
ARTIFICIAL INTELLIGENCE AND ENVIRONMENTAL SUSTAINABILITY IN NIGERIAN SMALL AND MEDIUM ENTERPRISES: A MIXED-METHOD REVIEW

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ABSTRACT

Small and medium-sized enterprises (SMEs) form the backbone of Nigeria's economy, comprising over 80% of registered businesses and contributing approximately 48% of national GDP. Yet, despite this strategic importance, artificial intelligence (AI) adoption for environmental sustainability among Nigerian SMEs remains limited, with scarce empirical evidence of outcomes. This study examines the pathways through which AI tools influence green practices in Nigerian SMEs, identifies structural and contextual barriers to adoption, and proposes policy and institutional interventions to accelerate environmentally beneficial AI uptake. Using a concurrent mixed-methods design, quantitative data were gathered from 144 SMEs across Nigeria's six geopolitical zones, complemented by qualitative case studies of three agri-tech firms: AirSmat Inc. (Lagos), Green Eden (Plateau State), and Anatsor (Plateau State). Analysis was grounded in the Socio-Technical-Environmental (STE) model. Five key AI-enabled sustainability pathways were identified: resource optimisation, climate adaptation planning, demand forecasting for waste reduction, real-time anomaly detection, and automated ESG reporting. SMEs applying AI in precision agriculture recorded economic gains of 22–35%. Overall adoption stands at just 32.6%, constrained by high technology costs (81%), inadequate digital skills (71%), unreliable infrastructure (69–77%), and insufficient regulatory incentives (67%). Access to external partnerships emerged as the strongest predictor of positive AI-sustainability outcomes. Edge computing shows promise in low-connectivity contexts. Policy recommendations include stable energy infrastructure, targeted AI financing, and capacity-building programmes. This study offers the first systematic empirical assessment of AI's ecological impact within Nigerian SMEs, with implications for business owners, policymakers, financial institutions, and development organisations.

Keywords: Artificial Intelligence, Environmental Sustainability, Nigerian SMEs, Precision Agriculture, Digital Agriculture and Socio-Technical Systems.

1. INTRODUCTION

1.1 Background and Statement of the Problem

Nigeria ranks as Africa's most populous nation, with over 227 million inhabitants, and its economy is driven primarily by a vast ecosystem of small and medium-sized enterprises. These entities account for approximately 80% of all registered businesses and contribute nearly half of national economic output, spanning agriculture, manufacturing, financial services, technology, hospitality, and construction. The cumulative environmental impact of operational improvements—whether through reduced material consumption, waste minimisation, or more efficient resource use—across this large SME base can generate substantial ecological benefits at the national level. However, despite growing global interest in the deployment of artificial intelligence (AI) as an instrument for environmental sustainability, Nigerian SMEs remain at an early and largely undocumented stage of AI adoption for green purposes.

Agriculture constitutes a critical dimension of this challenge. The sector contributes approximately 25% of Nigeria's GDP and employs more than one-third of the national workforce. Yet agricultural productivity remains significantly below global benchmarks, averaging 1.64 tons of grain per hectare compared to a world average of 4 tons (Ritchie et al., 2022). Compounding these productivity deficits are structural vulnerabilities including climate variability, soil degradation, and limited access to precision technologies. Emerging evidence, however, indicates that AI-enabled tools—including machine learning platforms, remote sensing systems, and IoT-based sensor networks—are beginning to transform outcomes in specific Nigerian enterprises. For example, Green Eden documented a 20% improvement in crop yield and a 30% reduction in water consumption following AI integration, while Anatsor's poultry monitoring system significantly reduced livestock mortality through continuous environmental surveillance (Mabaya et al., 2025; The Hindu, 2025).

Despite this nascent evidence of promise, systemic adoption of AI for environmental sustainability among Nigerian SMEs remains severely constrained. A 2025 assessment conducted by the Bank of Industry across more than 300 firms identified financing barriers as the predominant obstacle, with approximately two-thirds of respondents citing digital skills deficits and inadequate regulatory incentives as additional impediments (Olusi, 2025). These enterprise-level challenges are compounded by deep-seated infrastructural deficiencies: only about 40% of Nigeria's population has internet access, and reliable electricity supply remains unavailable across much of the country (World Bank, 2024a). The convergence of these constraints creates a fundamentally different adoption environment from that which characterises most existing AI sustainability research, which is disproportionately situated in high-income economies with robust digital infrastructure.

The scholarly literature reflects this geographical imbalance. Academic discourse on AI and green growth has largely centred on large corporations and well-resourced SMEs in Europe and North America—contexts distinguished by strong digital infrastructure, abundant technical talent, and comprehensive regulatory frameworks (European Commission, 2025; Gholami et al., 2022). Systematic empirical investigation of AI-driven environmental outcomes in sub-Saharan African SME contexts is conspicuously absent. This research gap constitutes the central problem motivating the present study: the absence of contextually grounded evidence on how AI adoption for environmental sustainability functions within the structural realities of Nigerian SMEs, and what policy and institutional conditions are necessary to accelerate beneficial outcomes.

1.2 Research Questions

This study is guided by the following research questions:

RQ1: What pathways facilitate AI-enabled environmental sustainability within Nigerian SMEs, and how can these pathways be systematically categorised?

RQ2: What barriers constrain AI adoption for environmental sustainability in Nigerian SMEs, and how do these barriers vary by enterprise size, sector, and geographic location?

RQ3: What contextual factors moderate the relationship between AI adoption and environmental sustainability outcomes in Nigerian SMEs?

RQ4: What policy and enterprise-level interventions are most likely to accelerate AI-driven environmental sustainability outcomes in Nigerian SMEs?

1.3 Research Objectives

In alignment with the above research questions, this study pursues four primary objectives:

- (i) To identify and systematically categorise the mechanisms through which Nigerian SMEs deploy AI tools for environmental sustainability purposes;
- (ii) To assess the prevalence, severity, and differential distribution of adoption barriers across enterprises of varying sizes, sectors, and geographic locations;
- (iii) To examine the contextual conditions that moderate the relationship between AI adoption and environmental sustainability outcomes; and
- (iv) To develop evidence-based policy recommendations applicable to government agencies, financial institutions, and international development organisations.

1.4 Significance of the Study

This study makes three distinct contributions to the scholarly and policy literature. First, it extends and empirically validates the Socio-Technical-Environmental (STE) model as an analytical framework for studying AI-sustainability nexuses in developing economy contexts—a theoretical application that has not been systematically undertaken in prior research. Second, it furnishes the first mixed-methods empirical dataset specifically focused on AI's environmental outcomes in Nigerian SMEs, thereby addressing a documented void in the existing literature. Third, it generates actionable findings directly relevant to Nigerian business owners, government planners, commercial banks, and international development partners who frequently operate in the absence of locally grounded empirical evidence.

2. LITERATURE REVIEW

2.1 Theoretical Framework: The Socio-Technical-Environmental Model

This study adopts and extends the Socio-Technical Systems (STS) theory, originally articulated by Trist and Bamforth (1951) and subsequently elaborated by Baxter and Sommerville (2011), to incorporate an explicit environmental dimension. The resulting Socio-Technical-Environmental (STE) model conceptualises AI-driven environmental outcomes as a product of the interaction among four interdependent subsystems: (1) the technological subsystem, encompassing AI software, data infrastructure, and sensor networks; (2) the human capital subsystem, comprising employee competencies, managerial cognition, and leadership quality; (3) the organisational-institutional subsystem, including

financing arrangements, regulatory compliance mechanisms, and inter-organisational partnerships; and (4) the environmental context subsystem, encompassing physical infrastructure, regulatory frameworks, and market conditions.

The model posits that the ecological benefits of AI adoption are not determined solely by the technological sophistication of the systems deployed, but by the extent to which all four subsystems function in alignment. A deficiency in any single subsystem—inadequate power infrastructure, insufficient human capital, or weak regulatory incentives—constrains environmental outcomes irrespective of the quality of the AI technology in use. This framework informed both the survey instrument design and the thematic structure of the case study analysis, ensuring theoretical consistency across the qualitative and quantitative components of the study.

2.2 AI Tools in Environmental Management

The AI applications most relevant to environmental sustainability in small enterprise contexts span five functional categories. Predictive analytics models enable resource use optimisation by identifying consumption patterns and forecasting demand, thereby minimising waste of energy, water, and agricultural inputs. Machine learning optimisation algorithms improve operational decision-making by detecting demand signals ahead of consumption cycles. Computer vision systems facilitate precise land condition assessments, crop health monitoring, and waste stream classification without requiring continuous human oversight. Natural Language Processing (NLP) tools extract sustainability-relevant data from unstructured business documents, enabling automated ESG metric generation and transparency reporting. Finally, multi-variable integration systems synthesise weather data, soil conditions, and market pricing to support adaptive decision-making in climate-sensitive operations. Collectively, these tools represent a diverse and scalable AI toolkit for environmental management purposes (Russell & Norvig, 2021).

2.3 AI and SME Environmental Impact: Global Evidence

The global evidence base for AI-enabled environmental improvements in SMEs is expanding, though it remains geographically concentrated in high-income economies. Notably, the European Commission's AIRISE initiative (2025) has demonstrated that AI-driven sustainability improvements are achievable even under resource-constrained conditions, having supported more than 500 manufacturing SMEs with methodologies applicable to environments with intermittent power and limited broadband connectivity. Similarly, a collaboration between Barclays and ExpectAI produced the Una platform, which demonstrated the capacity to simultaneously track carbon emission reductions and enhance enterprise profitability. The Sea the Change project, operating under the European Digital Innovation Hubs network, further illustrated the potential of machine learning tools to extract actionable sustainability metrics from routine business filings.

However, the applicability of these findings to the Nigerian context must be qualified by significant structural differences. Most extant research emerges from institutional environments characterised by reliable infrastructure, well-developed financial systems, and comprehensive environmental regulatory frameworks, conditions that diverge substantially from those encountered by Nigerian SMEs (World Bank, 2024b). For Nigerian enterprises, operational survival often takes precedence over voluntary sustainability investment, and the daily realities of intermittent electricity, limited connectivity, and constrained capital access fundamentally reshape the adoption calculus. As Mabaya and Porciello (2022) note, this context has stimulated the emergence of locally designed AI architectures including edge

computing solutions that process data locally before synchronising with remote servers that may ultimately have broader applicability to low-resource environments globally.

2.4 The Nigerian SME Landscape

Nigeria hosts approximately 37 million SMEs operating across a wide range of sectors, with agriculture and agri-tech representing the most AI-receptive segment given the acute productivity and food security challenges confronting the country. Official data indicate that more than 133 million Nigerians face food insecurity (National Bureau of Statistics Nigeria, 2024), situating agricultural AI applications within a context of considerable developmental urgency. The technological environment within which these enterprises operate is, however, characterised by severe structural constraints: only two in five Nigerians have internet access, with rural connectivity substantially lower, while frequent electricity supply disruptions—even in major metropolitan centres—compel many SMEs to rely on diesel-powered generators, significantly increasing operational costs and carbon emissions (World Bank, 2024a).

Despite these constraints, Nigeria's digital agriculture sector has demonstrated remarkable dynamism. The number of agri-tech startups increased from 156 in 2016 to more than 390 by 2018, positioning Nigeria as a leading hub for agricultural technology innovation in sub-Saharan Africa (Phatty-Jobe et al., 2020). Local innovators have responded pragmatically to infrastructural deficits, designing AI systems capable of functioning under low-connectivity conditions—an approach that represents not merely an adaptation to necessity, but a potential template for AI deployment in similarly constrained environments across the developing world.

2.5 Barriers to AI and ESG Adoption in Nigerian SMEs

The literature consistently identifies a multi-layered barrier architecture constraining AI adoption for environmental sustainability among Nigerian SMEs. Financial barriers constitute the most pervasive constraint: high upfront technology costs, combined with the near-absence of AI-specific lending instruments, deter investment particularly among micro-enterprises with limited balance sheet capacity (Mohammed et al., 2025). Human capital deficits compound the financial challenge, as university curricula have been slow to produce graduates with applied expertise in data science and machine learning. The absence of mandatory ESG reporting requirements or meaningful regulatory incentives for green AI investments removes a further driver of adoption that is operative in many comparable economies.

Infrastructure deficits create additional systemic barriers: intermittent electricity supply and inadequate broadband connectivity disrupt the real-time data pipelines upon which many AI applications depend, while the absence of local technical support services constrains enterprise capacity for maintenance and troubleshooting. Critically, these barriers are structurally interdependent: inadequate financing constrains human capital development, which in turn limits the enterprise's capacity to navigate regulatory frameworks or access green financing opportunities, creating self-reinforcing cycles of constraint that resist single-intervention remediation. As Mohammed et al. (2025) observe, this interconnectedness means that piecemeal policy responses—such as extending credit without concurrent investment in training or infrastructure—are unlikely to produce durable adoption outcomes.

3. METHODOLOGY

3.1 Research Philosophy and Design

This study adopts a positivist philosophical orientation, premised on the epistemological position that research questions pertaining to complex, contextually embedded phenomena are best addressed through methodological pluralism. A concurrent mixed-methods design was employed, in which quantitative survey data and qualitative case study data were collected simultaneously and subsequently integrated during the interpretive phase (Fetters et al., 2013). This approach was selected because the drivers and impediments of AI adoption in Nigerian SMEs are simultaneously measurable at the population level and deeply contingent on firm-specific contextual factors that require interpretive investigation. The STE model provided the overarching theoretical structure for organising constructs, specifying variables, and interpreting convergences and divergences between the two methodological strands.

3.2 Quantitative Component: Survey Design and Administration

The quantitative sample was drawn from the Bank of Industry's SME register, with 250 enterprises—defined as firms employing between 10 and 200 personnel—selected through stratified purposive sampling. Stratification criteria included industry sector, enterprise size category, and geopolitical zone, to ensure that the sample composition reflected the structural diversity of the broader SME population. At an anticipated response rate of approximately 60%, a total of 144 fully completed questionnaires were returned and deemed usable for analysis, consistent with the sample size thresholds established for complex multivariate analysis (Tabachnick & Fidell, 2019) and comparable to those employed in analogous research (Mohammed et al., 2025).

The survey instrument comprised five sections: (i) organisational characteristics, including sector, employee count, geopolitical zone, years of operation, and ownership structure; (ii) AI adoption status and application typology; (iii) self-reported environmental performance across five ecological metrics; (iv) perceived adoption barriers rated on a five-point Likert scale across 15 items spanning financial, infrastructural, technical, knowledge-related, regulatory, and organisational dimensions; and (v) perceived effectiveness of ten prospective policy and enterprise-level interventions. Data collection was conducted by trained field enumerators using tablet-based instruments between November 2024 and January 2025, with paper-based fallback protocols activated in locations with insufficient connectivity. Informed consent was obtained from all participants, and firm-level identifying information was removed during data processing.

Quantitative data were analysed using SPSS Version 28. Descriptive statistics characterised adoption prevalence and barrier frequency distributions. Chi-square tests assessed the statistical association between enterprise characteristics and barrier perception profiles. Hierarchical multiple regression examined the relationship between AI adoption and self-reported environmental outcomes, controlling for AI application type and sector. Exploratory factor analysis was employed to identify latent clusters among the 15 barrier items.

3.3 Qualitative Component: Case Studies

Three Nigerian agri-tech enterprises were selected for qualitative case study investigation using purposive sampling criteria that prioritised documented AI application with evidence of environmental outcomes, a minimum operational history of two years, and sectoral and geographic diversity (Yin, 2018). The selected enterprises—AirSmat Inc. (Lagos), Green Eden (Plateau State), and Anatsor (Plateau State)—are described in Table 4. Each case study

integrated three data collection methods: semi-structured interviews (12 per enterprise, averaging 75 minutes, conducted with founders, technology managers, and end-users), documentary analysis (company reports, technical specifications, and secondary media sources), and, where consent was granted, direct observation of system operations. Interview guides were tailored to participant roles. Recordings were transcribed verbatim and anonymised prior to analysis.

Qualitative data were analysed through reflexive thematic analysis following the method of Braun and Clarke (2006), adopting a hybrid deductive-inductive approach. A priori themes were derived from the STE model's four subsystems, while inductive codes were allowed to emerge freely from the data. Preliminary themes were iteratively refined through cyclical re-engagement with the data and validated through member-checking with key informants.

3.4 Mixed-Methods Integration

Integration of the quantitative and qualitative strands was achieved through a triangulation protocol applied at the interpretive stage, consistent with the principles articulated by Fetters et al. (2013). Survey-identified barrier patterns were assessed against case study evidence of how enterprises actually encountered and resolved those barriers. Case-level experiential accounts enriched and contextualised the statistical patterns, while quantitative regularities provided a population-level backdrop against which to assess the typicality or exceptionality of individual case outcomes. Points of convergence strengthened inferential confidence, while divergences generated theoretically productive insights into moderating mechanisms.

3.5 Ethical Considerations and Limitations

Ethical approval for this research was obtained from the institutional review board of Rivers State University. Written informed consent was secured from all participants, with the right to withdraw guaranteed at any point. Data were stored in password-protected encrypted repositories accessible only to the research team, and all participants received summary reports of aggregate findings upon study completion.

Several limitations merit acknowledgement. The cross-sectional design precludes causal inference regarding the relationship between AI adoption and environmental outcomes. Social desirability bias may have influenced self-reported environmental performance data. The sample of 144 enterprises, while analytically adequate, represents a small fraction of Nigeria's approximately 37 million SMEs. The qualitative component is concentrated in agri-tech enterprises in Lagos and the North-Central zone, limiting sectoral and geographic generalisability. Future research employing longitudinal designs with objectively measured environmental outcomes would substantially strengthen the evidence base.

4. RESULTS AND DISCUSSION

4.1 Sample Characteristics

Table 1 presents the demographic and operational characteristics of the 144 participating enterprises across four dimensions: sector, enterprise size, geopolitical zone, and years in operation. The agricultural and agri-tech sector is overrepresented relative to its national share, reflecting the study's deliberate focus on sectors with the highest documented AI-sustainability nexus. The geographic distribution aligns reasonably with the known concentration of agri-tech venture activity in Nigeria.

Table 1
Sample Characteristics of Participating SMEs (N = 144)

Characteristic	Category	n (%)
Sector	Agriculture/Agri-tech	46 (31.9%)
	Manufacturing	27 (18.8%)
	Financial Services	20 (13.9%)
	Digital/ICT Services	18 (12.5%)
	Healthcare	12 (8.3%)
	Hospitality/Tourism	11 (7.6%)
	Creative Industries	7 (4.9%)
	Construction/Engineering	5 (3.5%)
	Other	3 (2.1%)
Enterprise Size	Micro (1–9 employees)	40 (27.8%)
	Small (10–49 employees)	75 (52.1%)
	Medium (50–200 employees)	29 (20.1%)
Geopolitical Zone	South-West (Lagos)	55 (38.2%)
	North-Central (Jos/Abuja)	33 (22.9%)
	South-South	20 (13.9%)
	North-West	17 (11.8%)
	South-East	12 (8.3%)
	North-East	7 (4.9%)
Years in Operation	Under 2 years	17 (11.8%)
	2–5 years	45 (31.3%)
	6–10 years	45 (31.3%)
	Over 10 years	37 (25.7%)

Note. The agricultural and agri-tech sector is overrepresented relative to its national share, consistent with the study's focus on sectors demonstrating the highest AI-sustainability activity. N = 144.

4.2 AI Adoption and Environmental Sustainability Outcomes (RQ1)

Of the 144 enterprises surveyed, 47 (32.6%) reported current AI utilisation in some operational capacity, with the agricultural and agri-tech sector recording the highest adoption rate at 40.4%. Among AI-adopting enterprises, predictive analytics constituted the most common application (53.2%), followed by machine learning optimisation (38.3%), computer vision (21.3%), and NLP/text analytics (12.8%). These findings are presented in full in Table 2.

Analysis of survey and case study data identified five principal pathways through which AI enables environmental sustainability outcomes. The most frequently reported pathway—

resource use optimisation (cited by 82% of AI adopters)—involves the precise adjustment of water, fertiliser, and energy inputs based on real-time sensor data and predictive modelling. One agri-tech enterprise in Jos, for instance, documented a reduction in water consumption of approximately one-third following the installation of soil moisture monitoring technology, with concurrent improvements in crop health. Climate adaptation planning was reported by 75% of adopters, with enterprises employing machine learning to integrate historical climate records, real-time sensor data, and meteorological forecasts to optimise planting and harvesting decisions. Demand forecasting for waste reduction was cited by 61% of respondents, while real-time anomaly detection was reported by 49%—notably, Anatsor's poultry monitoring system demonstrated this pathway through automated alerts triggered by deviations in temperature and air quality, substantially reducing livestock mortality. Automated ESG reporting, while limited to 33% of adopters, was particularly salient among medium-sized enterprises with international market exposure.

Table 2
AI Adoption Profile and Self-Reported Environmental Improvements

Indicator / Metric	Value	Remarks
Current AI Adopters	47 (32.6%)	Approx. 33% of all SMEs surveyed
Agriculture/Agri-tech adopters	19 (40.4%)	Highest sector-level adoption rate
Primarily use predictive analytics	25/47 (53.2%)	Most prevalent AI application type
Machine learning optimisation	18/47 (38.3%)	Second most common
Computer vision applications	10/47 (21.3%)	Third most common
NLP/text analytics	6/47 (12.8%)	Least common AI application
Water use efficiency (mean improvement)	28.3% 86% reporting	Self-reported by AI-adopting SMEs
Energy efficiency (mean improvement)	22.1% 79% reporting	Self-reported
Fertiliser/input efficiency	30.7% 84% reporting	Self-reported
Waste reduction	34.9% 76% reporting	Self-reported
Yield/productivity gains	24.2% 88% reporting	Self-reported

Note. Environmental improvement figures are self-reported by AI-adopting SMEs (n = 47) and have not been independently verified, except where corroborated by case study documentation. Results should be interpreted accordingly.

4.3 Barriers to AI Adoption for Environmental Sustainability (RQ2)

Table 3 presents the full barrier profile ranked by the proportion of respondents rating each item as a major or moderate constraint. Financial barriers dominate the adoption landscape,

with high upfront technology costs identified by 81% of respondents, difficulty accessing AI-specific financing by 76%, and ongoing maintenance costs by 74%. Infrastructure barriers were similarly prominent, with unreliable electricity supply cited by 77% of respondents—a figure that rises to above 90% among North-East zone enterprises, compared to 65% in the South-West, reflecting the pronounced regional disparity in grid reliability. Technical and human capital barriers were reported by 71% (insufficient internal AI expertise) and 68% (difficulty recruiting qualified AI professionals) of respondents respectively, with rural enterprises exhibiting a markedly higher deficit (approximately 80%) than their urban counterparts (around 55%).

Exploratory factor analysis revealed that the 15 barrier items loaded onto two principal factors: a structural constraint factor (encompassing financial, infrastructure, and technical barriers, collectively explaining 61.3% of variance) and an institutional context factor (comprising knowledge, regulatory, and organisational barriers, explaining a further 18.7% of variance). This finding has important policy implications: the structural constraint factor is largely susceptible to targeted public investment and financing innovation, while the institutional context factor requires longer-term governance and capacity-building responses. Notably, institutional resistance to process change—the least frequently cited barrier at 48%—suggests that motivational and cultural factors represent a relatively minor impediment compared to structural constraints, contrary to assumptions embedded in some global AI adoption frameworks.

Table 3

Barrier Profile: Percentage of Respondents Rating Each Item as a Major or Moderate Constraint (N = 144)

Barrier Category	Specific Barrier	% Major/Moderate
Financial	High upfront technology costs	81%
Financial	Difficulty accessing AI-specific financing	76%
Financial	Ongoing maintenance and upgrade costs	74%
Infrastructure	Unreliable electricity supply	77%
Infrastructure	Limited internet/broadband connectivity	69%
Infrastructure	Absence of local technical support services	63%
Technical	Insufficient internal AI expertise	71%
Technical	Difficulty recruiting qualified AI professionals	68%
Technical	Data management and quality challenges	59%
Knowledge	Limited awareness of AI sustainability applications	62%
Knowledge	Absence of sector-specific use-case templates	59%
Regulatory	No government incentives for green AI investments	67%
Regulatory	Absence of mandatory ESG reporting requirements	52%

Barrier Category	Specific Barrier	% Major/Moderate
Organisational	Unclear return on investment for AI adoption	55%
Organisational	Institutional resistance to process change	48%

Note. Figures represent the percentage of respondents (N = 144) rating each item as 'major' or 'moderate' on a five-point Likert scale. Financial and infrastructure barriers consistently rank as the most severe constraints, while organisational resistance represents the least cited impediment to AI adoption.

4.4 Contextual Factors Moderating AI-Sustainability Outcomes (RQ3)

Hierarchical regression analysis, controlling for AI application type and sector classification, identified four contextual factors as significant moderators of the AI-sustainability relationship. Their magnitude of influence and key empirical findings are summarised in Tables 4 and 5.

Table 4
Case Study Enterprise Profiles

Enterprise	Location	Founded	AI Application	Documented Environmental Outcome
AirSmat Inc.	Lagos	2019	AnyFarm precision agriculture platform (ML, remote sensing, data analytics)	28–31% reduction in input wastage; measurable yield improvement; enhanced data-driven decision-making
Green Eden	Jos, Plateau State	2022	Soil analytics and IoT-based microclimate monitoring (sensor networks, predictive modelling)	20% yield increase; 30% reduction in water consumption; improved crop planning
Anatsor	Jos, Plateau State	2022	Poultry environmental monitoring system (IoT sensors: temperature, humidity, water quality)	Significant reduction in livestock mortality; decreased labour burden; rapid anomaly response

Note. Documented outcomes are drawn from company reports, interview data, and secondary sources (Mabaya et al., 2025; The Hindu, 2025). AirSmat Inc. was founded in 2019 (Lagos); Green Eden and Anatsor were both founded in 2022 (Plateau State).

Table 5
Contextual Factors Moderating AI-Sustainability Outcomes

Contextual Factor	Influence Level	Key Finding
Infrastructure Quality	High	Stable electricity and broadband significantly amplify AI-linked environmental gains; infrastructure deficits constrain outcomes regardless of AI system sophistication.
Enterprise Size	Moderate–High	Medium-sized SMEs (50–200 employees) achieve larger environmental improvements than micro-enterprises, attributable to structured workflows and greater absorptive capacity.
Founder Technical Literacy	High	AI adoption by enterprises led by STEM-trained founders produces stronger environmental outcomes; technical leadership reduces implementation failure and vendor dependency.
External Partnership Networks	Very High	Linkages to universities, development organisations, or international donors represent the single strongest predictor of positive AI-sustainability outcomes in this study.
Sector Classification	Low	After controlling for the above factors, sector affiliation does not significantly moderate the AI-sustainability relationship.

Note. Influence levels are based on regression coefficient magnitude and qualitative corroboration from case study data. External partnership networks emerged as the strongest single predictor of AI-sustainability outcomes, superseding both technology sophistication and enterprise size as explanatory variables.

These findings reveal several important theoretical and practical insights. The primacy of infrastructure quality as a moderator reaffirms the STE model's core proposition that environmental AI outcomes are systemically constrained by the broader socio-technical context within which they operate. The significant moderating role of founder technical literacy—evident across all three case study enterprises, each of which was established by STEM-trained individuals—underscores the importance of technical leadership in navigating AI implementation challenges and reducing dependence on external expertise. Most strikingly, the identification of external partnership networks as the single strongest predictor of positive outcomes, above both technology sophistication and enterprise size, suggests that relational capital—specifically, access to university knowledge, development organisation support, and international funding—constitutes a critical but frequently overlooked enabler of AI-driven sustainability in resource-constrained contexts. The insignificance of sector classification as a moderator, after controlling for infrastructure, human capital, and partnership factors, implies that the environmental mechanisms through which AI delivers value—resource optimisation, waste reduction, predictive adaptation—are sector-agnostic, operating comparably across agriculture, manufacturing, and services when structural preconditions are met.

4.5 Policy and Enterprise-Level Interventions (RQ4)

Survey respondents rated the effectiveness of ten prospective interventions using a five-point scale. Results, presented in Table 6, reveal a clear hierarchy of perceived effectiveness. Reliable electricity supply received the highest effectiveness rating (94%), followed by expanded broadband connectivity (88%), reflecting the respondents' recognition that infrastructural foundations underpin all other technological investments. Among short-term interventions, subsidised AI financing with extended repayment periods and lower interest rates attracted the strongest support (89%), followed by AI literacy and data management training programmes (86%), expert mentorship schemes (81%), and tax incentives for green AI investments (82%). Phased mandatory ESG reporting—introduced gradually with compliance support—was rated effective by 59% of respondents, suggesting cautious receptivity to regulatory mandates when accompanied by meaningful institutional support.

Table 6
Perceived Effectiveness of Policy and Enterprise-Level Interventions (N = 144)

Intervention	Rated Highly Effective (%)	Implementation Horizon
Reliable electricity supply (urban and rural)	94%	Long-term
Expanded broadband and connectivity infrastructure	88%	Long-term
Subsidised AI financing (extended repayment, lower rates)	89%	Short-term
AI literacy and data management training programmes	86%	Short-term
Tax incentives for green AI investments	82%	Short-term
Expert mentorship schemes for AI implementation	81%	Short- to Medium-term
Grant funding for AI pilot projects	79%	Short-term
Sector-specific AI sustainability toolkits	78%	Short-term
Preferential government procurement for ESG-compliant SMEs	71%	Medium-term
Phased mandatory ESG reporting with compliance support	59%	Long-term

Note. Effectiveness ratings reflect respondent assessments (N = 144). Implementation horizons are indicative estimates derived from expert interview data and policy analysis. 'Short-term' = feasible within 1–2 years; 'Medium-term' = 3–5 years; 'Long-term' = 5+ years.

4.6 Discussion

The findings collectively affirm that AI technology can meaningfully advance environmental sustainability outcomes among Nigerian SMEs, but that such outcomes are strongly contingent on the socio-technical environment—a finding consistent with the STE model and with the broader literature on technology adoption in developing economies. The self-reported environmental improvements documented among AI-adopting enterprises (22–35%

reductions in resource consumption and waste generation) are consistent with improvements documented in the three case study enterprises, lending cross-method credibility to the findings, though independent verification remains a priority for future research.

The low overall adoption rate of 32.6%, concentrated disproportionately among mid-sized, urban, and technically-led enterprises, indicates that AI-driven sustainability benefits have not yet achieved the broad diffusion necessary to generate economy-wide ecological impact. The barrier architecture identified—structured around mutually reinforcing financial, infrastructural, human capital, regulatory, and knowledge-related constraints—explains this limited diffusion and points toward the inadequacy of single-instrument policy responses. Previous studies have documented similar constraint interdependencies in other sub-Saharan African technology adoption contexts, and the present findings extend this literature by demonstrating its specific application to the AI-sustainability nexus.

A theoretically significant finding concerns the adaptation strategies documented in the case study enterprises. Rather than replicating AI architectures designed for high-resource environments, AirSmat Inc., Green Eden, and Anatsor each developed contextually tailored systems—including edge computing approaches that perform local data processing to reduce dependence on continuous internet connectivity—that represent genuine innovation responses to structural constraints. This finding challenges linear technology transfer narratives and suggests that resource-constrained contexts may stimulate locally relevant AI architectures with potential transferability to similarly constrained environments in other low- and middle-income countries. The concentration of enterprise founders below the age of 30 in all three case studies further underscores the strategic importance of investing in Nigeria's emerging technology talent pipeline as a driver of sustainable AI innovation.

Comparisons with global evidence reveal both convergences and substantive divergences. The AI sustainability pathways identified in Nigeria closely parallel those documented in European SME contexts, confirming that the technology's environmental mechanisms are not context-specific. However, the priority hierarchy of sustainability objectives differs markedly: Nigerian SMEs primarily apply AI to address climate vulnerability and input efficiency challenges arising from agricultural fragility and environmental exposure, whereas European counterparts more frequently target regulatory emissions compliance and net-zero transition pathways. This divergence reflects the different material starting points—survival-oriented adaptation versus regulatory-compliance-oriented decarbonisation—that characterise sustainability action in low versus high-income economies, and should inform how international development frameworks are calibrated to local priorities.

5. CONCLUSION

This study demonstrates that AI technology possesses meaningful potential to advance environmental sustainability outcomes among Nigerian SMEs, with documented improvements in resource use efficiency, waste reduction, and ecological resilience ranging between 22% and 35% among adopting enterprises. These results hold even within an operational context characterised by infrastructural deficits and structural constraints, as evidenced by the adaptive technological approaches developed by AirSmat Inc., Green Eden, and Anatsor. The case study enterprises illustrate that thoughtfully designed, contextually tailored AI systems can deliver material environmental value under conditions of intermittent power and limited connectivity—and that these architectures may represent exportable templates for sustainable AI deployment in other resource-constrained settings globally.

Nevertheless, adoption remains narrowly concentrated: only 32.6% of surveyed enterprises currently deploy AI in any operational capacity, with AI-for-sustainability applications

representing a still smaller subset. This concentration—skewed toward mid-sized, urban, and technically-led enterprises—reflects the operation of a mutually reinforcing barrier architecture encompassing financial, infrastructural, human capital, and regulatory constraints. Addressing this barrier architecture requires coordinated, multi-stakeholder responses that tackle structural constraints simultaneously rather than sequentially. Enterprises, government agencies, financial institutions, and international development organisations each occupy distinct but complementary roles in constructing the enabling environment necessary for broad-based AI-sustainability adoption.

From a theoretical standpoint, this study makes two principal contributions. First, it provides the first empirical application and validation of the Socio-Technical-Environmental (STE) model in the context of AI adoption for sustainability in a developing economy, demonstrating the model's explanatory power across both quantitative and qualitative evidence streams. Second, it generates an original empirical dataset—the first of its kind focused specifically on AI's environmental outcomes in Nigerian SMEs—that provides a foundation for future research, longitudinal tracking, and policy evaluation.

Several directions for future inquiry merit attention. Longitudinal research designs employing objective, instrument-based environmental measurements would substantially strengthen causal inference. Cross-national comparative studies across sub-Saharan African SME ecosystems could illuminate regional variation and transferable lessons. Sector-specific investigations extending beyond agri-tech to manufacturing, construction, and services would broaden the evidence base. Finally, the carbon footprint and electronic waste implications of expanding AI hardware deployment in Nigeria—potential countervailing environmental costs that the present study was not designed to capture—deserve dedicated scholarly attention to ensure that the sustainability calculus of AI adoption is assessed comprehensively.

6. RECOMMENDATIONS

6.1 For Nigerian SME Owners and Managers

Enterprises should prioritise the internalisation of AI and data management competencies by investing in the recruitment of data science professionals and the delivery of structured staff training programmes, thereby reducing dependence on external vendors and improving implementation fidelity. Technology selection should be anchored in the realities of the operating environment: edge computing architectures, solar-compatible hardware, and offline-capable systems are not merely acceptable compromises but strategically appropriate responses to Nigerian infrastructure conditions. Adoption should be initiated through bounded pilot applications—such as predictive irrigation management or demand forecasting—with rigorous performance tracking to generate the documented evidence base necessary for scaling decisions. Strategic linkages with universities, industry associations, and development agencies should be actively cultivated, given the empirical identification of external partnership networks as the strongest predictor of positive AI-sustainability outcomes. Finally, the business case for AI investment should be articulated primarily in terms of operational efficiency and risk mitigation, with environmental benefits positioned as a complementary value proposition rather than the primary rationale, given current investor and stakeholder expectations in the Nigerian market.

6.2 For Nigerian Policymakers and Regulators

The most urgent policy priority identified in this study is investment in the foundational infrastructure that enables AI adoption: stable electricity supply and expanded broadband connectivity, which received the highest effectiveness ratings of 94% and 88% respectively

among survey respondents. Existing financing instruments, including the Bank of Industry's green technology lending programme, should be extended to encompass AI-for-sustainability investments, with loan structures redesigned to accommodate the longer payback periods, cash flow profiles, and non-traditional collateral assets (such as software portfolios and data infrastructure) characteristic of AI-enabled SMEs. SMEDAN training curricula should be redesigned to incorporate applied AI literacy components grounded in real enterprise use cases. A phased and incentive-supported pathway to mandatory ESG reporting—initiated on a voluntary basis for larger SMEs before progressive extension—is likely to achieve broader compliance and market transformation than immediate regulatory mandates. Investment in domestic AI research capacity and indigenous start-up development should be increased to reduce import dependency and ensure that AI solutions are calibrated to Nigerian structural realities from the point of design.

6.3 For Financial Institutions

Commercial banks and development finance institutions should redesign SME lending criteria to accommodate the asset profiles typical of AI enterprises, including recognition of verified data infrastructure, operational algorithms, and demonstrated user bases as eligible collateral. Loan repayment schedules should be aligned with the longer value realisation timelines of digital technology investments. Credit risk assessment frameworks require enhancement through the development of in-house capability to evaluate AI business models and technology assets, rather than defaulting to traditional balance sheet metrics that systematically disadvantage early-stage digital enterprises. Integrating AI sustainability performance into ESG-linked lending products—consistent with approaches being piloted by development finance institutions internationally—would simultaneously incentivise adoption and align lending portfolios with environmental objectives.

6.4 For International Development Partners and Donors

International development organisations should prioritise the facilitation of institutional partnerships—between Nigerian SMEs and universities, research institutions, and global technical networks—over the direct provision of technology equipment, given the empirical evidence that relational capital is the strongest predictor of positive AI-sustainability outcomes. Funding programmes should explicitly privilege locally designed and maintained AI solutions over imported technology, in recognition that contextually grounded systems demonstrate superior reliability, community acceptance, and sustainability. Development partners should also support the design and implementation of longitudinal tracking studies incorporating objective environmental measurement instruments, to generate the rigorous long-term evidence base necessary for optimal resource allocation and evidence-informed policy development.

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