

Review

Artificial Intelligence for Sustainable Development in Low-Resource African Contexts: A Structured Review and Adaptive Deployment Framework

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Abstract

Artificial intelligence (AI) is increasingly discussed as a tool for supporting sustainable development in Africa, particularly in healthcare, agriculture, education, and environmental management. However, the feasibility of AI deployment in low-resource contexts is shaped by fragmented data ecosystems, infrastructural limitations, governance capacity, human-capital constraints, and risks of digital exclusion. This study presents a structured literature review of AI for sustainable development in African contexts, with a specific focus on low-resource deployment conditions. The review synthesises evidence across sectoral applications, governance and ethical considerations, and resource-efficient AI approaches. It shows that AI systems may support prediction, classification, monitoring, and decision support, but technical potential does not automatically translate into sustained implementation or measurable sustainable development outcomes. In response, the study proposes a synthesis-based conceptual framework linking structural enablers, sectoral AI applications, potential sustainable development outcomes, and adaptive feedback mechanisms. The framework is intended as an analytical and decision-support tool for assessing whether AI systems can be responsibly deployed, maintained, governed, and adapted under different African deployment conditions. The research contributes to AI-for-sustainable-development research by shifting attention from general AI potential to context-sensitive deployment feasibility in low-resource African settings.

Keywords: artificial intelligence; sustainable development; low-resource AI; Africa; deployment feasibility; AI applications; adaptive framework



Academic Editor: Camelia Delcea

Received: 16 May 2026

Revised: 25 June 2026

Accepted: 26 June 2026

Published: 3 August 2026

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1. Introduction

Artificial Intelligence (AI) has become a central domain of technological development with increasing implications for economic systems, public governance, and environmental management. Research has documented the potential of AI to influence multiple dimensions of the United Nations Sustainable Development Goals (SDGs), including health, food security, climate action, and infrastructure resilience [1,2]. At the same time, the literature recognises that AI systems may exacerbate inequality or introduce governance risks if deployed without contextual safeguards [3,4]. These dual dynamics are particularly relevant in African contexts, where structural development constraints interact with emerging digital transformation initiatives.

Africa faces interrelated sustainability challenges spanning healthcare access, agricultural productivity, educational quality, urban infrastructure, and environmental vulnerability. Recent reviews indicate that AI applications have been explored in African sectors such as automated disease diagnostics, precision agriculture, environmental monitoring, and intelligent transport systems. These applications align with SDG priorities, including Good Health and Well-being, Zero Hunger, Climate Action, and Industry, Innovation, and Infrastructure. However, prior research also emphasises that infrastructural fragility, inconsistent electricity supply, limited broadband penetration, and skill shortages constrain large-scale AI integration across the continent.

Global AI innovation ecosystems typically assume high-resource computational environments characterised by continuous connectivity, cloud-based infrastructure, extensive annotated datasets, and stable power systems. Such assumptions may not hold uniformly across African regions. Machine learning (ML) systems frequently depend on high-performance computing resources and large-scale data processing pipelines [5,6]. When transferred into low-resource contexts without adaptation, these systems may face operational inefficiencies, reliability limitations, and deployment barriers. Consequently, the question is not solely whether AI can contribute to sustainable development in Africa, but under what infrastructural and computational conditions such contributions remain feasible.

Existing research on AI and sustainable development in Africa has largely focused on sectoral opportunities and governance challenges [7]. While these analyses provide valuable insights, comparatively less attention has been directed toward the technical and operational implications of deploying AI under explicitly low-resource conditions. Low-resource AI deployment encompasses issues such as energy-efficient model design, edge computing architectures, data sparsity adaptation, bandwidth-aware system optimisation, and robustness under intermittent connectivity. These considerations are central to translating theoretical AI potential into sustainable implementation pathways within constrained environments.

Recent work by [7] provides a valuable broad review of AI and sustainable development in Africa, highlighting sectoral opportunities, adoption challenges, and strategic pillars for AI integration. The present study builds on this contribution but adopts a more specific analytical lens. Rather than reviewing AI potential in Africa in general terms, this research focuses on deployment feasibility under low-resource conditions. In this context, low-resource deployment is understood as the interaction of computational constraints, fragmented data ecosystems, infrastructure limitations, governance capacity, and human-capital availability. This distinction allows the review to examine not only what AI could contribute to sustainable development, but also under what operational conditions such contributions are likely to be feasible, inclusive, and sustainable.

Broader AI ethics and governance literature further reinforces the need for context-aware deployment strategies. Transparency, accountability, and fairness have been identified as foundational principles for responsible AI development [3]. In low-resource settings, data representativeness and infrastructural inequality may compound risks of bias and exclusion [4]. Without deliberate adaptation, AI systems developed in high-income contexts may reproduce structural imbalances rather than mitigate them. Thus, technological feasibility, ethical safeguards, and infrastructural readiness must be examined concurrently [8,9].

This study addresses this analytical gap by synthesising peer-reviewed research on AI applications in African sustainable development and examining them through the lens of low-resource deployment constraints. Rather than presenting new empirical evidence, the research adopts a structured literature review methodology to identify patterns, limitations,

and operational considerations documented across sectors. By centring infrastructural and computational constraints within the analysis, the study reframes AI-for-SDG discourse from a capability-focused narrative towards a deployment feasibility perspective.

The contribution is presented conservatively. First, the research consolidates cross-sectoral research on AI applications relevant to African SDGs while explicitly analysing infrastructural and resource limitations. Second, it proposes a context-aware conceptual framework outlining key pillars for low-resource AI integration aligned with sustainable development priorities. The framework is not positioned as a validated implementation model; rather, it offers structured guidance for researchers and policymakers seeking to design AI initiatives consistent with African operational realities.

The rest of the paper is structured as follows. Section 2 reviews related work on AI, sustainable development, and African deployment contexts. Section 3 outlines the methodology adopted for the structured literature review, while Section 4 presents the results of that review and summarises the low-resource deployment constraints identified in the reviewed literature. Section 5, Section 6, and Section 7 then draw out three distinctive implications of the review findings. Section 5 examines sustainable development in resource-constrained contexts, Section 6 analyses AI application sectors under low-resource deployment conditions, and Section 7 discusses cross-cutting AI deployment challenges. Section 8 proposes the adaptive conceptual framework for low-resource AI deployment, Section 9 presents future research directions, and Section 10 concludes the study.

2. Related Work

Research examining the intersection of AI and sustainable development has expanded significantly in recent years. Global assessments have attempted to map AI capabilities to the United Nations Sustainable Development Goals (SDGs), often identifying both enabling and inhibiting effects. The authors of [1] provide one of the most comprehensive analyses, demonstrating that AI may contribute positively to the majority of SDGs while simultaneously posing risks related to inequality, institutional fragility, and environmental cost. Similarly, [2] synthesises opportunities and threats associated with AI adoption, arguing that contextual governance structures determine whether technological interventions generate inclusive outcomes. These studies establish AI as a conditional enabler of sustainable development rather than an inherently transformative force [10].

Parallel work has focused on AI applications in environmental systems, energy optimisation, and agricultural forecasting. The authors of [6] survey ML techniques for climate mitigation and adaptation, noting substantial computational requirements associated with large-scale predictive modelling. The authors of [5] analyse macroeconomic implications of AI diffusion, emphasising structural adjustment pressures and uneven productivity gains. While these contributions underscore AI's relevance to sustainability transitions, they largely assume stable digital infrastructure and high computational capacity. The operational preconditions embedded in these analyses remain insufficiently interrogated when considering low-resource environments.

Within African contexts, research has increasingly documented sector-specific AI applications aligned with development priorities. Reviews of AI deployment in healthcare, agriculture, water management, and urban systems highlight emerging experimentation across the continent [7]. These studies emphasise diagnostic automation, crop yield prediction, environmental monitoring, and smart infrastructure optimisation. However, they concurrently identify persistent infrastructural constraints, including unreliable electricity supply, limited broadband penetration, fragmented data ecosystems, and shortages of advanced technical expertise. These structural limitations materially affect the feasibility of AI system deployment at scale.

The governance literature further complicates this landscape. Global AI ethics frameworks emphasise transparency, fairness, accountability, and human oversight [3]. Refs. [4,11] argue that sustainable AI implementation requires alignment between technological design and institutional capacity. In low-resource settings, regulatory gaps and data governance weaknesses may increase vulnerability to algorithmic bias or technological dependency. African policy analyses indicate uneven readiness for AI regulation and limited cross-border harmonisation. Consequently, governance capacity interacts directly with infrastructural constraints in shaping deployment trajectories.

Despite these advances, the majority of SDG-oriented AI research adopts a capability-centric orientation. That is, such research typically catalogues potential sectoral benefits or evaluates normative governance frameworks without systematically analysing the computational and infrastructural assumptions underlying AI deployment. Contemporary ML systems frequently depend on high-performance hardware, extensive labelled datasets, and cloud-based training pipelines [6]. Data-intensive architectures such as deep neural networks often require substantial energy consumption and sustained connectivity [12]. These requirements may not align with environments characterised by intermittent electricity, bandwidth volatility, and data sparsity.

Technical research on resource-efficient AI provides relevant but under-integrated insights. Model compression techniques [13], energy-aware hardware design [12], and federated learning architectures enabling decentralised training [14] collectively demonstrate that computational burdens can be reduced under certain constraints. Edge computing frameworks further enable inference on local devices, mitigating reliance on persistent cloud infrastructure. However, this body of research is predominantly framed within performance optimisation paradigms rather than development feasibility contexts. Explicit integration with SDG-aligned deployment challenges in African environments remains limited.

A second limitation in the existing literature concerns analytical granularity. Continental level discussions often treat Africa as a uniform technological environment. Yet empirical studies of digital infrastructure reveal substantial heterogeneity in connectivity, energy access, and institutional capacity across regions. Overgeneralisation risks obscuring differentiated deployment conditions and may produce policy prescriptions insufficiently sensitive to contextual variability. A constraint-aware perspective requires recognition of this heterogeneity rather than reliance on aggregate characterisations [15,16].

Thus, the literature can be organised into three principal parts. First, global SDG-oriented analyses establish AI's conditional developmental potential while highlighting governance risks. Second, African-focused studies document sectoral experimentation and infrastructural constraints. Third, technical research advances resource-efficient AI methodologies without systematically situating them within sustainable development frameworks. What remains underdeveloped is an integrative synthesis explicitly centred on low-resource deployment feasibility in African contexts.

This gap is not merely semantic. Deployment feasibility determines whether AI transitions from conceptual promise to operational utility. Without explicit attention to energy reliability, bandwidth availability, data representativeness, and computational efficiency, AI-for-SDG narratives risk overstating implementability. Conversely, resource-efficient methodologies developed in technical domains may overlook socio-institutional constraints shaping adoption. Bridging these strands requires a structured review that jointly examines sectoral applications, infrastructural realities, and emerging low-resource AI techniques [17,18].

The study addresses this gap through a synthesis-oriented analysis rather than empirical experimentation. By consolidating evidence across development focused and technical

literatures, it advances a deployment feasibility lens that foregrounds operational constraints as central analytical variables. This positioning reframes the discussion from technological capability toward contextual viability. The contribution is framed conservatively: the study does not claim to resolve infrastructural barriers, nor does it validate specific AI architectures. Instead, it provides a structured analytical foundation for examining how low-resource AI integration can be aligned with SDG priorities under African deployment conditions. To clarify the positioning of the present study in relation to closely related work, Table 1 summarises how this review builds on Mienye et al. [7].

Table 1. Positioning of the present study in relation to Mienye et al. [7].

Analytical Area	Mienye et al. [7]	Present Study
Main focus	Broad review of AI applications and sustainable development in Africa.	Low-resource deployment feasibility of AI for sustainable development in African contexts.
Sectoral scope	Healthcare, agriculture, education, environmental protection, and infrastructure.	Healthcare, agriculture, education, and environmental management, analysed through deployment constraints.
Core analytical lens	Opportunities, challenges, strategies, and broad integration pillars.	Computational, infrastructural, data, governance, equity, and human-capacity conditions shaping AI feasibility.
Framework emphasis	Strategic pillars for AI integration, including infrastructure, human capital, innovation, policy and governance, and partnerships.	Adaptive deployment feasibility framework linking technological foundations, sectoral applications, enabling conditions, and sustainable development outcomes.
Main extension	Establishes a broad foundation for AI-enabled sustainable development in Africa.	Extends this foundation by examining when and how AI deployment can be sustained under low-resource conditions.

3. Research Methodology

This study adopts a structured literature review methodology to synthesise peer-reviewed research on low-resource AI deployment in African sustainable development contexts. Structured reviews are appropriate in interdisciplinary domains where technological innovation intersects with policy, infrastructure, and socioeconomic systems [19,20]. Given the conceptual and cross-sectoral nature of this study, the review design was used to consolidate fragmented literature across machine learning, sustainable development, infrastructure systems, digital governance, and African development contexts [1,2].

3.1. Review Design Rationale

AI for sustainable development constitutes a multidisciplinary research area characterised by heterogeneous methodologies and sectoral applications. Traditional meta-analytic techniques are not suitable due to variability in study designs, datasets, and outcome measures. Instead, structured narrative synthesis enables analytical integration across qualitative policy studies, technical machine learning research, and applied sectoral case analyses [20]. The purpose of the review was not to conduct a quantitative meta-analysis or estimate pooled effect sizes. The reviewed studies varied considerably in their methods, evidence types, sectoral focus, and outcome measures. A structured narrative synthesis was therefore considered appropriate because it allows conceptual, technical, policy-oriented, and sectoral studies to be analysed together. The review focused specifically on how

computational, infrastructural, data-related, governance, and human-capacity constraints influence the feasibility of AI deployment in African sustainable development contexts.

3.2. Literature Search Strategy

The literature search was conducted between January 2026 and April 2026. Search was carried out using Google Scholar alongside major academic databases relevant to artificial intelligence, computing, sustainability, and interdisciplinary technology research, including IEEE Xplore, ACM Digital Library, and ScienceDirect. Google Scholar was used as a broad discovery source, while the selected academic databases were used to identify peer-reviewed research across computing, engineering, sustainability, and development-related fields [21,22].

The search strategy combined terms from five conceptual domains: artificial intelligence, sustainable development, Africa, low-resource deployment, and sectoral application areas. The following representative Boolean search strings guided the search process:

- (“artificial intelligence” OR “machine learning” OR “deep learning”) AND (“sustainable development” OR “SDG” OR “Sustainable Development Goals”) AND (“Africa” OR “African contexts”);
- (“artificial intelligence” OR “machine learning”) AND (“low-resource” OR “resource-constrained” OR “infrastructure constraints” OR “limited connectivity”) AND (“Africa” OR “developing countries”);
- (“AI” OR “machine learning”) AND (“healthcare” OR “agriculture” OR “education” OR “environment” OR “climate”) AND (“Africa” OR “Sub-Saharan Africa”) AND (“sustainable development” OR “SDG”);
- (“edge computing” OR “model compression” OR “federated learning” OR “TinyML”) AND (“low-resource” OR “resource-constrained”) AND (“AI deployment” OR “machine learning deployment”);
- (“AI governance” OR “algorithmic bias” OR “data governance” OR “AI ethics”) AND (“Africa” OR “developing countries”) AND (“sustainable development” OR “public sector”).

The search focused primarily on publications from 2013 to 2024, reflecting the period of accelerated AI development and post-SDG adoption research. Foundational sources outside this period were included only where they provided essential conceptual or methodological grounding, such as sustainable development theory, systematic review methodology, or AI ethics principles [1].

3.3. Inclusion and Exclusion Criteria and PRISMA-Based Study Selection

The study clearly defined inclusion and exclusion criteria aligned with PRISMA 2020 guidance [21,22]. Peer-reviewed journal articles and conference proceedings were prioritised. Grey literature, non-peer-reviewed reports, tutorials, promotional white papers, and non-indexed sources were excluded from the final analytical synthesis.

Studies were included if they met at least one of the following criteria:

- Examined AI applications relevant to SDG-aligned sectors within African contexts.
- Analysed infrastructure, governance, data, or human-capacity constraints affecting AI deployment in low- and middle-income environments.
- Proposed or evaluated resource-efficient AI methodologies applicable to constrained or low-resource settings.
- Contributed to understanding the relationship between AI, sustainable development, and socio-technical deployment feasibility.

Studies were excluded if they:

- Focused exclusively on high-resource industrial or commercial applications without relevance to development contexts.
- Addressed theoretical AI concepts without practical or deployment-related implications.
- Discussed digital transformation broadly without explicit reference to artificial intelligence or machine learning.
- Did not provide sufficient relevance to African, low-resource, or sustainable development contexts.
- Were non-academic or non-peer-reviewed sources.

The study selection process followed the PRISMA stages of identification, screening, retrieval, eligibility assessment, and inclusion. During identification, 144 records were retrieved across the selected search sources. After removing 15 duplicates, 129 unique records were screened by title and abstract. Both authors independently screened the records against the inclusion and exclusion criteria. Disagreements were discussed and resolved by consensus.

At the screening stage, 48 records were excluded because they did not meet the thematic scope of the review. This left 81 reports sought for retrieval. Of these, 16 reports could not be retrieved, resulting in 65 full-text articles assessed for eligibility. During full-text eligibility assessment, 39 studies were excluded for the following reasons: domain-specific technical studies lacking alignment with AI-SDG applications ($n = 14$), education-focused or no-code systems without substantive AI components ($n = 10$), studies lacking practical deployment relevance or applied AI implementation ($n = 8$), and non-academic or non-peer-reviewed sources ($n = 7$). Following this process, 26 studies were retained for final inclusion in the structured synthesis [19–22]. The study selection process is summarised in Figure 1, and the PRISMA 2020 checklist is provided as Supplementary Materials.

3.4. Data Extraction Procedure

A structured extraction template was used to ensure consistency across the 26 included studies. The unit of analysis was the individual study. For each included study, the following information was extracted: author and year, geographical focus, sectoral domain, AI methodology or technology discussed, data source where available, evidence type, key contribution, main deployment constraint, and relevance to the proposed framework. The extraction process was designed to support analytical comparison across heterogeneous studies rather than to aggregate quantitative outcomes. This was necessary because the included studies differed in design, ranging from conceptual and review-based studies to technical, sectoral, and implementation-oriented contributions.

3.5. Coding and Thematic Synthesis

The extracted evidence was analysed through thematic coding. Coding was conducted deductively and inductively. Deductive coding was guided by research focused on AI-SDG alignment, governance and ethical considerations, and resource-efficient or infrastructure-aware AI. Inductive coding was used to capture recurring constraints and implementation conditions emerging from the included studies.

The initial coding categories included sectoral AI application, SDG alignment, data ecosystem maturity, infrastructure reliability, computational resource requirements, governance and regulatory capacity, human capital and skills, equity and inclusion, cross-sector coordination, and evidence maturity. These codes were then clustered into three higher-level analytical domains:

- AI-SDG alignment and sectoral applications.
- Governance, ethical, and regulatory considerations.
- Resource-efficient and infrastructure-aware AI deployment.

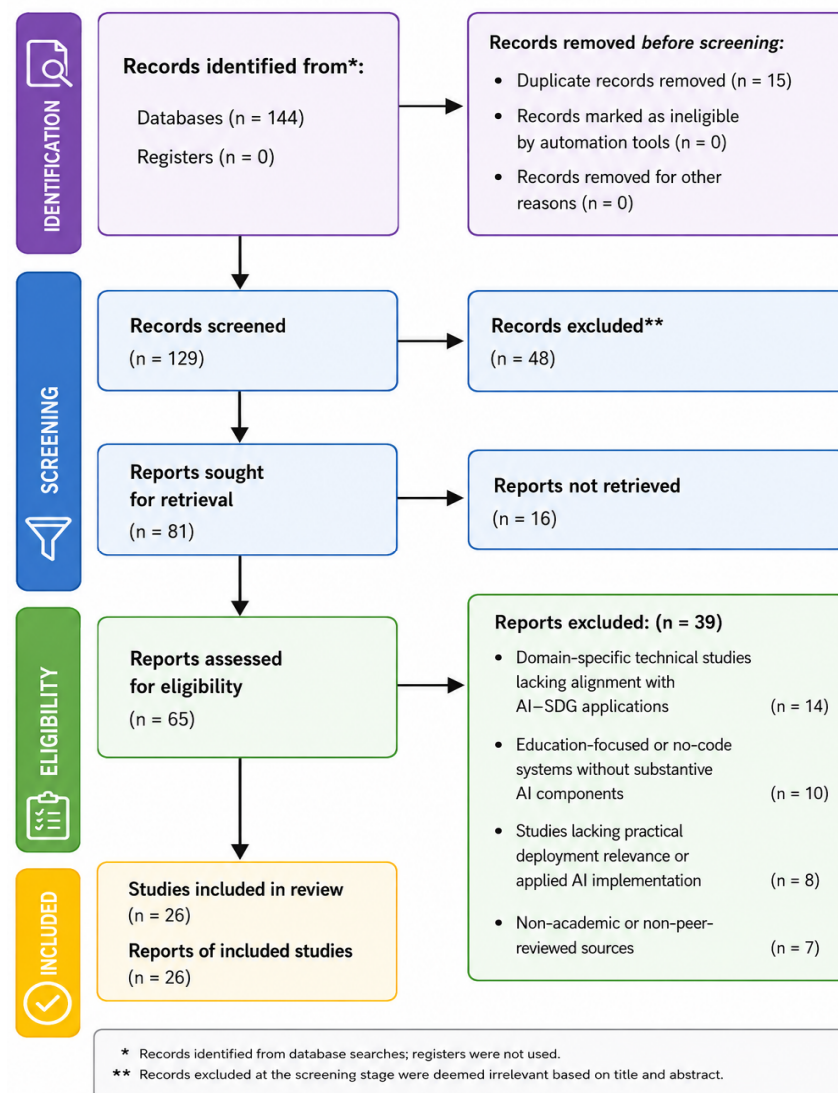


Figure 1. PRISMA flow diagram of the study selection process.

The coding process informed the development of the conceptual framework by linking recurring review themes to framework components. For example, studies highlighting data fragmentation and limited local datasets informed the data ecosystems component of the technological foundations layer. Studies emphasising broadband gaps, unreliable electricity, and hardware limitations informed the infrastructure and low-resource deployment components. Governance, ethics, accountability, and regulatory concerns informed the deployment conditions layer. Sector-specific studies informed the healthcare, agriculture, education, and environmental management application layer.

3.6. Analytical Link Between the Review and the Conceptual Framework

The extracted evidence was analysed through thematic coding. Coding was conducted deductively and inductively. Deductive coding was guided by research focused on AI–SDG alignment, governance and ethical considerations, and resource-efficient or infrastructure-aware AI. Inductive coding was used to capture recurring constraints and implementation conditions emerging from the included studies. This approach ensures that the framework is grounded in the review synthesis while remaining appropriately cautious in its claims. The framework is not presented as a tested intervention model. Instead, it is intended as a structured decision-support lens for researchers, policymakers, and practitioners examining the feasibility of AI deployment under low-resource African conditions.

3.7. Methodological Limitations

Several limitations are inherent to this structured literature review. First, database indexing and search visibility may have affected the range of studies identified. Although multiple academic sources were searched, relevant regional publications that were not indexed or easily retrievable through these sources may be underrepresented. Second, the review does not conduct quantitative meta-analysis and therefore does not estimate aggregate effect sizes. Third, the heterogeneity of African contexts limits the extent to which conclusions can be generalised across all countries, regions, and institutional settings. Fourth, the coding and synthesis process was interpretive, although it was guided by predefined extraction fields, author consensus, and transparent thematic categories. These limitations are consistent with the nature of structured reviews in interdisciplinary and policy-relevant research [23].

4. Results of the Structured Literature Review

This section presents the results of the structured literature review described in Section 3. The final synthesis was based on 26 studies retained after the PRISMA-guided screening and eligibility process. The included studies were grouped into five analytical domains: healthcare, agriculture, education, environment, and governance/infrastructure. Across these domains, the review identified two recurring patterns. First, AI applications are most frequently presented as tools for improving prediction, classification, monitoring, and decision support in SDG-aligned sectors. Second, the feasibility of these applications is shaped by constraints relating to data availability, infrastructure reliability, computational resources, governance capacity, local skills, and equitable access. Table 2 provides a domain-level synthesis of the included studies.

Table 2. Domain-level analytical synthesis of the 26 included studies.

Domain	Representative Studies	Main AI Focus	Key Contribution	Recurrent Limitation	Link to Framework
Healthcare	Topol [19]; Rajaraman et al. [20]; Esteva et al. [21]; Litjens et al. [22]; Jiang et al. [23]; Obermeyer et al. [24]	Diagnostic support, medical imaging, disease prediction, algorithmic bias	Demonstrates the potential of AI to support diagnosis, screening, and clinical decision support	Dataset limitations, bias, limited local validation, infrastructure requirements	Sectoral AI applications; data ecosystems; governance and accountability
Agriculture	Lajoie-O'Malley et al. [25]; Ramcharan et al. [26]; Ferentinos [27]; Kamilaris and Prenafeta-Boldú [28]; Liakos et al. [29]; Wolfert et al. [30]	Crop disease detection, precision agriculture, smart farming, agricultural data systems	Shows how AI can support productivity, crop monitoring, and resource optimisation	Data quality, adoption barriers, technical expertise requirements, infrastructure limitations	Sectoral AI applications; infrastructure readiness; human capacity
Education	Holmes et al. [31]; Luckin et al. [32]; Zawacki-Richter et al. [33]; Roll and Wylie [34]	Intelligent tutoring, adaptive learning, learning analytics	Highlights AI's potential to support personalised learning and educational planning	Digital divide, implementation gaps, privacy concerns, high development cost	Sectoral AI applications; equity and inclusion; governance
Environment	Rolnick et al. [6]; Tyukavina et al. [35]; Willi et al. [36]; Reichstein et al. [37]	Climate modelling, remote sensing, biodiversity monitoring, Earth system science	Demonstrates the value of AI for environmental monitoring and climate-related analysis	High computational demand, large data set requirements, limited local data availability	Sectoral AI applications; computational constraints; environmental sustainability

Table 2. Cont.

Domain	Representative Studies	Main AI Focus	Key Contribution	Recurrent Limitation	Link to Framework
Governance and infrastructure	Jobin et al. [3]; Floridi et al. [38]; Cruz-Jesus et al. [39]; Aker and Mbiti [40]; Osei [15]; Kairouz et al. [14]	AI ethics, digital divide, infrastructure, mobile technologies, federated learning	Identifies governance, fairness, infrastructure, and decentralised learning as important enablers of responsible AI deployment	Weak enforcement, regulatory fragmentation, digital inequality, implementation complexity	Deployment conditions; governance; equity; cross-sector coordination

The synthesis indicates that evidence strength varies across sectors. Healthcare and environmental studies provide relatively strong technical evidence for classification, diagnosis, imaging, and monitoring tasks, although many of these studies rely on controlled datasets or high-resource computational assumptions. Agricultural AI studies include practical examples such as crop disease detection and smart farming, but scalability depends on local data, affordability, connectivity, and user adoption. Education studies highlight strong conceptual and platform-level potential, but the evidence base is constrained by digital access, privacy, and institutional readiness. Governance and infrastructure studies provide cross-cutting insights rather than sector-specific performance evidence, showing that successful AI deployment depends on regulation, accountability, data systems, connectivity, and human capacity. Table 3 summarises the cross-sector deployment readiness patterns identified from the synthesis. The purpose of this table is not to rank sectors absolutely, but to clarify the main feasibility conditions emerging across the reviewed literature.

Table 3. Cross-sector analytical synthesis of AI deployment readiness.

Sector	Evidence Maturity	Deployment Readiness	Data Intensity	Infrastructure Dependence	Governance Sensitivity	Main SDG Relevance
Healthcare	Moderate to high for controlled diagnostic and imaging studies	Medium	High	High	Very high, due to privacy, safety, bias, and accountability concerns	SDG 3
Agriculture	Moderate, with practical examples in disease detection and precision farming	Medium	Medium to high	Medium to high	Medium, especially for data ownership, affordability, and inclusion	SDG 2
Education	Emerging to moderate, with emphasis on adaptive learning and analytics	Low to medium	High	High	High, due to student data, equity, and digital divide concerns	SDG 4
Environment and climate resilience	Moderate to high for remote sensing and environmental monitoring	Medium	Very high	High	Medium, especially for public-sector use and environmental decision-making	SDGs 13 and 15
Governance and infrastructure	Conceptual and policy-oriented evidence is strong, but implementation evidence varies	Cross-cutting	Medium	High	Very high, as governance affects all sectors	SDGs 9, 16, and 17

The cross-sector synthesis indicates that the central issue is not whether AI has potential relevance to sustainable development, but whether AI systems can be deployed,

maintained, governed, and adapted under low-resource conditions. The implications of these findings are discussed in Section 5, Section 6, and Section 7 from the perspectives of sustainable development objectives, sectoral AI applications, and cross-cutting deployment challenges, respectively. These discussions then inform the conceptual framework developed in Section 8.

5. Sustainable Development in Resource-Constrained Contexts

This section focuses on establishing the theoretical and conceptual foundation of sustainable development as it relates to AI. It explains how sustainability is understood through the interconnected economic, social, and environmental dimensions, and critically examines how AI influences each of these areas. Rather than treating AI purely as a technological tool, the section positions it as a transformative system that affects productivity, equity, governance, and ecological balance simultaneously. It highlights key issues such as inclusive economic growth, digital access and fairness, ethical governance, and environmental trade-offs, including the resource demands of AI itself.

5.1. Artificial Intelligence in Resource-Constrained Environments

AI systems are typically developed and benchmarked within high-resource computational ecosystems characterised by stable electricity supply, high-performance hardware, persistent broadband connectivity, and access to large, annotated datasets [6,12]. These infrastructural assumptions shape model architecture, training protocols, and deployment pipelines. While such conditions are attainable in advanced research environments, they may not be consistently present in resource-constrained contexts.

The distinction between algorithmic capability and deployment feasibility is therefore analytically significant. A model demonstrating high predictive accuracy under laboratory conditions may encounter operational instability when deployed in environments characterised by intermittent power supply, bandwidth volatility, or limited hardware availability. This distinction has implications for sustainable development contexts where infrastructural reliability varies across regions [7].

In this study, low-resource AI refers to AI development and deployment conditions in which one or more resources required for reliable implementation are limited, unstable, fragmented, or unevenly distributed. The term is used in a socio-technical sense rather than only a computational sense. It includes constraints relating to computing capacity, data availability, digital infrastructure, institutional governance, human expertise, and equitable access. This distinction is important because AI systems that perform well in controlled or high-resource environments may face operational limitations when transferred into settings characterised by intermittent electricity, limited broadband connectivity, sparse local datasets, weak regulatory capacity, or shortages of technical skills.

Low-resource deployment therefore differs from general AI adoption. General AI adoption asks whether an organisation, sector, or public system can use AI. Low-resource deployment asks whether AI systems can be operated, maintained, governed, adapted, and scaled under constrained conditions. This distinction is central to the present review because sustainable development outcomes depend not only on technical model performance, but also on operational feasibility, institutional readiness, and local capacity.

Research has responded to computational intensity concerns through the development of resource-efficient AI methodologies. Model compression techniques, including pruning and quantisation, reduce model size or computational cost while attempting to preserve acceptable performance. Hardware-aware optimisation enables neural networks to operate on energy-constrained devices [12]. Federated learning decentralises aspects of model training across distributed data sources, reducing the need to centralise all data. Edge

inference enables AI models to run locally on devices such as smartphones, sensors, or local servers, thereby reducing dependence on continuous cloud connectivity. These approaches do not remove low-resource constraints, but they may reduce dependence on high-bandwidth connectivity, centralised computing, and continuous cloud access [24].

However, these innovations are rarely analysed through a sustainable development lens. Most resource-efficient AI research is motivated by performance optimisation or mobile device deployment rather than infrastructural compatibility in low-income regions. Bridging this conceptual gap requires systematic examination of how computational assumptions interact with contextual deployment realities. Table 4 is a summary of key contrasts between conventional high-resource AI paradigms and low-resource deployment conditions.

Table 4. Dimensions of low-resource AI deployment.

Dimension	High-Resource AI Assumption	Low-Resource Deployment Condition	Operational Implication
Computational resources	Access to high-performance hardware, cloud services, and scalable processing capacity.	Limited local computing capacity, restricted access to advanced hardware, or high cloud-service costs.	Need for lightweight models, model compression, and hardware-aware optimisation.
Data resources	Large, labelled, standardised, and representative datasets are available.	Datasets may be sparse, fragmented, incomplete, locally unrepresentative, or difficult to access.	Need for local data collection, careful validation, transfer learning, or decentralised approaches such as federated learning.
Infrastructure resources	Stable electricity, persistent broadband connectivity, and reliable digital devices are assumed.	Electricity supply, connectivity, bandwidth, and device access may be unstable or unevenly distributed.	Need for offline-capable systems, intermittent synchronisation, edge inference, and resilient deployment architectures.
Institutional resources	Strong regulatory oversight, procurement capacity, and data governance are available.	Regulatory capacity, enforcement, procurement safeguards, and data governance may be limited or uneven.	Need for accountability mechanisms, transparent governance, and context-sensitive regulatory safeguards.
Human-capacity resources	Skilled AI developers, maintainers, users, and decision-makers are available.	AI expertise, maintenance capacity, and user literacy may be limited.	Need for training, participatory design, local technical support, and long-term capacity building.
Equity and access	Users have relatively consistent access to digital tools and services.	Access differs across regions, income groups, languages, institutions, and rural or urban settings.	Need for inclusive design, affordability, multilingual access, and attention to exclusion risks.

This distinction between computational intensity and infrastructural readiness forms the analytical basis for examining AI integration in African sustainable development contexts. In particular, variability in electricity reliability, broadband penetration, and hardware accessibility across African regions introduces deployment conditions that differ materially from those assumed in high-resource AI development environments. Consequently, assessing AI feasibility in African contexts requires explicit consideration of how computational design interacts with infrastructural heterogeneity rather than reliance on benchmark performance metrics alone.

Figure 2 illustrates the interactions between AI-enabled systems and the SDGs within resource-constrained African contexts. The diagram positions AI capabilities, including predictive analytics, natural language processing, and computer vision, as key enablers of development outcomes. However, their impact is not direct; it is mediated by critical factors such as governance structures, data ecosystems, adaptation strategies, and partnerships. At the same time, structural challenges, including infrastructure limitations, data gaps, resource constraints, and limited governance capacity, can inhibit the effective deployment of AI systems. These interacting forces shape whether AI contributes positively or negatively to SDG progress. The framework highlights that achieving SDG-aligned outcomes depends on balancing enabling conditions with contextual constraints through strong mediating mechanisms [25,26]. Thus, Figure 2 emphasises that AI's contribution to sustainable development is contingent upon governance quality, institutional capacity, and the alignment of technological deployment with local socioeconomic realities.

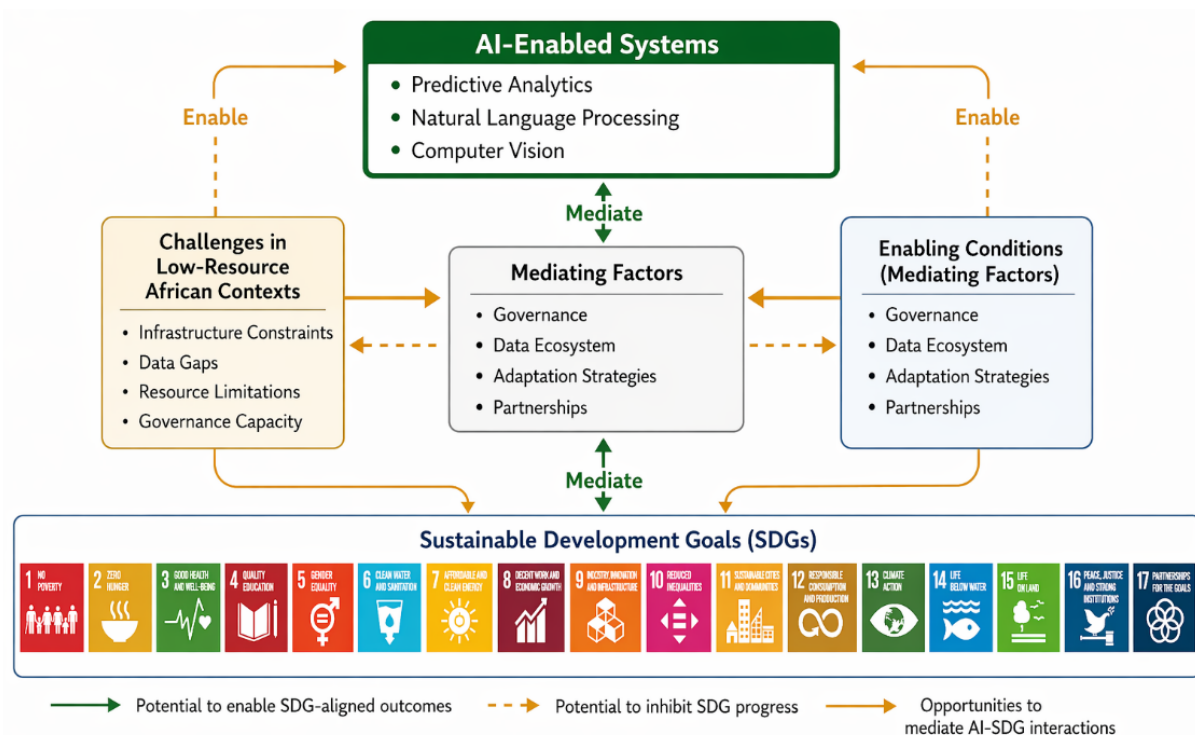


Figure 2. Interaction between AI and SDGs in African resource-constrained contexts.

5.2. Sustainable Development: Conceptual Foundations

Sustainable development constitutes a normative and analytical framework that integrates economic advancement, social equity, and environmental stewardship within an intergenerational perspective. The foundational articulation in the Brundtland Report defines sustainable development as development that meets present needs without compromising the ability of future generations to meet their own needs, thereby establishing intergenerational equity and ecological constraint as central principles [27]. Subsequent research has expanded this foundation through systemic models emphasising the interdependence of economic, social, and environmental systems, often conceptualised through the “triple bottom line” framework [27]. More recent developments further highlight planetary boundaries and systemic resilience, underscoring that sustainability requires alignment between human activity and biophysical limits [11,28].

Within this framework, sustainability is best understood as a multidimensional and interconnected system rather than a set of isolated objectives. The economic dimension extends beyond aggregate output growth to encompass structural transformation, produc-

tive capacity, and long-term resilience. Technological innovation has historically driven economic restructuring, and AI, as a general-purpose technology, is associated with automation, predictive optimisation, and enhanced decision-making efficiency [5]. At a systems level, AI-enabled analytics can improve supply chain coordination, infrastructure management, and financial forecasting. However, the distribution of these gains is often uneven, with adoption concentrated among actors possessing advanced infrastructure and skilled labour. Economic sustainability therefore depends not only on technological diffusion but also on institutional coordination, human-capital development, and inclusive innovation systems capable of translating technological advances into broadly shared benefits [12].

The social dimension evaluates whether development processes enhance human well-being in equitable and inclusive terms. It encompasses issues of access, institutional trust, health, education, and participatory governance. In digitally mediated environments, social sustainability is closely linked to digital inclusion and equitable access to technological resources. While AI has the potential to improve service delivery and decision-making across sectors, disparities in access to infrastructure and technical capabilities may reinforce existing inequalities. Governance frameworks are therefore central to shaping socially sustainable outcomes. Principles such as transparency, accountability, and fairness are essential for ensuring responsible AI deployment, particularly in contexts where algorithmic systems influence public services or socioeconomic decision-making processes [3,4]. Moreover, sustainable development emphasises capability expansion, requiring that AI systems augment human decision-making and support knowledge access rather than contribute to displacement or exclusion.

The environmental dimension introduces an additional layer of complexity by placing sustainability within ecological limits and planetary boundaries [28]. AI interacts with environmental sustainability in a dual capacity. On the one hand, it serves as an enabling technology, supporting applications such as climate modelling, energy optimisation, and ecosystem monitoring [1,6]. On the other hand, AI systems themselves entail material and energy costs, particularly in the training and deployment of large-scale machine learning models, which can result in significant carbon emissions and resource consumption [29]. This dual role introduces trade-offs that require lifecycle-based evaluation rather than narrow functional assessment. While advances in model efficiency and hardware optimisation can reduce computational demands, environmental sustainability ultimately depends on aligning technological innovation with broader energy systems and resource constraints [12].

Across these dimensions, resilience emerges as a unifying principle. Economic systems must adapt to technological disruptions, social systems must maintain inclusivity and trust, and environmental systems must remain within ecological limits. AI has the potential to enhance resilience through improved forecasting, adaptive decision-making, and system optimisation. However, it may also introduce new vulnerabilities, particularly where systems become dependent on centralised infrastructure or opaque decision processes. These considerations demonstrate that the sustainability of AI cannot be assessed within a single dimension. Instead, it requires an integrated perspective that simultaneously evaluates economic inclusiveness, social equity, and environmental compatibility [28,29].

Importantly, sustainable development operates as an evaluative framework rather than a descriptive label. It provides criteria for assessing whether technological systems contribute to systemic resilience, distributive equity, and ecological sustainability. Within this context, AI should not be evaluated solely in terms of predictive performance or efficiency gains. Rather, its deployment must be examined across interconnected economic, social, and environmental dimensions [28,29]. This multidimensional perspective provides the conceptual foundation for analysing the alignment between AI systems and the Sustainable

Development Goals in the subsequent section. Figure 3 illustrates this integrated sustainability framework, highlighting the interactions between AI systems and the economic, social, and environmental dimensions within resource-constrained development contexts.

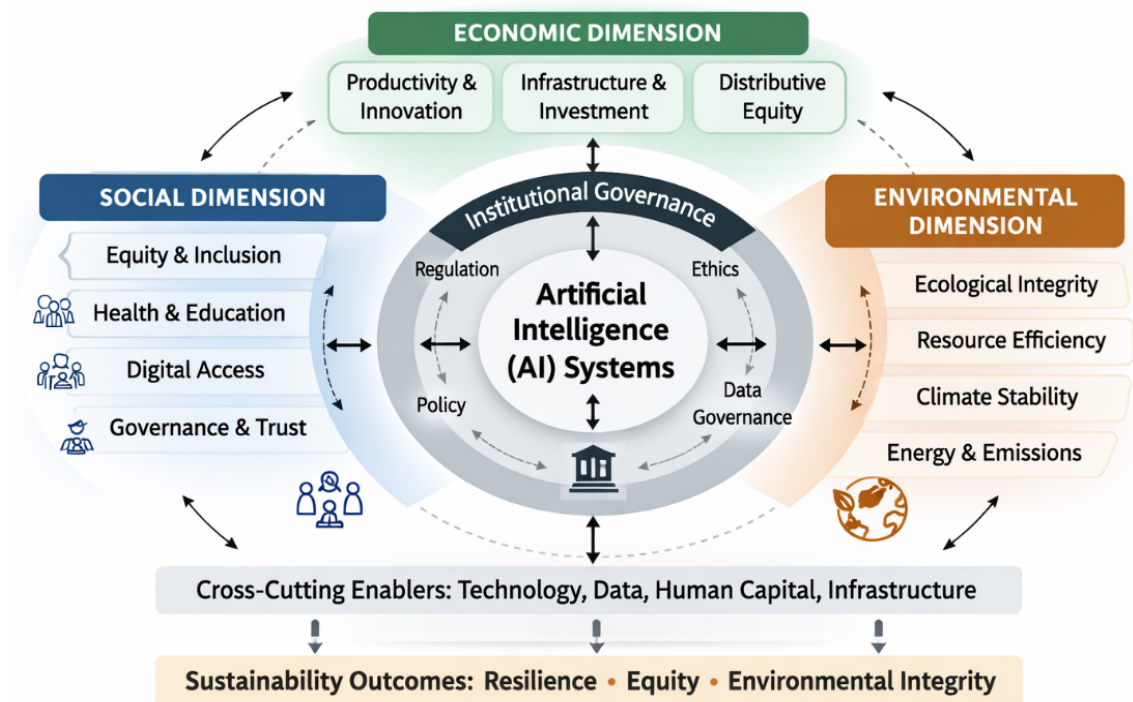


Figure 3. Integrated sustainability dimensions for AI deployment in resource-constrained contexts.

5.3. The SDG Framework and AI Alignment

The SDGs translate the normative principles of sustainable development into operational policy architecture comprising 17 goals and 169 targets. While the preceding subsection established sustainability as an evaluative framework, the SDGs provide measurable domains through which development interventions can be assessed and monitored. Unlike earlier development paradigms focused primarily on economic growth, the SDG framework institutionalises multidimensional progress across health, education, inequality reduction, environmental protection, and institutional governance [23,27].

Artificial intelligence has increasingly been analysed in relation to this operational structure. Systematic mapping exercises demonstrate that AI techniques can influence a substantial proportion of SDG targets. Predictive analytics, natural language processing, and computer vision applications have been associated with improvements in health diagnostics, agricultural forecasting, infrastructure optimisation, and environmental modelling. However, the same analyses caution that AI may inhibit SDG progress in domains where technological adoption exacerbates inequality, displaces labour without compensatory adaptation, or introduces governance vulnerabilities [1].

The SDG framework is inherently interconnected. Progress toward one goal may produce trade-offs in another. For example, industrial innovation (SDG 9) may stimulate economic productivity but generate environmental externalities if energy consumption increases without mitigation. AI systems embedded within such domains must therefore be evaluated through cross-goal interaction rather than single-goal optimisation. The authors of [2] argue that AI–SDG alignment requires systemic analysis that accounts for enabling effects, trade-offs, and contextual mediation.

Governance constitutes a cross-cutting mediator within the SDG architecture. Goal 16, focusing on institutions and justice, reinforces that institutional capacity underpins

sustainable implementation across other domains. In AI deployment contexts, governance mechanisms influence data protection, algorithmic accountability, and regulatory compliance [3,4]. Without institutional safeguards, AI applications may undermine social trust or create unintended exclusionary outcomes, thereby impeding SDG advancement.

Environmental goals within the SDG framework introduce additional complexity. Goals related to climate action (SDG 13), responsible consumption (SDG 12), and life on land and below water (SDGs 14 and 15) require long-term ecological stewardship. AI-enabled climate modelling and resource monitoring may contribute to these objectives [6]. Yet environmental alignment must also consider the energy footprint of AI infrastructure itself. The SDG framework therefore necessitates dual evaluation of AI as both enabler and resource consumer [29].

Importantly, the SDG architecture emphasises universality while permitting contextual adaptation. Goals are globally defined but implemented through national and regional policy environments. As such, AI–SDG alignment cannot be assessed in abstraction from infrastructural, institutional, and socioeconomic conditions. The SDG framework provides the evaluative categories, but deployment feasibility depends on contextual compatibility with those categories. This operational lens reinforces the need for deployment feasibility analysis introduced earlier. AI applications aligned with SDG objectives must be examined not only for potential contribution but also for their compatibility with governance structures, environmental constraints, and distributive equity requirements. The subsequent subsection narrows this evaluation to African development contexts, where SDG implementation interacts with infrastructural heterogeneity and institutional variability [7,8,10].

5.4. Sustainable Development in African Contexts

Sustainable development in African contexts is shaped by structural heterogeneity in infrastructure, institutional capacity, demographic dynamics, and economic composition. While the SDG framework provides a universal set of objectives, implementation conditions vary substantially across African regions. Rapid population growth, accelerating urbanisation, and climate exposure interact with uneven digital infrastructure expansion, producing development trajectories that differ from those assumed in high-income technological environments [23].

Infrastructure remains a central mediating factor. Electricity access has expanded over the past decade; however, grid reliability and supply stability remain inconsistent in several jurisdictions. Broadband penetration exhibits pronounced urban–rural disparities, and high-speed connectivity is concentrated in metropolitan centres and innovation hubs. These infrastructural conditions influence the operational feasibility of digital and AI-enabled systems, particularly those dependent on continuous connectivity and stable power supply [30].

Economic structure further shapes sustainable development pathways. Many African economies are characterised by significant informal sectors, commodity dependence, and varying levels of industrial diversification. Technological adoption trajectories therefore differ from contexts where advanced manufacturing or large-scale automation dominate. While digital innovation ecosystems have expanded in countries such as Kenya, South Africa, Nigeria, and Rwanda, regional disparities persist. Development strategies must therefore account for intra-continental variability rather than assume uniform readiness [8,11].

Institutional and governance capacity constitutes another critical variable. Regulatory frameworks addressing data protection, digital trade, and AI governance are emerging across several African jurisdictions, yet enforcement capacity and regulatory harmonisation remain uneven. Institutional readiness influences not only compliance with ethical stan-

dards but also cross-border collaboration, data sharing, and regional integration initiatives. Sustainable development outcomes are therefore contingent on governance maturity as well as technological capability [7,31].

Human capital and skills distribution also affect development feasibility. Concentration on advanced technical expertise in urban innovation clusters may limit the scalability of digital systems in peripheral regions. Educational infrastructure, digital literacy, and research capacity interact with technological deployment, influencing whether AI systems can be locally maintained, adapted, and sustained over time. Without complementary capacity-building investments, technology adoption may remain pilot-based rather than systemic [8,32].

Environmental vulnerability introduces additional complexity. Several African regions face heightened exposure to climate variability, drought, flooding, and biodiversity loss. Sustainable development strategies must therefore balance economic expansion with ecological resilience. Technological systems, including AI-enabled monitoring tools, may support adaptation planning and risk forecasting [1]. However, infrastructural instability and resource constraints may affect the reliability of such systems under crisis conditions.

Importantly, African contexts cannot be treated as homogeneous analytical units. Variability in electricity reliability, connectivity penetration, regulatory capacity, and human-capital distribution creates differentiated deployment environments. Overgeneralisation risks obscuring these distinctions and may produce policy prescriptions insufficiently sensitive to local realities. A context-aware perspective therefore requires examining sustainable development through structural variables rather than continental abstraction. To operationalise this heterogeneity, this study distinguishes between broad categories of African AI deployment contexts. These categories are not intended to rank countries or provide a fixed classification. Rather, they provide an analytical guide for understanding how deployment feasibility may vary across settings. Table 5 outlines principal structural dimensions and their potential implications for technology-enabled initiatives.

Table 5. Typology of African AI deployment contexts.

Deployment Context	Typical Characteristics	AI Deployment Implication
Urban digital innovation hubs	Relatively stronger broadband access, universities, start-up ecosystems, technical talent, and public or private innovation activity.	More suitable for AI pilots, applied research, digital platforms, and early-stage scaling, although inclusion and governance risks remain.
Rural low-connectivity settings	Limited broadband access, unstable electricity, fewer digital devices, and reduced access to technical support.	Requires mobile-first, offline-capable, low-power, and locally maintainable AI solutions.
Public-sector service-delivery contexts	AI used or proposed in healthcare, education, agriculture, environmental management, or administrative systems.	Requires governance safeguards, procurement capacity, accountability, privacy protection, and staff training.
Institutionally constrained contexts	Limited regulatory enforcement, fragmented data systems, weak administrative capacity, or restricted technical oversight.	Requires cautious deployment, risk assessment, human oversight, and avoidance of high-dependency systems that cannot be locally maintained.
Emerging regulatory environments	Data protection, digital transformation, or AI-related policy frameworks are developing but may remain unevenly implemented.	Requires alignment with evolving regulation, cross-border data governance, and institutional capacity building.

This typology reinforces the study's deployment feasibility perspective. An AI system that is technically feasible in an urban innovation hub may require redesign before it can operate in a rural low-connectivity setting. Similarly, an AI tool that appears promising in a controlled study may be unsuitable for public-sector deployment if governance, accountability, procurement, data protection, and staff capacity are weak. The analytical focus of this study is therefore on matching AI system design to deployment conditions rather than assuming uniform applicability across African contexts [11,15].

5.5. Deployment Constraints as Analytical Variables

The preceding subsections have established three interrelated foundations: the technical characteristics of artificial intelligence (AI) systems under resource constraints (Section 5.1), the normative structure of sustainable development (Section 5.2), and the operational articulation of sustainability through the SDG framework within heterogeneous African contexts (Sections 5.3 and 5.4). Integrating these strands requires identifying deployment constraints not as incidental barriers but as structured analytical variables shaping feasibility.

First, infrastructural stability functions as a systemic variable rather than a background condition. AI architectures vary in their tolerance for interruptions in power supply, connectivity, and hardware performance. Computationally intensive systems trained or deployed under assumptions of continuous resource availability may exhibit fragility when these assumptions are not met [12]. Resource-efficient design approaches, including model compression and edge inference, partially mitigate such dependency. However, feasibility depends on alignment between model architecture and infrastructural reliability rather than technical optimisation alone.

Second, data ecosystem maturity influences model robustness and ethical compliance. Representative datasets are foundational for reliable inference. Where labelled datasets are sparse or fragmented, performance variability and bias risks increase. Federated and distributed learning approaches offer mechanisms for collaborative model development under decentralised data conditions. Yet the viability of such approaches depends on governance coordination and interoperability standards [12,14].

Third, institutional capacity mediates both compliance and sustainability. Governance frameworks addressing transparency, accountability, and data protection shape whether AI systems can be integrated without undermining social trust [3,4]. Institutional maturity determines whether regulatory oversight can keep pace with technological adoption, particularly in cross-sector or cross-border contexts. Deployment feasibility therefore requires not only technical compatibility but also regulatory coherence.

Fourth, human capital and localisation capacity influence long-term sustainability. AI systems require contextual adaptation, maintenance, and continuous evaluation. Concentration of expertise in limited institutional clusters may restrict scalability. Sustainable deployment thus intersects with educational systems, research infrastructure, and professional training pipelines. These variables interact dynamically. Infrastructure instability may increase reliance on external cloud services, raising governance and data sovereignty considerations. Data fragmentation may constrain model transferability, requiring localised training processes that depend on technical capacity. Governance fragmentation may inhibit regional collaboration, limiting dataset expansion and knowledge sharing. Evaluating AI deployment feasibility therefore requires an integrated assessment across structural dimensions rather than isolated performance metrics [16,24].

Conceptually, these deployment variables operate at the intersection of technical architecture and sustainability evaluation. They translate normative sustainability principles into operational feasibility criteria. In the context of SDG-aligned development strategies,

AI initiatives must be assessed against these structured variables to determine whether implementation pathways are resilient, inclusive, and ecologically compatible. The following section applies this analytical lens to specific development sectors, examining how deployment feasibility interacts with SDG priorities under constrained conditions.

6. AI Application Sectors in Resource-Constrained Contexts

Building on the structured review synthesis presented earlier, this section examines sectoral AI applications in healthcare, agriculture, education, and environmental management. The discussion does not treat AI relevance as equivalent to demonstrated sustainable development impact. Instead, each sector is considered through three linked issues: potential contribution, implementation feasibility, and evidence limitations. This structure maintains the paper's focus on low-resource deployment conditions while avoiding repeated discussion of the same cross-cutting constraints across each subsection.

6.1. Healthcare (SDG 3: Good Health and Well-Being)

Healthcare systems across Sub-Saharan Africa operate under significant structural constraints, including shortages of trained medical personnel, uneven distribution of healthcare facilities, limited diagnostic infrastructure, and restricted access in rural areas. These challenges directly relate to Sustainable Development Goal 3 (SDG 3), which aims to ensure healthy lives and promote well-being for all. Within this context, artificial intelligence (AI) has been increasingly explored as a decision-support tool to enhance diagnostic capacity and improve healthcare delivery efficiency [1,7,33].

AI applications in this sector are primarily centred on medical imaging, disease detection, and predictive analytics. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated strong performance in detecting diseases such as tuberculosis and malaria using radiographic and microscopic image data. Studies have shown that AI systems can achieve diagnostic performance comparable to medical experts in controlled environments [34–36]. These systems offer the potential to augment clinical decision-making, especially in environments where specialist expertise is limited. In principle, such applications contribute to improved diagnostic accuracy, reduced workload for healthcare professionals, and faster patient triage [33].

However, the effectiveness of AI in healthcare within African contexts is not determined solely by algorithmic performance. A critical constraint lies in the availability and representativeness of local datasets. Many AI models are trained on data from high-resource environments, which may not reflect the epidemiological characteristics of African populations. As a result, model generalisability and reliability can be compromised when deployed in different clinical contexts. This introduces risks of biased or inaccurate predictions, as highlighted in studies examining algorithmic bias in healthcare AI systems. These limitations emphasise the importance of context-specific data collection and model adaptation [37,38].

Infrastructure limitations further constrain deployment feasibility. AI-enabled diagnostic systems often depend on stable electricity, digital imaging equipment, and computational resources, which may not be consistently available in low-resource settings. In such environments, reliance on cloud-based processing can lead to operational disruptions due to intermittent connectivity. Research on efficient deep learning highlights the importance of resource-aware AI techniques, including model optimisation and edge computing, to support deployment in constrained environments [12,13]. Additionally, integrating AI into healthcare systems requires alignment with existing infrastructure and operational capacity [39].

In addition to technical challenges, institutional and human-capacity factors significantly influence the sustainability of AI integration. Healthcare professionals must be able to interpret AI outputs and integrate them into clinical workflows. Without adequate training and organisational support, AI systems risk remaining misapplied. Furthermore, governance frameworks related to data protection, accountability, and ethical oversight are still evolving in many African countries, which may limit trust and adoption of AI-driven healthcare solutions [3,4].

From a deployment feasibility perspective, healthcare AI requires caution because model performance in controlled datasets does not automatically translate into safe or equitable clinical use. Local validation, representative health data, privacy protection, clinical accountability, and integration with existing health-system workflows are essential. In low-resource African settings, the central issue is therefore not only whether diagnostic or predictive AI can achieve high technical accuracy, but whether it can be governed, maintained, audited, and used safely within constrained health systems [29,40].

6.2. Agriculture (SDG 2: Zero Hunger)

Agricultural systems across Sub-Saharan Africa operate under conditions of climate variability, pest outbreaks, soil degradation, and limited access to timely agronomic information. These challenges directly align with Sustainable Development Goal 2 (SDG 2), which focuses on ending hunger, achieving food security, and promoting sustainable agriculture. Given that a significant proportion of agricultural production in Africa is driven by smallholder farmers, improving productivity and resilience remains a critical development priority [7].

Artificial intelligence (AI) has been increasingly applied in agriculture through crop disease detection, yield prediction, and climate-informed decision-support systems. Deep learning techniques, particularly convolutional neural networks, have demonstrated effectiveness in identifying crop diseases using image-based data. For instance, AI models have been successfully applied to cassava disease detection using smartphone images collected in African farming environments. These applications enable early detection of plant diseases, reducing crop losses and improving agricultural productivity [34,41].

Beyond disease detection, machine learning has been integrated with remote sensing and environmental data to monitor drought conditions and predict agricultural output. Predictive models leveraging satellite imagery and climate data can support early warning systems, enabling farmers and policymakers to respond proactively to environmental risks. Such applications are particularly relevant in regions where agricultural output is highly dependent on rainfall patterns and climate stability [42].

Despite these benefits, the effectiveness of AI in agriculture is constrained by several structural factors. One major limitation is the availability and quality of agricultural data. Many machine learning models require large, labelled datasets for training; however, agricultural data in African contexts are often fragmented, inconsistent, or locally specific. This reduces the transferability of models developed in high-resource settings and necessitates context-specific data collection and model adaptation [24,43].

Infrastructure limitations also play a significant role. Many AI-enabled agricultural solutions rely on mobile devices, internet connectivity, and cloud-based platforms, which may not be consistently accessible in rural areas. In such environments, the effectiveness of AI systems depends on the development of lightweight and offline-capable solutions, including mobile-based applications with embedded machine learning models [12,13]. Without such adaptations, adoption remains limited to regions with better connectivity.

Adoption dynamics further influence the scalability of AI applications in agriculture. While digital tools can enhance decision-making, their effectiveness depends on farmer

awareness, affordability, and trust in technology. Studies have shown that mobile technology can significantly improve information access for farmers; however, the integration of AI-driven advisory systems requires alignment with local practices and socioeconomic conditions. Without user-centred design and participatory implementation, AI solutions may face resistance or underutilisation. From a sustainability perspective, AI has the potential to support precision agriculture, optimising the use of water, fertilisers, and pesticides. This contributes to both productivity gains and environmental protection. However, these benefits must be balanced against the resource requirements of digital infrastructure, particularly in energy-constrained settings [29,44].

From a deployment feasibility perspective, agricultural AI depends strongly on local data quality, affordability, rural connectivity, and farmer adoption. Crop disease detection, yield prediction, and precision agriculture tools may be technically promising, but their usefulness depends on whether they can operate with locally relevant crops, soil, weather, and pest data. In low-resource settings, agricultural AI should therefore be assessed not only by predictive performance, but also by accessibility, cost, offline usability, extension-service integration, and farmer trust.

6.3. Education (SDG 4: Quality Education)

Educational systems across many African countries face persistent challenges related to access, instructional quality, and resource availability. These challenges align with Sustainable Development Goal 4 (SDG 4), which aims to ensure inclusive and equitable quality education and promote lifelong learning opportunities for all. Rapid population growth, combined with shortages of trained educators and limited infrastructure, continues to affect learning outcomes across primary, secondary, and higher education systems [7].

Artificial intelligence (AI) has emerged as a potential tool to enhance educational delivery through adaptive learning systems, intelligent tutoring platforms, and predictive analytics. AI-driven educational technologies enable personalised learning by adjusting instructional content based on individual student performance and engagement patterns. Studies have shown that such systems can improve learner engagement and support differentiated instruction, particularly in large classroom settings. Additionally, predictive analytics models have been applied in higher education to identify students at risk of academic failure or dropout, enabling early intervention strategies [45–47].

Despite these opportunities, the effectiveness of AI in education is significantly influenced by digital access and infrastructure availability. Many AI-enabled learning platforms depend on reliable internet connectivity, access to digital devices, and stable electricity supply. In many African contexts, these resources are unevenly distributed, particularly between urban and rural areas. As a result, the benefits of AI-driven education systems may be disproportionately concentrated among already advantaged populations, reinforcing existing inequalities [48,49].

Data-related challenges further affect the deployment of AI in education. Educational AI systems rely on large volumes of student data to optimise learning pathways and improve predictive accuracy. However, in many developing contexts, educational data systems are fragmented, incomplete, or inconsistently managed. This limits the effectiveness of machine learning models and raises concerns regarding data quality and reliability. Furthermore, the use of student data introduces important ethical and privacy considerations, particularly in environments where data protection frameworks are still evolving [3,4].

Institutional capacity also plays a critical role in the sustainability of AI adoption in education. The integration of AI technologies requires not only technical infrastructure but also teacher training, curriculum alignment, and organisational readiness. Educators must be able to interpret AI-generated insights and integrate them into pedagogical practices.

Without adequate training and support, AI tools may remain underutilised or fail to produce meaningful improvements in learning outcomes [46,47].

From a socioeconomic perspective, affordability and accessibility remain key determinants of adoption. While AI-driven educational platforms can expand access to learning resources, their implementation often requires investments in devices, connectivity, and software systems. In low-resource environments, these costs may limit scalability. Research in educational technology emphasises the importance of inclusive design and context-aware implementation, ensuring that solutions are adapted to local needs and constraints [49].

From a deployment feasibility perspective, AI in education is shaped by digital access, teacher readiness, institutional capacity, and student data protection. Adaptive learning platforms and learning analytics may support personalised education, but they can thus reproduce digital inequalities if learners, schools, or regions have unequal access to devices, connectivity, and trained staff. In low-resource African contexts, educational AI should therefore be evaluated in terms of inclusion, privacy, curriculum relevance, teacher support, and long-term affordability.

6.4. Environment and Climate Resilience (SDGs 13 and 15)

Environmental vulnerability is a defining characteristic of sustainable development challenges across many African regions. Issues such as drought, flooding, deforestation, and loss of biodiversity directly relate to Sustainable Development Goals 13 (Climate Action) and 15 (Life on Land). These challenges are intensified by climate variability and limited environmental monitoring infrastructure, creating a need for data-driven approaches to support environmental management and resilience [1,7].

Artificial intelligence (AI) has been increasingly applied in environmental contexts through remote sensing, predictive modelling, and ecosystem monitoring. Machine learning techniques, particularly deep learning models, have demonstrated strong capabilities in analysing satellite imagery for land-use classification, forest monitoring, and climate pattern detection. Studies have shown that AI-based approaches can significantly improve the accuracy and efficiency of environmental monitoring systems compared to traditional methods [6,50]. These applications enable early detection of environmental changes and support more informed decision-making in climate adaptation strategies.

AI is being used in climate forecasting and disaster prediction, where predictive models analyse meteorological and environmental data to identify patterns associated with droughts, floods, and extreme weather events. Such systems contribute to early warning mechanisms and disaster preparedness, which are critical for reducing vulnerability in climate-sensitive regions. Additionally, AI-driven biodiversity monitoring systems, including image recognition and acoustic sensing, have been deployed to track wildlife populations and detect illegal activities such as poaching [51,52].

Despite these advantages, the deployment of AI in environmental applications faces several constraints. A key limitation is the availability and continuity of environmental data, particularly in regions with limited monitoring infrastructure. Many machine learning models depend on high-quality, long-term datasets; however, in many African contexts, environmental data may be sparse, inconsistent, or geographically uneven. This affects model accuracy and limits the reliability of predictive systems. Infrastructure and computational requirements thus present challenges. Environmental AI applications, especially those involving large-scale geospatial analysis, often require significant computational resources and data processing capabilities. In resource-constrained environments, limited access to high-performance computing and reliable connectivity can restrict the scalability of such systems. As a result, there is increasing emphasis on efficient and distributed AI approaches, which reduces dependency on centralised infrastructure [12,53].

Governance and institutional capacity further influence the effectiveness of AI in environmental management. While AI systems can generate valuable insights, their impact depends on the ability of institutions to interpret, implement, and act upon these insights. Weak regulatory frameworks, limited coordination between agencies, and insufficient enforcement mechanisms can reduce the effectiveness of AI-driven environmental interventions [3,4]. This highlights the importance of integrating technological solutions with governance structures and policy frameworks.

From a sustainability perspective, AI presents both opportunities and trade-offs. On one hand, it supports more efficient resource management, climate monitoring, and conservation efforts. On the other hand, energy consumption associated with large-scale machine learning models raises concerns about environmental impact, particularly in regions where energy systems are not fully sustainable. This dual role of AI as both an enabler and a resource consumer must be carefully balanced [29].

From a deployment feasibility perspective, environmental AI depends on access to reliable geospatial, climate, biodiversity, and land-use data, as well as institutional capacity to act on AI-generated insights. Remote sensing and climate modelling tools may strengthen environmental monitoring, but their contribution to sustainable development depends on whether findings are usable by local agencies, communities, and policymakers. In low-resource settings, environmental AI should therefore be assessed not only as a monitoring tool, but as part of a broader decision-support system requiring data infrastructure, interpretability, and institutional response capacity. Table 6 consolidates the sectoral discussion by linking each SDG-related application area to its potential contribution, enabling conditions, and evidence interpretation. The table is used to compare how AI applications differ across healthcare, agriculture, education, and environmental management, while maintaining the distinction between technical promise, deployment feasibility, and demonstrated development impact.

Table 6. Sectoral AI applications, deployment feasibility and evidence interpretation.

Sector and SDG Relevance	Studies	Common AI Application Areas	Potential Contribution	Key Deployment Conditions	Evidence Interpretation
Healthcare, SDG 3	Gulshan et al. [54], McKinney et al. [55], Ting et al. [56], Rajpurkar et al. [57], Davenport & Kalakota [58]	Medical imaging, disease screening, clinical decision support, patient monitoring	May support earlier diagnosis, triage, and service efficiency	Representative clinical data, local validation, privacy safeguards, clinical accountability, workflow integration	Strong technical evidence exists for some diagnostic tasks, but sustained low-resource deployment and long-term health-system impact require further validation.
Agriculture, SDG 2	El-Sayed et al. [59], Altalak et al. [43], Benos et al. [60], Kamilaris & Prenafeta-Boldú [61], Wolfert et al. [62]	Crop disease detection, yield prediction, precision farming, pest monitoring	May support productivity, crop protection, and more efficient resource use	Local crop and soil data, farmer access, affordability, rural connectivity, extension-service support	Practical and experimental examples exist, but scalability depends on cost, usability, local data quality, and adoption by farmers.
Education, SDG 4	Krstić et al. [63], Baker & Inventado [64], Holmes et al. [45], Holmes & Luckin [46], Menashy & Dryden-Peterson [65]	Adaptive learning, intelligent tutoring, learning analytics, administrative decision support	May support personalised learning and educational planning	Device access, connectivity, teacher readiness, data protection, curriculum alignment, affordability	Evidence is promising but uneven; implementation risks include digital exclusion, privacy concerns, and limited institutional readiness.
Environmental management, SDGs 13 and 15	Jean et al. [66], Ma et al. [67], Nishant et al. [68], Rolnick et al. [6], Willi et al. [51]	Remote sensing, climate modelling, biodiversity monitoring, disaster-risk analysis	May improve monitoring, forecasting, conservation, and environmental decision support	Geospatial data availability, computational resources, interpretability, agency capacity, policy response mechanisms	Technical evidence is relatively strong for monitoring tasks, but development impact depends on institutional capacity to act on AI-generated insights.

7. Cross-Cutting AI Challenges in Resource-Constrained Contexts

While sectoral applications demonstrate the potential relevance of AI to sustainable development, low-resource deployment also introduces cross-cutting risks that cannot be addressed at the sector level alone. These risks include algorithmic bias, limited data sovereignty, digital exclusion, weak regulatory enforcement, technological dependency, inadequate local maintenance capacity, and unclear accountability. This section therefore examines the enabling and constraining conditions that affect whether AI systems can be deployed responsibly and sustainably in African low-resource contexts.

Table 7 summarises the main cross-cutting risks identified in the review and the corresponding mitigation considerations. The table is not intended to present new empirical findings. Rather, it synthesises recurring implementation concerns relevant to responsible AI deployment under constrained conditions.

Table 7. Cross-cutting risks and mitigation considerations for AI deployment in low-resource African contexts.

Risk Area	Why it Matters	Mitigation Consideration
Algorithmic bias	Models trained on unrepresentative datasets may produce inaccurate or discriminatory outputs for underrepresented groups.	Local validation, bias audits, representative datasets, and human oversight.
Data sovereignty	Data collected in African contexts may be stored, processed, or governed outside local institutional control.	Local data governance frameworks, clear data-sharing agreements, and compliance with applicable national or regional data protection rules.
Digital inequality	Unequal access to devices, connectivity, electricity, and digital literacy may exclude rural, low-income, or marginalised users.	Inclusive design, affordability planning, offline functionality, multilingual interfaces, and participatory implementation.
Governance limitations	Weak or fragmented regulation may limit accountability, transparency, procurement oversight, and redress mechanisms.	Transparent procurement, regulatory capacity building, accountability procedures, and independent oversight.
Technological dependency	Over-reliance on external vendors, proprietary systems, or foreign cloud infrastructure may limit local control and long-term sustainability.	Open standards where appropriate, local capacity building, knowledge transfer, and maintainable system architectures.
Operational sustainability	AI systems may fail after pilot stages if funding, maintenance, training, and institutional ownership are insufficient.	Lifecycle planning, local technical support, monitoring, evaluation, and adaptive management.
Public trust and legitimacy	AI systems may face resistance if communities do not understand, trust, or participate in their design and deployment.	Co-design, community engagement, transparency, explainability, and user feedback mechanisms.

Responsible AI deployment in low-resource settings should include co-design and inclusion alongside transparency, accountability, and fairness. Co-design involves engaging intended users, local institutions, domain experts, and affected communities in the design, testing, and evaluation of AI systems. This is particularly important where language diversity, rural access barriers, uneven digital literacy, and institutional capacity constraints may affect adoption. Inclusion also requires attention to affordability, accessibility, gendered access to technology, disability access, and the needs of communities that may be underrepresented in training datasets or excluded from digital services.

Data sovereignty and technological dependency are also important concerns in African AI deployment. Where data are collected locally but processed through external platforms or proprietary systems, local institutions may have limited control over data access, storage, reuse, and accountability. Similarly, dependence on externally maintained AI systems may create long-term sustainability risks if local staff cannot audit, adapt, repair, or govern the systems after pilot funding ends. For this reason, low-resource AI deployment should include data governance arrangements, knowledge transfer, maintainable architecture, and clear institutional ownership.

A further challenge is the gap between pilot-stage AI experimentation and sustained deployment. Many AI systems demonstrate technical promise in controlled studies, prototypes, or limited pilots, but fewer are shown to operate reliably over time in low-resource settings. Scaling requires more than model performance. It requires stable funding, maintenance capacity, user training, institutional ownership, governance safeguards, and monitoring mechanisms. This distinction is important because short-term technical success should not be interpreted as evidence of long-term sustainable development impact.

These cross-cutting challenges reinforce the need for an adaptive deployment framework. In low-resource African contexts, responsible AI implementation requires alignment between technical design, local data ecosystems, infrastructure reliability, governance safeguards, human capacity, and inclusion. The framework developed in the next section responds to this need by organising these conditions into a structure for assessing deployment feasibility and sustainability.

8. Conceptual Framework for Low-Resource AI Deployment in African Sustainable Development Contexts

The framework proposed in this study was developed from the structured literature review and thematic synthesis presented in the preceding sections. It is not intended as an empirically validated implementation model. Rather, it is a synthesis-based conceptual framework for assessing the feasibility of AI deployment under low-resource African conditions.

The framework builds on existing AI-for-sustainable-development research, including the strategic pillars proposed by [7], which emphasise infrastructure, human capital, innovation, policy and governance, and partnerships. The present framework extends this foundation by reorganising these enabling conditions around the specific problem of low-resource deployment feasibility. Its contribution lies in connecting resource-efficient AI design, local data ecosystems, infrastructure reliability, governance capacity, human-capital development, equity, and adaptive monitoring to sectoral AI applications and sustainable development outcomes [7,28].

The framework is organised around four interacting layers. The first layer consists of structural enablers for low-resource deployment. These include technological foundations and deployment conditions, such as AI methods, resource-efficient model design, data ecosystems, digital infrastructure, governance safeguards, human capacity, equity, and cross-sector coordination [1,2,14,28]. The second layer consists of sectoral AI applications in healthcare, agriculture, education, and environmental management [24,32,34,45,46,50,69,70]. The third layer represents potential sustainable development outcomes, including improved service delivery, productivity, inclusion, resilience, and environmental monitoring [6,7]. The fourth layer is an adaptive feedback mechanism through which monitoring, evaluation, user feedback, and learning inform redesign, governance adjustment, and implementation improvement [7,28].

This structure reflects the central argument of the review: AI relevance to sustainable development does not automatically imply deployment feasibility or development impact.

In low-resource contexts, AI systems require continuous alignment between technical design, institutional capacity, infrastructure reliability, local skills, governance safeguards, and social inclusion [3,14,44,71]. The framework therefore treats sustainable AI deployment as an adaptive socio-technical process rather than a one-time technological intervention [28].

Figure 4 presents the proposed adaptive framework. The lower layer groups technological foundations and deployment conditions as structural enablers. These enablers support sectoral AI applications, which are positioned closer to sustainable development outcomes to show that outcomes are mediated through practical deployment in specific domains. The feedback pathway captures learning from structural enablers, sectoral implementation, and observed outcomes into the adaptive feedback mechanism. The response pathway then returns this learning to the structural enablers and sectoral application layers, supporting redesign, governance adjustment, implementation improvement, and adaptive management.

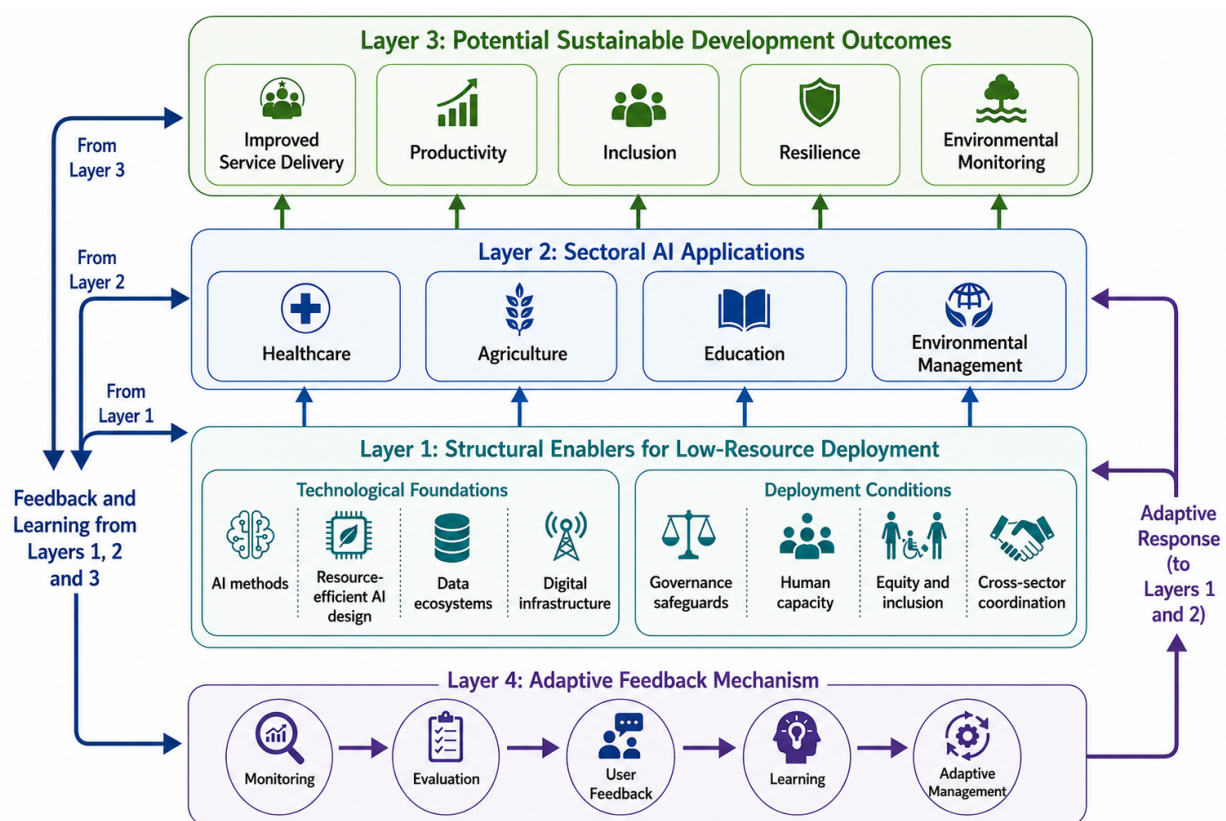


Figure 4. Adaptive framework for low-resource AI deployments in African sustainable development contexts.

The framework should be interpreted as a research and policy framing, decision-support, and analytical tool rather than a universal implementation blueprint. It helps identify whether the conditions required for AI deployment are present, weak, or absent in a given context. For example, a healthcare AI system may require locally representative clinical datasets, regulatory safeguards, workflow integration, and trained staff before it can be safely deployed [24,34,37,42]. Similarly, an agricultural AI application may require local crop data, offline usability, farmer trust, and extension-service support before it can contribute meaningfully to productivity or resilience [32,62,69,72].

A limitation of the framework is that it has not yet been empirically validated across specific African countries, sectors, or institutions. Future research should therefore test and

refine the framework through case studies, stakeholder evaluation, and implementation research in diverse low-resource settings.

9. Future Research Directions

The findings of this review suggest that research and policy on AI for sustainable development in Africa should move beyond general discussions of AI potential and focus more directly on deployment feasibility, local validation, governance, and long-term sustainability. Building on earlier work on AI and sustainable development in Africa [7], this study identifies five priority areas.

First, the proposed framework should be empirically tested and refined across diverse African deployment contexts. Case studies are needed in urban innovation hubs, rural low-connectivity settings, public-sector service-delivery environments, institutionally constrained contexts, and emerging regulatory environments. Such studies would help assess whether the framework captures the conditions that shape AI feasibility across different levels of infrastructure reliability, governance capacity, data availability, and human expertise.

Second, greater attention is needed to low-resource AI infrastructure. Studies should examine how model compression, edge inference, federated learning, offline-capable systems, intermittent synchronisation, and hardware-aware optimisation can support AI deployment where electricity, broadband, cloud access, and computing resources are limited. This research should not focus only on technical efficiency, but also on maintainability, affordability, local repair capacity, and institutional ownership.

Third, research should distinguish more clearly between AI technical performance, pilot-stage implementation, sustained deployment, and measurable sustainable development outcomes. Many studies demonstrate that AI can support prediction, classification, monitoring, or decision support, but fewer examine whether these systems remain functional, trusted, governed, and useful over time. Longitudinal studies are therefore needed to examine whether AI systems continue to deliver value after pilot funding, external technical support, or short-term project cycles end.

Fourth, governance, data sovereignty, and equity require deeper investigation. This includes local data governance, algorithmic accountability, procurement safeguards, community participation, multilingual access, gendered digital inclusion, disability access, and mechanisms for redress where AI systems cause harm or exclusion. Such work is especially important in public-sector applications where AI systems may affect healthcare access, educational opportunity, agricultural support, environmental decision-making, or administrative services.

Fifth, practical monitoring and evaluation tools are needed for adaptive AI deployment. These tools should help policymakers, researchers, and implementing organisations assess whether AI systems are technically reliable, locally usable, ethically governed, institutionally maintainable, and aligned with sustainable development priorities. Monitoring should also include user feedback and learning mechanisms so that AI systems can be adjusted when deployment conditions change.

Thus, these priorities point towards a research agenda focused on responsible implementation rather than technological possibility alone. Future work should therefore evaluate not only whether AI can contribute to sustainable development, but also whether it can be deployed, maintained, governed, and adapted in ways that are locally appropriate, inclusive, and sustainable.

10. Conclusions

This study examined how artificial intelligence can support sustainable development in low-resource African contexts, with particular attention to the conditions that shape implementation and sustainability. Building on existing AI-for-sustainable-development research, including [7], the paper contributes a more specific deployment feasibility lens. Rather than treating AI potential as equivalent to development impact, the review examined how computational constraints, fragmented data ecosystems, infrastructure limitations, governance capacity, human expertise, and equity considerations influence whether AI systems can be implemented, maintained, and adapted.

The structured literature review showed that AI applications are increasingly discussed across healthcare, agriculture, education, and environmental management. These applications may support diagnosis, crop monitoring, personalised learning, environmental monitoring, and decision support. However, the synthesis also indicates that technical promise does not automatically translate into sustained implementation or measurable SDG outcomes. Across sectors, responsible deployment depends on local validation, reliable infrastructure, representative data, accountable governance, user trust, institutional ownership, and long-term maintenance capacity.

The conceptual framework proposed in this paper organises these conditions into an adaptive structure linking structural enablers, sectoral AI applications, potential sustainable development outcomes, and feedback mechanisms. The framework is intended as a research and policy framing, decision-support, and analytical tool, not as an empirically validated implementation model. Its value lies in helping researchers, policymakers, and practitioners assess whether the conditions required for responsible AI deployment are present, weak, or absent in a specific context.

The findings also reinforce the need to avoid treating Africa as a homogeneous deployment environment. Differences in connectivity, electricity reliability, regulatory readiness, institutional capacity, technical skills, and social inclusion shape whether AI systems can be used responsibly and sustainably. Future research should therefore test and refine the framework through empirical case studies, longitudinal evaluation, and stakeholder engagement across diverse African settings.

Overall, AI may contribute to sustainable development in Africa, but only where technical design is aligned with local data systems, infrastructure realities, governance safeguards, human capacity, and inclusive implementation. The central challenge is therefore not only to develop AI systems, but to ensure that they can be responsibly deployed, maintained, governed, and adapted under low-resource conditions.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18157835/s1>. PRISMA 2020 Checklist.

Author Contributions: Conceptualisation, I.D.E. and E.E.; methodology, I.D.E. and E.E.; validation, I.D.E. and E.E.; investigation, I.D.E. and E.E.; writing—original draft preparation, I.D.E.; writing—review and editing, I.D.E. and E.E.; visualisation, I.D.E. and E.E.; supervision, E.E. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflicts of interest.

List of Abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
CNN	Convolutional Neural Network
DL	Deep Learning
GDP	Gross Domestic Product
GIS	Geographic Information System
ICT	Information and Communication Technology
IoT	Internet of Things
ML	Machine Learning
NLP	Natural Language Processing
SDGs	Sustainable Development Goals
UNESCO	United Nations Educational, Scientific and Cultural Organization
WHO	World Health Organization

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