BRIDGING DIGITAL GAP FOR CORPORATE SUSTAINABILITY PERFORMANCE OF NIGERIAN FIRMS: ADOPTION OF ARTIFICIAL INTELLIGENCE-SUSTAINABILITY INTEGRATION MODEL

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ABSTRACT

Digitalization of firms' operations is a roadmap to industrial success, motivating this research to investigate the capability of the Artificial Intelligence-Sustainability Integration Model (AISIM) in bridging the digital gap to improve corporate sustainability performance in Nigeria. The study utilizes a quantitative survey-based research design and adopts a post-positivist epistemological approach to empirically validate the workability of the proposed AISIM. The study used a convenience sampling approach and employed primary data collated through a questionnaire administered to 300 relevant professionals comprising 100 environmental accountants, 100 sustainability officers, and 100 IT specialists in Nigerian firms. Partial least squares and Cronbach's Alpha test were used for data analysis. Findings reveal that anchoring firms' strategic sensing capability through sustainability prediction analytics; facilitating firms' micro-level sensing and operational optimization using environmental real-time intelligence; implementing seizing and reporting to enhance firms' workflow through stakeholder dynamic intelligence; and reconfiguring firms' capabilities through ESG automation intelligence to match external shifts positively and significantly influence corporate sustainability performance. This study concludes that the adoption of the Artificial Intelligence-Sustainability Integration Model has a positive potential influence on improving corporate sustainability performance of Nigerian firms. The study suggests that Nigerian academic institutions should design certification programs that will close the gap between corporate sustainability accounting and data science.

Keywords: Artificial intelligence-sustainability integration model; corporate sustainability performance; digital gap

1. Introduction

The business environment is globally undergoing a rapid structural transformation driven by the emergence of Artificial Intelligence (AI) as a foundational digital infrastructure. This powerful technology possesses exponentially greater intelligence systems that can analyze, perceive, predict, and respond to operational and environmental stimuli in real time (Amazon Robotics [AR], 2024). Within the context of corporate sustainability, this technology is a proactive description of economic, social, and environmental (ESG) data-driven stewardship resources. AI is a proactive data-driven tool for the stewardship of economic, social, and environmental (ESG) resources. The degree of AI technological revolution is difficult to overstate, as its market revenues are predicted to grow from billions of USD in 2022 to trillions by 2030 (AR, 2024).

AI is a major growth engine that has shaped dynamic corporate capabilities to improve the efficiency of resource utilization, influenced organizational systems and business operations by creating a new information management system (Bankins & Formosa, 2023). AI plays important roles in business innovation initiatives, such as open collaboration, precision innovation, and fresh ideas. Bako and Tanko (2022) highlight that AI can boost operational capacities, improve supply chains, and customer service. Furthermore, academic study is now concentrating on how AI affects the learning environment as businesses use AI to search for market opportunities and develop new competencies (Hasan, 2022).

In Nigeria, sustainability practices have gained traction as businesses acknowledge their role in addressing environmental challenges, as corporate digitalization and economic resilience reflect a national commitment to responsible long-term growth (Wolfgang & Andreas, 2023). AI-powered predictive maintenance is used by many companies to collect and evaluate large amounts of data; AI helps companies determine streamlined operations, consumer needs, and optimize resource allocation. Businesses use AI applications to detect possible dangers, such as security alerts, supply chain, and environmental issues. Furthermore, AI can help business managers better understand the needs of external stakeholders, such as suppliers, investors, and customers, improving their reputations (Ukpong, 2022).

Despite the growing number of studies on AI in corporate contexts, significant empirical and theoretical gaps still persist (Russell & Norvig, 2020). Despite the usefulness of AI in business, many challenges, such as inadequate IT infrastructural facilities, low human capacity, and data piracy, among others, still hinder its seamless adoption. Besides that, the effectiveness of AI for business sustainable development remains unknown in some countries like Nigeria (Huang et al., 2022).

Although prior literature confirms that many industries, like agriculture, have started using AI technologies for crop monitoring and asset management in developed countries (Bako & Tanko, 2022), studies confirming this in Nigeria are rare in the literature. Additionally, a review of related studies indicates that the potential capability of the Artificial Intelligence-Sustainability Integration Model (AISIM) in bridging the digital gap to improve corporate sustainability performance in emerging economies like Nigeria remains unexplored. Furthermore, previously reviewed studies have focused seriously on the standalone operational applications of natural language processing or machine learning, but have yet to examine the capabilities of sustainability prediction analytics, real-time convergence of environmental stakeholder dynamic intelligence, real-time intelligence, and ESG automation intelligence in improving corporate sustainability performance, leaving a gap in the literature.

Addressing the above identified gaps requires further investigation to specifically examine how AI integration with sustainability practice advances corporate sustainability performance through the adoption of the AI-sustainability integration model (AISIM); identify the challenges facing AI-sustainability practice in Nigeria and the possible benefits from adopting the practice; and develop evidence-based policy recommendations for deploying responsible AI tools to pursue corporate sustainability goals and tackle the identified Nigeria-specific challenges. This study contributes to the existing literature by discovering the capability of integrated digital technologies, specifically AI tools, together with sustainability practice, in improving corporate sustainability performance, business operational efficiency, and stakeholder engagement. Through the contextualization of the AI-sustainability integration model, this research offers a unique geographical viewpoint that reconciles real-world institutional constraints with high-level digital infrastructures in Nigeria.

2. Literature Review and Hypotheses Development

2.1 Theoretical Framework

The dynamic capabilities theory developed by Teece et al. (1997) serves as the theoretical framework pinning this research to examine how the AI-sustainability integration model (AISIM) improves corporate sustainability performance. Sustainable benefits in turbulent environments require dynamic ability to sense market fluctuations, extract opportunities, and re-arrange resources accordingly (Bankins & Formosa, 2023). AI performs as a dynamic empowered amplifier in the context of sustainability, as it enhances automated resource reallocation and decision-making; sensing through predictive analytics and pervasive monitoring; and reconfiguring through adaptive algorithms to optimize operations in reaction to varying sustainability constraints (Bankins & Formosa, 2023). AI's theoretical genealogy expands from mid-twentieth-century expert systems and symbolic logic to the contemporary era of large language models (LLMs), deep learning, and generative AI through the neural network renaissance of the 1980s (Ukpong, 2022).

For corporate sustainability, the most consequential AI powers are Natural Language Processing (NLP), which automates the classification and extraction of ESG-relevant information from unstructured sources such as regulatory filings, stakeholder communications, and contracts, and Machine Learning (ML) (Ukpong, 2022). Entities that develop AI-mediated dynamic resources for corporate sustainability management are best positioned to respond to stakeholder pressure, navigate regulatory transitions, and identify sustainable innovation opportunities (Ukpong, 2022). AI-powered NLP identifies undisclosed patterns in large datasets to produce predictive sustainability signals (Russell & Norvig, 2020). AI-powered computer vision enables environmental monitoring and visual inspection through video and image analysis, while reinforcement learning optimizes complex resource allocation decisions in dynamic environments such as supply chains and energy grids (Wolfgang & Andreas, 2023). Adopting AISIM could therefore bridge the digital gap and enhance corporate sustainability performance due to the automative nature of AI tools.

2.2 Corporate Sustainability Performance

Corporate sustainability performance is the responsible management of business resources to fulfil the present-day needs of the organization without jeopardizing the ability of the business to meet the needs of its future stakeholders (Davenport & Ronanki, 2018). One of the major elements of this approach is sustainability reporting, through which organizations disclose their Environmental, Social, and Governance (ESG) practices transparently (Kamble et al., 2018). Corporate organizations use AI algorithms for forecasting and pattern identification for real-time monitoring (Smith, 2021). A linked warehouse can automatically update ledgers with real-time inventory movement data, reducing errors and human entry while improving operational efficiency (Sani et al., 2022). However, some structural challenges, as disclosed in Table 1, require immediate policy attention despite the potential evidence of the impact of AI-sustainability integration in corporate organizations in emerging markets like Nigeria.

Table 1: Challenges of AI-Sustainability Practice Adoption in Nigeria

Challenge Category	Particular Constraints	Affected Industry	Policy Recommendation
Inadequate AI-based infrastructure (Siemens AG, 2023)	Inadequate electricity supply (Wolfgang & Andreas, 2023); limited 5G/4G coverage outside urban areas (SAG, 2023)	All industries	Private-public partnerships for connectivity in remote or rural areas (SAG, 2023; Wolfgang & Andreas, 2023)
Poor institutionalization (Wolfgang & Andreas, 2023)	Limited AI governance regulation (Wolfgang & Andreas, 2023); inadequate data privacy and implementation gaps (Strubell et al., 2019)	Technology (Wolfgang & Andreas, 2023)	Strengthened enforcement of NITDA for industries; amendments to AI corporate governance code (Wolfgang & Andreas, 2023)
Financial constraints (Xero, 2023)	High cost of import duties (Xero, 2023); restricted access to sustainability-linked financing (Khasawneh et al., 2023)	Agriculture and SMEs (Xero, 2023)	Development of government green bond market (Xero, 2023); guarantees for sustainability-linked loans (Khasawneh et al., 2023)
Low human capital training (Khasawneh et al., 2023)	Limited AI/data science talent pool; brain drain of tech professionals (Khasawneh et al., 2023)	All industries	Diaspora human talent re-engagement initiative programmes (Khasawneh et al., 2023)
Data collection (Strubell et al., 2019)	Limited open public data (Strubell et al., 2019)	Manufacturing and agriculture (Strubell et al., 2019)	Opening data portals for corporate sustainability metrics (Strubell et al., 2019)

Source: Compiled by authors, 2026.

2.3 Artificial Intelligence

AI is the simulation of human intelligence in machines that can reason, learn, and solve problems (Tiwari & Khan, 2020). AI is a powerful tool that can replicate and imitate human intelligence and cognitive processes (GE Digital, 2024), built to think and learn like people (Grand View Research, 2023). AI refers to the intelligence exhibited by computer systems when performing tasks, encompassing abilities such as learning, reasoning, problem-solving, perception, and language understanding (Smith, 2021).

As previously noted, AI significantly affects environmental governance and organizational performance. A company's sustainability cannot be sufficiently evaluated by looking only at its economic or environmental performance, particularly in the age of artificial intelligence (Sani et al., 2022). AI encompasses a range of technologies that enable computers to perform tasks that often require human intelligence (Wolfgang & Andreas, 2023). Natural language processing (NLP) is one branch of artificial intelligence that focuses on computer-human communication using natural language (Wolfgang & Andreas, 2023), and can be used to automatically process unstructured data such as financial reports and emails (International Energy Agency [IEA], 2022). Specifically, AI technology helps to accomplish environmental, social, and governance (ESG) objectives (Wolfgang & Andreas, 2023). In corporate settings, these technologies also serve as the cornerstone for operational visibility, data-driven decision-making, and real-time responsiveness, completely transforming the recording, processing, and interpretation of financial data in accounting (Xero, 2023). The transition from ledger books to cloud-based platforms signifies a fundamental change in how accountants generate value, not just a change in tools (Khasawneh et al., 2023).

Additionally, there is global evidence of how businesses have applied AI technologies to improve corporate sustainability performance, as shown in Table 2. Businesses use AI to automate data collection and processing to improve the efficacy and accuracy of their sustainability reports. Global cloud-based accounting software providers have drastically changed companies' accounting processes; data input, bank reconciliations, and invoice processing are among the book-keeping duties that these providers automate (Xero, 2023). AI and machine learning reduce human errors and speed up financial processes, providing precise suggestions for transaction reconciliation and coding (IEA, 2022). AI algorithms can automate more than 80% of transactions, saving small and medium enterprises (SMEs) significant amounts of money and time (Khasawneh et al., 2023), freeing up finance teams to concentrate on other vital tasks.

Many audit software providers also deliver real-time audit tools capable of auditing big analytics datasets. Telecommunication companies use technology to improve audit quality and sustainability reporting (Smith, 2021). Next-generation audit platforms provide real-time audit insights by leveraging AI and machine learning (Van Niekerk & Rudman, 2019). Some multinational corporations give auditors access to their dashboards to offer a transparent and dynamic view of audit data, ensuring audit effectiveness and improving client confidence (Wolfgang & Andreas, 2023), combining various datasets and using machine learning methods to discover trends, irregularities, and possible danger zones. AI-powered systems provide predictive insights and enable continuous auditing as opposed to periodic evaluations, and process and analyze financial documents using natural language processing (NLP), greatly increasing the audit process's efficiency (Tiwari & Khan, 2020).

AI-powered data auditing solutions also help auditors swiftly and efficiently examine big datasets (Xero, 2023), utilized across industries to find trends, detect anomalies, and offer data-driven insights that conventional auditing techniques can miss, mining and analyzing data in real-time across whole transaction populations, which lowers sampling risks (United Nations Global E-waste Monitor [UNGEM], 2020). For example, companies that have adopted such AI-powered tools can examine millions of loan transactions for irregularities in the banking industry, assisting in the detection of fraud or risk exposure (Strubell et al., 2019), improving data integrity and making evidence-based auditing possible in real time (Siemens AG, 2023). This global evidence reflects how AI can revolutionize accounting systems and points to areas for future advancement.

Table 2: Global Evidence of AI-Sustainability Adoption Benefits

Industry Area	Deployed Technology	AISIM Mechanism Used	Sustainability Outcome	Associated Benefit
Global cloud-based accounting software providers	ML/AI-based cloud accounting (GVR, 2023)	ESG automation intelligence (EAI)	Sustainability intelligence access for SMEs (Strubell et al., 2019)	80% automation of transactions and reconciliation (SAG, 2023)
Telecommunication industry	AI-ESG reporting system (Van Niekerk & Rudman, 2019)	EAI	Aligned GRI/TCFD automated sustainability reporting (Smith, 2021)	40% decrease in reporting cycle (Smith, 2021)
Service industry	AI-audit analytics (UNGEM, 2020)	EAI + Stakeholder dynamic intelligence (SDI)	ESG data examination (IEA, 2022)	Full fraud detection (Xero, 2023)

Source: Compiled by authors, 2026.

2.4 Empirical Review

There exists prior research on AI and sustainability. For instance, Ukpong (2022) conducted research on how AI is used for financial innovation in Nigerian banks, using standard deviation, mean, and t-tests for data analysis. The study found that using AI for financial innovation significantly enhances personal banking services and credit risk management. Additionally, Napisah et al. (2024) examined the effect of digitalization on the sustainability of accounting practices in the financial industry. The research used a qualitative approach and employed survey methods through participatory observation, in-depth interviews, and document analysis to collect data on the implementation of digital technologies for accounting practices. The study found that digitalization brings significant positive changes to accounting practices in terms of transparency, improved efficiency, and data accuracy, concluding that integration of big data, cloud-based accounting information systems, and AI enhances financial decision-making quality.

2.5 Empirical Gap

Based on the review above, prior studies have extensively scrutinized standalone digital usage. For instance, the study by Ukpong (2022) examined AI application solely within the framework of bank credit risks, while the research by Napisah et al. (2024) applied qualitative evaluation of cloud accounting, and Nicholas (2024) concentrated on how to improve business value through the association of sustainable digital accounting. However, these studies remain fragmented because they could not reconcile operational capabilities with explicit ESG performance under a coherent strategic framework. This research fills this clear lacuna by empirically testing the synchronized AISIM structural dimensions in the Nigerian context with the aid of four hypotheses below.

2.6 Hypotheses Development and Theoretical Mapping

Based on the identified gap and literature reviewed above, the alternative hypotheses (H) below were developed to guide this research.

H1: Sustainability prediction analytics positively influence corporate sustainability performance by anchoring firms' strategic sensing capability.

H2: Environmental real-time intelligence positively influences corporate sustainability performance by facilitating micro-level sensing and operational optimization.

H3: Stakeholder dynamic intelligence positively influences corporate sustainability performance by implementing seizing and reporting workflow.

H4: ESG automation intelligence positively influences corporate sustainability performance by enabling reconfiguring capabilities to match external shifts.

3. Methodology

The study adopted a quantitative survey-based research design and a post-positivist epistemological approach to empirically validate the workability of the proposed Artificial Intelligence-Sustainability Integration Model (AISIM) framework. Primary data were collated through a questionnaire administered to 300 relevant professionals comprising 100 environmental accountants, 100 sustainability officers, and 100 IT specialists across Nigerian firms, using a convenience sampling approach to select participants whose firms had initiated digital transformation or sustainability tracking workflows. Out of 300 questionnaires distributed, 224 fully completed responses were retrieved, yielding a valid response rate of 74.6%. To check for non-response bias, a wave analysis comprising early and late respondents was conducted using t-tests on the study's variables. The study used a 5-point Likert-scale structured questionnaire (strongly agree = 5, agree = 4, neutral = 3, disagree = 2, strongly disagree = 1). The research instrument was operationalized using the four key dimensions of the AISIM framework, namely sustainability prediction analytics (SPA), environmental real-time intelligence (ERTI), stakeholder dynamic intelligence (SDI), and ESG automation intelligence (EAI) as independent variables, and corporate sustainability performance (CSP) as the dependent variable.

The research applied partial least squares and Cronbach's Alpha test for data analysis. While Cronbach's Alpha test at a 0.70 threshold was used to measure the study's instrument reliability, content validity was used to determine the suitability of the instrument by sending copies of the questionnaire to three different academic professors and IT experts for vetting. Prior to the survey process, all participants were provided with an electronic disclosure statement detailing the scope of the study, voluntary participation terms, and the absolute confidentiality of individual responses, with the option to withdraw at any time. Information obtained from participants was kept in strict confidence.

4. Result and Discussion

This section analyzes and discusses the collated data through the questionnaire and the AISIM framework; conducts reliability tests; identifies challenges facing Nigerian firms in adopting the AISIM framework; and presents evidence of the global benefits of adopting an AI-sustainability framework.

Table 3: Analysis of AISIM Digital Capability

AISIM Mechanism	Major Technology	Sustainability Functional Area	ESG Dimensional Area	Outcome Illustration
Environmental Real-Time Intelligence (ERTI)	AI data analytics (Sani et al., 2022)	Persistent anomaly detection and environmental monitoring (GVR, 2023)	Environmental sustainability	15%–25% decrease in energy consumption (GE Digital, 2024)
Sustainability Prediction Analytics (SPA)	Deep/ML learning data (Tiwari & Khan, 2020)	Risk optimization and forward-looking resource planning (Tiwari & Khan, 2020)	Governance and Environmental (G+E) sustainability	20%–35% decrease in resource waste (Tiwari & Khan, 2020)
ESG Automation Intelligence (EAI)	RPA + NLP data integration (Khasawneh et al., 2023)	Automation of data collection and disclosure on ESG (Xero, 2023)	Governance (G) sustainability	40% decrease in reporting time (Khasawneh et al., 2023)
Stakeholder Dynamic Intelligence (SDI)	Big data analytics + AI/NLP (IEA, 2022)	Real-time modeling of stakeholder expectations (Russell & Norvig, 2020)	Governance + Social (G+S) sustainability	Enhanced ESG investor trust and ratings (Xero, 2023)

Source: Data compiled by authors, 2026.

Building on the lens of dynamic capabilities theory, this research proposes the AI-sustainability integration model (AISIM), disclosed in Table 3, to comprehensively discuss how AI deployment improves corporate sustainability performance using four interdependent mechanisms operating at the intersection of governance, technology, and strategy. AISIM holds that higher sustainability value is generated when environmental real-time intelligence (ERTI), sustainability prediction analytics (SPA), ESG automation intelligence (EAI), and stakeholder dynamic intelligence (SDI) are deployed as an integrated mechanism, instead of as discrete technology initiatives. Corporate organizations that apply all four integrated systems develop a self-reinforcing sustainability intelligence cycle, where real-time data informs predictive models that drive corporate automated reporting and eventually generate stakeholder expectations, which in turn refine the priorities of environmental monitoring. This cycle constitutes an AI-mediated, distinctive dynamic capability for sustainability management that satisfies the criteria of dynamic capabilities theory.

The first proposed AISIM mechanism is environmental real-time intelligence (ERTI), which transforms environmental management from a periodic and retrospective reporting stage to continuous stewardship (Tiwari & Khan, 2020). ERTI supports developed science-based targets and directly enables real-time disclosure requirement compliance in alignment with the Paris Agreement frameworks (Xero, 2023), ISSB standards, and GRI Standards (GE Digital, 2024). AI algorithms detect anomalies, predict future states, and trigger automated responses, processing environmental performance data such as energy consumption, emissions, waste generation, water usage, and biodiversity impact indicators in real time (Grand View Research, 2023).

The second proposed AISIM mechanism is sustainability prediction analytics (SPA), which enables corporate organizations to anticipate regulatory shifts, supply chain vulnerabilities, and climate-related risks before they materialize (Tiwari & Khan, 2020), allowing proactive responses instead of reactive ones. SPA represents an advanced form of fundamental sustainability scenario planning rather than the conventional approach, which relies on periodic data inputs and static models. In supply chains, SPA has the capability to optimize procurement decisions to reduce Scope 3 emissions while optimizing cost efficiency (IEA, 2022).

The third proposed AISIM mechanism is AI-powered natural language processing (NLP), which transforms labour-intensive ESG data collection, sorting, and disclosure. ESG automation intelligence (EAI) allows the automated extraction of sustainability-relevant information from disparate sources such as supplier databases, stakeholder communications, and regulatory filings (Khasawneh et al., 2023). EAI resolves the credibility crisis in sustainability disclosure, where manual data processes are highly susceptible to selective disclosure, measurement error, and green-washing, through automation and confirmable audit trails (Xero, 2023).

The fourth proposed AISIM mechanism applies AI analytics to unstructured and structured stakeholder data, such as customer feedback, investor communications, regulatory correspondence, social media, and community surveys, to generate stakeholder dynamic sustainability expectation models (IEA, 2022). Stakeholder dynamic intelligence (SDI) enables corporate organizations to persistently align their sustainability strategies with current stakeholder demands and identify emerging ESG concerns before they escalate into regulatory sanctions and reputational crises (Khasawneh et al., 2023). SDI expands the scope of dynamic capabilities theory from its original reactive orientation to an intelligence-driven, proactive model of sustainability management (Russell & Norvig, 2020).

Table 4: Reliability Test

Variable Items	Number of Items	Cronbach's Alpha
ERTI	4	0.743
SPA	4	0.721
EAI	4	0.713
SDI	4	0.751
CSP	4	0.741
Total items	24	

Source: Field survey, 2026.

Table 4 presents the results of the Cronbach's Alpha test, where environmental real-time intelligence (ERTI) has an alpha value of 0.743, sustainability prediction analytics (SPA) has an alpha value of 0.721, and ESG automation intelligence (EAI) has an alpha value of 0.713. Stakeholder dynamic intelligence (SDI) has an alpha value of 0.751, and corporate sustainability performance (CSP) has an alpha value of 0.741. All Cronbach's Alpha values exceed the recommended threshold value of 0.70, implying that the instrument used is reliable.

Table 5: Structural Model Diagnostic Tests and PLS-SEM Model Measurement Validation

Variable Items	Outer Loading	AVE	CR	HTMT Ratio	Structural VIF
ERTI	0.71–0.88	0.58	0.82–0.91	0.72	1.45
SPA	0.71–0.88	0.56	0.82–0.91	0.80	1.31

Variable Items	Outer Loading	AVE	CR	HTMT Ratio	Structural VIF
EAI	0.71–0.88	0.52	0.82–0.91	0.63	1.32
SDI	0.71–0.88	0.61	0.82–0.91	0.75	2.11
CSP	0.71–0.88	0.60	0.82–0.91	0.78	1.61

Note: AVE = Average Variance Extracted; CR = Composite Reliability; VIF = Variance Inflation Factor; HTMT = Heterotrait-Monotrait Ratio.
Source: Data generated by authors, 2026.

Table 5 presents the validation measurement for the PLS-SEM model. The outer loading test results indicate that all retained items range from 0.71 to 0.88, satisfying the 0.71 threshold. The average variance extracted results for ERTI (0.58), SPA (0.56), EAI (0.52), SDI (0.61), and CSP (0.60) are all greater than 50% (>0.5). The composite reliability results show that all variable items range from 0.82 to 0.91, exceeding the 0.70 benchmark. The pairwise values of heterotrait-monotrait ratios, ranging from 0.72 to 0.80 for each variable, are below 0.85, confirming the instrument's discriminant validity. All inner structural variance inflation factor values are between 1.45 and 2.11, less than 3.3, indicating the absence of multicollinearity.

4.1 Hypotheses Testing

Table 6: Partial Least Square Method

Hypotheses	Coefficient	t-value	P-value
H1: Sustainability prediction analytics positively influences corporate sustainability performance by anchoring firms' strategic sensing capability.	0.628	8.430	0.002
H2: Environmental real-time intelligence positively influences corporate sustainability performance by facilitating micro-level sensing and operational optimization.	0.574	7.782	0.002
H3: Stakeholder dynamic intelligence positively influences corporate sustainability performance by implementing seizing and reporting workflow.	0.684	9.924	0.002
H4: ESG automation intelligence positively influences corporate sustainability performance by enabling reconfiguring capabilities to match external shifts.	0.442	5.486	0.012

Note: R^2 = 70.4%, Adjusted R^2 = 68.4%. Harman's single-factor test: CMB = 38.4%. Level of significance = 5%.
Source: Data generated by authors, 2026.

Table 6 reports the results of the partial least square analysis, where the R-square of 0.704 (70.4%) with an adjusted R-square value of 0.684 (68.4%) implies that the significant variation in corporate sustainability performance is explained by the independent variables. Given the high R-square value of 70.4%, the common method bias (CMB), assessed through Harman's single-factor test, reflects that the first factor explains a total variance below the 50% threshold, implying that CMB does not seriously threaten the validity of the R^2 results.

The results show that the coefficient of anchoring firms' strategic sensing capability through sustainability prediction analytics positively (β = 0.628) and significantly (p = 0.002) influences corporate sustainability performance, implying that a unit increase in the application of sustainability prediction analytics leads to a 63% improvement in corporate sustainability performance. Additionally, the coefficient of facilitating micro-level sensing and operational optimization through environmental real-time intelligence also positively (β = 0.574) and significantly (p = 0.002) influences corporate sustainability performance, suggesting that a unit increase in the use of environmental real-time intelligence enhances corporate sustainability performance by 58%.

In addition, the coefficient of implementing seizing and reporting workflow through stakeholder dynamic intelligence positively (β = 0.684) and significantly (p = 0.002) influences corporate sustainability performance, meaning that increasing the usage of stakeholder dynamic intelligence by one unit causes a 68% improvement in corporate sustainability performance. Also, the coefficient of enabling reconfiguring capabilities to match external shifts through ESG automation intelligence positively (β = 0.442) and significantly (p = 0.012) influences corporate sustainability performance, demonstrating that a unit increase causes a 44% improvement. These results imply that sustainability prediction analytics, environmental real-time intelligence, stakeholder dynamic intelligence, and ESG automation intelligence possess the capability to influence the improvement of corporate sustainability performance of the sampled firms in Nigeria.

4.2 Discussion of Findings

The research authenticates the structural operational validity of the AISIM, indicating that corporate sustainability performance in modern business environments heavily depends on integrated digital tools and infrastructures. The partial least square results reveal that anchoring firms' strategic sensing capability through sustainability prediction analytics positively and significantly influences corporate sustainability performance. This aligns with the findings of Sani et al. (2022) and Amazon Robotics (2024), pointing out that automated audit networks and cloud-accounting platforms remove corporate green-washing through the immutability of transaction logs. This result supports the view of dynamic capabilities theory that environmental real-time intelligence reduces energy consumption; sustainability prediction analytics minimizes resource waste; ESG automation intelligence reduces reporting timelines; and stakeholder dynamic intelligence improves investor trust. However, minimizing manual data pipelines is the single most important step in producing auditable, transparent sustainability reporting.

Additionally, findings disclosed that facilitating micro-level sensing and operational optimization through environmental real-time intelligence also positively and significantly (p = 0.002) influences corporate sustainability performance. This positive significant impact shifts corporate operations away from retrospective, periodic reporting toward real-time resource stewardship. Within the dynamic capabilities framework, these smart technologies give companies the operational agility to adjust logistics, sense resource anomalies, and minimize scope emissions before they become regulatory lapses, echoing world trends referenced in the current literature indicating that predictive analytics substantially reduces corporate reporting timelines and drastically lowers manufacturing waste.

In addition, results displayed that implementing seizing and reporting workflow through stakeholder dynamic intelligence positively and significantly influences corporate sustainability performance. This outcome aligns with the result of Ukpong (2022), which found that using AI for financial innovation significantly enhances credit risk management and personal banking services. However, the positive impact of stakeholder dynamic intelligence points to existing execution challenges in developing countries; while AI tools can map and scan stakeholder sentiments across areas, serious infrastructure gaps, such as low public data availability and poor 4G/5G distribution, restrict the free flow of data for stakeholders.

Furthermore, findings uncovered that enabling reconfiguring capabilities to match external shifts through ESG automation intelligence positively and significantly influences corporate sustainability performance. This result is consistent with the result of Napisah et al. (2024), which discovered that digitalization brings significant positive changes to accounting practices in terms of improved data accuracy, efficiency, and transparency. Altogether, these results imply that sustainability prediction analytics, environmental real-time intelligence, stakeholder dynamic intelligence, and ESG automation intelligence possess the capability to influence the improvement of corporate sustainability performance of the sampled firms in Nigeria. As a result, despite AISIM performing well as a theoretical loop, its functioning in emerging countries is constrained by external structural challenges, leading to a performance gap between multinational organizations and localized firms.

5. Conclusion

This study concludes that adoption of the Artificial Intelligence-Sustainability Integration Model has a positive potential influence on improving corporate sustainability performance of Nigerian firms. The study's findings demonstrate that firms' capability to anchor strategic sensing capability through sustainability prediction analytics; facilitate micro-level sensing and optimize operations using environmental real-time intelligence; implement seizing and reporting of workflow using stakeholder dynamic intelligence; and enable the reconfiguration of capabilities through ESG automation intelligence to match external shifts, will improve their corporate sustainability performance.

This research provides evidence that artificial intelligence functions as a strong driver of corporate sustainability through structural hypothesis testing that moves beyond conceptual assumptions. These findings establish that a business's long-term environmental compliance essentially requires AI-driven infrastructure integration to meet global demands. The research operationalizes dynamic capabilities theory to link specific AI-powered systems to corporate actions involving seizing, sensing, and reconfiguring to track digital-ESG capabilities in volatile economic environments. This research quantifies how digital infrastructure shortages lower the impact of corporate stakeholder intelligence tools, necessitating global comparative studies. However, findings confirm that the transition to automated corporate sustainability in Nigeria faces infrastructure challenges that need to be addressed.

5.1 Recommendations

This research recommends that corporate stakeholders embrace unified smart platforms, combining environmental tracking and natural language processing, to reduce green-washing risks and remove human bias. Business platforms should collaborate with government to introduce digital shared sub-stations in main economic centers, allowing small and medium-scale enterprises to access cloud-based ESG tracking tools without a massive demand for individual capital investment. Corporate organizations and academic institutions should design certification programs that close the gap between corporate sustainability accounting and data science. Making use of local expertise for engineering ESG data will assist businesses in reducing their reliance on expensive international technical consultants and militate against brain-drain bottlenecks.

5.2 Study Limitation and Future Research Agenda

This research relies on a cross-sectional survey design, which prevents the definitive assignment of long-term causal trajectories among the variables. Future studies should therefore utilize longitudinal architectures to track post-implementation AISIM dynamics. Besides, the coverage of the present study is limited to Nigeria, while the reliance on a convenience sample drawn from reachable professionals introduces geographical bias. Future studies should expand sampling frames to include cross-regional firms across other emerging economies to further confirm the possible influence of AISIM adoption on improving the sustainability performance of corporate organizations.

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