and transparency in sustainability reporting, especially regarding ESG challenges. AI technologies enable firms to fulfill these expectations by improving the accuracy, comparability and timeliness of ESG disclosures. Stoelhorst (2023) emphasises that attaining these outcomes necessitates that firms address challenges related to trust and perceived opportunism. Stakeholders may be reluctant to invest in firm-specific resources, including data provision or collaboration on sustainability initiatives, due to concerns about exploitation or marginalisation.

3 | Methodology

This study employs SLR and bibliometric analysis to rigorously explore the intersection of AI and sustainability reporting. The decision to adopt an SLR stems from its proven ability to synthesise expansive and interdisciplinary bodies of knowledge systematically, minimising bias and enhancing the accuracy of findings compared to traditional narrative reviews (Massaro et al. 2015; Haddaway et al. 2015; Mahran and Elamer 2024; Marzi et al. 2025; Manes-Rossi et al. 2020; Nicolò et al. 2024).

Systematic reviews are particularly beneficial in fields where knowledge is rapidly expanding, such as AI applications in sustainability (Kumar, Sahoo, et al. 2022). By adhering to established protocols, this study ensures transparency, replicability and reliability, distinguishing it from less structured review methods (Palmaccio et al. 2021; Songini et al. 2023). Specifically,

TABLE 1 | Procedure for reviewing using the SPAR-4-SLR protocol.

Assembling	
Identification	
Research questions	• What are the primary trends in AI and sustainability reporting research, geographical areas, yearly publications, research methods, authors, and theoretical frameworks? • What are the main themes investigated in the context of AI and sustainability reporting in the research context? • What gaps and limitations need to be addressed in future academic research?
Source quality	• Association of Business Schools (ABS, 2018) • Scimago Journal & Country Rank (SJR) journal ranking systems. • According to the ABS • Papers rated 3, 4 and 4* • Q1 papers the SJR system
Acquisition	
Keywords	'sustainability report*', 'sustainable report*', 'ESG report*', 'integrated report*', 'Artificial intelligence', 'AI', 'intelligent system*', 'machine learning', 'deep learning', 'AI algorithm*', 'algorithmic intelligence', 'natural language processing', 'NLP', 'neural network*', 'predictive analytics', 'automated financial reporting', 'augmented intelligence', 'sentiment analysis tool', 'supply chain optimisation', 'real-time risk assessments', 'quantum computing', 'sustainability disclosure', 'environmental, social, and governance disclosure', 'ESG AND disclosure*', 'non*financial AND report*', 'corporate social responsibility report*', 'corporate responsibility report*', 'sustainable finance report*', 'social AND * AND report*', 'CSR report*', 'responsible business report*', 'triple bottom line report*', 'TBL reporting', 'sustainable finance performance', 'corporate citizenship reporting', 'human rights reporting', 'social responsibility disclosure', 'social sustainability performance', 'social AND * AND disclosure'.
Search period	1996 to July 2024
Arranging	
Language	English
Document Type	Articles
Source	Academic journal
Assessing	
Performance analysis	Research question 1
Themes	Research question 2
Research gap, Discussion and Conclusions	Research question 3
Convention	Tables, figures and narrative
Fund	There is no fund

we follow the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) and Scientific Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) frameworks (Kumar, Sahoo, et al. 2022; Kazemi et al. 2023; Palmaccio et al. 2021; Marzi et al. 2025).

3.1 | Assembling

In the first phase of the SPAR-4-SLR protocol—assembling—we aimed to compile a comprehensive body of literature on AI and sustainability reporting to address the research questions as presented in Table 1. The study focused on two journal ranking systems: the Association of Business Schools (ABS, 2018) and the Scimago Journal & Country Rank (SJR). Articles rated 3, 4 and 4* in ABS, as well as those ranked Q1 in SJR, were included to ensure high-quality sources (Mustafa, Lodh, et al. 2022; Lim et al. 2021; Palmaccio et al. 2021; Nicolò et al. 2024).

For the data collection process, Scopus and Web of Science were chosen due to their extensive coverage of peer-reviewed journal articles across multiple disciplines, including business, accounting, finance, management and economics (Kazemi et al. 2023; Lu et al. 2022). Unlike grey literature (e.g., conference proceedings, working papers and book chapters), which may represent ongoing or preliminary work, we exclusively included peer-reviewed journal articles to ensure the incorporation of rigorously evaluated research.

Our SLR search was conducted up to July 2024, with no start date limitation to include all relevant articles. Guided by preliminary reviews from topic experts, we used macro keywords such as 'sustainability report*', sustainable report*', ESG report*' and 'integrated report*' for the reporting side. Keywords for artificial intelligence included 'Artificial intelligence' and 'AI.' Other keywords were identified based on the search and through a review of the top-cited and recent articles on sustainability reporting and AI in Google Scholar. These keywords include 'intelligent system*', 'machine learning', 'deep learning', 'AI algorithm*', 'algorithmic intelligence', 'natural language processing', 'NLP', 'neural network*', 'predictive analytics', 'automated financial reporting', 'augmented intelligence', 'sentiment analysis tool', 'supply chain optimisation', 'real-time risk assessments' and 'quantum computing'. The sustainability reporting keywords include 'sustainability disclosure', 'environmental, social, and governance disclosure', 'ESG AND disclosure*', 'nonfinancial AND report', 'corporate social responsibility report*', 'corporate responsibility report*', 'sustainable finance report*', 'social AND * AND report*', 'CSR report*', 'responsible business report*', 'triple bottom line report*', 'TBL reporting', 'sustainable finance performance', 'corporate citizenship reporting', 'human rights reporting', 'social responsibility disclosure', 'social sustainability performance' and 'social AND * AND disclosure'.[1]

3.2 | Arranging

During the arranging phase, we refined and organised the initial search results to yield a final sample for analysis. Our initial search produced 4051 articles. These were filtered based on subject areas, language, document type and source type, redundancy between databases, this reduced the number to 2381 papers. A structured two-stage screening and review was implemented on the initial pool of 2381 articles to ensure rigour, transparency and replicability in the exclusion process. A title and abstract review were performed in the initial stage to exclude studies that were evidently irrelevant. This included articles that referenced terms like 'AI' or 'sustainability' only at a superficial level, failing to address their integration within the framework of sustainability reporting. Papers that concentrated solely on technical advancements in AI, such as algorithmic development or engineering applications, were excluded if they lacked relevance to reporting practices, corporate sustainability or ESG disclosures. After removing irrelevant studies, we further narrowed the sample to 524 articles based on the ranking criteria (ABS 3, 4, 4* or SJR Q1), resulting in a final dataset of 135 articles.

The PRISMA chart (Figure 1) illustrates the article selection process (Kumar, Sahoo, et al. 2022; Kazemi et al. 2023; Palmaccio et al. 2021; Mustafa, Lodh, et al. 2022; Manes-Rossi et al. 2020). Discrepancies in judgement were addressed by the authors through discussion to ensure consistency and mitigate selection bias. This systematic approach improved the reliability of the final sample and ensured the inclusion of only those studies that significantly contributed to the intersection of AI and sustainability reporting.

3.3 | Assessing

In the assessing phase, we focused on analysing and synthesising the final sample of 135 articles. Performance analysis was conducted using Excel to identify trends such as top authors, journals, citation counts and geographical distribution of research. This helped us address the first research question concerning the primary trends in AI and sustainability reporting research.

For the second research question, we performed science mapping using VOSviewer, allowing us to visualise and identify key research themes and clusters within the literature. These methods enabled us to uncover both well-established and emerging research themes, highlighting areas of concentration as well as gaps in the literature. This dual approach of performance analysis and science mapping provided a comprehensive understanding of the current state of AI applications in sustainability reporting.

4 | Systematic Literature Review Results

4.1 | Publication Year

Figure 2 illustrates the number of publications on AI and sustainability reporting by year. The earliest identified paper in our dataset was authored by Miller (1996), followed by Lin et al. (2003), who explored the application of neural networks in fraud detection, marking the first notable academic inquiry into AI's role in reporting.

The number of publications remained relatively low from 1999 to 2015, with only one to six papers published annually. This period coincides with limited corporate focus on sustainability reporting, largely due to the lack of stringent legal

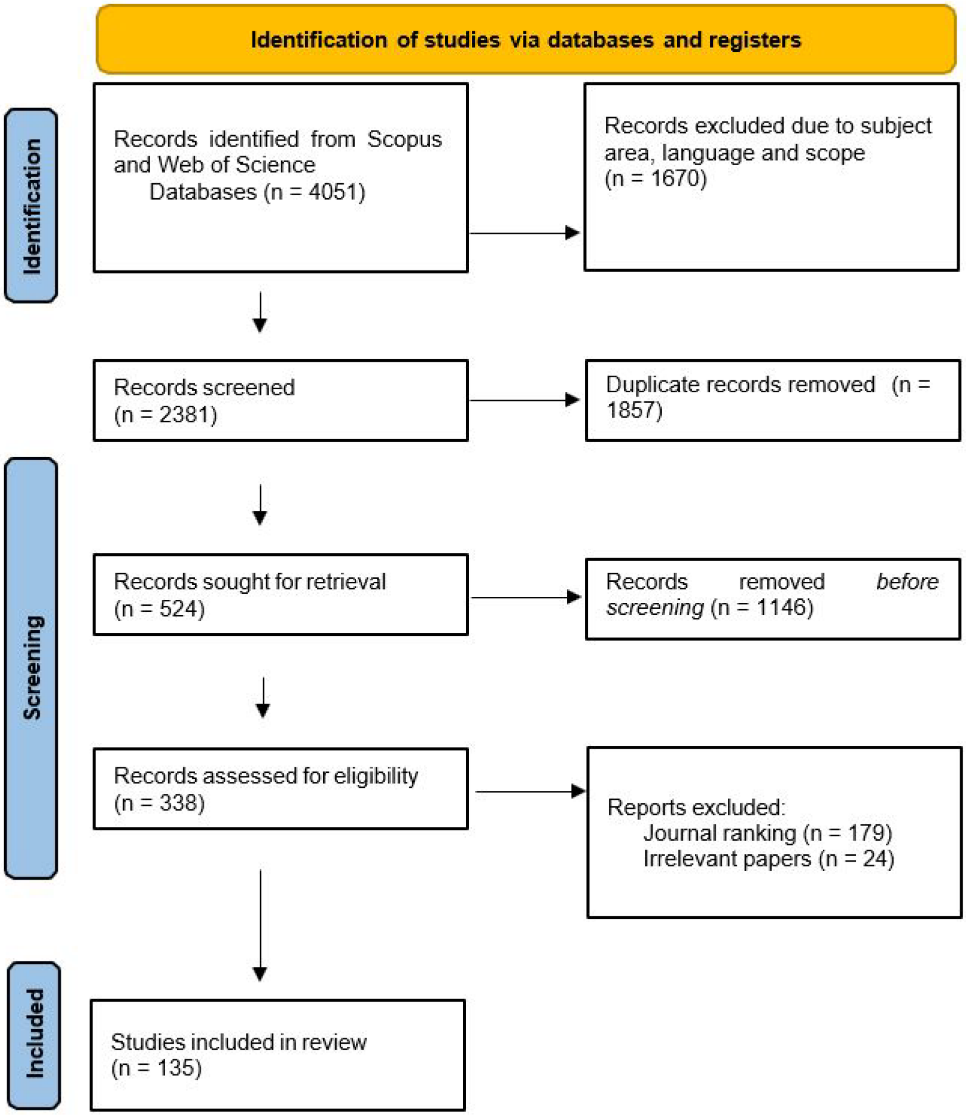

FIGURE 1 | PRISMA chart.

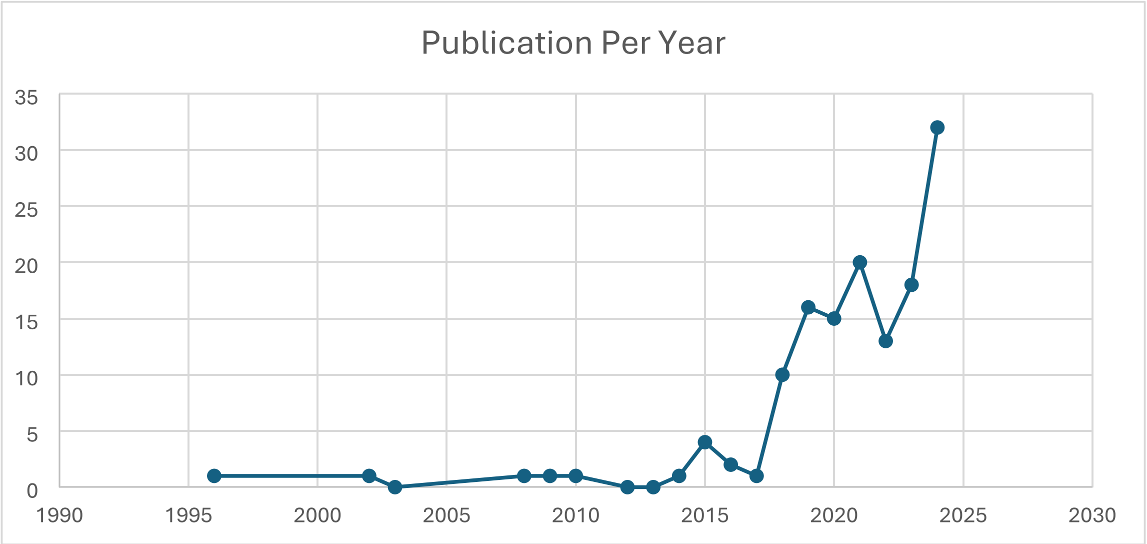

FIGURE 2 | Publications per year.

frameworks requiring action on environmental and social issues (Angelakoglou and Gaidajis 2015).

However, a significant increase in publications occurred in 2016, 2017 and 2019, corresponding to the rising global focus on sustainability after key events such as the 2015 Paris Climate Agreement (Bamgbade et al. 2017), which drove heightened research interest and publication rates, as reflected in Table 2.

TABLE 2 | Number of publications per year.

Year	Number of papers	Number of citations
1996	1	1
2002	1	42
2003	0	72
2008	1	95
2009	1	127
2010	1	135
2012	0	132
2013	0	168
2014	1	187
2015	4	272
2016	2	293
2017	1	341
2018	10	651
2019	16	1088
2020	15	1126
2021	20	720
2022	13	229
2023	18	124
2024	32	102

TABLE 3 | Number of citations by journal.

Rank	Journal	Number of papers	Number of citations
1	Journal of Cleaner Production	46	2735
2	Technological Forecasting and Social Change	4	780
3	International Journal of Accounting Information Systems	5	322
4	International Journal of Production Economics	4	278
5	International Journal of Production Research	4	266
6	Journal of Economic Behavior and Organization	1	183
7	British Accounting Review	1	179
8	Journal of Business Ethics	1	170
9	Managerial Auditing Journal	1	130
10	Business Strategy and the Environment	7	90

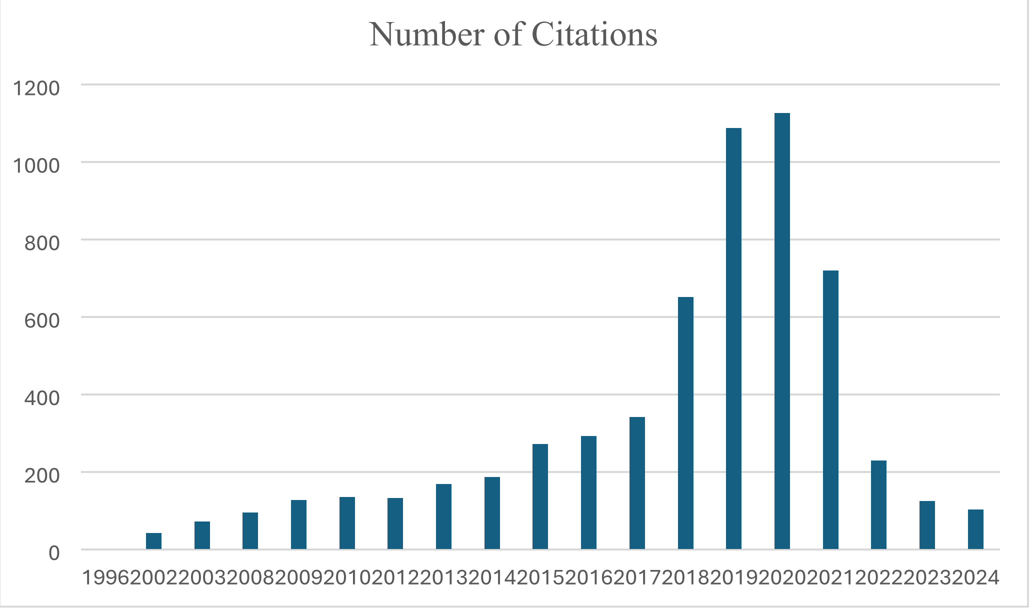

FIGURE 3 | Citation per year.

The surge in publications after 2015 can be attributed to regulatory developments and international agreements, prompting businesses to take sustainability reporting more seriously, such as the 2015 Paris Climate Agreement (Bamgbade et al. 2017; Mustafa, Lodh, et al. 2022) and the International Integrated Reporting Council's (IIRC) framework from 2013, focusing on sustainability reporting models in different countries (Mustafa, Lodh, et al. 2022; Kazemi et al. 2023). This trend is also evident in the increasing citation count over the years, as shown in Figure 3, underscoring the growing academic and practical interest in the field to answer the research question.

4.2 | Journal Analysis

Our analysis of 135 papers reveals that these were spread across 46 academic journals. The diversity of journals indicates a broad interest in AI and sustainability reporting but also highlights the fragmented nature of the research. Among these, 26 journals published only one paper each, while 19 journals published fewer than 10 papers, reflecting the need for more concentrated research efforts.

Notably, the Journal of Cleaner Production emerged as the most prominent publication platform, with 46 papers and 2735 citations, demonstrating its central role in disseminating research on AI and sustainability. Following this, Business Strategy and the Environment and Technological Forecasting and Social Change were also leading outlets in terms of citations, further emphasising their influence in shaping the discourse on sustainability reporting and AI (Table 3).

Figure 4 illustrates the number of citations per journal.

4.3 | Authors

Table 6, panel A, highlights the most prolific authors based on the number of publications and citations. Angappa Gunasekaran emerged as the leading author with two publications and 652 citations, reflecting his significant impact on the field. Other notable contributors include Miklos Vasarhelyi and Ana Carvalho, who have also shaped research on AI and sustainability through their highly cited work.

4.4 | Regional Analysis and Geographical Focus

The geographical distribution of research in AI and sustainability reporting reflects a concentration of studies in a few key regions. The United States, United Kingdom and China were the most prolific, collectively accounting for a significant portion of the literature, as shown in Table 4.

The United States led with 54 papers, followed by the United Kingdom (41 papers) and China (42 papers). Countries such as India, France and Australia also contributed significantly. In contrast, regions like Sweden, Hong Kong and South Africa had minimal representation. This indicates a global interest in sustainability reporting but highlights disparities in research output across different regions as seen in Figure 4.

4.5 | Methodology Analysis

The analysis of methodologies employed in the reviewed papers shows a growing trend toward quantitative research, with 59 studies using quantitative methods. These typically involved survey data and secondary data analysis. Qualitative

TABLE 4 | Authors and citations.

Authors	Number of papers	Number of citations
Gunasekaran, Angappa	2	652
Vasarhelyi, Miklos	2	425
Carvalho, Ana	2	407
Mittelstadt, Brent	2	341
Wachter, Sandra	2	339
Sarkis, Joseph	2	339

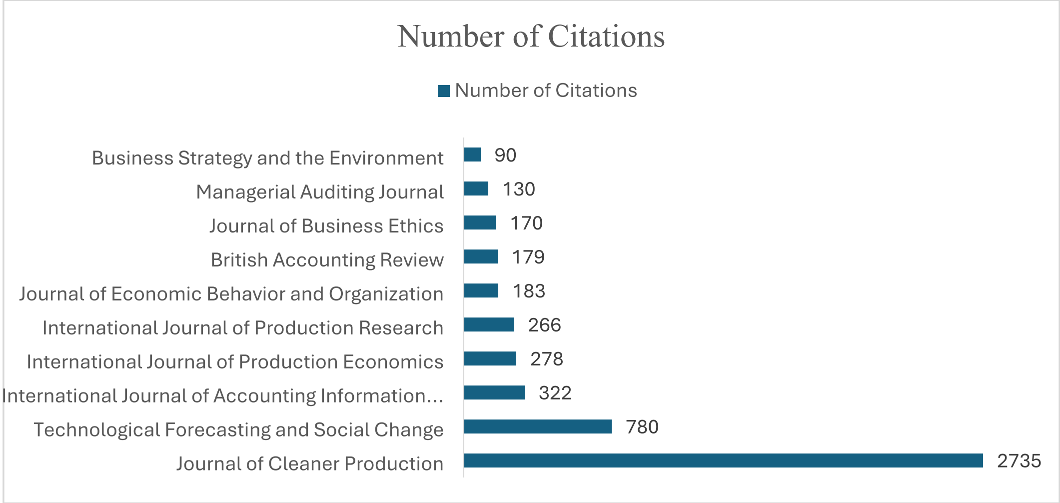

FIGURE 4 | Citation per journal.

TABLE 5 | Number of papers per country.

Country	Number of papers	Number of citations
United States	54	2929
United Kingdom	41	2983
China	42	1231
India	28	1172
France	13	914
Australia	19	334
Italy	17	288
Canada	12	303

TABLE 6 | Number of papers per method.

Country	Number of papers	Number of citations
Quantitative methods	59	5429
Qualitative methods	32	2925
Mixed methods	44	4174

TABLE 7 | Theoretical foundation.

Theory	Number of papers
Resource-based view	59
Stakeholder theory	42
Technology acceptance model (TAM)	37
Diffusion of innovation theory	32
Fuzzy set theory	28
Game theory	18
Circular economy theory	19
Legitimacy theory	15
Signalling theory	13
Voluntary disclosure theory	9

methodologies, although less common, have gained traction in recent years, with 32 studies employing case studies and interviews. Additionally, 44 studies utilised mixed-method approaches, combining both qualitative and quantitative analyses.

The preference for quantitative and mixed-method approaches reflects the increasing need for empirical validation of AI applications in sustainability reporting, especially as regulatory pressures and the demand for environmental transparency grow. The rise of mixed-methods research also points to the complexity of AI's role in sustainability, which often requires multiple methodological perspectives for comprehensive analysis as seen in Table 5.

4.6 | Theoretical Perspectives

A significant portion of the reviewed literature (42%) lacked a clear theoretical foundation. However, of the papers that did incorporate theory, the most frequently used were the RBV, stakeholder theory and technology acceptance model (TAM), as shown in Table 6, panel B. Theories such as diffusion of innovation and fuzzy set theory were also commonly applied, particularly in studies focusing on the adoption and implementation of AI technologies in sustainability reporting.

This study utilised specific theoretical frameworks and methodologies to address research question 3, which aims to identify gaps and limitations in existing literature and suggest future research directions. Game theory underscores the problem of selective disclosure by firms, highlighting the necessity for enhanced transparency and comprehensive reporting mechanisms. This insight identified a significant gap in the provision of unbiased and balanced sustainability reports regarding organisational performance, a gap that AI-driven systems could potentially mitigate.

Tables 7 and 8 outline the key theories applied in the reviewed literature and their respective contributions to the understanding of AI and sustainability reporting. Notably, game theory has been utilised to examine how companies often selectively disclose information, emphasising positive details while omitting negative aspects. This tendency, historically associated with financial reporting, has extended to non-financial disclosures, influencing analysts' ability to form a comprehensive understanding of a company's operations (Bonsón et al. 2023; Allaoui et al. 2019; Chalmardi and Camacho-Vallejo 2019). The literature suggests that applying game theory in sustainability reporting could foster more transparent and balanced disclosures through models that combine multi-agent systems to create mutually beneficial partnerships in both centralised and decentralised reporting scenarios. The TAM is another frequently applied framework that focuses on factors influencing users' intentions to adopt new technologies, such as AI, in sustainability reporting. These factors include individual motivations, demographic attributes and organisational environments (Esposito et al. 2024). TAM provides valuable insights into how the interaction between these factors can shape the successful adoption of AI tools in sustainability practices. The RBV theory offers a perspective on how firms leverage resources to respond to environmental pressures, particularly through non-financial disclosures. Studies applying RBV suggest that corporate sustainability strategies often stem from a firm's need to innovate in response to growing stakeholder demands for environmental accountability (Liu et al. 2024; Sufi et al. 2024; Esposito et al. 2024). In this context, AI's role in enhancing sentiment analysis and the transparency of disclosures is highlighted as a critical tool for firms to improve sustainability reporting. Stakeholder theory provides a framework for analysing the discrepancy between stakeholder expectations and corporate commitments to sustainability. Research grounded in this theory reveals that while stakeholders are increasingly focused on environmental transparency, companies' involvement in sustainability

TABLE 8 | Theories and literature outcomes.

Theory	Theory description	Authors	Key outcomes
Game theory	Game theory emphasises the strategic actions of firms in the selective disclosure of information, a significant concern in sustainability reporting. This study integrates game theory principles to address the challenges of balancing positive and negative disclosures for transparency purposes. This framework facilitates the examination of how AI can promote equitable and thorough reporting by reducing biases in corporate disclosures.	Bonsón et al. (2023); Allaoui et al. (2019); Chalmardi and Camacho-Vallejo (2019); Wu et al. (2023)	Proposed the game theory in our context as companies have a tendency to willingly reveal mostly positive information while frequently leaving out negative details. Originally, this inclination was predominantly noticed in the realm of financial reporting, but it has now expanded to encompass non-financial disclosures as well. Both kinds of data are essential for analysts aiming to cultivate a thorough comprehension of a company's operations. Annual and sustainability reports have a crucial role in providing information to investors and other market participants, therefore influencing their decision-making processes. In order to tackle these dynamics, a model will be created and merged, including principles from game theory and multi-agent systems. The objective is to construct mutually beneficial partnerships in both centralised and decentralised scenarios.
Technology acceptance model (TAM)	TAM examined the factors that affect AI adoption in sustainability reporting. The study identifies critical adoption enablers, including user attitudes and organisational readiness, by examining the technological, individual and organisational drivers and barriers. This addresses the gaps in adoption identified in the literature and suggests pathways for overcoming resistance to technological innovation.	Esposito et al. (2024); Asif et al. (2023)	The TAM suggests that users' intentions to adopt a new technology and their subsequent usage can be influenced by a range of factors. The factors influencing the situation include individual characteristics (such as motivations, attitudes, resistance, demographic attributes and user type), technological aspects (such as the type of innovation) and the organisational environment.
Resource-based view	The RBV framework directed the examination of how organisations leverage their resources, including AI technologies, to fulfil environmental and stakeholder requirements. This research emphasises the use of AI technologies in sustainable resource management and decision-making by concentrating on non-financial disclosures and evaluating their tone via sentiment analysis.	Liu et al. (2024); Sufi et al. (2024); Esposito et al. (2024).	According to this theoretical foundation, the resource consumption and emission activities of corporate operations make a substantial contribution to the environmental difficulties we are currently facing. Simultaneously, firms are compelled to innovate in ways that are environmentally beneficial due to mounting pressure from diverse stakeholders to uphold their environmental credibility. Consequently, numerous organisations are implementing sustainable operations strategies to conform with environmentally friendly practices and resources. Within this framework, the research investigates nonfinancial disclosures as predictor factors, with a specific emphasis on various disclosure tones detected through sentiment analysis of annual reports as well.

(Continues)

TABLE 8 | (Continued)

Theory	Theory description	Authors	Key outcomes
Stakeholder theory	Stakeholder theory serves as a framework for analysing the gap between stakeholder expectations and corporate sustainability initiatives. This perspective highlights the significance of voluntary environmental disclosures and their advantages, including enhanced transparency and alignment with global sustainability objectives. This study evaluates the potential of AI to enhance reporting through improved accuracy, timeliness and stakeholder engagement.	Calciolari et al. (2024); Kazemi et al. 2023; Mustafa, Lodh, et al. (2022); Bénabou and Tirole (2010); Asif et al. (2023)	Following this theoretical framework, research reveals a notable discrepancy in the expectations of stakeholders and the level of dedication towards tackling climate change. Stakeholders demonstrate a greater focus on sustainability, as indicated by elevated levels of scholarly investigation and environmental disclosures. In contrast, the lack of attention demonstrates comparatively less involvement in environmental reporting and sustainability initiatives in some industries and sectors. Nevertheless, this theory reveals a favourable pattern in the voluntary dissemination of environmental data in the financial reports and the benefits by doing these actions, including gaining stakeholder trust, promoting environmental sustainability, enhancing transparency in reporting, aligning with global sustainability objectives, improving their reputation and minimising their environmental footprint.
Diffusion of innovation theory	This theory provides a framework for analysing the adoption of emerging technologies, including AI, within the context of sustainability reporting. The study assesses how organisations perceive the business value of AI in sustainability practices by identifying factors such as compatibility, complexity and relative advantage. The findings identify barriers to adoption and propose strategies to enhance the diffusion of AI innovations.	Fosso Wamba et al. (2024); Mustafa, Lodh, et al. (2022); Govindan (2022)	The diffusion of innovation theory provides a comprehensive framework for analysing and comprehending the first uptake of different technologies such as Generative AI. According to this theory, IT innovation indicates that organisations primarily adopt technological innovations based on their perception of the business value. The literature on IT innovation has thoroughly examined the fundamental causes of organisational innovation, identifying both the elements that promote or hinder it, and the tactics used to foster innovation. The diffusion of innovations is influenced by various factors. These include technological characteristics such as compatibility, complexity, relative advantage, trialability and observability.

(Continues)

reporting varies significantly across industries (Calciolari et al. 2024; Kazemi et al. 2023; Mustafa, Lodh, et al. 2022). This theory supports the idea that voluntary sustainability disclosures can lead to tangible benefits, such as improved trust and alignment with global sustainability goals. The diffusion of innovation theory is particularly relevant for understanding the adoption of emerging technologies like AI in sustainability reporting. This theory suggests that firms adopt technological innovations based on perceived business value, and the diffusion of AI tools in this context is driven by factors like compatibility, complexity and relative advantage (Fosso Wamba et al. 2024; Mustafa, Lodh, et al. 2022). Finally, fuzzy set theory is employed to address the inherent uncertainty and ambiguity in sustainability reporting. It provides a framework for integrating subjective variables, such as environmental and social responsibility, into decision-making processes. The theory enhances the ability of AI systems to manage imprecise data, improving reasoning and decision-making capabilities in sustainability reporting (Calabrese, Costa, Levialdi, et al. 2016). Together, these theories provide a multi-faceted understanding of how AI can be integrated into sustainability reporting, offering insights into both the drivers and challenges of adoption, as well as the implications for transparency and decision-making.

TABLE 8 | (Continued)

Theory	Theory description	Authors	Key outcomes
Fuzzy set theory	Fuzzy set theory guided the methodological approach of the study in analysing imprecise and qualitative data, commonly found in sustainability reporting. This study integrates fuzzy logic into AI-driven sustainability practices to address uncertainty and ambiguity, thereby enhancing decision-making and improving the quality of sustainability disclosures.	Calabrese, Costa, Levialdi, et al. (2016).	Fuzzy set theory is a useful tool for both sustainability reporting and AI, providing a framework to tackle the inherent uncertainty and ambiguity in these domains. Sustainability reporting facilitates the measurement and combination of subjective variables such as environmental effect and social responsibility, resulting in more accurate and detailed assessments of organisational performance. According to this theoretical approach, this approach improves the process of making decisions by effectively addressing the inherent lack of precision in qualitative data. According to this theoretical framework, fuzzy set theory in the field of AI enhances the capacity of systems to manage imprecise data, hence improving reasoning, natural language processing and decision-making. By utilising fuzzy set theory in AI-driven sustainability reporting, organisations may effectively analyse intricate data, simulate uncertain situations and ultimately make well-informed and sustainable choices.

5 | Themes

The thematic analysis of the identified clusters provides important insights into the integration of AI and sustainability reporting. The clusters, labelled as green, red and blue in the network visualisation, represent distinct yet interconnected thematic areas: Sustainability and Industry 4.0, Dependence on Machine Learning and Innovation, Decision Support Systems, Environmental Impact and Supply Chain Management. Figure 5 provides the basis for categorising these themes through the clustering of keywords found in the literature.

The blue cluster emphasises technological advancements such as IoT, robotics and quantum computing that promote sustainability initiatives within the context of Industry 4.0. This research analyses the potential for innovation alongside the challenges posed by societal and environmental impacts.

The red cluster highlights the significance of AI technologies, especially ML and decision support systems (DSS), in improving sustainability reporting and decision-making. This cluster demonstrates the capabilities of AI-driven solutions in facilitating predictive analysis, enhancing reporting accuracy and guiding sustainable strategies, while also considering issues related to transparency, interpretability and ethical implications.

The green cluster examines the environmental impact and supply chain management, focusing on AI's role in optimising resource utilisation, reducing emissions and improving the efficiency of global supply chains. This cluster examines deficiencies in addressing social sustainability, labour rights and regulatory challenges that impede wider adoption in particular contexts.

The analysis organises themes into clusters, mapping the current state of research and identifying significant gaps, especially in the practical application of AI technologies within sustainability contexts. The following subsections present a detailed examination of these themes, analysing their contributions, limitations and implications for future research as presented in Table 9.

5.1 | Sustainability and Industry 4.0

The convergence of Industry 4.0 with sustainability has emerged as a focal point in both business and academic research. Studies such as those by Tiwari and Khan (2020), Narula et al. (2021) and Asokan et al. (2022) demonstrate the technological advancements in IoT, robotics, quantum computing and additive manufacturing, which are transforming business models. These innovations enhance operational efficiency and resource management, positioning Industry 4.0 as a critical enabler of sustainable business practices. However, these technological developments also raise concerns about potential societal and environmental implications, as noted by Mustafa, Lodh, et al. (2022). While the literature celebrates the benefits of Industry 4.0, there is a notable gap in addressing the unintended consequences these technologies

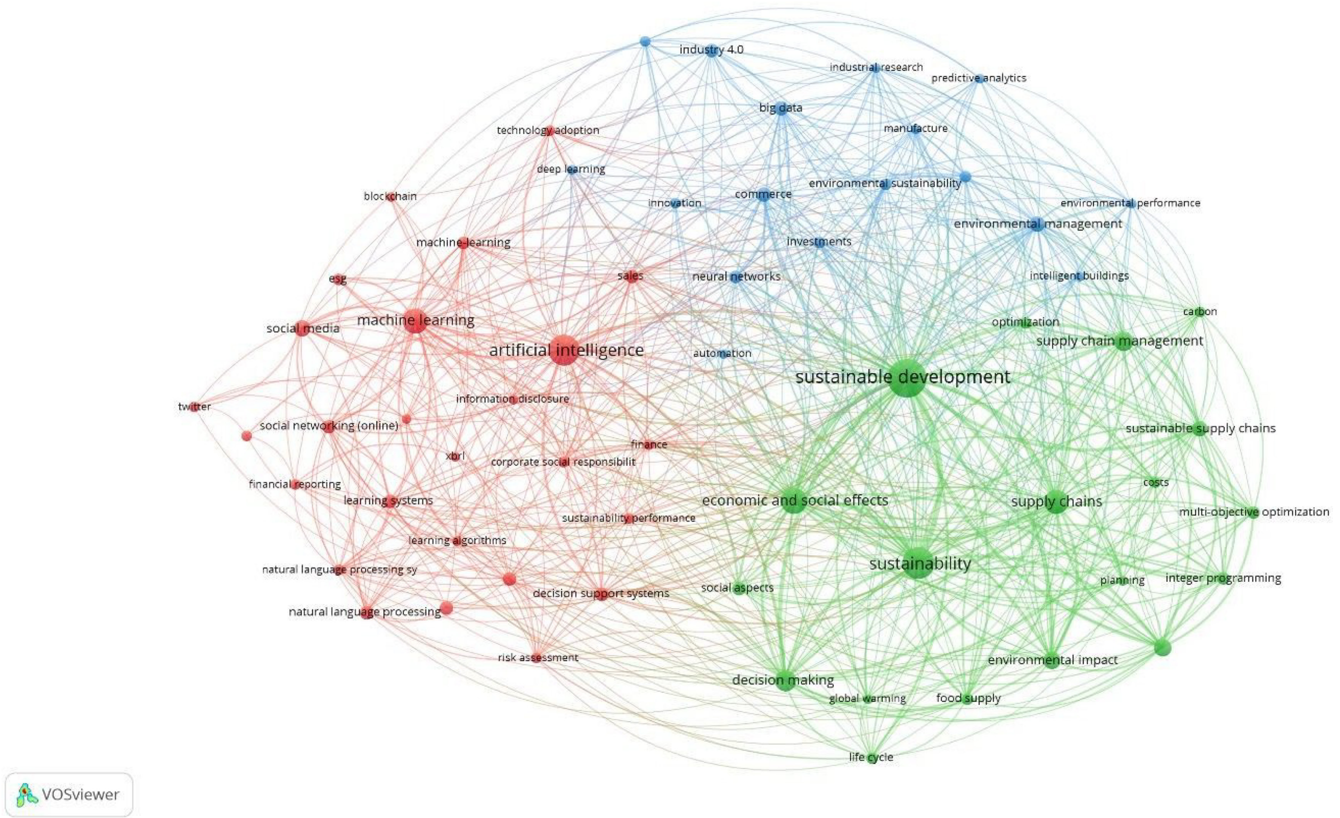

FIGURE 5 | Themes and keywords.

may have on sustainability (Narula et al. 2021). For instance, the social and environmental costs—such as energy consumption and the potential for increased inequalities—are often overlooked in favour of economic benefits (Essiz and Senyuz 2024). Studies like Mastos et al. (2020) highlight the opportunities but fail to consider the complex trade-offs between advancing technological progress and adhering to sustainability principles like the triple bottom line (Bag, Telukdarie, et al. 2021). This lack of critical evaluation, particularly regarding the long-term sustainability implications of Industry 4.0 technologies, leaves a gap in both academic and practical discussions. Furthermore, while the GRI and other frameworks such as the Sustainability Accounting Standards Board (SASB) are widely acknowledged as essential for sustainability reporting, research often fails to explore how these frameworks can be effectively integrated into Industry 4.0 contexts (Kazemi et al. 2023; Marimon et al. 2012). Scholars such as Buchholz et al. (2009) and Calabrese, Costa, Levialdi Ghiron, et al. (2019) have noted the existence of over 300 criteria for assessing sustainability, yet their application to rapidly evolving technological landscapes remains underdeveloped. Future research must examine how the principles of sustainability frameworks like the GRI can be seamlessly incorporated into the digital transformation driven by Industry 4.0. In addition, scholars should explore how these frameworks can evolve to address the negative externalities of technological advancements, particularly in terms of environmental degradation and social equity. Empirical research should also focus on developing models that measure the real-world impacts of Industry 4.0 technologies on sustainability, offering practical solutions for mitigating adverse effects (Narula et al. 2021).

5.2 | Dependence on Machine Learning and Innovation

ML has gained prominence as a powerful tool for advancing sustainability reporting, particularly through AI-driven solutions. Studies by Yao and Li (2023), Crocco et al. (2024) and Hoang and Wiegratz (2023) highlight how ML algorithms harness patterns in large datasets to enable predictive capabilities and decision support in carbon-intensive industries. The ability of ML to identify trends in historical data allows for the prediction of future scenarios, such as temperature increases, as seen in the work of Nishant et al. (2020). These predictions are invaluable for informing sustainability strategies across sectors such as energy, agriculture and transportation (Sufi et al. 2024). However, while the technical capabilities of ML are well-documented, there remains a gap in understanding how these tools can be integrated into sustainability reporting processes in a way that supports long-term innovation. Research by Liu et al. (2024) and Sabahi and Parast (2020) demonstrates that while ML can provide accurate predictions, there are challenges related to the interpretability of these predictions and their alignment with existing sustainability reporting frameworks. Moreover, despite the growing use of ML in sectors such as finance and governance, its application to sustainability reporting remains limited, as noted by Abdella et al. (2020) and Yao and Li (2023). This suggests that while ML has the potential to revolutionise sustainability reporting, its full potential has not yet been realised. Future research should prioritise the development of integrated frameworks that combine ML with established sustainability reporting standards like GRI and SASB. Additionally, there is a

TABLE 9 | Themes and key outcomes.

Theme	Authors	Key outcomes
Sustainability and Industry 4.0	Tiwari and Khan (2020); Asokan et al. (2022); Narula et al. (2021); Mustafa, Lodh, et al. (2022)	The intersection of Industry 4.0 and sustainability is a significant focus in both business and academic research. Advancements in technologies like IoT, robotics and nanotechnology are fostering new business models, but their societal impacts raise concerns. Researchers highlight the complexity of balancing environmental, social and economic dimensions while integrating these technologies. The adoption of sustainability standards like GRI is seen as essential for documenting and managing these dimensions. However, there is a noted tension between the rapid technological advancements of Industry 4.0 and the principles of sustainability, particularly in adhering to the triple bottom line.
Dependence on machine learning and innovation	Yao and Li (2023); Crocco et al. (2024); Hoang and Wiegratz (2023)	Machine learning plays a pivotal role in advancing sustainability, particularly through AI-driven solutions. Research shows that machine learning algorithms can predict future scenarios, enhance decision-making in carbon-intensive industries and forecast green innovations. The strength of machine learning lies in its ability to learn from data without preset assumptions, making it a powerful tool in various domains, including finance and corporate governance. Despite its advantages, the integration of machine learning in sustainability reporting and decision-making is still evolving, with ongoing research needed to fully harness its potential.
Decision support systems	Diaz-Balteiro et al. (2017); Esposito et al. (2024)	Decision support systems (DSS) are increasingly integrated with sustainability reporting to improve decision-making and promote sustainable practices across industries. These systems enhance the transparency, accuracy and reliability of sustainability reports, thereby supporting more informed and responsible decisions. The fusion of DSS with sustainability efforts underscores the critical role of advanced data analytics and AI in achieving sustainability goals. Ethical considerations and industry-specific applications are crucial, with ongoing research exploring the broader implications and benefits of DSS in sustainable decision-making.
Environmental impact	Essiz and Senyuz 2024; Zhang et al. (2020); Ouyang et al. (2020)	Environmental sustainability faces numerous challenges, including population growth, financial barriers and infrastructural limitations. Research emphasises the responsible management of natural resources to ensure future well-being, often through the lens of resource-based view theory. AI and machine learning are identified as key tools in reducing emissions, improving resource efficiency, and supporting environmental sustainability. Studies also highlight the importance of government policies and advanced technologies like blockchain in managing environmental impacts, with a strong focus on water management as critical to achieving global sustainability goals.
Supply chain	Czinkota et al. (2014); Tate et al. (2010); Hussain and Malik (2020); Nayal et al. (2022); Kumar, Mangla, et al. (2021)	The integration of sustainability into supply chains has become a global priority, with research focusing on sustainable supplier management, product safety and optimisation under uncertainty. AI and decision support systems are essential in managing the economic, environmental and social impacts within supply chains, particularly in complex areas like agri-food production. The literature proposes frameworks to enhance sustainability in supply chains within the context of Industry 4.0, emphasising the need for empirical research and regulatory support to overcome challenges and harness the potential of these advancements

need for more interdisciplinary research that addresses both the technical and ethical dimensions of using ML in sustainability reporting. Scholars should also investigate how ML algorithms can be designed to ensure transparency and accountability, particularly in high-stakes industries like energy and finance (Sabahi and Parast 2020).

5.3 | Decision Support Systems

DSS are increasingly being utilised in sustainability reporting to enhance decision-making and promote sustainable practices across industries (Diaz-Balteiro et al. 2017; Esposito et al. 2024). DSS enable organisations to consolidate complex datasets and generate actionable insights, improving the accuracy and transparency of sustainability reports. Studies such as those by Diaz-Balteiro et al. (2017) demonstrate how DSS can be integrated with AI and ML to support more informed and responsible decision-making, particularly in sectors where data is fragmented or difficult to interpret. However, despite their potential, the adoption of DSS remains uneven across industries. In developing countries or industries with limited technological infrastructure, the use of DSS is still rare (Bonsón et al. 2023). Furthermore, while DSS are increasingly used to optimise sustainability reporting, ethical concerns surrounding their application—such as the potential for data manipulation or biased decision-making—remain underexplored (Imaz and Eizagirre 2020). Future research should explore the institutional and cultural barriers to the adoption of DSS in sustainability reporting, particularly in sectors with limited access to advanced technologies. Additionally, there is a need for empirical studies that examine the ethical implications of DSS use in decision-making processes, focusing on issues such as bias, transparency and accountability (Esposito et al. 2024). Research should also consider how DSS can be integrated with other AI tools to create more holistic decision-making frameworks that address both economic and environmental sustainability challenges.

5.4 | Environmental Impact

The environmental impact of AI technologies, particularly their role in reducing emissions and optimising resource use, is a central theme in the literature (Crocco et al. 2024; Mustafa, Lodh, et al. 2022). AI-driven systems have been shown to enhance sustainability by improving energy efficiency, tracking emissions and predicting environmental risks (Brodny and Tutak 2022). However, despite these advancements, the environmental footprint of AI itself—such as the energy consumption of data centres and the carbon emissions associated with AI systems—remains a largely underexplored area of research. Studies by Bai et al. (2020) and Mustafa, Lodh, et al. (2022) highlight how financial barriers and infrastructural limitations prevent many organisations from adopting AI technologies for environmental management. Furthermore, while AI has the potential to improve resource management in industries such as agriculture and manufacturing, research by Zhang et al. (2020) shows that its adoption is often limited by a lack of regulatory frameworks and standardised practices. Future research should critically assess the environmental costs of AI technologies, focusing on the energy consumption and carbon footprint associated with AI-driven supply chains and data centres. Additionally, interdisciplinary studies are needed to evaluate how AI can be deployed in a way that aligns with global sustainability goals, particularly in industries with high environmental impacts. There is also a need for more policy-oriented research that addresses the regulatory challenges of AI adoption in environmental management (Mustafa, Lodh, et al. 2022).

5.5 | Supply Chain Management

Sustainable supply chain management (SCM) has become a global priority, with AI playing a key role in optimising complex, global supply chains (Bag, Srivastava, et al. 2024; Benzidia et al. 2021; Czinkota et al. 2014; Joardar and Sarkis 2021; Tarigan et al. 2021). AI-driven technologies enable companies to enhance the transparency and efficiency of their supply chains, particularly in areas like agri-food production, where environmental and social impacts are significant (Hussain and Malik 2020). Studies such as those by Nayal et al. (2022) and Kouhizadeh et al. (2021) demonstrate how AI can be used to optimise logistics, reduce waste and improve product safety, as presented in Table 9. However, while the economic and environmental benefits of AI in SCM are well-documented, there is limited research on its potential to address social sustainability issues such as labour rights and ethical sourcing (Nayal et al. 2022). Additionally, as Bag, Srivastava, et al. (2024) note, AI's ability to manage uncertainties in supply chains—such as fluctuating demand and market risks—remains under-researched. This suggests a need for more comprehensive frameworks that consider the full range of sustainability challenges in SCM. Future research should focus on integrating social sustainability considerations into AI-driven SCM systems. Scholars should also investigate how AI can be used to manage uncertainties in global supply chains, particularly in industries with volatile demand and supply conditions. More empirical studies are needed to validate the effectiveness of AI in addressing both environmental and social sustainability challenges in SCM (Pournader et al. 2021).

6 | Sustainability Reporting and AI Framework

Building on the extensive review of the existing literature, this section presents a synthesised framework that encapsulates the dynamic relationship between artificial intelligence (AI) and sustainability reporting. This framework is designed to address the key areas where AI can drive advancements in sustainability practices, specifically focusing on the factors that promote AI adoption, the collaborative mechanisms involved and the ultimate outcomes of these integrations. As identified through the systematic literature review (SLR), four critical themes—sustainability assessment and indicators, determinants of AI adoption, strategic management in AI-driven sustainability efforts and the outcomes of AI integration in reporting—form the backbone of this framework. The purpose is to bridge theoretical gaps and offer a structured approach for both scholars and practitioners to understand how AI can be leveraged to enhance transparency, accountability and overall performance in sustainability reporting. The framework, illustrated in Figure 6, serves as a holistic guide to navigating the complexities and opportunities at the intersection of AI and sustainability reporting. By delineating key

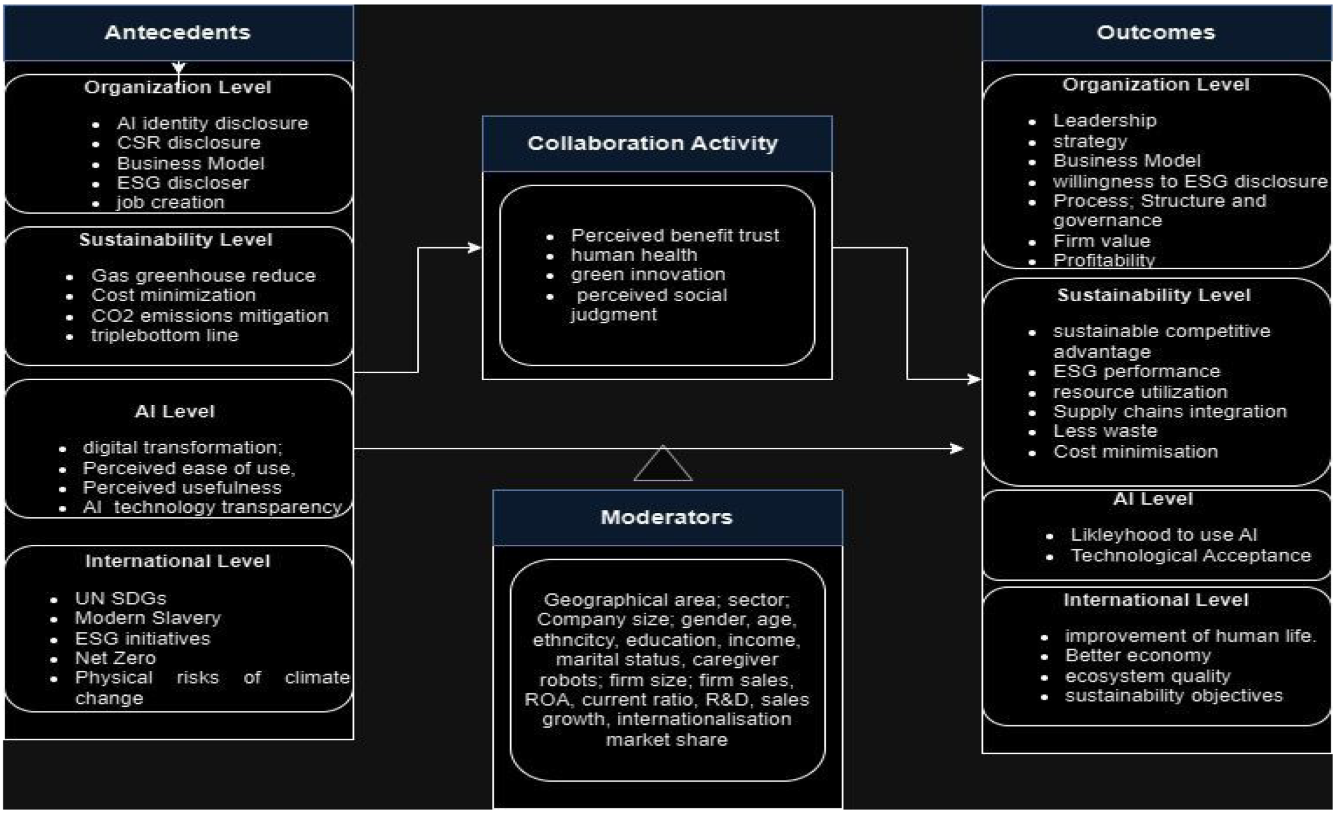

FIGURE 6 | Framework for studies.

antecedents, collaboration activities, moderators and outcomes, this framework aims to stimulate future research while providing practical insights for effective AI adoption.

6.1 | Antecedents

The antecedents segment explores the critical factors that drive organisations to adopt AI in their sustainability reporting processes. These factors operate at different levels, including organisational, sustainability, AI technology and international contexts.

6.1.1 | Organisation Level

Proposition 1. Organisations with higher levels of transparency and CSR disclosure are more likely to adopt AI in their sustainability reporting, thereby enhancing stakeholder trust and engagement.

6.1.2 | Sustainability Level

At the sustainability level, specific environmental and economic goals drive the integration of AI into sustainability reporting. One of AI's key contributions is in greenhouse gas reduction, where it plays a significant role in enhancing energy efficiency and optimising industrial processes to minimise emissions (Sufi et al. 2024; Liu et al. 2024). By improving operational efficiency, AI helps firms achieve cost minimisation and ensures that sustainability initiatives remain financially viable (Esposito et al. 2024). In addition, AI contributes to CO_2 emissions mitigation by leveraging advanced technologies like predictive analytics and machine learning, which monitor and reduce carbon footprints (Rotondo et al. 2019). This aligns with the triple bottom line framework, which emphasises balancing economic, environmental and social dimensions. Firms that adopt AI-driven strategies are better positioned to address these three pillars in their sustainability efforts (Rotondo et al. 2019).

Proposition 2. AI technologies will play an increasingly important role in helping organisations meet their sustainability goals, particularly in reducing greenhouse gas emissions and minimising operational costs.

6.1.3 | AI Technology Level

At the AI technology level, several factors shape the adoption of AI in sustainability practices. Digital transformation is at the core of how firms are rethinking their business models and operations, with AI technologies facilitating this transition (Esposito et al. 2024). Critical to AI adoption are the perceived ease of use and perceived usefulness of AI, as outlined in the TAM. When stakeholders perceive AI as both easy to implement and useful for enhancing sustainability practices, its integration into sustainability reporting is more likely (Mustafa, Lodh, et al. 2022). Another key factor is AI transparency, as the ethical and clear communication of how AI processes data and generates insights is crucial for maintaining stakeholder trust, especially in the sensitive realm of sustainability (Esposito et al. 2024).

Proposition 3. The perceived ease of use and transparency of AI technologies will significantly influence their adoption in sustainability reporting practices.

6.1.4 | International Level

On a global scale, international frameworks and global sustainability initiatives serve as critical drivers for AI adoption in sustainability reporting. The SDGs provide a global agenda that prompts organisations to incorporate AI into their sustainability reporting to meet these internationally recognised targets. Emerging concerns such as modern slavery and the physical risks of climate change necessitate advanced AI technologies to monitor, report and mitigate adverse impacts. In this context, Net Zero initiatives have become a global standard, pushing organisations to adopt AI solutions to track and achieve these goals (Mustafa, Lodh, et al. 2022; De Guimarães et al. 2020; Songini et al. 2023).

Proposition 4. Global frameworks like the SDGs and Net Zero initiatives will drive the adoption of AI in sustainability reporting, particularly in addressing climate change and resource optimisation.

6.2 | Collaboration Activity

The collaboration activity segment highlights the interactions between AI and sustainability reporting, focusing on how organisations perceive the benefits of adopting AI. Perceived benefit trust refers to the trust stakeholders place in AI-driven sustainability initiatives, which plays a pivotal role in fostering AI integration (Camilleri et al. 2024). Another critical area of collaboration is human health, where AI can optimise healthcare delivery and environmental conditions, directly supporting sustainability goals. Moreover, AI drives green innovation, encouraging the development of environmentally friendly technologies and practices, crucial for achieving long-term sustainability (Camilleri et al. 2024).

Proposition 5. Trust in the perceived benefits of AI will encourage greater adoption of AI-driven sustainability reporting initiatives, particularly in promoting human health and green innovation.

6.2.1 | Moderators

Moderators such as geographical area, sector and company size influence how effectively AI is adopted in sustainability reporting. For instance, regulatory frameworks and technological infrastructure vary significantly across regions, influencing the impact of AI (Liu et al. 2024). Similarly, different sectors such as manufacturing, agriculture and services have unique needs and capabilities regarding AI adoption (Kazemi et al. 2023). Organisational factors such as firm size, R&D intensity and internationalisation efforts further moderate AI adoption outcomes. Firms with robust R&D capabilities or strong international ties tend to experience different levels of success in integrating AI into their sustainability practices (Liu et al. 2024; Camilleri et al. 2024).

Proposition 6. The impact of AI on sustainability reporting is moderated by geographical, sector-specific and organisational factors, which shape the adoption and effectiveness of AI technologies.

6.3 | Outcomes

The outcomes segment categorises the results of AI and sustainability reporting collaboration into organisational, sustainability, AI and international levels.

6.3.1 | Organisation Level

At the organisational level, AI integration enhances leadership capabilities, providing data-driven insights that inform strategic decisions (Camilleri et al. 2024). This often leads to business model evolution, where AI facilitates the shift towards more sustainable practices. Firms also experience improved ESG disclosure, as AI enables more accurate and comprehensive tracking of sustainability metrics (De Guimarães et al. 2020).

Proposition 7. AI integration in sustainability reporting will lead to improved business models, enhanced leadership capabilities and more comprehensive ESG disclosures.

6.3.2 | Sustainability Level

At the sustainability level, AI supports organisations in achieving a sustainable competitive advantage by optimising their sustainability practices (Wang and Qiu 2024; Kazemi et al. 2023). AI also contributes to better resource utilisation and supply chain integration, making sustainability efforts more efficient and reducing costs (De Guimarães et al. 2020; Mustafa, Lodh, et al. 2022).

Proposition 8. AI-enhanced sustainability reporting will result in improved resource utilisation, cost minimisation and better supply chain integration.

6.3.3 | AI Level

Successful AI integration creates a feedback loop that encourages broader technological adoption within the organisation. Increased technological acceptance leads to AI being applied in other areas, driving innovation across business operations (Liu et al. 2024).

6.3.4 | International Level

On a global scale, AI-enhanced sustainability practices contribute to improved human life, addressing critical issues like health, safety and environmental quality. These efforts also result in a better economy and ecosystem quality, reinforcing global sustainability objectives (De Guimarães et al. 2020; Liu et al. 2024; Wang and Qiu 2024; Mustafa, Lodh, et al. 2022).

Proposition 9. AI-driven sustainability practices will lead to significant international outcomes, improving global human well-being, ecosystem quality and economic performance.

In conclusion, the proposed framework offers a detailed understanding of the complex relationships between AI and sustainability reporting, covering antecedents, collaboration activities, moderators and outcomes. By leveraging AI, organisations can enhance their sustainability efforts, contributing to both organisational success and global sustainability goals. Future research should further investigate the interactions within this framework and explore how different contexts influence the adoption and effectiveness of AI in sustainability reporting.

7 | Discussion

7.1 | Insights From the Cluster Analysis

Sustainability is a multifaceted challenge that has increasingly drawn the attention of researchers, practitioners and policymakers. While the discourse on sustainability has traditionally centred on financial aspects, there is a growing recognition of the need to balance environmental and social dimensions. However, despite the widespread focus on sustainability in various domains, our systematic literature review (SLR) reveals a significant gap in understanding the role of AI in sustainability reporting. Our study represents the first comprehensive attempt to address this gap, positioning AI as a transformative tool for enhancing the scope, accuracy and impact of sustainability reporting.

We conducted an extensive analysis of 135 studies, covering topics such as environmental performance, supply chain management, Industry 4.0 applications and decision support systems (DSS) within the sustainability domain. This research draws on diverse methodological approaches, geographical contexts and theoretical frameworks to map out the existing landscape of AI applications in sustainability reporting. The resulting thematic classification sheds light on the major research streams, gaps and future directions in this field.

This study highlights the significant relationship between AI applications in sustainability reporting and the theoretical frameworks of the RBV and stakeholder theory. The RBV emphasises AI as a strategic asset that, when integrated with firm-specific capabilities like strong data governance and technical expertise, improves operational efficiency and the reliability of sustainability disclosures. The analysis of themes such as Industry 4.0 and machine learning illustrates the potential of these technologies to enhance resource management and facilitate predictive capabilities, thereby addressing significant ESG challenges. Achieving these benefits necessitates overcoming barriers, including algorithmic bias and the energy-intensive nature of AI systems, which require additional investment in ethical frameworks and sustainable practices. The study results directly address the first research question by investigating how AI can enhance sustainability reporting and promote higher levels of organisational accountability. This finding challenges the RBV's premise that competitive advantage is exclusively derived from resource optimisation, highlighting that energy consumption and environmental costs may offset these benefits, especially when sustainability is prioritised.

Stakeholder Theory offers a framework for understanding these findings, highlighting the importance of collaboration among stakeholders to maximise AI's potential. Themes including decision support systems and supply chain management demonstrate the enhancement of transparency and accountability through AI-driven tools, addressing the growing demand from investors, regulators and consumers for reliable sustainability reporting. These findings respond to the second research question by demonstrating how AI technologies contribute to greater transparency and decision-making processes in sustainability reporting. However, the study identifies ongoing concerns, such as trust and perceived opportunism, which may impede stakeholder participation and restrict resource sharing. The findings build upon Nassar and Kamal (2021) by illustrating that AI-driven decision support systems mitigate fragmented data issues yet fail to enhance trust, reflecting ethical concerns highlighted in studies such as Sabahi and Parast (2020).

Our analysis reveals several important trends. There is a noticeable shift toward AI-driven methods for improving sustainability reporting processes, especially in areas such as real-time data analytics, predictive modeling and automated report generation. These developments have the potential to drastically reduce the time and cost associated with sustainability reporting, while simultaneously increasing the precision and reliability of the data reported. This result aligns with the third research question by highlighting the current gaps in AI integration and the capability for improving sustainability reporting. This is a significant advancement, given the complexity of sustainability metrics and the challenges organisations face in collecting and analysing large amounts of ESG-related data. However, our findings also underscore the uneven distribution of research efforts across geographical regions and industries. The majority of studies focus on developed economies, particularly the United States and Europe, leaving significant gaps in understanding how AI could be applied to sustainability reporting in emerging markets. Additionally, sectors such as finance, manufacturing and energy have received more attention, while other industries, such as agriculture and services, remain underexplored. These understandings highlight the need for future research to address the gaps and spread AI applications to underrepresented countries and sectors.

This review enhances existing knowledge by critically evaluating the incorporation of AI into established sustainability frameworks, including GRI and SASB, while identifying gaps concerning the unintended consequences of AI implementation (Kazemi et al. 2023). The results highlight the theoretical implications of AI's integration, specifically its potential to challenge current sustainability frameworks and lead innovation in reporting practices. This review distinguishes itself from earlier studies (e.g., Mustafa, Lodh, et al. 2022) by emphasising the unintended externalities of AI, such as heightened inequalities and carbon emissions, which necessitate the adaptation of existing frameworks. Addressing these gaps and aligning AI applications with sustainability principles will enable future studies to develop comprehensive strategies that integrate technological innovation with ethical responsibility, thereby contributing to long-term sustainable value creation.

7.2 | Future Research Directions

The results of this study point to several promising avenues for future research. First, future studies should aim to expand the geographical and sectoral coverage of AI in sustainability reporting. More empirical research is needed in emerging markets and underrepresented industries to better understand how AI can be effectively adapted to diverse contexts and to identify the unique challenges and opportunities that exist in these regions. This would provide a more holistic view of AI's potential in driving sustainability reporting globally.

Second, further research is needed to explore the ethical implications of AI in sustainability reporting. As AI becomes more integrated into organisational processes, concerns about data privacy, bias and transparency in AI algorithms must be addressed. Future studies could focus on developing guidelines or frameworks to ensure that AI is deployed ethically and responsibly, particularly in the context of sustainability reporting, where transparency and accountability are critical.

Third, there is significant potential for future research to explore the intersection of AI and other emerging technologies, such as blockchain, in sustainability reporting. Blockchain's ability to provide immutable and transparent records could complement AI's data processing capabilities, creating a more robust system for sustainability reporting. Exploring the synergies between these technologies could yield new insights into how organisations can enhance the reliability and efficiency of their reporting systems.

Fourth, as AI tools become more sophisticated, it will be crucial to examine the long-term impacts of AI-driven sustainability reporting on organisational behaviour and decision-making. Future studies should investigate how AI influences strategic decisions related to sustainability and whether it leads to more proactive, rather than reactive, approaches to sustainability management.

Finally, future research should focus on the practical application and validation of the AI models and frameworks discussed in the literature. Empirical studies that assess the effectiveness of AI-driven sustainability reporting in real-world settings are needed to bridge the gap between theory and practice. This would involve case studies or longitudinal research examining how organisations implement AI in their reporting processes and the tangible outcomes of these efforts.

8 | Conclusion

This paper concludes by presenting the core theoretical contributions, practical implications and limitations of this systematic review. Each subsection below outlines these points distinctly to guide future research and inform practice.

8.1 | Theoretical Implications

This study makes several significant contributions. From a theoretical standpoint, it offers a critical synthesis of existing literature, outlining how AI technologies can be leveraged to enhance sustainability reporting and promote better organisational accountability. Our findings suggest that AI not only improves the efficiency of sustainability reporting processes but also enhances the quality of disclosures by providing more granular, real-time data and enabling more sophisticated analysis of ESG performance. This aligns with the first and second research questions by showing key trends and themes in the academic literature around AI in sustainability reporting. Also, the comprehensive understanding of the current state of AI in sustainability reporting serves as a foundation for future theoretical developments in this area. It emphasises a need for new conceptual models that consider the dynamic relationship between accountability mechanisms in ESG disclosures and digital innovation.

Second, we contribute a new integrated framework that encompasses the antecedents, collaboration activities, moderators and outcomes associated with the application of AI in sustainability reporting. By categorising these elements, we provide a structured approach for academic researchers to better understand the dynamics of AI integration in this domain. This framework offers insights into how AI can transform reporting processes, improve operational efficiency and drive innovation in sustainability practices. Furthermore, our work invites more theoretical exploration of interdisciplinary connections between digitalisation, accounting and sustainability sciences.

8.2 | Practical Implications

This study's findings provide important insights into the integration of AI technologies in sustainability reporting, with significant implications for corporate strategies, policymaking and sustainability initiatives. The study results support organisations in utilising AI technologies, including NLP, to automate the analysis of ESG data, thereby enhancing the efficiency and accuracy of corporate disclosures. This automation decreases errors and enhances data quality. Our results also emphasise the use of AI-driven predictive analytics, which enables companies to anticipate potential sustainability risks and failures in environmental compliance, thereby fulfilling stakeholder expectations and regulatory requirements.

Moreover, machine learning algorithms can assist organisations in aligning their reporting practices with established frameworks such as the GRI and ISSB. This confirms a credible approach to sustainability disclosure, which is particularly valuable for multinational corporations that handle diverse reporting mandates. The results help in implementing standardised frameworks that align with SDGs.

The results support the advancement of tailored AI applications in sustainability reporting across various industries. Energy companies may utilise AI to enhance renewable energy forecasting, whereas manufacturing sectors could implement AI to decrease energy consumption. These cases illustrate the significant potential of AI in fulfilling environmental and economic objectives.

Finally, the research has important implications for policymakers, as it encourages the integration of AI into sustainability reporting practices. Policymakers, in their turn, can also encourage business investment in AI-driven reporting tools by offering tax incentives to promote the adoption of technologies that enhance the quality and credibility of sustainability disclosures among companies. Embedding AI-driven solutions within regulatory frameworks for corporate sustainability disclosures can mitigate instances of greenwashing and enhance overall accountability. In doing so, our research directly informs regulatory design and influences the global agenda for responsible digital innovation in sustainability.

8.3 | Limitations

While this study provides a comprehensive overview of AI's role in sustainability reporting, several limitations should be acknowledged. First, our analysis is limited by the selection of databases and peer-reviewed articles, which may exclude relevant studies published in other sources, including industry reports, government publications and non-English literature. This restricts the geographical and linguistic scope of our findings, potentially limiting the generalizability of our conclusions, particularly in non-English-speaking and developing regions. Second, the rapidly evolving nature of AI technology means that the findings presented here may become outdated as new developments emerge. Given the dynamic landscape of AI research, our study captures a snapshot of current trends but may not fully reflect future advancements in AI capabilities or their application to sustainability reporting.

Third, our thematic classification and framework are based on secondary data from existing literature, which could introduce bias due to the limitations of the original studies reviewed. Furthermore, many of the studies in our analysis rely on conceptual frameworks or simulations, rather than empirical data from real-world AI implementations. As a result, the practical applications of AI in sustainability reporting may differ from those suggested by the theoretical models.

Ethics Statement

This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data available on request from the authors.

Endnotes

[1] Refer to Appendix 1 for the search criteria and keywords.

References

Abdella, G. M., M. Kucukvar, N. C. Onat, H. M. Al-Yafay, and M. E. Bulak. 2020. "Sustainability Assessment and Modeling Based on Supervised Machine learning Techniques: The Case for Food Consumption." *Journal of Cleaner Production* 251: 119661.

Acquisti, A., L. Brandimarte, and G. Loewenstein. 2015. "Privacy and Human Behavior in the Age of Information." *Science* 347, no. 6221: 509–514.

Alkaraan, F., M. Elmarzouky, K. Hussainey, V. G. Venkatesh, Y. Shi, and N. Gulko. 2024. "Reinforcing Green Business Strategies With Industry 4.0 and Governance Towards Sustainability: Natural-Resource-Based View and Dynamic Capability." *Business Strategy and the Environment* 33, no. 4: 3588–3606.

Allaoui, H., Y. Guo, and J. Sarkis. 2019. "Decision Support for Collaboration Planning in Sustainable Supply Chains." *Journal of Cleaner Production* 229: 761–774.

Alshahrani, A., D. Dennehy, and M. Mäntymäki. 2022. "An Attention-Based View of AI Assimilation in Public Sector Organizations: The Case of Saudi Arabia." *Government Information Quarterly* 39, no. 4: 101617.

Angelakoglou, K., and G. Gaidajis. 2015. "A Review of Methods Contributing to the Assessment of the Environmental Sustainability of Industrial Systems." *Journal of Cleaner Production* 108: 725–747.

Asif, M., C. Searcy, and P. Castka. 2023. "ESG and Industry 5.0: The Role of Technologies in Enhancing ESG Disclosure." *Technological Forecasting and Social Change* 195: 122806.

Asokan, D. R., F. A. Huq, C. M. Smith, and M. Stevenson. 2022. "Socially Responsible Operations in the Industry 4.0 Era: Post-COVID-19 Technology Adoption and Perspectives on Future Research." *International Journal of Operations & Production Management* 42, no. 13: 185–217.

Bag, S., G. Srivastava, A. Cherrafi, A. Ali, and R. K. Singh. 2024. "Data-Driven Insights for Circular and Sustainable Food Supply Chains: An Empirical Exploration of Big Data and Predictive Analytics in Enhancing Social Sustainability Performance." *Business Strategy and the Environment* 33, no. 2: 1369–1396.

Bag, S., A. Telukdarie, J. C. Pretorius, and S. Gupta. 2021. "Industry 4.0 and Supply Chain Sustainability: Framework and Future Research Directions." *Benchmarking: An International Journal* 28, no. 5: 1410–1450.

Bai, C., J. Sarkis, F. Yin, and Y. Dou. 2020. "Sustainable Supply Chain Flexibility and Its Relationship to Circular Economy-Target Performance." *International Journal of Production Research* 58, no. 19: 5893–5910.

Bamgbade, J. A., A. M. Kamaruddeen, and M. N. M. Nawi. 2017. "Malaysian Construction Firms' Social Sustainability via Organisational Innovativeness and Government Support: The Mediating Role of Market Culture." *Journal of Cleaner Production* 154: 114–124. https://doi.org/10.1016/j.jclepro.2017.03.187.

Barney, J. 1991. "Firm Resources and Sustained Competitive Advantage." *Journal of Management* 17, no. 1: 99–120.

Barney, J. B. 2018. "Why Resource-Based Theory's Model of Profit Appropriation Must Incorporate a Stakeholder Perspective." *Strategic Management Journal* 39, no. 13: 3305–3325.

Bénabou, R., and J. Tirole. 2010. "Individual and Corporate Social Responsibility." *Economica* 77, no. 305: 1–19.

Benzidia, S., N. Makaoui, and O. Bentahar. 2021. "The Impact of Big Data Analytics and Artificial Intelligence on Green Supply Chain Process Integration and Hospital Environmental Performance." *Technological Forecasting and Social Change* 165: 120557.

Bonsón, E., M. Bednárová, and D. Perea. 2023. "Disclosures About Algorithmic Decision Making in the Corporate Reports of Western European Companies." *International Journal of Accounting Information Systems* 48: 100596.

Brodny, J., and M. Tutak. 2022. "Challenges of the Polish Coal Mining Industry on Its Way to Innovative and Sustainable Development." *Journal of Cleaner Production* 375: 134061.

Buchholz, T., V. A. Luzadis, and T. A. Volk. 2009. "Sustainability Criteria for Bioenergy Systems: Results From an Expert Survey." *Journal of Cleaner Production* 17: S86–S98.

Calabrese, A., R. Costa, N. Levialdi Ghiron, and T. Menichini. 2019. "Materiality Analysis in Sustainability Reporting: A Tool for Directing Corporate Sustainability Towards Emerging Economic, Environmental and Social Opportunities." *Technological and Economic Development of Economy* 25, no. 5: 1016–1038.

Calabrese, A., R. Costa, N. Levialdi, and T. Menichini. 2016. "A Fuzzy Analytic Hierarchy Process Method to Support Materiality Assessment in Sustainability Reporting." *Journal of Cleaner Production* 121: 248–264.

Calciolari, S., M. Cesarini, and M. Ruberti. 2024. "Sustainability Disclosure in the Pharmaceutical and Chemical Industries: Results From Bibliometric Analysis and AI-Based Comparison of Financial Reports." *Journal of Cleaner Production* 447: 141511.

Camilleri, M. A., L. Zhong, M. S. Rosenbaum, and J. Wirtz. 2024. "Ethical Considerations of Service Organizations in the Information age 信息时代服务组织的道德思考." *Service Industries Journal* 44, no. 9–10: 634–660.

Chalmardi, M. K., and J. F. Camacho-Vallejo. 2019. "A Bi-Level Programming Model for Sustainable Supply Chain Network Design That Considers Incentives for Using Cleaner Technologies." *Journal of Cleaner Production* 213: 1035–1050.

Cheng, X., K. Chen, and Y. Su. 2023. "Green Innovation in Oil and Gas Exploration and Production for Meeting the Sustainability Goals." *Resources Policy* 87: 104315.

Crocco, E., L. Broccardo, H. Alofaysan, and R. Agarwal. 2024. "Sustainability Reporting in Carbon-Intensive Industries: Insights From a Cross-Sector Machine Learning Approach." *Business Strategy and the Environment* 33, no. 7: 7201–7215.

Czinkota, M., H. R. Kaufmann, and G. Basile. 2014. "The Relationship Between Legitimacy, Reputation, Sustainability and Branding for Companies and Their Supply Chains." *Industrial Marketing Management* 43, no. 1: 91–101.

Damaceno, E. R., J. D. S. Pinto, T. F. Sigahi, G. H. S. M. D. Moraes, W. Leal Filho, and R. Anholon. 2025. "Incorporating Local Communities Into Sustainability Reporting: A Grey Systems-Based Analysis of Brazilian Companies." *AppliedMath* 5, no. 2: 42.

De Guimarães, J. C. F., E. A. Severo, L. A. F. Júnior, W. P. L. B. Da Costa, and F. T. Salmoria. 2020. "Governance and Quality of Life in Smart Cities: Towards Sustainable Development Goals." *Journal of Cleaner Production* 253: 119926.

De Villiers, C., R. Dimes, and M. Molinari. 2024. "How Will AI Text Generation and Processing Impact Sustainability Reporting? Critical Analysis, a Conceptual Framework and Avenues for Future Research." *Sustainability Accounting, Management and Policy Journal* 15, no. 1: 96–118.

de Villiers, C., S. Kuruppu, and D. Dissanayake. 2021. "A (New) Role Forbusiness–Promoting the United Nations' Sustainable Developmentgoals Through the Internet-of-Things and Blockchain Technology." *Journal of Business Research* 131: 598–609. https://doi.org/10.1016/j.jbusres.2020.11.0661164 MUSTAFA ET AL.

Di Vaio, A., R. Palladino, R. Hassan, and O. Escobar. 2020. "Artificial Intelligence and Business Models in the Sustainable Development Goals Perspective: A Systematic Literature Review." *Journal of Business Research* 121: 283–314.

Diaz-Balteiro, L., J. González-Pachón, and C. Romero. 2017. "Measuring Systems Sustainability With Multi-Criteria Methods: A Critical Review." *European Journal of Operational Research* 258, no. 2: 607–616.

Esposito, P., G. Antonucci, G. Palozzi, and J. Fijałkowska. 2024. "Cognitive Systems for Improving Decision-Making in the Workplace: An Explorative Study Within the Waste Management Field." *Management Decision*. https://doi.org/10.1108/MD-08-2023-1320.

Essiz, O., and A. Senyuz. 2024. "Predicting the Value-Based Determinants of Sustainable Luxury Consumption: A Multi-Analytical Approach and Pathway to Sustainable Development in the Luxury Industry." *Business Strategy and the Environment* 33, no. 3: 1721–1758.

Fosso Wamba, S., C. Guthrie, M. M. Queiroz, and S. Minner. 2024. "ChatGPT and Generative Artificial Intelligence: An Exploratory Study of Key Benefits and Challenges in Operations and Supply Chain Management." *International Journal of Production Research* 62, no. 16: 5676–5696.

Getahun, S., H. Kefale, and Y. Gelaye. 2024. "Application of Precision Agriculture Technologies for Sustainable Crop Production and Environmental Sustainability: A Systematic Review." *Scientific World Journal* 2024, no. 1: 2126734.

Govindan, K. 2022. "How Artificial Intelligence Drives Sustainable Frugal Innovation: A Multitheoretical Perspective." *IEEE Transactions on Engineering Management* 71: 638–655.

Haddaway, N. R., P. Woodcock, B. Macura, and A. Collins. 2015. "Making Literature Reviews More Reliable Through Application of Lessons From Systematic Reviews." *Conservation Biology* 29, no. 6: 1596–1605.

Helo, P., and Y. Hao. 2022. "Artificial Intelligence in Operations Management and Supply Chain Management: An Exploratory Case Study." *Production Planning & Control* 33, no. 16: 1573–1590.

Hoang, D., and K. Wiegratz. 2023. "Machine Learning Methods in Finance: Recent Applications and Prospects." *European Financial Management* 29, no. 5: 1657–1701.

Hoehndorf, R., and N. Queralt-Rosinach. 2017. "Data Science and Symbolic AI: Synergies, Challenges and Opportunities." *Data Science* 1, no. 1–2: 27–38.

Hussain, M., and M. Malik. 2020. "Organizational Enablers for Circular Economy in the Context of Sustainable Supply Chain Management." *Journal of Cleaner Production* 256: 120375.

Imaz, O., and A. Eizagirre. 2020. "Responsible Innovation for Sustainable Development Goals in Business: An Agenda for Cooperative Firms." *Sustainability* 12, no. 17: 6948.

Joardar, A., and J. Sarkis. 2021. "An Examination of Sustainable Development of Supply Chain Using Foreignness Perspective." *Business Strategy and the Environment* 30, no. 1: 630–642.

Kapp, S., J. K. Choi, and T. Hong. 2023. "Predicting Industrial Building Energy Consumption With Statistical and Machine-learning Models Informed by Physical System Parameters." *Renewable and Sustainable Energy Reviews* 172: 113045.

Kazemi, M. Z., A. A. Elamer, G. Theodosopoulos, and S. F. Khatib. 2023. "Reinvigorating Research on Sustainability Reporting in the Construction Industry: A Systematic Review and Future Research Agenda." *Journal of Business Research* 167: 114145.

Kouhizadeh, M., S. Saberi, and J. Sarkis. 2021. "Blockchain Technology and the Sustainable Supply Chain: Theoretically Exploring Adoption Barriers." *International Journal of Production Economics* 231: 107831.

KPMG. 2020. *The KPMG Survey of Sustainability Reporting 2020*. KPMG.

Kumar, A., S. K. Mangla, P. Kumar, and M. Song. 2021. "Mitigate Risks in Perishable Food Supply Chains: Learning From COVID-19." *Technological Forecasting and Social Change* 166: 120643.

Kumar, S., S. Sahoo, W. M. Lim, and L. P. Dana. 2022. "Religion as a Social Shaping Force in Entrepreneurship and Business: Insights From a Technology-Empowered Systematic Literature Review." *Technological Forecasting and Social Change* 175: 121393.

Li, D., Z. Zhang, and X. Gao. 2024. "Does Artificial Intelligence Deter Greenwashing?" *Finance Research Letters* 67: 105954.

Lim, W. M., S. F. Yap, and M. Makkar. 2021. "Home Sharing in Marketing and Tourism at a Tipping Point: What Do We Know, How Do We Know, and Where Should We Be Heading?" *Journal of Business Research* 122: 534–566.

Lin, J. W., M. I. Hwang, and J. D. Becker. 2003. "A Fuzzy Neural Network for Assessing the Risk of Fraudulent Financial Reporting." *Managerial Auditing Journal* 18, no. 8: 657–665.

Liu, F., R. Wang, and M. Fang. 2024. "Mapping Green Innovation with Machine Learning: Evidence from China." *Technological Forecasting and Social Change* 200: 123107.

Lu, Y., C. G. Ntim, Q. Zhang, and P. Li. 2022. "Board of Directors' Attributes and Corporate Outcomes: A Systematic Literature Review and Future Research Agenda." *International Review of Financial Analysis* 84: 102424.

Mahran, K., and A. A. Elamer. 2024. "Chief Executive Officer (CEO) and Corporate Environmental Sustainability: A Systematic Literature Review and Avenues for Future Research." *Business Strategy and the Environment* 33, no. 3: 1977–2003.

Manes-Rossi, F., G. Nicolò, and D. Argento. 2020. "Non-Financial Reporting Formats in Public Sector Organizations: A Structured Literature Review." *Journal of Public Budgeting, Accounting & Financial Management* 32, no. 4: 639–669.

Marimon, F., M. del Mar Alonso-Almeida, M. del Pilar Rodríguez, and K. A. C. Alejandro. 2012. "The Worldwide Diffusion of the Global Reporting Initiative: What Is the Point?" *Journal of Cleaner Production* 33: 132–144.

Marzi, G., M. Balzano, A. Caputo, and M. M. Pellegrini. 2025. "Guidelines for Bibliometric-Systematic Literature Reviews: 10 Steps to Combine Analysis, Synthesis and Theory Development." *International Journal of Management Reviews* 27, no. 1: 81–103.

Massaro, M., J. Dumay, and A. Garlatti. 2015. "Public Sector Knowledge Management: A Structured Literature Review." *Journal of Knowledge Management* 19, no. 3: 530–558.

Mastos, T. D., A. Nizamis, T. Vafeiadis, et al. 2020. "Industry 4.0 Sustainable Supply Chains: An Application of an IoT Enabled Scrap Metal Management Solution." *Journal of Cleaner Production* 269: 122377.

McGahan, A. M. 2021. "Integrating Insights From the Resource-Based View of the Firm Into the New Stakeholder Theory." *Journal of Management* 47, no. 7: 1734–1756.

Mhlanga, D. 2023. "Artificial Intelligence and Machine Learning for Energy Consumption and Production in Emerging Markets: A Review." *Energies* 16, no. 2: 745.

Miller, J. H. 1996. "The Coevolution of Automata in the Repeated Prisoner's Dilemma." *Journal of Economic Behavior & Organization* 29, no. 1: 87–112.

Moloi, T., and H. Obeid. 2024. "Perceptions of South African Accountants on Factors With a Role in the Adoption of Artificial Intelligence in Financial Reporting." *Journal of Risk and Financial Management* 17, no. 9: 389.

Mustafa, F., S. Lodh, M. Nandy, and V. Kumar. 2022. "Coupling of Cryptocurrency Trading With the Sustainable Environmental Goals: Is It on the Cards?" *Business Strategy and the Environment* 31, no. 3: 1152–1168.

Mustafa, F., C. Mordi, and A. A. Elamer. 2024. "Green Gold or Carbon Beast? Assessing the Environmental Implications of Cryptocurrency Trading on Clean Water Management and Carbon Emission SDGs." *Journal of Environmental Management* 367: 122059.

Narula, S., H. Puppala, A. Kumar, et al. 2021. "Applicability of Industry 4.0 Technologies in the Adoption of Global Reporting Initiative Standards for Achieving Sustainability." *Journal of Cleaner Production* 305: 127141.

Nassar, A., and M. Kamal. 2021. "Ethical Dilemmas in AI-Powered Decision-Making: A Deep Dive Into Big Data-Driven Ethical Considerations." *International Journal of Responsible Artificial Intelligence* 11, no. 8: 1–11.

Nayal, K., S. Kumar, R. D. Raut, M. M. Queiroz, P. Priyadarshinee, and B. E. Narkhede. 2022. "Supply Chain Firm Performance in Circular Economy and Digital Era to Achieve Sustainable Development Goals." *Business Strategy and the Environment* 31, no. 3: 1058–1073.

Naz, F., R. Agrawal, A. Kumar, A. Gunasekaran, A. Majumdar, and S. Luthra. 2022. "Reviewing the Applications of Artificial Intelligence in Sustainable Supply Chains: Exploring Research Propositions for Future Directions." *Business Strategy and the Environment* 31, no. 5: 2400–2423.

Nicolò, G., S. Santis, A. Incollingo, and P. Tartaglia Polcini. 2024. "Value Relevance Research in Accounting and Reporting Domains: A Bibliometric Analysis." *Accounting in Europe* 21, no. 2: 176–211.

Nishant, R., M. Kennedy, and J. Corbett. 2020. "Artificial Intelligence for Sustainability: Challenges, Opportunities, and a Research Agenda." *International Journal of Information Management* 53: 102104.

Oppioli, M., M. J. Sousa, M. Sousa, and E. de Nuccio. 2023. "The Role of Artificial Intelligence for Management Decision: A Structured Literature Review." *Management Decision*. https://doi.org/10.1108/MD-08-2023-1331.

Ouyang, X., Q. Li, and K. Du. 2020. "How Does Environmental Regulation Promote Technological Innovations in the Industrial Sector? Evidence From Chinese Provincial Panel Data." *Energy Policy* 139: 111310.

Palmaccio, M., G. Dicuonzo, and Z. S. Belyaeva. 2021. "The Internet of Things and Corporate Business Models: A Systematic Literature Review." *Journal of Business Research* 131: 610–618.

Pournader, M., H. Ghaderi, A. Hassanzadegan, and B. Fahimnia. 2021. "Artificial Intelligence Applications in Supply Chain Management." *International Journal of Production Economics* 241: 108250.

Regona, M., T. Yigitcanlar, C. Hon, and M. Teo. 2024. "Artificial Intelligence and Sustainable Development Goals: Systematic Literature Review of the Construction Industry." *Sustainable Cities and Society* 108: 105499.

Rotondo, F., K. Corsi, and L. Giovanelli. 2019. "The Social Side of Sustainable Business Models: An Explorative Analysis of the Low-Cost Airline Industry." *Journal of Cleaner Production* 225: 806–819.

Sabahi, S., and M. M. Parast. 2020. "Firm Innovation and Supply Chain Resilience: A Dynamic Capability Perspective." *International Journal of Logistics Research and Applications* 23, no. 3: 254–269.

Singh, A., A. Kanaujia, V. K. Singh, and R. Vinuesa. 2024. "Artificial Intelligence for Sustainable Development Goals: Bibliometric Patterns and Concept Evolution Trajectories." *Sustainable Development* 32, no. 1: 724–754.

Songini, L., A. Pistoni, N. Comerio, and P. Tettamanzi. 2023. "A Decade of Integrated Reporting Studies: State of the Art and Future Research Implications." *Accounting, Auditing & Accountability Journal* 36, no. 9: 226–252.

Stoelhorst, J. W. 2023. "Value, Rent, and Profit: A Stakeholder Resource-Based Theory." *Strategic Management Journal* 44, no. 6: 1488–1513.

Sufi, U., A. Hasan, and K. Hussainey. 2024. "Improving the Prediction of Firm Performance Using Nonfinancial Disclosures: A Machine Learning Approach." *Journal of Accounting in Emerging Economies* 14, no. 5: 1223–1251.

Tarigan, Z. J. H., H. Siagian, and F. Jie. 2021. "Impact of Internal Integration, Supply Chain Partnership, Supply Chain Agility, and Supply Chain Resilience on Sustainable Advantage." *Sustainability* 13, no. 10: 5460.

Tate, W. L., L. M. Ellram, and J. F. Kirchoff. 2010. "Corporate Social Responsibility Reports: A Thematic Analysis Related to Supply Chain Management." *Journal of Supply Chain Management* 46, no. 1: 19–44.

Tiwari, K., and M. S. Khan. 2020. "Sustainability Accounting and Reporting in the Industry 4.0." *Journal of Cleaner Production* 258: 120783.

Truby, J. 2020. "Governing Artificial Intelligence to Benefit the UN Sustainable Development Goals." *Sustainable Development* 28, no. 4: 946–959.

Tsang, A., T. Frost, and H. Cao. 2023. "Environmental, Social, and Governance (ESG) Disclosure: A Literature Review." *British Accounting Review* 55, no. 1: 101149.

United Nations. 2015. "Transforming Our World: The 2030 Agenda for Sustainable Development." Accessed June 25, 2024, https://www.un.org/ga/search/view_doc.asp?symbol¼A/RES/70/1&Lang¼E.

Wang, X., and X. Qiu. 2024. "The Positive Effect of Artificial Intelligence Technology Transparency on Digital Endorsers: Based on the Theory of Mind Perception." *Journal of Retailing and Consumer Services* 78: 103777.

Wu, Z., S. Lin, T. Chen, C. Luo, and H. Xu. 2023. "Does Effective Corporate Governance Mitigate the Negative Effect of ESG Controversies on Firm Value?" *Economic Analysis and Policy* 80: 1772–1793.

Yao, T., and J. Li. 2023. "Environmental Sustainability Performance Assessment in Relation to Visibility in African Regions With Interpretable Machine Learning." *Journal of Cleaner Production* 428: 139414.

Zhang, A. Y., and J. H. Zhang. 2024. "Renovation in Environmental, Social and Governance (ESG) Research: The Application of Machine Learning." *Asian Review of Accounting* 32, no. 4: 554–572.

Zhang, J., G. Liang, T. Feng, C. Yuan, and W. Jiang. 2020. "Green Innovation to Respond to Environmental Regulation: How External Knowledge Adoption and Green Absorptive Capacity Matter?" *Business Strategy and the Environment* 29, no. 1: 39–53.

Appendix

Criteria	Query
Language = English Source type = Journal Subject area = {Business, Management and Accounting; Decision Sciences; Economics, Econometrics and Finance} Publication stage = final Exclude irrelevant keywords	TITLE-ABS-KEY (((artificial AND intelligence) OR (ai) OR (intelligent AND system*) OR (machine AND learning) OR (deep AND learning) OR (ai AND algorithm*) OR (algorithmic AND intelligence) OR (natural AND language AND processing) OR (nlp) OR (neural AND network*) OR (predictive AND analytics) OR (automated AND financial AND reporting) OR (augmented AND intelligence) OR (sentiment AND analysis AND tool) OR (supply AND chain AND optimization) OR (real-time AND risk AND assessments) OR (quantum AND computing)) AND ((sustainability AND reporting) OR (sustainable AND reporting) OR (sustainability AND disclosure) OR (esg AND reporting) OR (environmental, AND social, AND governance AND disclosure) OR (esg AND disclosure) OR (integrated AND reporting) OR (non*financial AND reporting) OR (corporate AND social AND responsibility AND reporting) OR (corporate AND responsibility AND reporting) OR (sustainable AND finance AND reporting) OR (social AND * AND reporting) OR (csr AND reporting) OR (responsible AND business AND reporting) OR (triple AND bottom AND line AND reporting) OR (tbl AND reporting) OR (sustainable AND finance AND performance) OR (corporate AND citizenship AND reporting) OR (human AND rights AND reporting) OR (social AND responsibility AND disclosure) OR (social AND sustainability AND performance) OR (social AND * AND disclosure))) AND (LIMIT-TO (SRCTYPE, “j”)) AND (LIMIT-TO (PUBSTAGE, “final”)) AND (LIMIT-TO (SUBJAREA, “SOCI”) OR LIMIT-TO (SUBJAREA, “BUSI”) OR LIMIT-TO (SUBJAREA, “ECON”)) AND (LIMIT-TO (DOCTYPE, “ar”)) AND (LIMIT-TO (LANGUAGE, “English”)) AND (EXCLUDE (EXACTKEYWORD, “Article”) OR EXCLUDE (EXACTKEYWORD, “Intelligent Buildings”) OR EXCLUDE (EXACTKEYWORD, “Integer Programming”) OR EXCLUDE (EXACTKEYWORD, “Building”) OR EXCLUDE (EXACTKEYWORD, “Adult”) OR EXCLUDE (EXACTKEYWORD, “Green Buildings”) OR EXCLUDE (EXACTKEYWORD, “Pandemic”) OR EXCLUDE (EXACTKEYWORD, “Waste Management”) OR EXCLUDE (EXACTKEYWORD, “Biomass”) OR EXCLUDE (EXACTKEYWORD, “Land Use”) OR EXCLUDE (EXACTKEYWORD, “Buildings”) OR EXCLUDE (EXACTKEYWORD, “COVID-19”) OR EXCLUDE (EXACTKEYWORD, “Higher Education”) OR EXCLUDE (EXACTKEYWORD, “Language”) OR EXCLUDE (EXACTKEYWORD, “E-learning”) OR EXCLUDE (EXACTKEYWORD, “Disasters”) OR EXCLUDE (EXACTKEYWORD, “Disaster Management”) OR EXCLUDE (EXACTKEYWORD, “GIS”) OR EXCLUDE (EXACTKEYWORD, “Crime”) OR EXCLUDE (EXACTKEYWORD, “Facebook”) OR EXCLUDE (EXACTKEYWORD, “Stochastic Models”) OR EXCLUDE (EXACTKEYWORD, “Stochastic Systems”) OR EXCLUDE (EXACTKEYWORD, “Air Pollution”) OR EXCLUDE (EXACTKEYWORD, “Air Quality”) OR EXCLUDE (EXACTKEYWORD, “Carbon”) OR EXCLUDE (EXACTKEYWORD, “Carbon Emission”) OR EXCLUDE (EXACTKEYWORD, “Carbon Footprint”) OR EXCLUDE (EXACTKEYWORD, “Climate Change”) OR EXCLUDE (EXACTKEYWORD, “Computational Journalism”) OR EXCLUDE (EXACTKEYWORD, “Environmental”) OR EXCLUDE (EXACTKEYWORD, “Environmental Economics”) OR EXCLUDE (EXACTKEYWORD, “Environmental Protection”) OR EXCLUDE (EXACTKEYWORD, “Environmental Regulations”) OR EXCLUDE (EXACTKEYWORD, “Travel Time”) OR EXCLUDE (EXACTKEYWORD, “Urban Growth”) OR EXCLUDE (EXACTKEYWORD, “Environmental Assessment”) OR EXCLUDE (EXACTKEYWORD, “Environmental Impact”) OR EXCLUDE (EXACTKEYWORD, “Environmental Management”) OR EXCLUDE (EXACTKEYWORD, “Environmental Sustainability”) OR EXCLUDE (EXACTKEYWORD, “Environmental Performance”))