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Artificial Intelligence-Powered Green Finance and Environmental, Social and Governance Tracking in Emerging Markets: A Systematic Review

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ABSTRACT

Artificial intelligence (AI) has been adopted to significantly enhance the quality (credibility, timeliness and comparability) of green finance and environmental, social and governance (ESG) reporting. Nevertheless, in emerging economies, fragmented data infrastructures and irregular regulatory structures complicate the adoption process. This review synthesises empirical evidence (2015-2025) on the AI methods and tools applied to green finance and ESG reporting analytics in emerging markets, identifying key methods, outcomes, barriers, drivers and quality of reporting. Following the PRISMA design, Scopus records (n = 49) were screened meticulously against the inclusion criteria to 27 studies for actual full-text extraction. We coded AI technique, ESG domain, data sources, outcomes, barriers and drivers. We also applied a hybrid quality appraisal (MMAT domains and AI-specific rubric for transparency, validation, provenance, emerging market relevance and reproducibility) to ensure quality conclusions. The research outcomes show that AI applications are dominated by machine learning (ML), natural language processing (NLP). Also, frequent tasks include carbon-based and climate-related disclosure analytics, ESG scoring, green-finance prediction and green bond verification. Furthermore, Asia accounts for the largest share (52%), followed by Africa (22%) and Latin America (19%). In addition, Key AI application barriers include data quality and coverage issues, standardisation gaps, knowledge and technical skills limitations and cost constraints. Furthermore, drivers for its application include AI integration and development, alignment with International Financial Reporting Standards (IFRS) (S1&S2), Taskforce on climate-related financial disclosures (TCFD) and a free data accessibility ecosystem. Also, quality scores cluster at a high range (mean 4.2/5; SD = 0.5), with recurrent limitations to data provenance and reproducibility. The study concludes that AI shows significant prospects to improve ESG credibility and sustainable finance in emerging economies, but strongly depends on strong disclosure taxonomies, quality datasets, transparency and validated AI frameworks.

Keywords: Artificial Intelligence, Environmental, Social and Governance, Green Finance, Emerging Markets, Preferred Reporting Items for Systematic Reviews and Meta-Analyses, International Financial Reporting Standards S1/S2, Green Reporting
JEL Classifications: O22, Q33, O16, Q55

1. INTRODUCTION

The rising need to address global climate change, green transitions and green investments has significantly shaped how organisations and prospective investors measure value and returns (Adebanjo et al., 2025; Kus and Jackson, 2025). Over the decade, environmental, social and governance (ESG) reporting has transformed from voluntary disclosure to a strategic, regulated and decision-useful form of green reporting (Villacampa-Porta et al., 2025). This needed shift is stirred by the efforts of the International Sustainability Standards Board (ISSB) and the release and transition into IFRS S1/S2, which offer global benchmarks for sustainability and climate disclosures. Coupled with the postulation of the Taskforce on climate-related financial disclosures (TCFD) and the global reporting initiative (GRI), it stimulates the transition towards a standardised, comparable, green reporting that integrates financial implications and climate outcomes into corporate mainstream accounting (Di Vaio et al., 2024).

As global markets develop, high-quality ESG data and reporting are crucial and key for capital allocation, risk management and reporting (Colak and Sarioglu, 2025; Nguyen et al., 2025). Recent global standards (TCFD framework, IFRS S1/S2, Global Reporting Initiatives [GRI]) outline expectations and guidelines for decision-useful sustainability reporting and climate-related disclosures to meet the growing stakeholders' demand for high-quality ESG information and signals. Notwithstanding, in emerging markets like Nigeria and South Africa, there exists a weak data infrastructure, inconsistent reporting and limited transparency (Kozan and Porcher, 2024; Alao et al., 2024; Afolabi, 2025), which constricts the translation and use of ESG information into investible insights. The absence of a robust digital infrastructure has also limited the production and integration of reliable sustainability reporting, leading to a weakened capital market, reduced transparency and limited credibility of sustainable finance.

Furthermore, AI techniques and tools such as machine learning (ML), deep learning (DL), natural language processing (NLP), and explainable AI (XAI) address these concerns by extracting and formatting unstructured disclosures at a large scale. This improves the predictive power for ESG and climate-related financial risks, opportunities and ensures Explainability through post-hoc tools and estimators (e.g. SHAP) that aid assessment of model drivers.

Conversely, AI can process unstructured ESG data while detecting elements of greenwashing and symbolic reporting (Ghaemi Asl, 2025), measuring carbon dioxide emissions (CO_2) (Aylani et al., 2024) and predicting climate financial risks (Elhady and Shohieb, 2025). In addition, AI supports the development of green bonds (Alshahmy and Sahiner, 2024; Çıtak and Meo, 2024) and ESG measurement metrics (Joshi et al., 2024) while providing extensive analytical rigour and predictive insights on the environmental risk-financial outcomes nexus. Despite improvements in emerging markets and the promising contributions of AI frameworks, their practical application and adoption in emerging markets remain underexplored.

Furthermore, empirical evidence in emerging markets is low, dispersed and spreads across sectors and methodologies. Most studies and commercialised AI-ESG tools are concentrated in developed nations (US, Japan, etc.), leaving a dearth of evidence on how emerging markets adopt AI for ESG/Green Finance analytics, disclosure and reporting. In addition, this study addresses a theoretical gap often overlooked by classical finance and sustainability theories by adopting the institutional theory and the dynamic capabilities theory (DCT), which offer valuable lenses and postulations. The institutional theory shapes the adoption and integration of digital reporting culture, while the DCT enable organisations to sense, seize and reconfigure AI frameworks and resources to improve green performance.

The integration of AI, ESG and green finance in emerging markets, therefore, offers opportunities and uncertainties regarding outcomes. Understanding how this relationship develops is crucial for achieving Sustainable Development Goals (SDG) 13 (Climate Action) and unifying local standards and accounting practices with the global reporting landscape. Despite growth in sustainability reporting, empirical evidence remains uneven, treating AI as a technical innovation and underexploring AI-driven ESG/Green finance analytics in emerging markets. This critical review bridges that gap by consolidating evidence to answer the following research questions:

i. What types of AI techniques are adopted for ESG/green-finance reporting in emerging markets?
ii. Which domains of ESG and Green Finance do these techniques address and their outcomes?
iii. Which barriers or drivers impact the adoption of AI-powered ESG/green finance analytics?
iv. How robust and transparent are the AI methodologies employed?

Drawing on institutional and dynamic capabilities theory, this paper addresses critical gaps by conducting a systematic review of AI adoption in ESG/Green Finance reporting across emerging markets from 2015 to 2025. The analysis outlines AI frameworks and techniques, ESG metrics, methodological quality and regional distribution. It also captures the institutional and technological adoption of AI in ESG/Green Finance analytics and reporting. The study's key contributions are a decade-long mapping (2015-2025) of AI-ESG adoption in emerging economies, a method by domains synthesis design (AI-ESG use case), a dual-quality appraisal (MMAT + AI-specific criteria), theory advancement and a research agenda tied to SDG 13 (climate actions), TCFD framework and IFRS S1/S2.

2. CONCEPTUAL FRAMEWORK

The conceptual framework in Figure 1 illustrates how AI capabilities serve as foundational enablers that drive AI applications in ESG and green finance, ultimately driving improved sustainability and financial outcomes in emerging markets. At the input level, technologies such as machine learning, natural language processing, deep learning, and explainable AI provide the analytical power required to process complex environmental, social, and governance data (Chen et al., 2026). These capabilities are operationalised through applications, including ESG data extraction and analytics, climate risk prediction, green-bond analytics, and the detection of greenwashing practices, thereby enhancing the credibility and depth of sustainability assessments. The framework further posits that these technological interventions translate into outcomes such as enhanced ESG disclosure quality, improved green finance efficiency, and stronger alignment with climate goals, particularly SDG 13 (Raman et al., 2025).

Importantly, this transformation is not linear but is conditioned by institutional readiness (including regulatory quality, data governance, and reporting standards) and reinforced by dynamic capabilities such as infrastructure, skills development, and innovation adoption. Grounded in Dynamic Capability Theory (Gao et al., 2025) and Institutional Theory (Okere & Ambe, 2026), the model underscores that the effectiveness of AI-driven sustainability initiatives depends on both firms' internal capacity and the external institutional environment, making it especially relevant for emerging markets navigating the transition toward transparent and climate-aligned financial systems.

3. METHODS

3.1. Protocol and Strategy

The study adopted the PRISMA methodology and its protocol to ensure transparency, reproducibility and comprehensiveness in literature synthesis. The research approach applies and incorporates both quantitative mapping (bibliometric trend and frequency analysis) and qualitative thematic synthesis (interpretive patterning process of results). Following the outlines by Okere et al (2026) and Snyder (2019), the systematic review followed the following five stages:

i. Planning the review by defining the research objectives, inclusion/exclusion criteria, and search boundaries
ii. Identification and retrieval of peer-reviewed literature from Scopus using controlled Keywords
iii. Screening process, which includes removing duplicates and

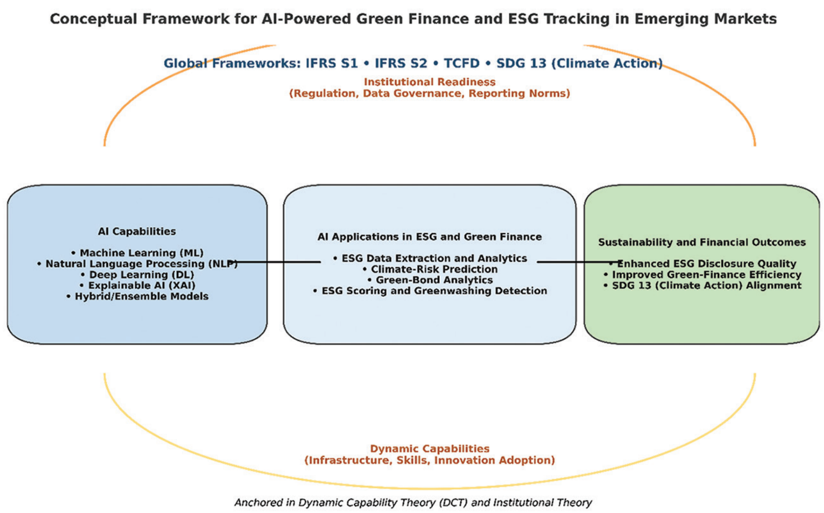


Figure 1: Preferred Reporting Items for Systematic Reviews and Meta-Analyses flow chart

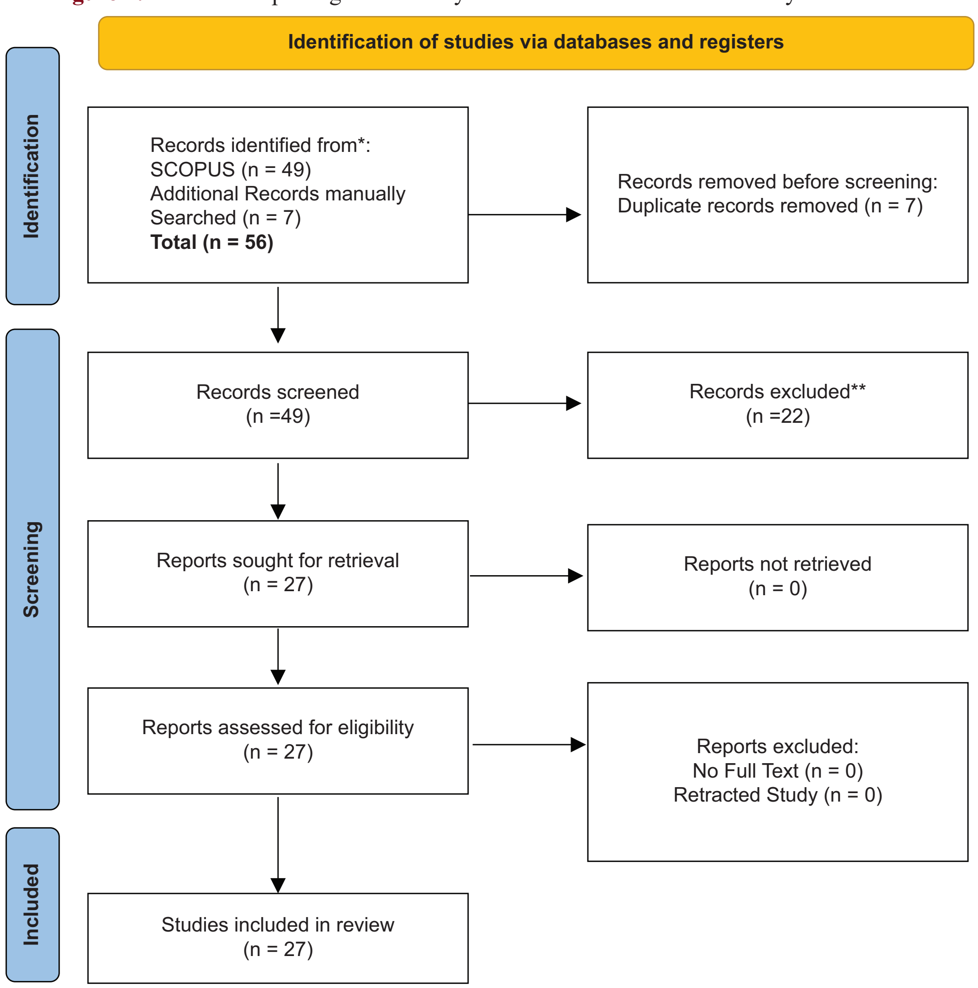


Table 1: Inclusion and exclusion criteria

Criterion	Inclusion	Exclusion
Study type	Peer-reviewed, empirical and systematic review papers	Editorials, notes, non-academic articles
Language	English	Non-English
Period	2015-2025	Pre-2015
Geographic location	Emerging Markets (Africa, Asia, Latin America, BRICS) or mixed with evidence of emerging market analysis	Developed economy studies
Focus	AI applied to ESG/Green finance activities	AI in non-finance disciplines or finance without ESG
Methods	ML/DP/NLP/explainability	Econometrics without AI application

Source: Authors' Compilation (2025)

filtering based on title/abstract relevance
iv. Eligibility screening by applying full text inclusion criteria (AI × ESG × emerging markets)
v. Inclusion and exclusion process through data extraction, appraisal and interpretation.

The Scopus database was selected due to its wide coverage of interdisciplinary sustainability and finance journals. It was accessed and queried with a Boolean combination of AI search terms ("machine learning," "deep learning," "NLP," "transformer,") and ESG/green-finance terms ("ESG," sustainable finance," "green bond," "climate disclosures," "TCFD," "IFRS S2") and emerging market terms ("emerging market(s)," "Africa," "Asia," "Latin America," "BRICS"). The study covers the time period from 2015 to 2025, focuses on studies in the English language, peer-reviewed articles and conference papers.

A total of 49 records were retrieved. Seven additional articles were manually sourced via reference screening of key articles on ESG/Green finance and disclosure automation, reaching a total of 56 records. After the removal of duplicates, 49 relevant studies were screened, with 27 meeting full inclusion criteria (Figure 1).

3.2. Eligibility Criteria

To ensure a quality review process, studies were included if they focused on AI applications in ESG, green finance, or sustainability within emerging or developing market contexts and demonstrated clear links to disclosure quality, climate risks, or financial outcomes. Studies were excluded if they lacked empirical or conceptual relevance to AI-driven sustainability frameworks or did not align with key standards such as IFRS S1/S2, TCFD, or SDG 13.

Table 1 below presents the inclusion and exclusion criteria for the review process.

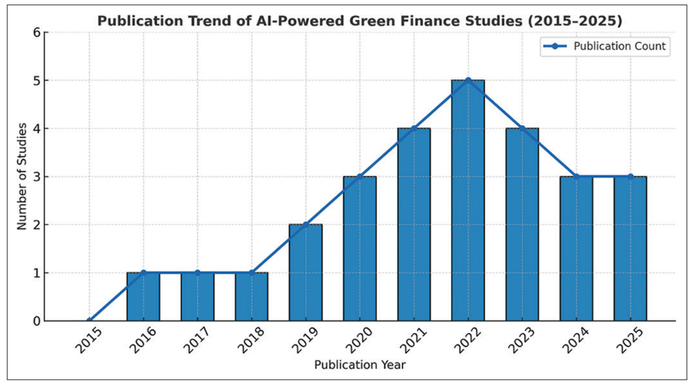
3.3. Study Counts and PRISMA Design

The study selection process followed the PRISMA in Figure 1 below protocol to ensure transparency and reproducibility. A total of 49 records were retrieved. Seven additional articles were manually sourced through reference screening of key articles on ESG/Green finance and disclosure automation, reaching a total of 56 records. After removing duplicates, 49 relevant studies were screened, of which 27 met full inclusion criteria (Figure 2).

3.4. Data Extraction and Synthesis

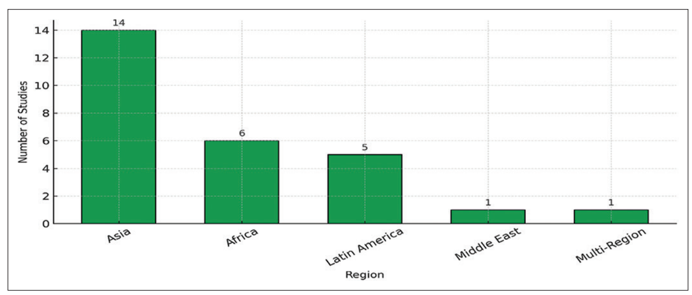
For each study that was considered, we extracted bibliographic information, AI techniques (NLP, gradient boosting), ESG/green-finance domain (climate disclosures, ESG scores, green bonds,

Figure 2: Publication trend



Source: Authors' Computation (2025)

Figure 3: Regional distribution of included studies



green finance analytics), data sources (corporate reports, indexes, indices, textual sources), outcomes (predictive metrics, effect sizes, interpretability, barriers/drivers and quality. Also, each study was coded in an Excel extraction sheet in Table 2 below:

Also, descriptive statistics were run to capture temporal and regional trends, technique frequencies and co-occurrence between AI-methods and ESG domains. A trend analysis was carried out covering the 2015-2025 period, focusing on annual publication counts. A regional analysis was also carried out to capture the different geographical spread of the studies. Also, a method domain mapping was conducted to capture the breadth of the research by cataloguing and describing existing evidence from the reviewed papers. In addition, a barrier/driver analysis of AI-powered ESG/Green finance analytics was carried out to identify its key determinants. This was achieved by using frequency counts.

Furthermore, the qualitative data were evaluated using NVIVO-assisted coding, identifying recurring concepts and terms such as "explainable AI," "ESG Transparency" and "Institutional Readiness." Also, the themes were triangulated against 3

Table 2: Data extraction sheet description

Descriptors	Data
Bibliographic details	Years, Authors, Country, Journal name
AI technique	ML, DL, NLP, Hybrid
ESG/finance domain	Carbon disclosure, ESG indexes, Green bonds, etc.
Data source type	Corporate filings, Market Data and Alternative Datasets
Model performance	MAE, MSE, AUC
Barriers and enablers	
Quality appraisal scores	MMAT+AI Rubric

Source: Authors' Computation (2025)

Table 3: Regional distribution

Region	Count	Share (%)
Asia	14	51.9
Africa	6	22.2
Latin America	5	18.5
Middle-East	1	3.7
Multiple Region	1	3.7
Total	27	100

Source: Authors' Computation (2025)

Table 4: AI technique frequencies

AI techniques	Studies (n)	Percentage of 27
NLP/text mining	9	33.3
Gradient boosting (XG Boost/LightGBM/ CatBoost)	8	29.6
Random forest	6	22.2
Recurrent net (LSTM/GRU)	4	14.8
SVM	3	11.1
NGBoost	2	7.4
Explainability (e.g. SHAP) reported	7	25.9

Source: Authors' Computation (2025)

Table 5: ESG/finance domain frequencies

ESG/finance domain	Studies (n)	Percentage of 27
Carbon/climate disclosure analytics	9	33.3
Sustainable/green finance analytics	8	29.6
ESG scorings/ratings	6	22.2
Green bond verification/pricing	4	14.8

Source: Authors' Computation (2025)

Table 6: AI×ESG co-occurrence

AI TOOL	Carbon/ climate	Sustainable/ green finance	ESG scoring	Green bonds
NLP/Text	5	3	1	0
XGBoost	1	2	1	2
Random forest	2	2	1	0
LSTM	1	2	1	0
SVM	0	1	1	0
NGBoost	0	1	0	1

Source: Authors' Computation (2025)

theoretical lenses (institutional theory, dynamic capabilities theory and stakeholder theory) to integrate managerial, technological and regulatory determinants of AI adoption in sustainable finance.

3.5. Quality Appraisal

The study applied MMAT domains (for clarity of objectives, adequacy of data, analysis integrity, interpretation, coherence and relevance. Also, AI-specific metrics such as transparency (model description and features), validation process, data provenance, emerging market relevance and reproducibility (code and data availability). Furthermore, each item scored Yes/No/Partial and was normalised between 0 and 5.

Table 7: Barriers and drivers

Category	Codes	Count (n)	Share (%)
Barriers	Data quality/coverage deficits	15	55.6
	Standardisation gaps (taxonomies, KPIs)	12	44.4
	Cost/skills constraints	11	40.7
	Limited reproducibility (code/data)	7	25.9
Enablers	Regulatory frameworks (IFRS S1/S2; TCFD)	10	37.0
	Explainable AI adoption	8	29.6
	Open ESG data initiatives	7	25.9
	Cloud/compute accessibility	5	18.5

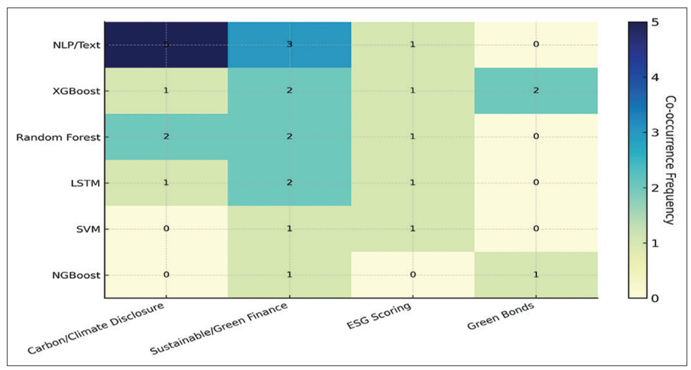
Source: Authors' Computation (2025)

Table 8: Quality appraisal summary MMAT and AI rubric)

Metric	Value
Studies scoring >4/5	20 74.1%)
Mean SD) score	4.2 0.5)
Common shortfalls	Data provenance, reproducibility, external validation

Source: Authors' Computation 2025)

Figure 4: Artificial intelligence technique × environmental, social and governance domain (Co-occurrence frequency)



4. RESULTS

4.1. Descriptive Statistics

From the trend analysis above, it can be seen that there was a surge of publications related to the research focus within the last 4 years (2022-2025). The surge affirms the growth of standardised disclosure regimes and investors' demand for ESG and climate-related analytics and reporting. The publication growth post-2019 infers a shift in global green policies, such as the EU taxonomy and the launch of IFRS S1/S2.

From the analysis in Figure 3 above, it can be seen that most studies emanate from Asia, followed by Africa. This captures the growth of sustainability and climate disclosures in Africa to meet stakeholders' demands. Asia's dominance is captured in Table 3

Figure 5: Barriers and drivers (Enablers) of artificial intelligence-powered environmental, social and governance/green-finance analytics

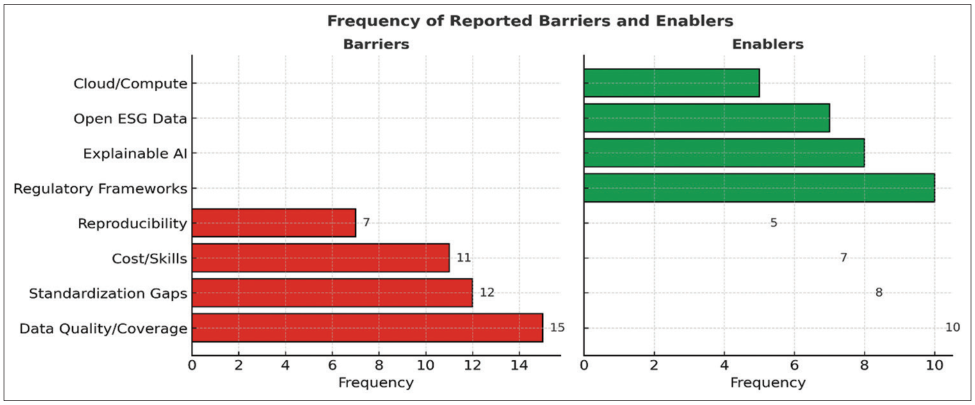
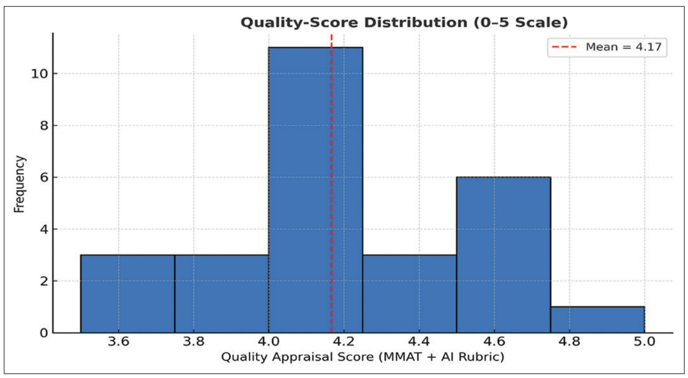


Figure 6: Quality score distribution



below, which shows China and India's significant investments in financial technology (FINTECH) and AI-powered ESG analytics (Jafri et al., 2025). African evidence, though smaller compared to Asia, shows rapid adoption in emerging markets like Nigeria and South Africa, where regulatory bodies promote sustainability reporting in line with IFRS S1 and S2 as well as the TCFD framework.

4.2. ESG Domains and AI Techniques

Table 4, 5 and 6 present the AI techniques, ESG/Finance domain frequencies and AI x ESG Co-Occurrence test results.

From the Figure 4 above, it can be seen that NLP is the main tool for disclosure analytics, boosting ensembles (XGBoost and NGBoost) are more relevant to green bond pricing and green financing prediction. Also, LSTM appears in time series ESG prediction tasks, capturing temporal dependencies in carbon intensity data (Sattar et al., 2025). Also, NLP successfully automated ESG disclosure extraction, which is evident in the work of Hu (2025), which revealed a 25% reduction in manual coding time for ESG text classification. In addition, explainable AI (SHAP) provides transparency by highlighting how ESG factors most affect financing costs, supporting regulators like the Financial Sector Conduct Authority (FSCA) in South Africa.

4.3. Outcomes

From the analysis, across forecasting/classification tasks, AI techniques outperform classical baselines reported in the reviewed studies (e.g. lower mean absolute error [MAE] and mean squared error [MSE] and higher area under the curve [AUC]). For textual analysis climate/ESG signals, NLP models exhibit economically meaningful associations with returns/financing costs (e.g. Climate-attention indices exhibiting nonlinear responses). This highlights that SHAP is increasingly used to capture drivers of AI-ESG analytics. In addition, Explainability bolsters trust and supports supervisory application. In summary, three empirical regularities exist which are:

i. AI improves ESG analytics and data credibility. This finding is consistent with those of Rane et al. (2024) and Molavi et al. (2025). In tandem, the ML-based ESG scoring framework reduces human subjectivity issues inherent in self-reported disclosures.
ii. Predictive AI promotes proactive financing. This is in line with the outcomes of Ghallabi et al. (2025), which reveal that AI forecasts and provide forward-looking information on green-asset prices and portfolios with higher stability (lower MAE and MSE).
iii. Explainability promoted the adoption of AI, in line with the findings of Salako et al. (2024), which reveal that regulators and investors are more likely to trust models that reveal a variable influence chain of command.

4.4. Barriers and Drivers of AI-Powered ESG/Green-Finance Analytics

Table 7 below presents the barriers and drivers of AI-ESG analytics in emerging economies.

From the review and analysis presented in Table 7 and Figure 5, the barriers to AI-driven ESG analytics in emerging markets are mainly structural and data quality deficits (56%) and standardisation gaps (44%), which limit reliability and comparability, while cost and skills limitations further limit scalable adoption outcomes. Conversely, enabling conditions are constitutionally founded, as regulatory frameworks such as IFRS S1/S2 and TCFD (37%) provide legitimacy and direction for AI integration in sustainability reporting. Furthermore, complementary drivers collectively enhance transparency, accessibility, and computational feasibility, thereby supporting broader AI diffusion in emerging markets.

4.5. Quality Appraisal

The quality appraisal analysis presented in Table 8 and Figure 6 below indicates a high level of methodological rigour, with

74% of studies scoring 4/5 or higher and an overall mean score of 4.2, reflecting generally robust and credible evidence. Despite this strength, recurring deficiencies persist in data governance, reproducibility, and external validation, signalling limitations in transparency and replicability across AI-driven ESG studies. Therefore, these gaps underscore the need for more standardised reporting protocols and open-data practices to enhance the reliability and scalability of AI applications in sustainable finance.

5. DISCUSSION

From the review above, the findings reveal that the application of AI in ESG and green finance analytics within emerging markets is both transformative and uneven, shaped not only by technological capability but, more critically, institutional readiness and data ecosystems. Evidence shows that NLP is particularly effective for disclosure-rich tasks (Climate and ESG narratives), while boosting ensembles (XGBoost & NGBoost) and LSTMs perform well in forecasting (green bond pricing; ESG-based indices). Also, Explainability is improving (26% reporting SHAP), thereby reinforcing trust and policy utility. This reflects the inherently textual and interpretive nature of sustainability, in which value-relevant information is often embedded in unstructured formats such as annual reports, sustainability disclosures, and management meetings. However, the relatively limited adoption of explainability tools across the reviewed studies indicates that transparency remains an emerging rather than established norm, raising concerns about the potential for algorithmic opacity and unintended bias.

Furthermore, Asia leads both methodologically and in data availability, empowered by larger capital markets and digitised disclosures. Also, Africa and Latin American studies are increasing but constrained by data coverage and inconsistent taxonomies. This divergence underscores a broader issue of data inequality, where the benefits of AI-driven sustainability analytics are unevenly distributed across global markets. From the dynamic capabilities perspective, this suggests that firms in emerging markets may lack the absorptive capacity required to effectively integrate, adapt, and scale AI technologies in ESG contexts.

In addition, adoption correlates with institutional readiness and regulatory clarity (IFRS S1/S2, TCFD), consistent with institutional and dynamic capabilities perspectives. In line with institutional theory, the findings posit that the adoption of advanced technologies is conditioned by regulatory structures, normative expectations, and cognitive legitimacy. Moreover, the research findings corroborate those of Deloitte (2024), who found that AI improves data traceability in sustainability reporting, while negating those of Halkos and Nomikos (2021), who caution that algorithms may pose issues because they may not provide context and clarifications on how they function, making decision-making logic unclear. This introduces a new bias to AI-powered ESG/Green finance analytics. Conversely, the consistency of findings across regions affirms the institutional readiness theory that AI adoption and integration follow regulatory maturity, data availability and firms' learning capacity. The interplay between these elements ultimately determines whether AI can move beyond experimental applications to become a reliable and scalable tool for advancing sustainability outcomes in emerging outcomes.

5.1. Policy and Practical Implications

Based on the research outcomes, it is crucial that policymakers harmonise their taxonomies and key performance indices (KPIs). They should also prioritise open and accessible ESG data, encourage, validate AI in regulated disclosures, and align supervisory teams with ISSB guidance to catalyse responsible AI adoption in emerging markets. In essence, aligning ESG taxonomies with IFRS S1 and S2, TCFD, GRI and King IV tenets will close data comparability gaps and promote regional AI development and adoption.

Based on outcomes, practitioners should integrate textual signals (calls, MD&A, sustainability reports) with numerical ESG and market data, operationalise XAI for audit trails, invest in data governance and conduct external validation to ensure portability across emerging economies.

6. CONCLUSION AND RECOMMENDATIONS

From the research outcomes, AI's integration into sustainable finance and ESG analytics across emerging markets is developing geometrically and unevenly across regions. Its most significant contribution lies in augmenting ESG-data credibility, improving the predictability of climate-related financial risks, opportunities and advancing disclosure standardisation under IFRS S1/S2. Furthermore, future progress depends on transparent, reproducible models and strong institutional collaborators between regulators, researchers, academia and industry.

A central insight emerging from this AI review is that AI does not merely function as a technical enhancement to ESG reporting, but as a transformative governance mechanism that reshapes how sustainability information is generated, interpreted, and utilised. However, this transformation remains limited in many emerging economies due to persistent challenges, including data fragmentation, weak standardisation, limited reproducibility, and insufficient technical expertise to execute and maintain. The study further contributes to the literature by demonstrating that the integration of AI into ESG analytics aligns both institutional and dynamic capabilities perspectives. From an institutional perspective, regulatory clarity (IFRS S1/S2 and TCFD) serves as a driver of adoption, providing legitimacy and structure to sustainability disclosures. From the DCT perspective, firms' ability to sense, invest, and reconfigure technological resources determines the extent to which AI can be effectively anchored to generate sustainability insights and competitive advantage.

Importantly, despite the generally high methodological quality of the reviewed studies, important limitations persist, particularly in relation to data provenance, external validation and reproducibility. These limitations not only limit the scalability of AI applications but also raise concerns regarding transparency and trust in AI-driven ESG analytics. Addressing these gaps is essential if AI is to champion a meaningful role in strengthening sustainable finance systems in emerging markets.

From the research findings, the study recommends that:

i. Policy makers and regulators could establish open ESG data hubs. For example, South Africa's JSE Sustainability Data Repository could model regional transparency, thereby promoting pan-African ESG databases. For instance, regional collaboration (particularly within BRICS and broader African markets) could accelerate the establishment of such data ecosystems.
ii. Policymakers should integrate IFRS S1/S2 into local codes and standards. For instance, the Nigerian Financial Reporting Council of Nigeria (FRCN) can harmonise its corporate governance codes with ISSB standards, thereby reducing duplicative reporting.
iii. Financial institutions and investors should invest in capacity building by partnering with local universities on AI and sustainability curricula. Strategic partnerships between universities and research agencies can support the development of AI-driven sustainability competencies, particularly in areas such as ESG data engineering, model validation, and explainability.
iv. Financial institutions should deploy AI-hybrid pipelines through combining NLP for unstructured ESG text and XGBoost for numeric risk scoring. Some pilot examples include HSBC Green Finance Lab and Standard Bank's AI-ESG toolkit. Importantly, the incorporation of explainable AI tools should be prioritised to enhance transparency, auditability, and regulatory legitimacy.
v. Researchers could develop a reproducible emerging market dataset with open metadata and cross-country ESG indicators.

This study is constrained by heterogeneous reporting and limited reproducibility in emerging market contexts. Therefore, future studies should publish reproducible pipelines, benchmark emerging markets-specific datasets, integrate AI with blockchain for immutable audit trails and examine real effects (cost of finance, portfolio diversification and climate outcomes.

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