Artificial Intelligence for ESG Reporting: A Knowledge Management Perspective

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Abstract: Artificial Intelligence (AI) is even more transforming the generation, validation, and circulation of sustainability-related knowledge within and across organizations. Although a growing body of research recognizes this transformation, its specific contributions to the robustness and reliability of Sustainability Accounting and Reporting (SAR) remain theoretically underexplored and empirically fragmented across disciplines. This paper addresses this gap through a systematic literature review and inductive content analysis, identifying nine empirically grounded categories of positive AI impact on SAR. By mapping these contributions onto the SECI Model of Knowledge Creation, the study conceptualizes AI not merely as a technical instrument, but as an enabling knowledge-creation infrastructure capable of reconfiguring sustainability disclosures and strengthening ESG information integrity. The findings show how AI enhances the organizational processes of knowledge conversion—socialization, externalization, combination, and internalization—thereby improving the consistency, traceability, and robustness of sustainability disclosures. The proposed framework further illustrates how AI can support compliance with leading ESG reporting standards, such as the Global Reporting Initiative Standards and the Corporate Sustainability Reporting Directive (CSRD) including the European Sustainability Reporting Standards (ESRS). By integrating insights from sustainability accounting, information systems, and knowledge management, the paper advances the theoretical understanding of AI-enabled knowledge governance in sustainability reporting and outlines directions for future research.

Keywords: Artificial intelligence, Sustainability accounting and reporting, ESG disclosure, Knowledge management, SECI model

1. Introduction

Corporate sustainability disclosure has undergone a structural transformation over the past decade. The European Union's Corporate Sustainability Reporting Directive (CSRD, 2022), implemented through the European Sustainability Reporting Standards (ESRS), requires approximately 50,000 companies to disclose over 1,100 sustainability data points, with mandatory XBRL tagging and external assurance (EFRAG, 2023). The International Sustainability Standards Board (ISSB) has simultaneously issued IFRS S1 and S2 as a global investor-focused baseline, while the Global Reporting Initiative (GRI) Standards underpin impact-based reporting for over 10,000 organisations worldwide (GRI, 2021). This regulatory convergence has created unprecedented demand for high-quality, comparable, and auditable ESG information—yet the volume, velocity, and variety of sustainability data far exceeds the capacity of traditional manual processes. Artificial Intelligence (AI) has emerged as a technology with the potential to close this gap. A growing but fragmented literature, spanning NLP for ESG text analysis (Kang and Kim, 2022; Moodaley and Telukdarie, 2023), AI-driven greenwashing detection (Khan et al., 2024; Li et al., 2024), automated assurance (de Villiers et al., 2024), carbon accounting (Alqahtani, 2023; Jarboui et al., 2026), and blockchain-AI verification (Liu et al., 2024), AI adoption and ESG disclosure quality (Yang, 2025; Naveed et al., 2025), ESG reporting automation (Berniak-Woźny, 2025; Hąbek, 2025), AI in accounting (Sampaio and Silva, 2025), NLP for sustainability disclosures (Ong et al., 2025), digital technologies in sustainability accounting (De Silva et al., 2025), and AI-based ESG assurance (Hoai, 2025), documents AI's transformative potential across the SAR value chain. However, no systematic synthesis linking these contributions to a unified theoretical framework currently exists. This paper addresses that gap through two contributions: (i) an inductive content analysis of twenty-five peer-reviewed articles yielding evidence-based categories of positive AI impact on SAR quality; and (ii) the AI-SECI-SAR Framework, which maps these categories onto Nonaka and Takeuchi's (1995) SECI model to explain how AI amplifies the four knowledge-conversion modes (Socialisation, Externalisation, Combination, Internalisation) embedded in sustainability reporting cycles. Knowledge Management (KM) theory provides the appropriate theoretical anchor. Nonaka and Takeuchi's (1995) SECI model—the most widely cited framework in KM (Farnese et al., 2019)—distinguishes between tacit knowledge (experiential, context-embedded) and explicit knowledge (codified, transferable), and identifies four recursive conversion modes. SAR is, at its core, a knowledge management challenge: practitioners hold tacit knowledge about environmental impacts and governance realities that must be *Externalised* into auditable disclosures, *Combined* across data sources into standardised reports, *Socialised* to diverse stakeholders, and

Internalised into strategic decision-making. AI accelerates and improves the reliability of each conversion step, motivating its integration with the SECI spiral. The paper is structured as follows: Section 2 describes the methodology, Section 3 presents the results, Section 4 develops the AI-SECI-SAR framework, and Section 5 concludes.

2. Research Methodology

This study adopts a two-stage qualitative design combining a Systematic Literature Review (SLR) with Inductive Content Analysis (ICA), following established protocols for rigorous qualitative synthesis in accounting and sustainability research. The SLR was conducted in accordance with the PRISMA 2020 protocol (Page et al., 2021). The database search was performed on Web of Science on 7 January 2026. The search string was structured as a Boolean query combining a fixed AI cluster with a broad sustainability reporting cluster, and was applied to title, abstract, keyword plus, and author keywords fields (Menichini et al., 2026):

"Artificial Intelligence" AND ("Global Reporting Initiative" OR "GRI report" OR "social report*" OR "environment* report*" OR "sustainab* report*" OR "CSR report*" OR "responsib* report*" OR "non-financ* report*" OR "TBL report*" OR "triple* report*" OR "integr* report*" OR "ESG report*" OR "SDG* report*" OR "sustainable development goal* report*" OR "sustainab* disclosure*" OR "impact report*" OR "annual report*").*

Retrieved records were screened against two sequentially applied sets of criteria. Publication screening criteria required: (i) publication year between 2020 and 2025, capturing the period of most rapid AI development and regulatory convergence in sustainability reporting; (ii) document type classified as article or review; and (iii) language of publication English. Eligibility criteria, applied at abstract and full-text level, required: (iv) the article to address SAR as a primary or substantive research theme, not merely as a contextual backdrop; and (v) the full text to identify at least one positive contribution of AI or AI-related technologies to the sustainability accounting and reporting (SAR) process or to ESG reporting quality. Articles focusing exclusively on AI risks, limitations, or governance concerns without documenting positive process impacts were excluded. After deduplication, title and abstract screening, and full-text quality assessment, twenty-five peer-reviewed articles published between 2022 and 2026 were retained for analysis (Figure 1). The retained corpus was analysed using Inductive Content Analysis (ICA; Elo and Kyngäs, 2008), a rigorous qualitative method appropriate when existing theoretical frameworks do not fully account for the phenomenon under investigation — in this case, the multidimensional and rapidly evolving role of AI across the SAR value chain. Unlike deductive content analysis, which applies pre-existing coding schemes to textual data, ICA allows categories to emerge from the evidence itself, making it particularly suited to an exploratory synthesis of a nascent and interdisciplinary literature. ICA was applied in three sequential phases. In the Open Coding phase, all passages in the twenty-five articles that attributed a positive effect to AI or AI-related technologies were extracted verbatim and assigned provisional codes reflecting their semantic content. Only passages with an explicit positive attribution were retained (not general descriptions of AI capabilities), yielding a corpus of over 200 coded passages across the twenty-five articles. In the Category Development phase, codes were iteratively compared and grouped by semantic similarity using the constant comparative method. Groupings were progressively refined (merging overlapping codes, splitting internally heterogeneous ones) until theoretical saturation was reached: the point at which continued analysis of remaining articles produced no new conceptually distinct code. This process yielded nine internally coherent categories, each representing a distinct dimension of SAR quality improved by AI. In the Framework Integration phase, the nine empirically derived categories were deductively mapped onto the four knowledge-conversion modes of Nonaka and Takeuchi's (1995) SECI model producing the AI-SECI-SAR Framework presented in Section 4. The mapping was guided by the theoretical definition of each SECI mode and by the directionality of knowledge conversion implicit in each category: categories concerned with codifying tacit operational realities into explicit data were assigned to Externalisation; those concerned with aggregating, standardising, and validating explicit knowledge were assigned to Combination; those concerned with transferring sustainability norms to external audiences were assigned to Socialisation; and those concerned with absorbing ESG insights into ongoing organisational practice were assigned to Internalisation. To ensure rigour and transparency throughout the analytical process, a structured codebook was developed specifying, for each of the nine categories: a mutually exclusive definition grounded in the coded passages, a coding rule designed to resolve boundary cases between adjacent categories, the primary AI mechanisms referenced across the contributing articles, and the key bibliographic sources providing convergent evidence. The codebook, presented in Table 1, constitutes both the central analytical output of the ICA and the empirical foundation of the AI-SECI-SAR Framework.

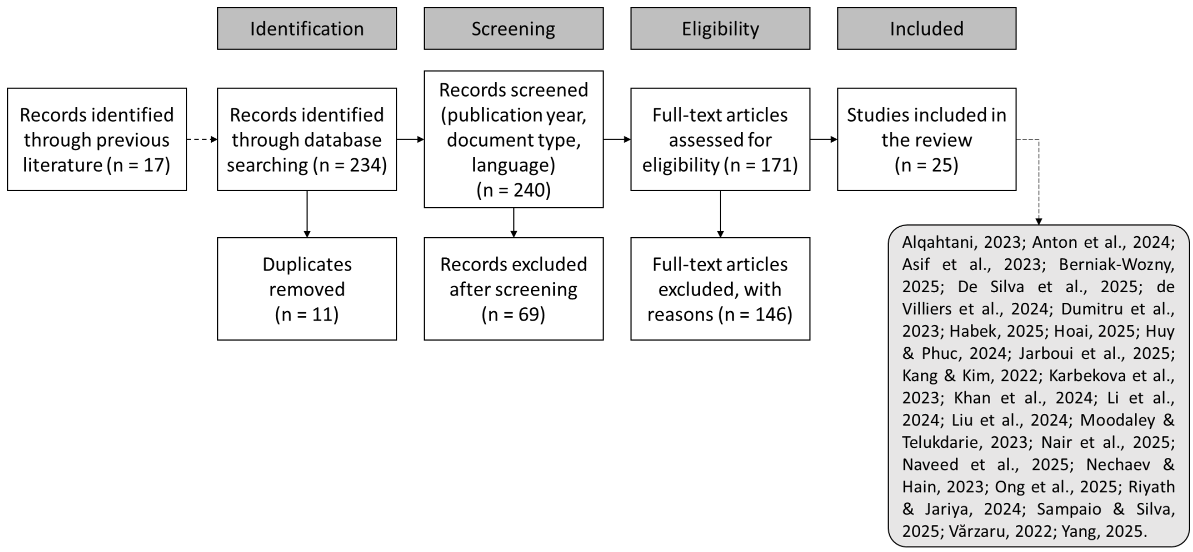

Figure 1: The PRISMA framework

3. Results: Nine Categories of AI Impact on SAR Quality

Inductive content analysis of the sample articles yielded over 200 coded passages distributed across nine empirically grounded categories (Table 1). Each category represents a distinct dimension of SAR quality improved by AI, supported by convergent evidence from multiple articles.

Table 1: Codebook: Categories of AI Impact on Sustainability Reporting Quality

ID	Category	Definition	Primary AI Mechanisms	Key Articles	SECI
C1	Data Quality, Accuracy & Reliability	C1 covers AI mechanisms that improve the factual correctness, completeness, and dependability of ESG data at the point of collection and measurement, before any reporting or control process begins.	IoT sensors, ML validation, OCR, web crawlers	Li et al., (2024); Khan et al., (2024); Huy & Phuc, (2024); Riyath & Jariya, (2024); Alqahtani, (2023); Nair et al., (2025); Yang, (2025); Berniak-Woźny, (2025); Hąbek, (2025); De Silva et al., (2025); Naveed et al., (2025)	E
C2	Transparency & Anti-Greenwashing	C2 covers AI mechanisms that detect or prevent misalignment between a company's public sustainability narrative and independently verifiable external evidence.	NLP sentiment analysis, LLMs, anomaly detection, validation	Li et al., (2024); Khan et al., (2024); Moodaley & Telukdarie, (2023); Kang & Kim, (2022); de Villiers et al., (2024); Ong et al., (2025); Hoai, (2025); Yang, (2025)	E/C
C3	Efficiency, Automation & Cost Reduction	C3 covers AI applications that reduce the time, labour, and cost of executing the reporting workflow itself — the sequence of tasks that transforms raw ESG data into a finished, published report.	RPA, IPA, ERP-AI integration, chatbots, ML pipelines	Karbekova et al., (2023); Dumitru et al., (2023); de Villiers et al., (2024); Anton et al., (2024); Vărzaru, (2022)	C
C4	Real-Time Monitoring & Continuous Reporting	C4 covers AI and IoT infrastructures that replace periodic, snapshot-based ESG measurement with a continuous, always-current information stream.	IoT, digital twins, streaming analytics, blockchain-AI audit	Li et al., (2024); Khan et al., (2024); de Villiers et al., (2024); Asif et al., (2023); Huy & Phuc, (2024)	I
C5	Stakeholder Communication & Engagement	C5 covers AI tools that improve the accessibility, personalisation, and interactivity of sustainability disclosures for audiences	Chatbots, NLP summarisation, data visualisation, interactive platforms	de Villiers et al., (2024); Huy & Phuc, (2024); Riyath & Jariya, (2024); Anton et al., (2024); Asif et al., (2023)	S

ID	Category	Definition	Primary AI Mechanisms	Key Articles	SECI
		external to the reporting organisation.			
C6	Regulatory Compliance, Comparability & Standardisation	C6 covers AI mechanisms that verify conformity of a completed or near-completed disclosure with external regulatory frameworks or reporting standards (GRI, ESRS, TCFD), and AI mechanisms that make ESG data structurally comparable across organisations.	Context-aware AI, blockchain assurance, compliance checking, audit automation, ML normalisation, XBRL tagging, cluster-based verification	Li et al., (2024); Liu et al., (2024); Kang & Kim, (2022); Jarboui et al., (2024); Nechaev & Hain, (2023); de Villiers et al., (2024); Riyath & Jariya, (2024); Nair et al., (2025); Hoai, (2025); Berniak-Wożny, (2025); Hąbek, (2025)	S/C
C7	Predictive Analytics & Strategic Decision Support	C7 covers AI models that transform historical ESG datasets into forward-looking organisational intelligence used for strategic planning, capital allocation, or risk management.	ANFIS, LSTM, FFNN, AutoML, scenario modelling, feature importance analysis	Li et al., (2024); Huy & Phuc, (2024); de Villiers et al., (2024); Alqahtani, (2023); Jarboui et al., (2024); Vărzaru, (2022)	I
C8	Anomaly Detection, Fraud & Internal Controls	C8 covers AI systems that scan internal ESG data pipelines and reporting processes for statistical outliers, procedural irregularities, and indicators of error or manipulation — before the data reaches external disclosure.	Anomaly analysis, process mining, fraud detection, cross-data validation	Li et al., (2024); Khan et al., (2024); de Villiers et al., (2024); Asif et al., (2023); Anton et al., (2024); Alqahtani, (2023)	C
C9	Unstructured & Textual Data Processing	C9 covers AI techniques applied to non-tabular, narrative, or visual sources of sustainability-relevant information — sources that traditional structured accounting systems cannot process.	NLP, LLMs, OCR, supervised ML classification, sentence similarity	Li et al., (2024); Moodaley & Telukdarie, (2023); Kang & Kim, (2022); Huy & Phuc, (2024); Nechaev & Hain, (2023); Ong et al., (2025); De Silva et al., (2025)	E

SECI: E = Externalisation; C = Combination; S = Socialisation; I = Internalisation.

C1 reflects AI's capacity to automate multi-source ESG data acquisition and validation, directly addressing the data reliability crisis that has historically undermined voluntary disclosure credibility. This finding is powerfully corroborated by the expanded corpus: Yang (2025) provides empirical evidence that AI adoption is positively and significantly associated with overall ESG disclosure quality across all three ESG pillars; Berniak-Wożny (2025) documents how ML and NLP improve ESG data quality by processing large heterogeneous datasets from IoT sensors and satellite imagery; Hąbek (2025) shows that ML models scan ESG data sets to flag outliers and inconsistent entries in real time; De Silva et al. (2025) demonstrate that AI enhances the accuracy and transparency of sustainability reports; and Naveed et al. (2025) establish that AI adoption improves data quality, standardisation, and comparability. C2 captures both passive transparency mechanisms and active AI-driven detection: Moodaley and Telukdarie (2023) demonstrate that LLMs enable automated identification of green claims at scale, while Khan et al. (2024) show that AI systems empower stakeholders to detect discrepancies between stated and genuine ESG performance. Ong et al. (2025) extend this category by showing how NLP and LLMs can evaluate sustainability disclosures for conformity to TCFD reporting guidelines; Hoai (2025) adds that AI-powered tools such as text mining and machine learning can systematically detect misleading sustainability claims, thereby strengthening ESG assurance reliability. C3 documents dramatic reductions in reporting effort through RPA, IPA, and AI-enhanced ERP systems, a finding reinforced by Berniak-Wożny (2025), who demonstrates that AI-automated reports reduce administrative burden and accelerate reporting cycles, and by Sampaio and Silva (2025), who confirm that AI automation improves the accuracy and timeliness of accounting information. C4 captures AI and IoT infrastructures that replace periodic, snapshot-based ESG measurement with a continuous information stream. Li et al. (2024) document how AI-based automation systems proactively monitor operations, detect anomalies, and generate alerts for potential irregularities, enabling a shift from retrospective to proactive sustainability governance. Hoai (2025) further demonstrates that automated assurance engines allow continuous monitoring of ESG performance indicators, while Berniak-Wożny (2025) shows that real-time AI-driven dashboards enable firms to track and adjust their sustainability performance on an ongoing basis — a capability directly relevant to the limited assurance requirements under ESRS/CSRD. C5 encompasses AI tools that improve the accessibility, personalisation, and interactivity of sustainability disclosures for audiences external to the reporting organisation. Anton et al. (2024) demonstrate that AI-powered chatbots enable personalised, dynamic engagement with integrated reporting content, while Huy and Phuc (2024) show that generative AI facilitates the development of sophisticated data visualisation tools and interactive platforms that empower stakeholders to engage with ESG data in more informed ways. Ong et al. (2025) extend this category by showing how RAG-powered dialogue systems allow analysts to query disclosure content directly, mitigating the obfuscation of key information within lengthy sustainability reports. C6 is the most cross-cutting category, operating across both Combination and Socialisation modes of the SECI spiral. In its compliance dimension, Hoai (2025) demonstrates that NLP and ML can support compliance monitoring and readability assessment of sustainability disclosures, while Liu et al. (2024) show that blockchain-AI hybrid systems create immutable audit trails that verify and standardise reported ESG information against external frameworks. In its comparability dimension, Hąbek (2025) shows that ML clustering enables peer benchmarking by size, region, and sector, and Ong et al. (2025) confirm that XBRL facilitates structured, standardised reporting of sustainability metrics across firms and jurisdictions. Organisations investing in AI-enabled compliance platforms appear better positioned for CSRD conformity, with Hąbek (2025) noting their stronger readiness for mandatory ESRS disclosures.C7 supports scenario analysis requirements across major ESG frameworks, with Alqahtani (2023) demonstrating that ANFIS, LSTM, and FFNN models significantly predict annual carbon emissions. C8 documents AI systems that scan ESG data pipelines for statistical outliers, procedural irregularities, and indicators of misrepresentation before data reaches external disclosure. Hoai (2025) establishes that AI-enabled technologies surpass the analytical capacity of conventional audit methodologies by processing extensive datasets and detecting patterns that remain undetected by human analysts. Sampaio and Silva (2025) confirm the role of AI-driven auditing and fraud detection systems in strengthening the reliability of financial and non-financial reporting, while de Villiers et al. (2024) note that AI now allows for verification of transactions in their entirety, adding a layer of assurance wholly absent from traditional manual processes. C9 addresses a capability wholly absent from traditional accounting systems: Kang and Kim (2022) show that NLP-based sentence similarity and sentiment analysis can automatically characterise the thematic balance of sustainability reports across firms and time, while Nechaev and Hain (2023) use supervised ML to identify social impacts in CSR texts aligned with GRI categories. Ong et al. (2025) enrich this category by demonstrating how BERT-like models classify ESG-related risk factors and how generative LLMs transform TCFD disclosures into structured, queryable formats; De Silva et al. (2025) confirm that AI and IoT enhance the precision of ESG reporting through automated data collection and real-time insights into environmental performance.

4. The AI-SECI-SAR Framework

The nine categories map systematically onto the four SECI modes (Figure 2), constituting the AI-SECI-SAR Framework, a conceptual model that positions AI as a knowledge-creation infrastructure amplifying every stage of the sustainability reporting knowledge spiral.

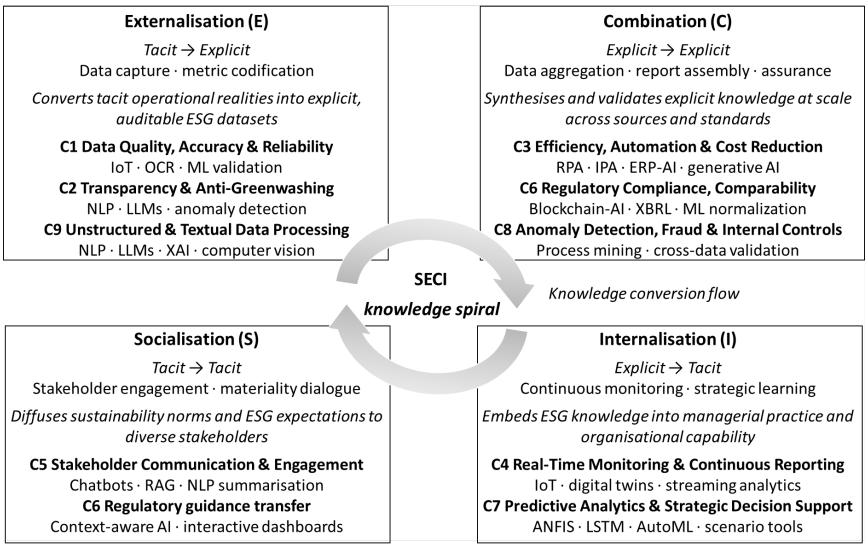

Figure 2: AI-SECI-SAR Framework: AI as knowledge-creation infrastructure for sustainability reporting

4.1 Externalisation: AI as Knowledge Codification Engine

Externalisation (i.e., transforming tacit operational knowledge into explicit, verifiable disclosures) is the SECI mode most fundamentally served by AI. Sustainability data initially exist as tacit realities: energy consumption patterns, supplier practices, biodiversity impacts embedded in production processes. AI codifies these realities through three primary mechanisms: automated data collection (IoT sensors, web crawlers, OCR) translating physical facts into structured ESG data at scale (Li et al., 2024); NLP and LLM-based analysis converting narrative texts into categorised, auditable datasets (Moodaley and Telukdarie, 2023; Kang and Kim, 2022); and ML validation detecting discrepancies that arise when tacit knowledge is imperfectly codified (Riyath and Jariya, 2024). Crucially, automated codification of physical and textual evidence reduces the scope for selective information omission that defines greenwashing, when emissions are IoT-measured rather than self-reported, the gap between stated and genuine ESG performance becomes structurally harder to sustain (Khan et al., 2024).

4.2 Combination: AI as Knowledge Synthesis and Validation System

The Combination phase (i.e., synthesising explicit knowledge into higher-order explicit knowledge) delivers AI's most transformative efficiency and analytical gains. AI-enhanced ERP and DOP platforms aggregate and reconcile data from heterogeneous sources across business units and supply chain tiers (Dumitru et al., 2023). ML algorithms simultaneously detect anomalies, benchmark performance against peers, and classify compliance gaps (Asif et al., 2023; Li et al., 2024). Blockchain-AI hybrids create immutable audit trails that verify and standardise reported information (Liu et al., 2024). Predictive models synthesise historical data into forward-looking risk assessments (Alqahtani, 2023; Jarboui et al., 2026). Context-aware compliance AI compares report content against multiple regulatory frameworks simultaneously, a critical capability for organisations managing concurrent ESRS and GRI obligations.

4.3 Socialisation: AI as Knowledge Mediator

Socialisation (i.e., the transfer of tacit knowledge through shared experience) corresponds in the SAR context to the diffusion of sustainability norms, expectations, and interpretive frameworks among stakeholders across organisational and institutional boundaries. AI mediates this transfer through conversational and personalised interfaces: chatbots (Anton et al., 2024) and interactive reporting platforms (Huy and Phuc, 2024) enable diverse audiences to engage with sustainability information dynamically. This shift from broadcast to dialogue reflects the SECI model's 'Ba' concept, shared contextual spaces enabling knowledge creation. De Villiers et al. (2024) note that AI can also explain complex sustainability regulations clearly, reducing the knowledge asymmetry that prevents smaller firms from engaging with mandatory frameworks.

4.4 Internalisation: AI as Strategic Learning Enabler

Internalisation (i.e., converting explicit knowledge into renewed organisational capability) is the phase in which sustainability disclosure data are absorbed into managerial practice, closing the SECI spiral. Real-time AI dashboards (C4) make performance data continuously available to decision-makers, enabling iterative adjustment: when a logistics manager receives an AI-generated anomaly alert on Scope 3 emissions, the insight is immediately internalised into procurement practice. AI-generated predictive analyses (C8) translate ESG datasets into strategic insights embedded in capital allocation, supplier selection, and product design decisions-making sustainability considerations part of the organisation's tacit knowledge base (Vărzaru, 2022; Nair et al., 2025). Together, the four phases form a self-reinforcing knowledge spiral: each cycle of AI-mediated SAR generates richer organisational knowledge as input for the next, progressively enhancing both reporting quality and learning capability (Nonaka et al., 2000).

5. Discussion and Conclusion

This study advances understanding of AI's role in SAR through four contributions. First, the nine-category taxonomy — grounded in over 200 coded passages from twenty-five peer-reviewed articles — provides the first systematic, evidence-based classification of AI impacts on SAR quality, offering a shared vocabulary for researchers across accounting, sustainability, and information systems disciplines. Second, integrating the SECI model into the SAR domain demonstrates that Nonaka and Takeuchi's (1995) framework provides a robust theoretical architecture: Externalisation (AI codifying tacit operational realities into verifiable ESG data), Combination (AI synthesising and validating explicit knowledge at scale), Socialisation (AI mediating knowledge transfer to diverse stakeholders), and Internalisation (AI enabling continuous learning through real-time feedback) map onto the full reporting cycle in ways prior literature had not formalised. Third, the AI-SECI-SAR Framework provides actionable guidance for strategic AI deployment: organisations with complex physical operations should prioritise Externalisation investments (IoT, OCR, NLP); those facing multi-framework compliance should invest in Combination tools (ERP-AI, blockchain); stakeholder-intensive organisations benefit most from Socialisation investments (chatbots, interactive dashboards); and those embedding sustainability in strategy should focus on Internalisation tools (real-time dashboards, scenario modelling). Fourth, the framework reveals differential alignment between AI capabilities and the two principal reporting regimes. Under the GRI Universal Standards, AI maps most strongly onto the quality principles of accuracy (C1), completeness (C2), and timeliness (C4), and onto the stakeholder-inclusive materiality process (C5); however, the absence of mandatory digital tagging limits scalability of AI-driven comparability (C6), and the lack of a real-time disclosure mandate leaves continuous monitoring (C4) an organisational choice. Under ESRS/CSRD, alignment is the broadest and most structurally embedded: mandatory XBRL tagging activates AI standardisation capabilities (C6) at scale, the phased assurance trajectory makes anomaly detection (C8) and data quality (C1) regulatory prerequisites rather than efficiency tools, and the double materiality requirement creates specific demand for predictive analytics (C7) and unstructured data processing (C9). Across both frameworks, real-time monitoring (C4), proactive greenwashing detection (C2), and narrative data processing (C9) remain systematically underactivated — representing the frontier where next-generation standard revisions should most urgently incorporate AI-specific provisions. Several limitations bound these findings. The corpus covers a specific window (2022–2026), is restricted to English-language peer-reviewed sources, and the AI-SECI-SAR Framework remains conceptual, requiring empirical validation through longitudinal studies, case research, and cross-industry surveys. Unintended consequences of AI in SAR — including algorithmic bias in ESG scoring, data privacy risks from continuous IoT monitoring, and the environmental footprint of large AI systems — deserve dedicated investigation. Future research should examine longitudinal impacts of AI adoption on SAR quality indices, SECI-phase-specific AI value across sectors, effects of AI-generated disclosures on investor judgement, and governance frameworks ensuring AI-enhanced SAR remains credible and resistant to new forms of data manipulation, positioning the AI-SECI-SAR model as a research programme rather than a terminal contribution.

Ethics Declaration: Ethical clearance was not required for this research.

AI Declaration: AI tools were used only for language refinement; the authors remain fully responsible for the work's integrity, accuracy, and originality of this work.

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