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Artificial Intelligence in ESG Reporting: A Scopus-Based Bibliometric Analysis and Conceptual Model for Data-Driven Decision Support

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Abstract
The purpose of this manuscript is to review the role of AI in evolving ESG reporting from a historical, compliance-driven approach toward an integrated analysis and decision-support system. The analysis is based on a bibliometric analysis of manuscripts gathered from the Scopus database, with 765 publications from 2004–2026. It was performed keyword co-occurrence analysis using VOSviewer to reveal the main thematic clusters and structure of the research field. An analysis was also performed by using the Ishikawa diagram and a Pareto–Lorenz analysis to determine whether this degree of concentration was indicative of the relative importance among key concepts. The results reflect an increased role for technologies like machine learning and natural language processing in the analysis of ESG data, notably unstructured information. Among the most common were key drivers of AI adoption, such as regulatory pressure, stakeholder expectations and the desire to improve data quality. In this context, the manuscript seeks to propose a conceptual model for AI–driven transformation of ESG reporting, whereby AI serves as an integrating factor connecting data processing and analytics, decision-making and due diligence and enforcement in practice.

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1. Introduction

In the last decade, ESG (Environmental, Social and Governance) reporting has evolved into one of the essential elements of enterprise management systems as well as a key driver in investment choices (Xue et al., 2025). There is heightened interest and urgency around ESG, fueled by global environmental issues such as climate change and decarbonization on one hand, and stakeholder expectations as well as regulatory pressures related to CSRD (Corporate Sustainability Reporting Directive) implementation and the global reporting standards from IFRS Foundation (Usman et al., 2023). Consequently, ESG reporting has become much more than a communication mechanism and more a part of strategic management, risk assessment and capital allocation processes (KPMG ESG Assurance Maturity Index 2025, 2026; Atan et al., 2018)

Even though ESG reporting has grown fast, many barriers are still present. These include data fragmentation, absence of standardization, lack of comparability and increasing complexity of disclosures (Tunyi et al., 2026; Engel, 2025; Tancke et al., 2023). In light of growing reporting requirements, these traditional approaches relying on manual data collection and processing have become increasingly inadequate. In addition, the quality and credibility of ESG disclosures is undermined by issues such as greenwashing, which casts doubt on reported information and reduces its utility in decision-making (Ruggeri et al., 2025). To address these challenges, digital technologies, mainly Artificial Intelligence (AI) are playing a crucial role in the automation of ESG reporting processes (Berniak-Woźny, 2025; Bogdan et al., 2025). While enterprise AI adoption started to widen in the later half of the 2010s, its massive acceleration has only taken place post-2020, fueled by breakthroughs in machine learning and natural language processing (NLP), as well as cloud initiatives. AI use in ESG reporting is very dynamic (evolves from both the tech side and regulatory perspective) during 2023–2025. As noted by PricewaterhouseCoopers (2026), the use of AI in sustainability reporting has grown from 11% to 28% within a year's timeframe, showcasing the integral nature of AI in ESG reporting initiatives

(PricewaterhouseCoopers, 2026). Simultaneously, over 80% of organizations claim to use AI-based solutions in their sustainability-related activities such as ESG data analysis for reporting and risk management (Deloitte, 2026). These findings indicate AI is moving from testing to a systematic use case in enterprise.

The research about ESG reporting and AI has been rapidly increasing in recent years, but they still lack the integration of digital technologies as well as an emerging paradigm shift for reporting (Abu-Allan, 2025; Xue et al., 2025). While extensive research has been conducted on the quality of ESG disclosure, little progress addressing individual case studies exists today focusing solely on the use of AI and digital tools (like machine learning, natural language processing or blockchain) in data processing and analysis (Chen & Zhang, 2025; Berniak-Woźny, 2025)

While most recent research highlights the barriers to digital technologies in risk and issue management, previous studies illustrate that they improve ESG reporting through facilitating better data collection, accuracy, transparency, and analysis capabilities (Chen & Zhang, 2025; Liu et al., 2025), further allowing improved assessment of risks and decision-making processes. However, these studies often regard digitalization as a tool rather than being a force changing the entire reporting logic. Importantly, the literature highlights increasing actions regarding this transition from traditional retrospective ESG reporting to dynamic real time data driven systems powered by AI and advanced analytics systems (Alshi, 2025) enable constant monitoring, predictive modeling, and automated verification of ESG data (Malik et al., 2025).

Although academic research interest in AI applications in the ESG reporting field has been steadily increasing, prior studies have mostly been restricted to either mapping bibliometric landscapes, or examining specific topics such as greenwashing and information disclosure quality. The studies by Berniak-Woźny (2025) and Moodaley and (Moodaley & Telukdarie, 2023) both align with this general pattern. This paper extends the aforementioned line of research, conceptualizes ESG reporting as a data-driven management system, and clarifies that AI can support four core processes. This manuscript uses an original research design, combining keyword co-occurrence analysis, the Ishikawa diagram, and Pareto-Lorenz analysis to sort out the thematic clusters, conceptual concentration, and influencing factors of AI adoption in ESG reports, and identifies the evolutionary trend of ESG reports shifting from a compliance-oriented focus to AI-powered empowerment.

There are the following objectives of the manuscript:

- To explore the current nature of ESG reporting, with a specific focus on core challenges such as data fragmentation, inconsistencies in disclosures, greater volumes of reported information and potential for greenwashing.
- To examine the role of AI in automating ESG reporting processes, such as data collection, integration and analysis, and enhancing data quality and reliability.
- Using bibliometric analysis and keyword co-occurrence techniques, to identify the main research trends and emerging directions in the intersection of ESG and AI.
- To identify the pervasiveness of digital technologies (e.g. IoT and Industry 4.0) in transforming ESG reporting systems: specifically through mechanisms such as real-time monitoring, data-driven decisions making and risk management.

2. Literature review

ESG reporting is a central part of a firm's infrastructure of information and governance architecture, providing insight into risk management capability, long-term value generation potential, and response to stakeholder and regulatory pressures (Eccles et al., 2014; Gillan et. Al., 2021). ESG reporting has transformed into a vehicle that weaves environmental, social and governance priorities together with decision-making of a strategic nature; thereby reframing the relationship between disclosure and management from communicative passive to managerial active (Amel-Zadeh & Serafeim, 2018; Friede et al., 2015).

Consequently, maturity in providing sustainable development is increasingly viewed as a sign of operational excellence and governance quality that can be proxy through consistent, reliable, and decision-useful ESG disclosures (Wamba et al., 2017). However, the increasing significance of ESG reporting has in many ways revealed basic deficiencies with the traditional model. Weighing in with a significant body of literature, authors depict traditional ESG reporting as consisting of disparate data structures, manual processes for gathering information, low analytical capability and a backward-looking focus (Kotsantonis & Serafeim, 2019; Christensen et al., 2021; Alshi, 2025). Instead, the ESG data that managers used were usually gathered from a patchwork of heterogeneous and decentralized sources (internal systems; departmental reports; operational documents) with non-uniform standards, leading to issues such as inconsistency, incompleteness and low comparability across firms (Engel, 2025; Tunyi et al., 2026). The analytical dimension of ESG reporting was also underdeveloped, as firms relied mostly on descriptive evaluations instead of sophisticated analytical tools able to discover complex interdependencies or detect emerging trends (Ruggeri et al., 2025). As a result, the preparation of ESG information was mostly reduced to a compliance activity, with little impact on strategic and operational decision-making processes (Atan et al., 2018). Table 1 presents characteristics of traditional ESG reporting.

Table 1. Characteristics of traditional ESG reporting

ESG area	Characteristic
Data acquisition and integration	It was obtained manually from several disparate sources, including internal systems, department reports and operational documents. It was a time-intensive process with lots of possible human error, and different standards for the kinds of charts being made led to difficulties in integrating the

	data. So datasets were patchy, inconsistent and hard to compare from organization to organization
Data processing and analysis	There was limited ESG data and manual analysis of relatively small datasets. Due to limited access to sophisticated analytical tools, these relationships and trends were difficult to identify. The reporting was thus mostly descriptive rather than analytical.
Analysis of ESG report content	Narrative ESG data was interpreted using subjective expert judgement, resulting in low reproducibility and limited comparability across reports. The lack of systematic analytical tools made it more challenging to identify inconsistencies and practices of greenwashing
ESG risk identification and modeling	ESG risk management was reactive and primarily rooted in historical data and expert experience. Without predictive tools, organizations lacked the ability to detect risks earlier and devise adaptive strategies.
ESG report preparation	ESG reports were sent periodically (usually on an annual basis) as static documents. It was a process that was time-consuming, required cross-departmental coordination and often introduced delays and inconsistencies.
ESG performance monitoring	ESG indicators were not monitored in real-time; they were reported a posteriori. Real-time tracking of environmental and social parameters was not within organizations' purview.
Data quality and reliability	Due to manual processing and lack of common standards the risk for errors was high, driving low comparability and limited reliability of ESG disclosures.
Role of ESG reporting	ESG reporting was mainly for compliance and reporting. ESG data were used only in a marginal way within decision-making and management processes, restricting their strategic relevance

Source: own study based on: (Ben Mahjoub, 2025; David et al., 2025; Janik & Ryszko, 2026; Zervoudi et al., 2025)

The reliance on these limitations highlighted a paradox in ESG reporting: while the relevance to investors, regulators and stakeholders intensified over time, its operational utility and analytical value remained limited. A significant driver identified within the literature for the adoption of AI in this context has been tensions between investors and suppliers that highlight structural inefficiencies of traditional reporting systems (Alshi, 2025; Berniak-Woźny, 2025; Aruwaji & Swanepoel, 2025; Gupta et al., 2025). Organizations, in particular, grappled with demands for improved data integration, analytical depth (Chen & Zhang, 2025; Zhou et al., 2025) consistency of data sources and shifting from historical reporting to more dynamic and forward-looking processes. Figure 1 depicts the state of adoption of essential digital technologies for ESG reporting among leading organizations in 2025, including the technological underpinnings of this process.

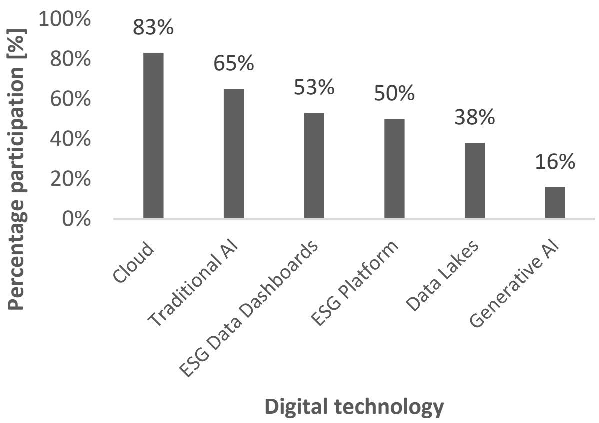

Fig. 1. Digital technology adoption in leading companies in ESG reporting in 2025.

Source: own study based on: KPMG (2026).

Cloud-based solutions (83%) have the widest adoption, underscoring their importance as a scalable infrastructure capable of storing, integrating and processing ESG data from diverse sources. Cloud technologies improve the efficiency, transparency, and credibility of ESG reporting due to real-time access and advanced analytics support (Marston et al., 2011; Hashem et al., 2015; Gürdür Broo et al., 2022).

A prominent place (65%) is held by artificial intelligence-based solutions, which play a key role in ESG data analytics, especially for establishing relationships between indicators, modeling risks, and supporting decision-making processes. Deloitte (2026) further asserts that organizations leverage AI for ESG-related activities such as environmental optimization (65%), data monitoring (58%) and risk analysis (53%). The increasing use of AI is largely linked to the growing complexity and volume of non-financial information that is also disjointed and unstructured. Given this background, advanced analytical technologies facilitate the move from simple reporting practices to more complex data analysis and interpretation.

Tools such as ESG dashboards (53%) and ESG platforms (50%) are being developed to meet a need for greater integration of ESG data in organizations. Dashboarding solutions (e.g., Microsoft Power BI, Tableau, or SAP Analytics Cloud) allow for real-time monitoring and visualization of critical metrics like greenhouse gas emissions, energy utilization, or social indicators—fostering data accessibility to support management decisions. In this context, ESG platforms (SAP Sustainability Control Tower; Workiva; Enablon; Sphera) help integrate, validate and report ESG data so that companies can prepare consistent disclosures in line with the respective regulations.

Data architecture technologies, like data lakes and data centers (38%), are also important for consolidating information from heterogeneous sources into a single one. This translates, in practice, to the incorporation of data from ERP systems and operational systems with IoT sensors measuring physical environment parameters and even supplier information across the value chain. This approach enables organizations to develop integrated ESG datasets providing for increased completeness, consistency and reliability with reduced reliance on manual processes.

The integration of Industry 4.0 and ESG should be analysed not only through technological adoption, but also through organizational maturity and data-driven capabilities. A Digital Sustainability Maturity Framework links Industry 4.0 maturity, digital enablement, ESG maturity and sustainability performance, supporting the interpretation of ESG reporting as an integrated management capability rather than a purely compliance-oriented disclosure process (Ingaldi & Ulewicz, 2026).

The emergence of generative AI adoption (16%) deserves special attention. Although still sparse, its existence among implemented technologies points to the embryonic integration of this solution in organisational practice. Generative AI adoption is a closely tied with the increasing need to automate ESG reporting processes, particularly in report content generation and qualitative analysis of disclosures, as well as processing text-based data such as non-financial reports, corporate communications and regulatory documents. These technologies allow for the conversion of high volumes of data into coherent and structured reporting outputs, thereby help increase the quality and credibility of ESG disclosures.

3. Research methodology

This manuscript was carried out by performing bibliometric analysis based on data obtained from Scopus database. This study strictly followed the PRISMA framework to carry out four-stage data collection. In the initial stage, the search query TITLE-ABS-KEY (“ESG” AND “artificial intelligence”) was applied to the Scopus database (fig. 2). The data were exported on 19 March 2026. The initial search yielded 925 records. The literature screening process for this study was implemented in two stages: In the first stage, we screened and removed duplicate records, incomplete records, and non-English literature. In the second stage, only eligible samples related to ESG reports and AI applications were retained, and all literature that did not align with the research topics was excluded. Following the selection process, the final dataset used for the bibliometric analysis comprised 765 records published between 2004 and 2026, including 314 articles, 202 book chapters, 193 conference papers, 27 books and 29 reviews).

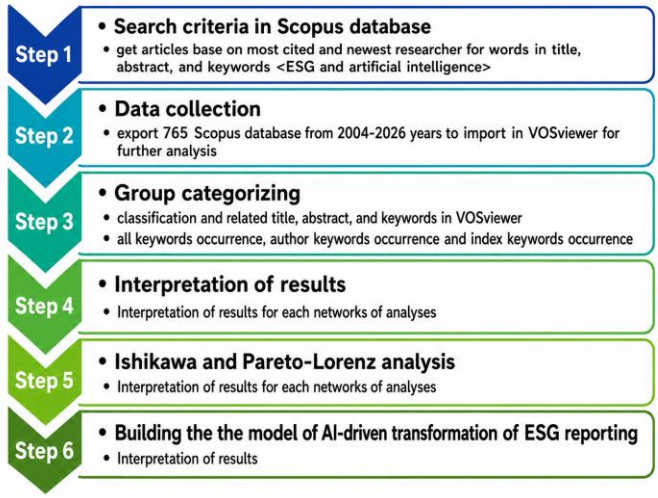

Fig. 2. Steps for conducting research.

Then, a 765 dataset was exported for analysis by VOSviewer software. Next, network analysis was conducted on individual keywords with keyword co-occurrence analysis while further explaining the results obtained. The next step was to ground this analysis with both a causal-structural and quantitative perspective. To this end, the Ishikawa diagram was utilized to identify key factors influencing AI use for ESG and the Pareto–Lorenz analysis was performed to evaluate the degree of concentration and relative importance of each keyword. The Ishikawa diagram’s analysis defined the unit as the driving factors that influence the application of artificial intelligence in ESG reporting. The identification of this unit is based on literature reviews and keyword co-occurrence structures. It relied on VOSviewer to extract all factors and categorize them into three major groups: stakeholder and regulatory requirements, data quality and accuracy, and competitive and strategic factors. Each factor is assigned to only one leading category. This study assigns explanatory weights of 40%, 35%, and 25% to the three types of coding factors respectively. The core basis for this weight assignment is the results of literature coding, the conclusions of keyword co-occurrence analysis, and the degree of matching between the factors and the research questions of this study.

This manuscript uses Pareto-Lorenz analysis to process its research dataset. The unit of analysis is the occurrence frequency of keywords extracted from the dataset generated via VOSviewer. First, all keywords are sorted in descending order of their occurrence frequency. Next, the percentage share and cumulative value of the total occurrences of the selected keywords are calculated. This method is applied to measure the concentration level of the field’s dominant concepts, and to identify the core keywords that contribute the most to research on AI-related ESG reporting.

The last stage was represented by synthesis of the received results and formulation of the model on formation of AI-driven transformation in ESG reports. The model is generalized representation of the disclosed relationships and mechanisms that shows AI as an integrating factor connecting data acquisition, analytics, decision-making steps and the digital transformation of ESG reporting systems.

4. Results and analysis

4.1. VOSviewer analysis

The bibliometric analysis results provide a better understanding of the structure and evolution paths of research on ESG reporting from an AI perspective. Keyword co-occurrence network analysis allows to identify the dominant research themes, their linkages and dynamics of evolution over time. Fig. 3. presents co-occurrence all key words (appendix 1).

The analysis of the co-occurrence network of keywords (minimum occurrence threshold = 5. Of the 4237 keywords, 280 meet the threshold) identifies five distinct thematic clusters that not only mirror the structure of ESG reporting literature, but more importantly depict its continuing evolution at the global scale. The network structure reveals an unambiguous transition in sustainability discourse from a more traditional to an integrated, data and technology-driven paradigm of resource usage, where AI, decarbonization and risk-prediction take a prominent place. The red cluster is around a core of terms such as “sustainable development”, “climate change”, “gas emissions” or “supply chains”; “blockchain”; and finally, the key concepts of industry 4.0 & digital transformation. The co-occurrence of both concepts signals a deep transformation towards decarbonisation and the implementation of sustainability in industrial systems.

As particularly noted, the connection between “gas emissions” and “industry 4.0” indicates that ESG report is more and more embedded in digitally enabled production and supply chain systems, where emissions are not only measured but constantly monitored and optimized. In addition, the use of blockchain highlights increasing focus on traceability and transparency of environmental data along global value chains. The blue cluster is focused on technological concepts, such as “artificial intelligence”, “machine learning”, “natural language processing” and “data analytics”, which also represent the most dynamic and evolutionary line of research. There is growing literature addressing the application of AI for automating ESG data collection, processing large quantities of unstructured data, recognizing patterns and identifying inconsistencies across disclosures. Notably, the use of natural language processing (NLP) allows for systematic analysis to be conducted on sustainability reports, and machine learning models provide predictions of ESG risks and performance. This illustrates the wider shift toward data-based ESG disclosure, in which digital solutions are necessary to handle complexity and scale. The yellow cluster is oriented toward financial and investment aspects such as “investments”, “decision making” or the “financial sector”. No longer a conduit for transparency and accountability, ESG reporting has emerged and not at the level of corporate and investment strategy as an instrument for valuing firms, mitigating financial risk, and dictating sustainable capital allocation. The “risk management”, “risk assessment” and “risk analysis” are associated with the purple cluster, which signifies risk-related dimensions. The evolution of these concepts is closely linked to the rise of advanced analytics and its improvement of facilities that identify the risks or opportunities related to ESG in particular, climate-related-, regulatory or reputational risk. Analysis suggests that ESG data are more often being used to assess forward-looking risk, allowing firms and investors to predict potential disruptions and build organizational resilience as a response. Fig. 4. presents co-occurrence author key words (appendix 2).

The structure of this network (minimum occurrence threshold = 10. Of the 1999 keywords, 76 meet the threshold) suggests that five significant thematic clusters have been identified, which provide a cohesive although diverse representation of current research around ESG reporting. The initial dominant cluster (green) covers the major ESG-related terms such as "ESG", "sustainability", "sustainable finance", “environment”, “social”,"governance" and “fintech”. This cluster forms the conceptual basis of the research field, but its topology shows clear signs of integration evolution with the financial system. The very focus on “sustainable finance” is significant and serves to validate that ESG reporting is more firmly tied to investment processes and financial risk in a way not possible before. Indeed, studies indicate that ESG data are increasingly becoming an integral part of institutional investors’ decision-making process, and call for more uniformity and higher-quality disclosures. The blue cluster is focused around topics related to digital transformation and organizational performance, including “digital transformation”, “digital economy”, “big data”, green innovation”, sustainable development” and ESG performance. Its structure draws attention to the increasing relevance of digital technologies in operationalizing ESG reporting. The close association with “ESG performance” is particularly noteworthy in this regard, denoting a move away from disclosure-driven initiatives towards the evaluation of real corporate sustainability outcomes. It shows that ESG reporting is increasingly embedded in a company's performance management systems and what drives strategic decision-making. The red cluster includes topics pertaining to reporting practices and corporate governance, such as “ESG reporting”, “sustainability reporting”, “corporate governance”, “corporate sustainability”, “greenwashing”. The appearance of “greenwashing,” one of the most common keywords, signals an important change in the literature toward skepticism about the reliability and validity of ESG disclosures. It implies that research is not only concerned with the scope of reporting, but more and more on the quality of report in terms of reliability, accountability and compatibility to real corporate behaviour. The yellow cluster indicates a specific line of research related to artificial intelligence applications, as “machine learning”, “deep learning”, “natural language processing”. The position of the keywords among the most frequent words indicates that this field is becoming more mature. The review of literature reveals that these are being used to analyze the content of ESG reports, disclose patterns and relationship modeling with respect to ESG factors and financial performance. For example, natural language processing facilitates automated analysis of narrative disclosures to tackle the increasing magnitude and complexity of non-financial data. The purple cluster is represented by the “internet of things” concept, signaling the recognition towards ESG reporting based on real-time data acquisition. Using IoT technologies in conjunction with reporting systems can allow for automatic checking of environmental indicators, leading to improved quality and timeliness of the data generated. Consequently, ESG reporting is transitioning from a retrospective exercise to an essential part of continuous management of corporations. Fig. 5. presents co-occurrence index key words (appendix 3).

Analysis of the network structure (minimum occurrence threshold = 10. Of the 2972 keywords, 94 meet the threshold) shows an emergence of five key thematic clusters, reflecting three main dimensions of ESG reporting today. They are as follows: sustainable development, technological transformation and non-financial metrics. At the centre of this structure one finds the ideas of “sustainable development” and “artificial intelligence”, as representing a new dimension in the research field, signalling a paradigm shift from traditional normative positions to an analytical and technology-driven focus.

The first red cluster, which is centered around “sustainable development”, covers a shared wide range of topics germane to bringing sustainability into operation in enterprise contexts, such as “big data”, “blockchain”, “supply chains”, “digital transformation”, “industry 4.0” and the “internet of things”. This cluster describes the increasing role of digital technologies as instruments for action and monitoring in respect to ESG. The strong links to “supply chains” are especially telling, implying that ESG reporting is increasingly about firms not in isolation but as part of wider global value chains.

Digital technologies in this sense act as an infrastructure to enable traceability, environmental impact assessment and better transparency of production processes. The advent of “industry 4.0” also emphasizes the importance of industry transformation as a major contributor to enabling decarbonization and resource efficiency. The second cluster (green), associated with the keywords “machine learning”, “natural language processing”, “financial markets” and “risk assessment”, indicates the release of advanced analytical approaches in the field of ESG. Its structure reflects the increasing role of artificial intelligence as a tool for analyzing non-financial data, forecasting trends and managing risk.

This finding correlates with strong associations with finance concepts, validating the conclusion that ESG data is increasingly used in the assessment of investment risk and within processes for making strategic decisions. The literature highlights the importance of AI not purely for analysing historical ESG data, but rather almost applying it on predictive models, which is one of the most crucial directions in its evolution. The blue cluster, which contains words such as “investments”, “decision making”, “sustainable development goals” and “regulatory compliance”, indicates the convergence of ESG with finance and regulatory systems.

Notably, the emphasis on “investments” is reflective of the increasingly important role that ESG reporting plays in capital allocation. And thus, ESG is turning from just a disclosure mechanism into an assessment tool for firm value and potential long-term performance. Alternately, the intersection with "regulatory compliance" reflects the growing impact of regulatory systems on shaping ESG reporting practices. The yellow cluster, containing words like “sustainability”, “innovation”, “governance approach” and “china”, reflects the geographical and institutional breadth of ESG research. The results regarding country-specific references and the occurrence of governance-related concepts support that institutional contexts and levels of economic development substantially impact ESG reporting. Simultaneously, its relationship with innovation underscores the increasing influence of ESG as an organizer and technologist transformer in enterprises.

4.2. Ishikawa diagram for the analysis of AI adoption in ESG reporting

The literature review laid the foundation for developing an Ishikawa diagram that identifies and systematizes underlying factors driving the adoption of AI in ESG reporting. It is often referred to as the cause-and-effect diagram and is a proven method in quality management analysis for finding relations and dependencies between causes and an issue (Wong et al., 2016). It provides a visual framework that aids in the comprehension and categorization of critical elements affecting a given occurrence. This angle was used to analyze the following research question in this study: Why do companies use AI in ESG reporting? (Fig. 6) (appendix 4).

Detailed analysis using the Ishikawa diagram suggests that the adoption of artificial intelligence within ESG reporting is due to the interplay between regulatory, informational, and strategic components. The ascription of stakeholder requirements (40%) emerges as the most important driver, confirming that ESG reporting is still mainly a reaction to external requirements, whether through regulation (e.g., CSRD) or investor expectations with respect to transparency and data reliability (Fale et al., 2026). In this scenario, AI is a pivotal enabler that empowers organizations to respond to the growing needs associated with disclosure quality, completeness and timeliness.

A second key group comprising data quality and accuracy factors (35%) demonstrate structural weaknesses of conventional ESG reporting frameworks. ESG information has low consistency and limited analytical value due to data fragmentation, lack of standardization, and the predominance of manual processes. Artificial intelligence helps to converge data from different sources, automates the processing of that data and develops the advanced analytical capabilities, which greatly enhances the quality of ESG reporting.

Competitive factors (25%) show that ESG reporting is being increasingly transformed from a compliance activity to management and value-focused tool. Organizations that implement AI capabilities to complement their existing ESG systems can improve not only the efficiency of reporting but also ensure more effective use of ESG data in decision-making, increase market credibility across its stakeholders, and respond better to emerging environmental and regulatory changes.

4.3. Pareto-Lorenz analysis

The Pareto–Lorenz analysis is a supplementary extension of the keyword co-occurrence analysis that identifies concentration levels and relative importance in individual research themes within the evaluated dataset. In contrast to the mapping of relational structures and identification of thematic clusters, provided by network analysis, the Pareto–Lorenz approach offers a quantitative assessment for the distribution of keyword occurrence frequencies associated with dominant concepts that shape the respective research domain under investigation (Cavalcanti et al., 2026). The keyword occurrences were summarized from a dataset created through VOSviewer software and all analysis was performed using this dataset. Table 2 shows the frequencies of occurrences and their respective cumulative ones of the keywords.

Table 2. All keywords frequency of occurrence

Symbol	Keyword	Percentage share [%]	Cumulative value [%]
P1	AI	30.21	30.21
P2	Sustainable development	16.63	46.84
P3	ESG	12.13	58.97
P4	Machine learning	8.52	67.49
P5	Sustainability	8.18	75.67
P6	Investments	7	82.67
P7	Blockchain	5.27	87.94
P8	Decision making	4.44	92.38
P9	Learning systems	3.81	96.19
P10	Digital transformation	3.81	100

Figure 7 shows a graphical presentation of the Pareto-Lorenz diagram.

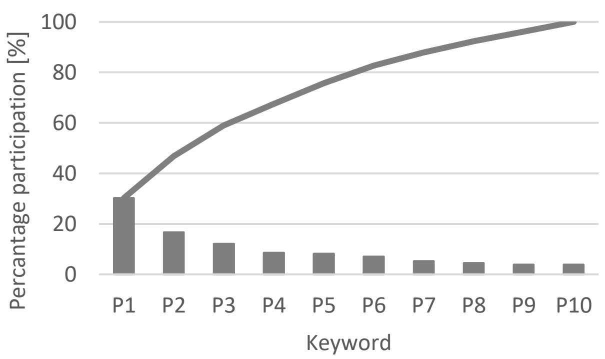

Fig. 7. Pareto-Lorenz diagram analysis for all keyword occurrences.

The analysis of figure 7 shows that AI and sustainable development, which account for 20% of keywords determine the contribution of 46.84% to the overall structure of keyword occurrence frequency, demonstrating their main position in the research territory regarding ESG reports and their technology integration. At the same time, many of the remaining keywords have a low individual share but they play an important complementary and structuring role in the evaluated domain.

Machine learning and blockchain, therefore, can be interpreted as manifestations of advanced technologies that enable data analytics, process automation as well as greater transparency and better security of data which is critical in mitigating the risk of greenwashing and enhancing the credibility of disclosures.

The use of ESG data for investments and decision making has come to prominence, with AI allowing for better risk modeling and discoverability around longer-term enterprise value. The adaptation and data driven learning capabilities of the organization are reflected by learning systems, which also connect with the intelligent organization approach that uses AI to continually improve reporting processes.

On the other hand, digital transformation gives a better scope of artificial intelligence implementation as it represents an entire systemic change to how organizations handle information and reporting activity.

5. Discussion

This manuscript provides insights that AI, especially ML and NLP, has a significant part in shifting effective ESG reporting beyond established analytical frameworks. Combinations of ML methods allow for the assessment of complex nonlinear relationships between ESG indicators and firm performance which improves the analytical power associated with sustainability reporting (Zhou et al., 2025; Liu et al., 2025). Such approaches enable predictive analytics to leverage the data and introduce transition from retrospective disclosure towards forward-looking risk assessment evaluation that has been getting prominent in ESG literature (Eccles et al., 2014; Gillan et al., 2021).

One of its most crucial contributions is to emphasize the use of NLP for ESG disclosures. In contrast to financial data, ESG reporting often consists of qualitative, narrative-based information that has historically proven difficult to analyze systematically. NLP techniques can automatically extract, classify and interpret textual data available in sustainability reports, corporate communications and regulatory filing. Previous research indicates that NLP is a viable tool for evaluating disclosure quality, sentiment extraction, and inconsistency detection in corporate stories (LI et al., 2013). The ESG space is particularly relevant in this regard, where narrative disclosures are often pivotal to stakeholder opinions.

Moreover, existing literature emphasizes the increasing use of NLP to reveal greenwashing by capturing gaps between symbolic disclosures and substantive action (Cho et al., 2012). However, one of the biggest flaws within existing reporting systems is a lack of transparency and accountability because they rely on outdated methods to present data. Recent research in the field shows that natural language processing (NLP), machine learning, large language models, and external ESG datasets provide robust support for corporate greenwashing detection. Janik and Ryszko (2026) reviewed traditional content analysis methods, and studies by (He, 2025; Davidescu et al., 2026; Cheng & Yang, 2026) verified the effectiveness of AI in identifying deviations between ESG disclosures and business operating practices.

Another important dimension identified in this manuscript is the integration of structured and unstructured ESG data. As reiterated by (Friede et al., 2015), the rising significance of ESG factors in investment decisions calls for sophisticated analytical tools that can handle heterogeneous datasets. Authors (Amel-Zadeh & Serafeim, 2018) show that investors rely more on ESG information when it is comparable, reliable and decision-useful. This integration is made possible through AI, which integrates both numerical indicators and textual insights to enhance the informational content of ESG disclosures. This manuscript finds that existing literature has increasingly conceptualized AI as a core mechanism underpinning the evolution of ESG reporting, driving its shift from retrospective disclosure model to an integrated, data-driven decision support model. The bibliometric conclusions of this study can be supplemented by empirical research on the frontiers of the relevant field, with arguments centered on the organizational impacts of enterprises' application of AI to ESG systems. Authors Chen and Zhang (2025) propose that AI-supported digital transformation can improve ESG performance, Zhou et al. (2025) point out that combining AI with information governance can optimize ESG quality, and Aruwaji et al. (2025) state that AI-integrated ESG reporting has important value for the valuation of enterprises in emerging markets.

6. Conclusion

This manuscript notes that existing literature positions AI as a core element of ESG reporting transformation, driving its shift from a retrospective process centered on formal compliance to an integrated analysis-oriented decision support system. It also shows that AI can function as a supporting mechanism to automate the collection, integration, and processing of multi-source heterogeneous information.

The tools used in this research, including keyword co-occurrence and thematic clustering, can map the mainstream research directions and evolutionary paths of AI-related studies in the field of ESG reporting. The analysis finds that existing literature has coalesced around three core research directions, and there remains a need to supplement enterprise-level empirical work that assesses the actual impacts of AI.

Results suggest that AI acts as a force in ESG reporting in a bottom-up manner by enabling not only the automation of data acquisition but also those integration and processing components that are secured from multiple heterogeneous sources.

This is especially significant given the increasing complexity of ESG disclosures, the degree of heterogeneity of data and mounting regulatory pressure. AI reinforces the analytical dimension of reporting by allowing for the use of ML and NLP techniques to explore patterns, analyze disclosure content, predict risks and discover divergences. The results suggest that AI makes ESG information more relevant to managerial processes like risk assessment and the creation of long-term stakeholder value through investment decisions.

In the context of Industry 4.0 and development of Internet of Things (IoT) and real-time monitoring, this analysis indicates that AI makes ESG reporting a core element in complete organizational digital transformation process (Ingaldi & Ulewicz, 2024). The socio-economic dimension of Industry 4.0 further supports this interpretation, as digital transformation affects not only production technologies but also organizational and social systems. Therefore, the use of AI in ESG reporting should be considered as part of a broader socio-economic evolution of Industry 4.0-enabled enterprises (Suchacka et al., 2023).

Analyses conducted through bibliometrics and Pareto–Lorenz indicate a concentration of the development of this area around a few key concepts, among which AI and sustainable development (SD) are particularly noteworthy. This means that instead of being just one among other supporting instruments for ESG reporting, AI is an integrating element providing a linkage across the technological, environmental, financial and organizational aspects. The findings show that AI is changing not only how ESG reports are generated, but also the very logic behind ESG reporting regimes.

It should be noted at the same time that there are significant limitations of practical AI application in ESG reporting. Of these, the most critical include quality and dispersion of source data; firm maturity is often limited organizationally to a subset of analytic models; difficulty in integrating qualitative and quantitative data within the models themselves while maintaining transparency and auditability. As a result, while technological enablers for AI implementation would decide the effectiveness of AI in ESG reporting; good data governance, sound organizational capabilities and integration of ESG reporting with managerial processes would make such technological enablers effective. This interpretation is also consistent with enterprise AI implementation research, which demonstrates that the main challenge is not technological adoption itself, but the gap between declared deployment and operational integration; consequently, AI-based ESG tools require strategic alignment, organizational capabilities and systematic performance measurement to improve data quality, analytical depth and decision usefulness (Sira, 2025).

Author proposed the model captures this transformation in a structured manner and identifies the mechanisms whereby AI assimilates data, improves analytics, and enables decision-making for use within ESG reporting systems (Fig. 8). The proposed model is conceptual and based on the literature analysis and bibliometric findings.

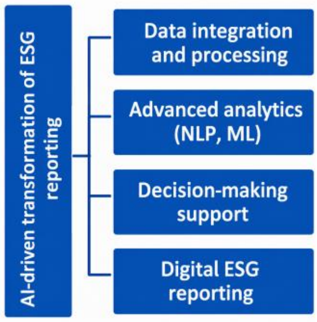

Fig. 8. Conceptual model of AI-driven transformation of ESG reporting.

Limitations. The major limitation of this study is its bibliometric nature. This analysis is based on data obtained from the Scopus database and deals with knowledge structure and frequency of co-occurrence of keywords, rather than provides di-

rect assessment regarding impacts of AI application in enterprises. This means that the results obtained identify dominant directions of development and conceptual axes of transformation, but do not allow to make a quantitative assessment of specific solutions in organizational practice. Furthermore, the results may be biased to some extent depending on the selection of database, keywords and applied analytical thresholds.
Future research. Future empirical research will investigate the effects of AI on the details of each ESG reporting stage (data quality) and timeliness of disclosure preparation, decision-usefulness (information relevance), and reduction in greenwashing risk.

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Appendix 1.

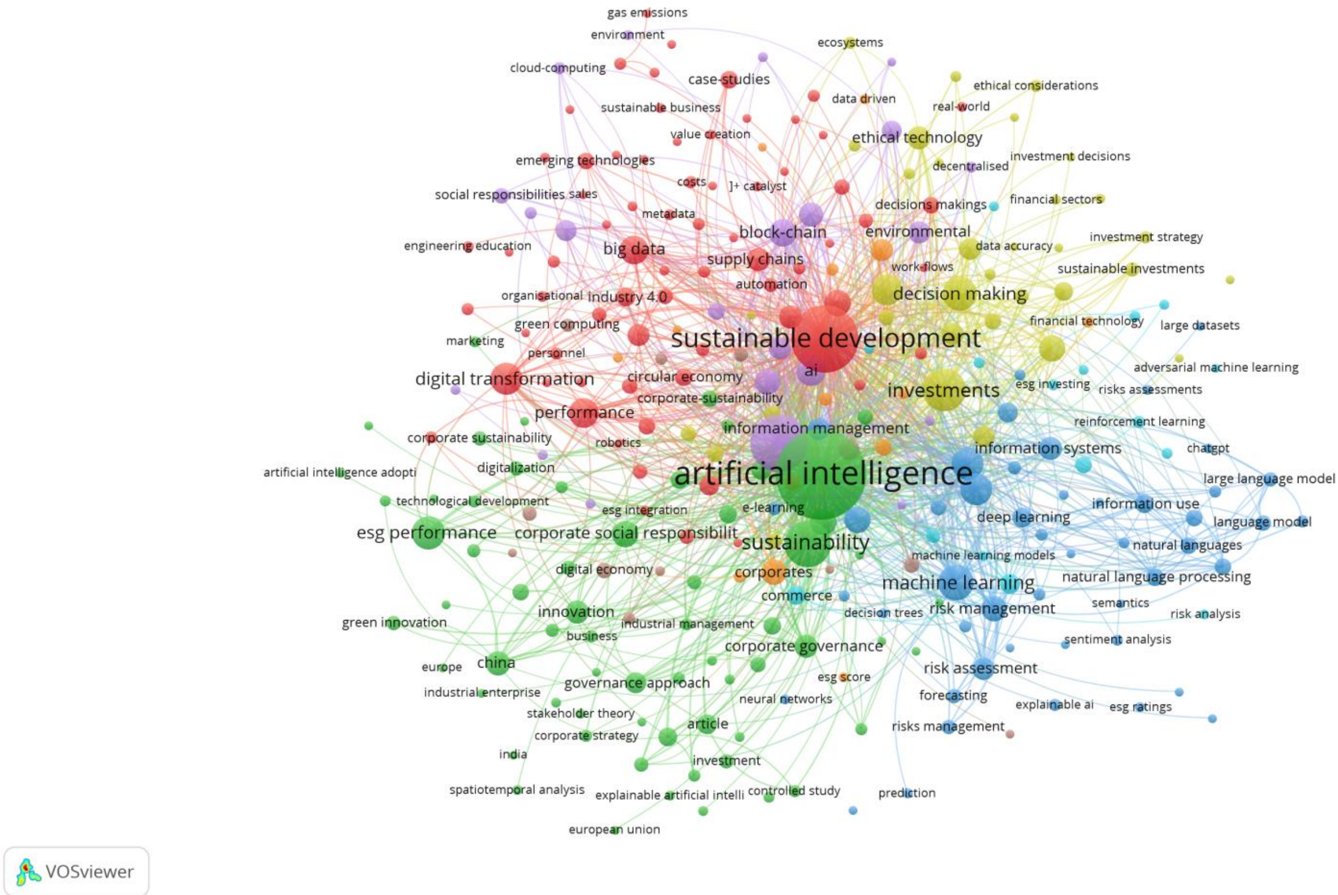

Fig. 3. Co-occurrence all key words.

Appendix 2.

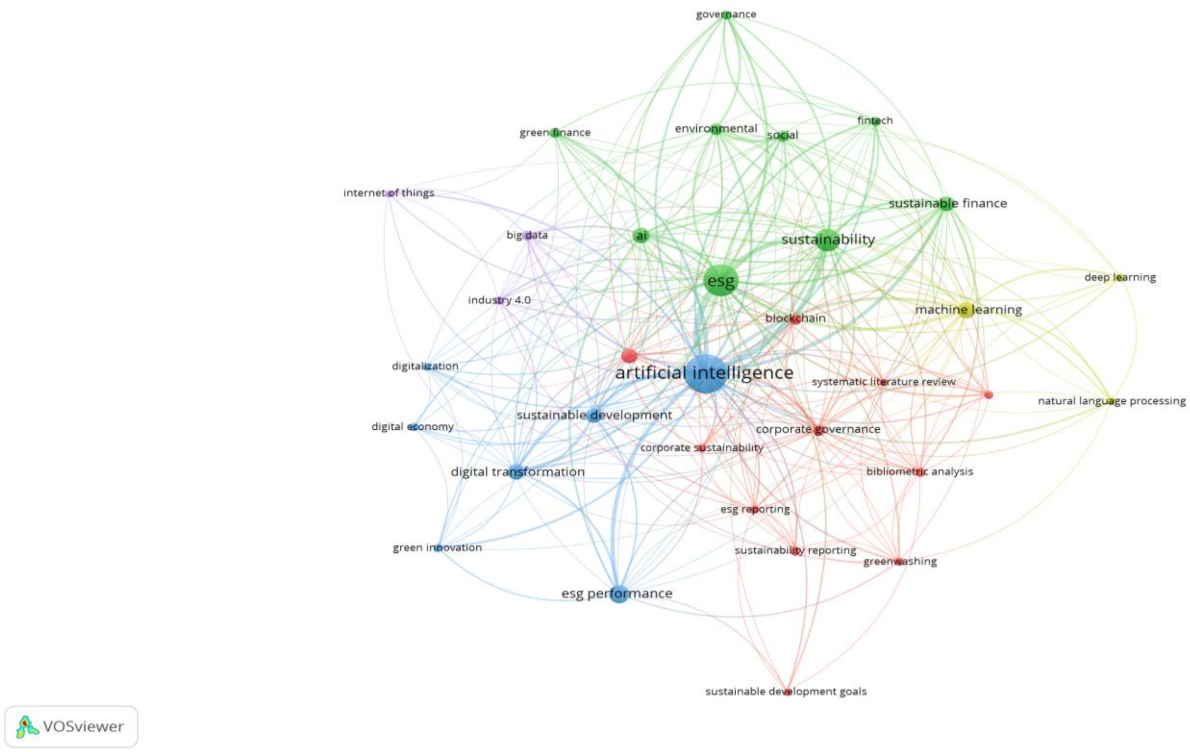

Fig. 4. Co-occurrence author key words (minimum number of occurrece 10).

Appendix 3.

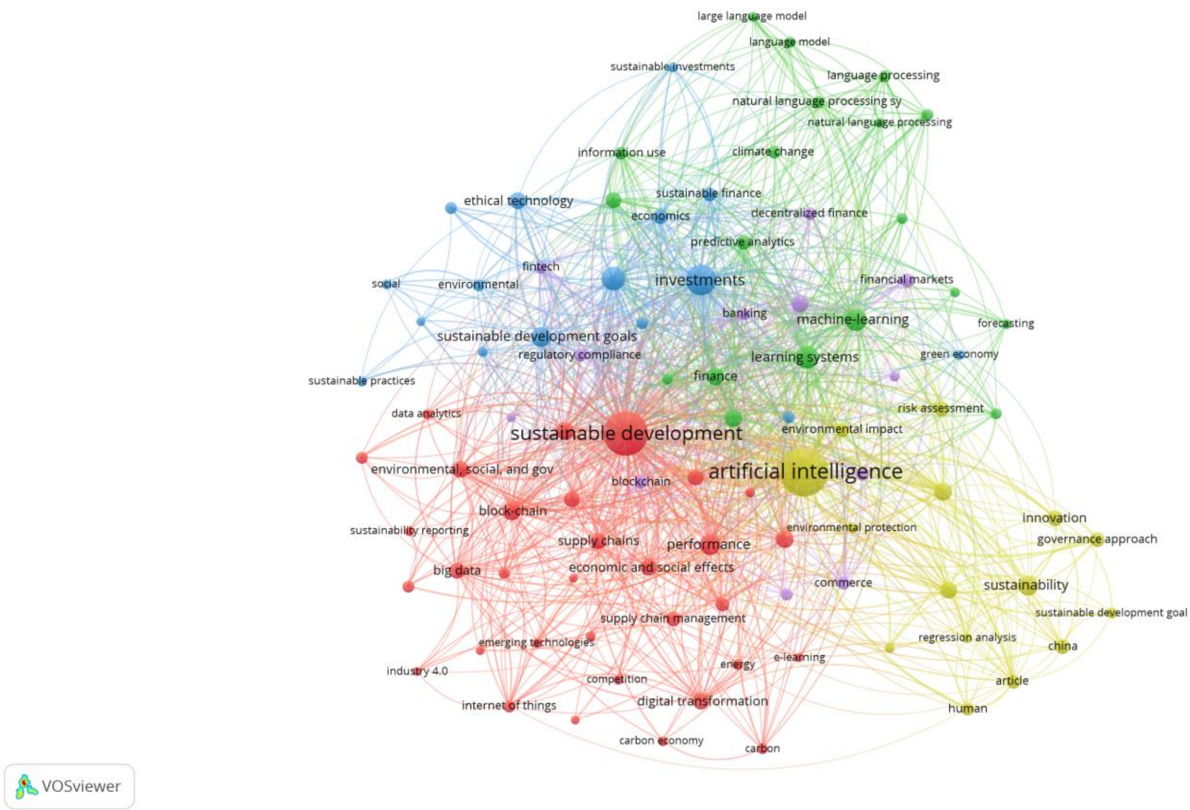

Fig. 5. Co-occurrence index key words (minimum number of occurrence 10).

Appendix 4.

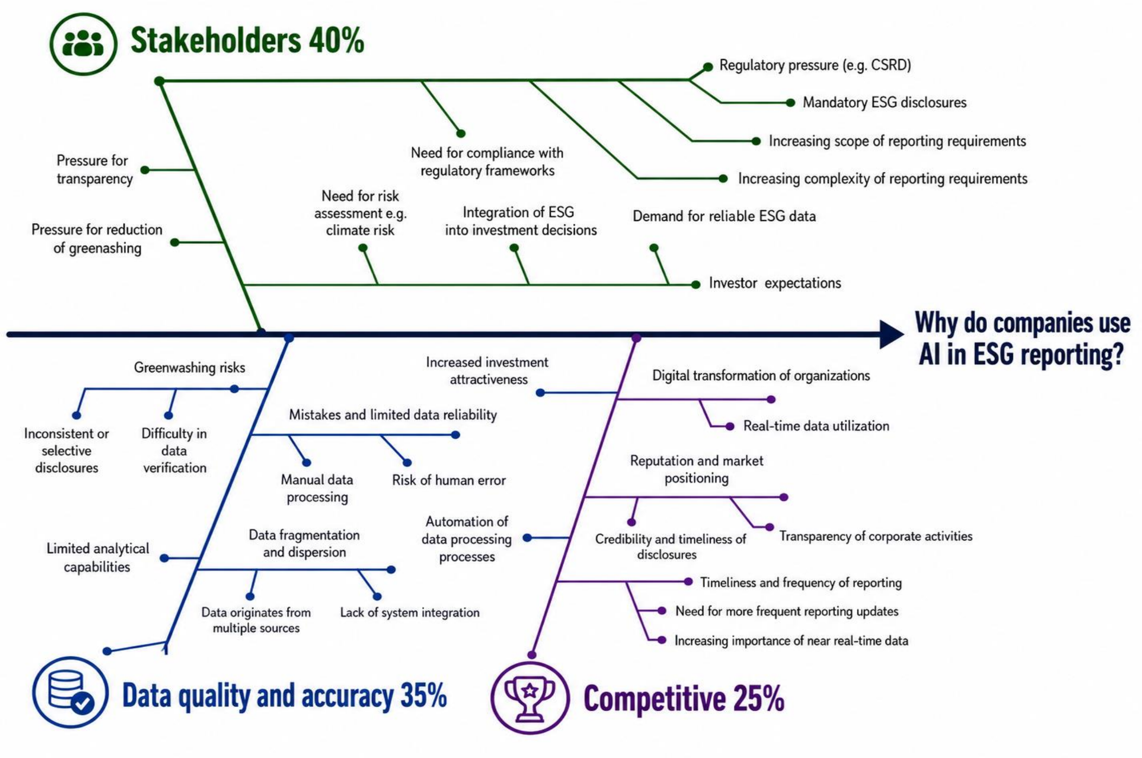

Fig. 6. Ishikawa diagram analysis for the question: Why do companies use AI in ESG reporting?