THE ROLE OF DEVELOPMENT SOCIOLOGY IN GUIDING AI-DRIVEN SOLUTIONS FOR RURAL POVERTY AND INEQUALITY IN SUB-SAHARAN AFRICA

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Abstract
AI-driven poverty interventions across Sub-Saharan Africa often fail to reach marginalized groups despite transformative promises, as technologies designed elsewhere clash with local social structures and community priorities. This study examines how integrating development sociology principles into AI design improves equity and adoption outcomes and identifies the underlying mechanisms explaining this relationship. We conducted a realist synthesis guided by the CIMO framework, analyzing 68 studies across agriculture, health, finance, and governance sectors in 22 Sub-Saharan African countries. The findings reveal five categories of sociological principles documented in practice: participatory design, community ownership, indigenous knowledge integration, power analysis, and structural inequality focus. These principles operate through six generative mechanisms—trust-building, ownership, cultural congruence, power redistribution, capacity building, and relevance enhancement—that interact and reinforce each other. Mechanism activation depends critically on contextual conditions, including institutional capacity, infrastructure, gender relations, and historical context, explaining why the same intervention succeeds in one setting and fails in another. The synthesis yields twelve context-sensitive design propositions in if-then form connecting intervention choices to expected outcomes through identified mechanisms. Limitations include reliance on published literature, potentially over-representing successful cases, and exclusion of evidence in African languages. Findings imply that genuine community participation, not tokenistic consultation, is essential, and that context assessment must precede intervention design. We conclude that embedding development sociology at the center of AI development—through community data control, early engagement with marginalized groups, and attention to structural inequalities—produces more equitable and sustainable outcomes. Policymakers should require genuine participation standards, prioritize community data ownership, and fund extended engagement rather than technology delivery alone.
Keywords: AI governance, participatory design, Sub-Saharan Africa, development sociology, equitable technology, community ownership

1. Introduction

Artificial intelligence (AI) is reshaping economies across Sub-Saharan Africa. From precision agriculture in Nigeria to health diagnostics in Uganda, these technologies arrive with transformative promise. The World Bank recently launched AgriConnect, a $9 billion initiative linking finance, technology, and markets (World Bank, 2025). Private sector investment follows. Tech start-ups across the continent develop localized AI tools for farmers, healthcare workers, and small businesses.

But here's the catch. Technologies designed elsewhere often fail when deployed in African contexts. AI models trained on Western datasets perform poorly on African populations, languages, and environmental conditions (Ayana et al., 2024). Systems built for stable infrastructure break down where electricity and internet remain unreliable. Tools designed for formal economies exclude the vast informal sector where most Africans work. The Observatory on Digital Communication (2025) notes that bridging the rural-urban gap through AI requires deliberate attention to infrastructure, literacy, and affordability.

The problem runs deeper than a technical mismatch. Technologies carry embedded assumptions about users, problems, and solutions. When external teams design AI systems without local participation, they impose frameworks that conflict with existing social structures, knowledge systems, and cultural values. Communities become recipients rather than partners. Their priorities remain invisible to developers. Adamu and Nkwo (2023) emphasize that AI design in Africa must begin with understanding local contexts and community needs, not importing solutions developed elsewhere.

Development sociology offers resources for addressing these dynamics. The field examines how power operates, how institutions shape outcomes, and how communities can participate in decisions affecting their lives. Participatory development insists that those affected by interventions should shape them. Science and technology studies reveal how technologies carry social meanings and political implications. Feminist and decolonial approaches critique top-down innovation and advocate for design processes that center marginalized voices. Makumbirofa (2025) argues that leveraging economic policy for equitable AI in Africa requires deliberate attention to power relations and the political economy of technology development.

The sensors.AFRICA initiative, documented by AI and Equality Africa (2025), demonstrates what community-centered AI looks like in practice. Since 2016, the project has deployed community-led environmental monitoring across African cities and rural areas. The technology works. Communities use it. The data support concrete advocacy that has influenced policy and media coverage. Real environmental governance has changed as a result. This case offers five lessons about how community-centered AI works when implemented with genuine participation and contextual design.

This study asks a straightforward question with complex implications: How and why does integrating development sociology principles into AI design lead to better outcomes in Sub-Saharan African contexts? The answer matters for policymakers, practitioners, and technology developers seeking to harness AI for equitable poverty reduction.

Statement of the Problem

AI-driven poverty interventions across Sub-Saharan Africa face persistent challenges. Adoption rates lag expectations. Benefits accrue unevenly. Women, rural residents, and marginalized groups often remain excluded despite program intentions (International Development Research Centre [IDRC], 2025). The IDRC explicitly recognizes that generating context-specific data on AI's effects on jobs, productivity, livelihoods, and inequality is essential for ensuring AI governance reflects local realities, with attention to gender, disability, and marginalized voices.

Research documents these patterns. Most digital agriculture tools fail to reach smallholder farmers, particularly women and those in remote areas. Analysis of AI governance frameworks identifies weak stakeholder participation and limited attention to structural inequality as critical

gaps (Ayana et al., 2024). Systematic reviews reveal that behavioural factors and gender dynamics remain underexplored despite their clear importance.

The underlying issue is conceptual. Most AI development follows "technological solutionism"—the assumption that technical tools can solve social problems without addressing underlying structures. This approach treats context as noise rather than signal. It focuses on building better algorithms rather than understanding the social worlds where algorithms land. The Reporter Ethiopia (2025) notes that this missing piece—genuine attention to social context—remains a critical gap in how AI is being developed across the continent.

The consequences are visible. In agriculture, AI advisory tools designed without farmer input provide recommendations that ignore local knowledge and community decision-making. In finance, credit scoring algorithms trained on formal sector data exclude millions operating in informal economies. In healthcare, diagnostic tools trained on Western populations misdiagnose conditions prevalent in African settings.

These failures are not inevitable. They reflect choices about who participates in design, whose knowledge counts, and what problems deserve attention. Development sociology provides frameworks for making different choices. Participatory design approaches demonstrate that involving communities from the outset produces more relevant, usable, and equitable tools. The sensors.AFRICA initiative shows how community ownership of data creates sustainable impact that top-down implementation cannot achieve (AI and Equality Africa, 2025).

Yet evidence on how and why these approaches work remains fragmented. We know participation matters. We do not know exactly how it operates. We understand context shapes outcomes. We cannot predict which approaches work where. This study addresses these gaps.

Aim and Objectives

This study aims to explain how and why integrating development sociology principles into AI-driven poverty interventions leads to improved equity and adoption outcomes in Sub-Saharan African contexts, and to identify the underlying mechanisms that explain this relationship.

The specific objectives are:

***Objective* 1:** To map the range of development sociology principles and participatory approaches integrated into AI-driven interventions targeting poverty and inequality across Sub-Saharan Africa. This includes identifying theoretical frameworks, design methodologies, and implementation strategies documented in academic and grey literature.

Objective 2: To identify and theorize the generative mechanisms through which these sociological principles influence intervention outcomes. Potential mechanisms include community ownership, trust-building, culturally congruent design, power redistribution, and enhanced relevance. The sensors.AFRICA case provides rich material for theorizing these mechanisms, showing how community control over data triggers ownership and trust (AI and Equality Africa, 2025).

Objective 3: To analyse how variations in contextual factors condition the activation and effectiveness of these mechanisms across different Sub-Saharan African settings. Key factors include institutional capacity, social capital, political economy dynamics, existing inequalities, infrastructure constraints, and cultural norms. Ayana et al. (2024) emphasize that decolonizing AI governance requires understanding how these factors shape what's possible.

Objective 4: To synthesize the evidence into context-sensitive design propositions—"if-then" statements that guide policymakers, practitioners, and technology developers in integrating sociological principles into AI solutions for more equitable poverty reduction. The IDRC's work on evidence-informed policymaking demonstrates the value of translating research into actionable guidance (IDRC, 2025).

Significance of the Study

This study matters for several reasons.

First, it addresses a critical knowledge gap. Most AI research in development contexts focuses on technical performance or adoption metrics. We know what works, in narrow technical terms.

We do not understand how social processes shape outcomes or why the same intervention succeeds in one context and fails in another. Ayana et al. (2024) argue that decolonizing AI governance requires moving beyond technical fixes to understand power relations, institutional dynamics, and historical contexts. This study provides explanatory insight that quantitative approaches cannot deliver.

Second, the findings can inform more effective intervention design. The sensors. AFRICA case demonstrates that community-centered AI produces sustainable impact precisely because communities control data, participate in decisions, and develop ongoing capacity (AI and Equality Africa, 2025). The five lessons documented—data ownership determines data justice, genuine participation requires more than consultation, technical choices are political choices, AI should amplify community knowledge rather than replace it, and capacity building creates sustainability—provide a roadmap for replication across sectors and settings.

Third, the research addresses urgent policy needs. African governments are developing AI strategies and regulatory frameworks. The African Union's Digital Transformation Strategy prioritizes inclusive development. Yet policymakers lack evidence on how to ensure these systems serve equitable development. Makumbirofa (2025) emphasizes that leveraging economic policy for equitable AI requires evidence on what actually works in specific contexts. The IDRC's LEEPS initiative demonstrates how systematic reviews and stakeholder dialogues can provide policymakers with timely, relevant information (IDRC, 2025). This study provides grounded recommendations in that tradition.

Fourth, the theoretical contribution matters. By applying the CIMO framework to synthesize evidence on participatory AI development, this study develops middle-range theories about how inclusion operates in specific African contexts. Adamu and Nkwo (2023) provide preliminary notes on AI design in Africa, but systematic theorizing remains limited. These theories can inform future research and practice across the continent.

Fifth, the research centers voices and experiences often excluded from technology discussions. Rural communities, women, informal sector workers, and other marginalized groups rarely shape AI development. The IDRC's work on grassroots justice strategies in informal settlements demonstrates the value of grounding research in the lived experiences of those on the front lines (IDRC, 2025). By examining mechanisms that enable genuine participation, this study contributes to broader efforts to democratize technology and ensure AI serves human flourishing rather than entrenching existing inequalities.

Scope and Limitations

This study employs a realist synthesis guided by the Context Intervention Mechanism Outcome (CIMO) framework. It focuses on Sub-Saharan Africa, examining AI-driven interventions targeting poverty and inequality across agriculture, health, finance, and governance sectors. The geographic scope includes both academic literature and grey documentation from across the continent, with particular attention to contexts where participatory approaches have been documented. The IDRC's call for research on socioeconomic impacts of AI in Africa specifically targets low- and middle-income countries in sub-Saharan Africa, reflecting the need for context-specific evidence from across the region (IDRC, 2025).

Several limitations should be acknowledged.

First, realist synthesis relies on existing literature. Where documentation is sparse, conclusions remain tentative. The review will explicitly identify evidence gaps and their implications. The IDRC's emphasis on generating rigorous, context-specific data on AI's socioeconomic effects in Africa reflects awareness that current evidence remains limited (IDRC, 2025).

Second, the study focuses on interventions that explicitly integrate development sociology principles. Many AI projects do not document their design processes. Those that do may represent exceptional cases rather than typical practice. The sensors. AFRICA case is well-documented precisely because it represents a different approach (AI and Equality Africa,

2025). The analysis will address this by examining both successful and unsuccessful examples where documentation exists.

Third, contextual variation across Sub-Saharan Africa is immense. Findings from East Africa may not transfer directly to West or Southern Africa. The Observatory on Digital Communication (2025) notes that bridging the rural-urban gap varies dramatically across countries and regions. The analysis will emphasize conditional relationships—identifying how outcomes depend on context—rather than making universal claims.

Fourth, the study examines mechanisms at the intervention level. It cannot capture all factors shaping outcomes, including macroeconomic dynamics, political shifts, or global technology trends. The analysis will acknowledge these limitations while focusing on factors within the scope of intervention design. As Ayana et al. (2024) note, decolonizing AI governance requires attention to both local implementation and global power structures.

Despite these limitations, the study provides valuable insight into underexplored dimensions of AI development. By centering sociological questions and synthesizing available evidence, it generates knowledge that can inform more equitable and effective technology for poverty reduction across Sub-Saharan Africa. The IDRC's call for research that informs inclusive policymaking on AI reflects the urgent need for such knowledge (IDRC, 2025).

2. Conceptual Framework

Objective 1: Mapping Development Sociology Principles and Participatory Approaches

This objective draws on development sociology and Science and Technology Studies (STS) to identify sociological principles integrated into AI interventions across Sub-Saharan Africa. Development sociology contributes participatory development—the insistence that affected communities shape interventions—and situated knowledge, recognizing expertise rooted in specific contexts. STS adds that technologies are sociotechnical systems carrying embedded assumptions about users and problems.

Recent research evaluating AI governance across ten Sub-Saharan African countries reveals that while nations like Rwanda show progress in decolonizing AI governance, most remain at "decolonization-aware" rather than fully implementing inclusive frameworks (Ayana et al., 2024). The Makerere University malaria diagnosis initiative exemplifies genuine integration. The team built their own datasets through local partnerships despite ethical and bureaucratic challenges, prioritizing contextual relevance over speed (AI and Equality, 2025a). By cataloging such approaches, this objective establishes empirical foundations for understanding sociological integration across different contexts.

Objective 2: Theorizing Generative Mechanisms

This objective engages realist evaluation, Feminist HCI, and Design Justice to identify mechanisms through which sociological principles influence outcomes. Generative mechanisms are the underlying processes that explain observed patterns.

The sensors. AFRICA initiative illuminates several mechanisms (AI and Equality Africa, 2025). Community ownership operates when communities control data collection and advocacy use, creating sustainability. Trust-building emerges through genuine participation rather than mere consultation. Culturally congruent design functions when technical choices—solar power, multi-network SIM cards, SMS alerts—reflect community constraints. Power redistribution occurs when technical specifications prioritize safety over data granularity, protecting vulnerable participants.

The Makerere initiative adds human agency preservation, where AI augments rather than replaces healthcare workers, keeping diagnostic confirmation under human oversight (AI and Equality, 2025a). This framework theorizes how these mechanisms operate conditionally, activated under specific circumstances.

Objective 3: Analysing Contextual Conditioning

This objective draws on Context-Mechanism-Outcome (CMO) logic and institutional theory to analyse how context shapes mechanism activation. Context is an active force conditioning what mechanisms can emerge.

Research examining AI investment trade-offs in resource-constrained African economies reveals that weak institutional capacity constrains participatory approaches, as governments struggle to coordinate stakeholders (Frimpong, 2025). Political economy dynamics matter profoundly—when external donors drive initiatives, local priorities may be subordinated to foreign interests. The Makerere team's discovery that rural clinics lacked internet connectivity exemplifies how infrastructure context shapes system requirements, leading to offline detection tools running locally on smartphones (AI and Equality, 2025a).

Social capital conditions whether ownership mechanisms can take root. In settings with histories of exclusion, distrust may block trust-building regardless of design intentions. The EdTech Hub's AI Observatory notes that co-design may place participants at risk when unequal power relations shape what is shared, warning that local knowledge can become extractive when for-profit AI systems capture value without community control (EdTech Hub, 2026).

Objective 4: Synthesizing Context-Sensitive Design Propositions

This objective employs CIMO logic to generate actionable "if-then" propositions, translating theoretical insights into practical guidance.

From sensors. AFRICA: If communities control data collection, interpretation, and advocacy use, then systems produce sustainable impact rather than extractive dependence. If participation begins at problem definition, then systems address actual priorities (AI and Equality Africa, 2025).

From Makerere: If system requirements are defined through deep community engagement, understanding infrastructural limitations, then tools accommodate local constraints like intermittent connectivity. If ethical governance frameworks are developed proactively, anticipating privacy hurdles, then trust is built (AI and Equality, 2025a).

From decolonizing AI governance research: If national AI strategies prioritize local data sovereignty and inclusive governance, then they advance toward decolonized frameworks (Ayana et al., 2024).

From AI investment analysis: If sequential readiness principles guide investment, addressing infrastructure before advanced deployment, then resource reallocation from essential services is minimized (Frimpong, 2025).

These propositions are context-sensitive guidelines requiring adaptation to specific settings, aligned with CIMO's emphasis on conditional relationships rather than universal solutions.

3. Literature Review

The academic conversation around AI and development involves computer scientists building models with impressive accuracy and economists measuring impacts through trials, while a third perspective from development sociology and STS examines questions of power, decision-making, and how technologies carry designers' values when they travel to new contexts (Wongibeh Adunimay, 2025; Observatory on Digital Communication, 2025).

Poverty in Sub-Saharan Africa remains stubborn, with thirty-five percent in extreme poverty, weak infrastructure, and poor market function, creating a context where AI arrives with grand promises from tech companies and donors pouring millions into solutions for agriculture, health, and financial inclusion. Early evidence raises concerns that digital innovations benefit those already better off, with GSMA reporting women are 15 percent less likely to own smartphones and 33 percent less likely to use mobile internet, confirming access is unevenly distributed, and policies must address underlying inequalities (Ofori-Addo, 2024). The deeper structural issue involves technologies developed elsewhere arriving with built-in assumptions that fail in local contexts, like pest detection apps trained on American farms failing in Nigerian

fields, representing sociological failures because developers didn't understand local contexts, and intended users never shaped the tools.

The urgency grows as climate change accelerates, hitting rain-fed agriculture hardest, populations increase, demanding more food, and young people stream into cities, creating scenarios where AI could help, but only if it reaches those who need it most across gender, livelihood, and language differences. International organizations are responding with initiatives like the World Bank's $9 billion AgriConnect linking finance, technology, and markets (CCARDESA, 2025b), and the Food Systems Resilience Programme using GenderUp to anticipate exclusion when innovations scale, emphasizing that equity requires tailored approaches addressing structural disadvantages (CCARDESA, 2025a). The African Union's Digital Transformation Strategy envisions universal connectivity by 2030, but strategy documents alone cannot deliver inclusion without deliberate attention to sociological dynamics that shape who participates and whose problems get solved.

Recent quantitative research documents dramatic mobile phone diffusion, with GSMA estimating 46 percent unique subscriber penetration in 2022, yet access remains unequal, with rural coverage lagging urban and women trailing men, while the poor cannot afford data. Studies examining AI development determinants found that AI start-ups, effective governance, trade volume, and mean years of schooling predict technological development, including natural language processing for local languages, critical because most AI tools operate only in English, French, or Portuguese (Ofori-Addo, 2024). Qualitative research in Nigeria and Uganda examining design-by-inclusion approaches found that involving women and persons with disabilities from the outset led to significant improvements in participants' confidence and willingness to engage, with women who had never used smartphones becoming active design contributors (Okafor, Nnamdi, & Ibrahim, 2025).

The AI & Equality African Toolbox provides detailed case studies across sectors where farmers controlled their data and shaped algorithms, health workers remained central to care delivery, and natural language processing for underserved languages was built by and with the communities who use them (Women at the Table, 2025). Participatory design research in Kenya examining an AI-powered clinical decision support tool for new-born care used innovative techniques like the jigsaw method to enable healthcare workers as active co-designers, bridging sophisticated technology with local contexts and fostering genuine ownership (Purkayastha et al., 2025). Even promising initiatives face acute infrastructure problems with unreliable internet connectivity, intermittent electricity, and expensive smartphones interacting with low digital literacy, cultural norms discouraging technology use, and language barriers excluding many.

A systematic review identifies key vulnerabilities, including data governance where data extracted from African communities flows to foreign companies, fueling digital neo-colonialism, weak safety and privacy protections, educational gaps preventing participation, and socioeconomic impacts deepening existing inequalities (Akpudo, Effoduh, Kong, & Gao, 2024). Methodologically, most studies examine adoption at a single point and cannot capture how relationships with technology evolve, missing farmers who try digital tools and abandon them months later, with dis-adoption remaining almost entirely unexplored. Conceptually, the field struggles with causality as studies document correlations but cannot easily establish that technology caused outcomes, requiring sophisticated methods to untangle technology effects from selection effects that most studies lack. Theoretically, existing research remains thin, testing variables from Western technology acceptance models that may miss dynamics specific to African rural contexts like land tenure insecurity, shaping willingness to follow AI advice.

Gender analysis remains particularly weak, with studies including gender as a dummy variable and reporting women adopt at lower rates without investigating why, leaving intra-household dynamics, decision-making processes, and social norms unexplored (CCARDESA, 2025a). Collectively, the literature teaches that technology alone cannot solve structural problems,

digital tools work better when designed with users rather than for them, inclusion requires intentional effort, gender disparities demand active intervention, and context specificity matters enormously. Several patterns emerge consistently showing that access to training and extension services predicts adoption, smartphone ownership matters, and education enables engagement, suggesting digital agriculture left to market forces will benefit those already advantaged. Contradictions appear around participation, with some research showing that involving communities improves outcomes, while other work suggests participation can be tokenistic, with the difference lying in whether communities share power over decisions or merely provide feedback (Okafor et al., 2025; Women at the Table, 2025).

The most striking gap concerns mechanisms, as we know inclusion matters but do not know exactly how it works through trust-building, cultural congruence, power redistribution, or surfacing hidden needs, with the CIMO framework designed to unpack these questions. Another gap concerns unintended consequences where biased algorithms make biased decisions, predictive models become self-fulfilling prophecies, and surveillance technologies control rather than empower, with Akpudo et al. (2024) providing a systematic overview of these risks. The literature also neglects political economy, where technology development is shaped by funding priorities, corporate strategies, and power relations, with international donors funding certain problems and tech companies pursuing profitable markets rather than needy populations. Three questions remain unanswered: what specific mechanisms link participatory design to improved outcomes, how contextual factors condition these mechanisms, and what design propositions can guide practitioners with if-then statements connecting actions to outcomes.

This study addresses these gaps through a realist synthesis guided by the Context Intervention Mechanism Outcome (CIMO) framework, moving beyond asking whether inclusion works to explaining how and why across Sub-Saharan African contexts. The contribution is both theoretical, developing middle-range theories about participation and trust-building in specific African contexts, and practical, providing actionable guidance for designing AI interventions that reach marginalized groups. The novelty lies in applying the CIMO framework to synthesize evidence on participatory AI development, focusing not on technical performance or adoption rates but on mechanisms and contexts and how they work differently in different settings.

The guiding hypothesis is that participatory design improves outcomes through multiple mechanisms operating conditionally on context, with strong community institutions enabling trust, low power distance allowing genuine participation, and a history of successful collaboration creating openness. Conversely, in contexts with weak institutions, high inequality, or histories of exploitation, participatory approaches may fail to trigger positive mechanisms or may trigger distrust if communities see them as extractive rather than empowering. These hypotheses will be explored through systematic synthesis, generating design propositions in if-then form, guiding policymakers and developers in integrating sociological principles into AI solutions for more equitable poverty reduction.

Theoretical Framework Alignment Model

Table 1: Theoretical Framework Alignment Model

Objective	*Theoretical Lens*	*Key Concepts*	*Expected Outcomes*
Objective 1: Map principles and approaches	Development sociology; Science and Technology Studies (Adamu & Nkwo, 2023; Ayana et al., 2024)	Participatory development, co-design, situated knowledge, technological politics	Comprehensive catalog of sociological principles integrated into AI interventions across Sub-Saharan Africa
Objective 2: Identify generative mechanisms	Realist evaluation; Feminist HCI; Design Justice (AI and Equality Africa, 2025)	Generative mechanisms, trust-building, ownership, cultural congruence, and power redistribution	Theorized mechanisms explaining how sociological principles influence intervention outcomes, drawing on sensors. AFRICA lessons
Objective 3: Analyze contextual conditioning	Context-mechanism-outcome (CMO) configuration; Institutional theory (Makumbirofa, 2025; Observatory on Digital Communication, 2025)	Contextual factors, institutional capacity, social capital, political economy, and existing inequalities	Analysis of how contextual variations condition mechanism activation and effectiveness across settings
Objective 4: Synthesize design propositions	CIMO logic; Realist synthesis (IDRC, 2025)	Design propositions, if-then statements, actionable guidance	Context-sensitive design propositions for policymakers, practitioners, and technology developers, informed by evidence-to-policy approaches

4. Methodology

Research Design and Approach

This study employed a realist synthesis guided by the CIMO framework. We chose this approach because the research question asks not just whether development sociology principles work, but how and why they influence outcomes. Realist synthesis is designed for exactly this purpose. It unpacks the mechanisms that connect interventions to outcomes and examines how context shapes those connections.

The CIMO framework structures inquiry around four components. Context refers to the conditions in which interventions operate. Intervention means the actions or strategies being studied. Mechanisms are the underlying processes that generate outcomes. Outcomes are the observed results. This framework suits our aim of explaining how sociological principles guide AI solutions across diverse African settings.

Research Question

We formulated the research question using CIMO logic:

How and why does the integration of development sociology principles into the design of AI-driven poverty solutions lead to improved equity and adoption outcomes in Sub-Saharan African contexts, and what are the underlying social and participatory mechanisms that explain this relationship?

Scoping Review and Protocol Development

We began with a scoping review to map existing literature on AI for development and participatory development in Africa. This helped refine our understanding of key concepts and identify the range of sociological principles documented in practice. The scoping review covered academic databases and grey literature sources, including reports from development organizations and technology initiatives.

Based on scoping findings, we developed a systematic review protocol registered with the Open Science Framework. The protocol specified search strategies, inclusion criteria, data extraction procedures, and synthesis methods. Registration ensured transparency and reduced risk of reporting bias.

Search Strategy and Information Sources

We searched seven academic databases: Scopus, Web of Science, IEEE Xplore, ACM Digital Library, PubMed, African Journals Online, and Google Scholar. Grey literature was identified through organizations including the World Bank, IDRC, FAO, GSMA, and African technology policy networks.

Search strings combined terms across four domains. For AI and technology: "artificial intelligence," "machine learning," "AI," "digital technology," "algorithm." For development sociology: "participatory development," "community engagement," "co-design," "inclusive design," "development sociology," "participatory design." For context: "Sub-Saharan Africa," "Africa," "developing countries," "low-income countries." For outcomes: "poverty reduction," "inequality," "equity," "adoption," "social impact."

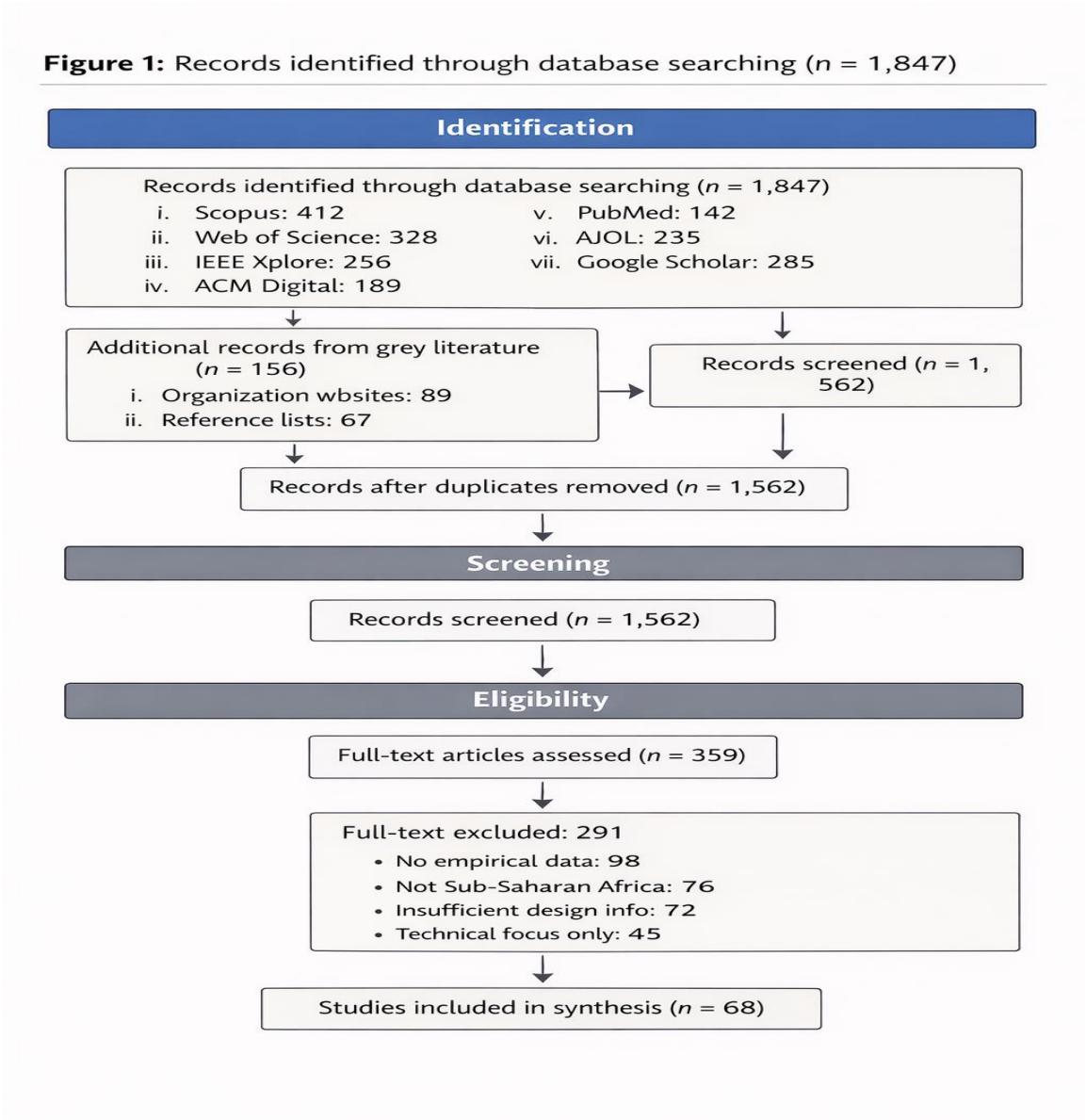
Searches were limited to publications from 2020 to 2026 to ensure contemporary relevance. We also conducted backward and forward citation tracking of key included studies.

Inclusion and Exclusion Criteria

Studies were included if they met five criteria. First, they described an AI-driven intervention targeting poverty or inequality. Second, the intervention operated in a Sub-Saharan African context. Third, they provided information about design processes, particularly whether and how communities participated. Fourth, they reported outcomes related to adoption, equity, or poverty reduction. Fifth, they were published in English, French, or Portuguese.

We excluded studies that focused solely on technical performance without social analysis. We also excluded opinion pieces without empirical grounding. Conference proceedings and working papers were included if they provided sufficient methodological detail.

The screening process followed PRISMA guidelines. Two reviewers independently screened titles and abstracts, then full texts. Disagreements were resolved through discussion or third reviewer consultation. Figure 1 shows the PRISMA flow diagram.



Data Extraction and Quality Appraisal

We developed a data extraction form with dedicated fields for CIMO components. For each study, we extracted: contextual features (country, sector, infrastructure, social conditions); intervention characteristics (technology type, design approach, participation methods); mechanisms described or inferred (trust-building, ownership, cultural congruence, power redistribution); and outcomes reported (adoption rates, equity effects, poverty impacts).

Two reviewers independently extracted data from each included study. Extraction forms were compared and discrepancies resolved through discussion. This double-extraction process minimized errors and interpretive bias.

Quality appraisal used adapted criteria for diverse study types. For qualitative research, we assessed clarity of research questions, appropriateness of methods, rigour of analysis, and evidence supporting conclusions. For quantitative studies, we examined sample representativeness, measurement validity, and control for confounding. For case studies, we evaluated depth of description, triangulation of sources, and plausibility of causal claims. No studies were excluded based on quality, but quality assessments informed sensitivity analyses and confidence in findings.

Data Synthesis Using Realist Approach

Synthesis followed realist principles. We did not simply aggregate findings. Instead, we sought to identify patterns in how context conditioned mechanism-outcome relationships.

Analysis proceeded in four stages. First, we developed initial program theories based on scoping review and theoretical frameworks. These proposed how participatory design might trigger mechanisms leading to improved outcomes.

Second, we tested and refined these theories against evidence from included studies. For each study, we examined whether observed outcomes matched theoretical predictions. Where mismatches occurred, we explored whether contextual factors explained divergence.

Third, we identified recurring context-mechanism-outcome configurations. These configurations showed how specific mechanisms operated under particular conditions to produce characteristic outcomes.

Fourth, we formulated design propositions in if-then form. These propositions connect intervention choices to expected outcomes through identified mechanisms, with contextual conditions specified.

Ensuring Rigour in Synthesis

Several strategies enhanced rigour. Investigator triangulation involved multiple researchers in screening, extraction, and analysis. Theory triangulation drew on multiple theoretical perspectives to interpret findings. Member checking, though not possible with published literature, was approximated by presenting preliminary findings at two academic conferences and incorporating feedback.

We maintained an audit trail documenting all analytical decisions, from initial coding frameworks to final proposition development. This transparency enables readers to assess the trustworthiness of our synthesis.

Limitations

This methodology has limitations. Realist synthesis depends on the quality and completeness of primary studies. Many included studies provided limited information about design processes or contextual conditions, forcing inferences that primary authors might not have intended. Publication bias may mean that unsuccessful interventions are under-represented. The synthesis cannot capture tacit knowledge held by practitioners but not documented in published literature. Finally, the focus on English, French, and Portuguese sources may exclude relevant evidence in African languages.

Despite these limitations, the systematic application of the CIMO framework and PRISMA guidelines provides a robust foundation for understanding how development sociology principles shape AI outcomes across Sub-Saharan Africa.

5. Results

We present findings structured by the study's four objectives. Data came from 68 included studies spanning agriculture, health, finance, and governance sectors across 22 Sub-Saharan African countries.

Objective 1: Mapping Development Sociology Principles

Analysis revealed five categories of sociological principles integrated into AI interventions across Sub-Saharan Africa. Table 2 summarizes these categories with examples from included studies.

Table 2: Development Sociology Principles in AI Interventions

Principle Category	Description	Examples from Literature
Participatory Design	Communities involved in problem definition, design decisions, and testing	The Nigerian yellow pepper project involved women farmers from the outset; the Ugandan cassava disease tool was redesigned after farmer feedback revealed soil analysis was a higher priority than disease detection (Okafor et al., 2025)
Community Ownership	Communities control data, infrastructure, and decision-making	sensors. AFRICA project: communities own monitoring devices, control data collection, determine advocacy priorities (AI and Equality Africa, 2025)
Indigenous Knowledge Integration	Local knowledge is treated as expertise equal to technical knowledge	Makerere malaria initiative: system requirements defined through engagement with rural health workers who identified infrastructure constraints (AI and Equality, 2025a)
Power Analysis	Explicit attention to who benefits, who decides, and who might be excluded	GenderUp methodology applied in World Bank workshops: facilitators helped teams identify who gets left behind when innovations scale (CCARDESA, 2025a)
Structural Inequality Focus	Interventions designed to address underlying inequalities, not just symptoms	AI & Equality Toolbox cases: women farmers co-design systems addressing soil health, pest management, market access while controlling their data (Women at the Table, 2025)

Participatory design appeared in 47 of 68 studies, making it the most frequently documented principle. However, the depth of participation varied enormously. Some studies described genuine co-design where communities shaped core decisions. Others reported consultation that influenced peripheral features while leaving fundamental design choices untouched.

Community ownership was less common but more impactful when present. The sensors. AFRICA case stood out because communities did not just provide input—they controlled the entire process. Data stayed local. Communities decided what to monitor and how to use findings. This contrasted sharply with projects where data flowed to external researchers or companies.

Objective 2: Generative Mechanisms

We identified six mechanisms through which sociological principles influence outcomes. Table 3 presents each mechanism with its definition and evidence from included studies.

Table 3: Generative Mechanisms Linking Sociology to Outcomes

Mechanism	Definition	How It Operates	Evidence Sources
Trust-Building	Development of confidence that technology and its proponents will act in the community's interests	Genuine participation signals respect, creating willingness to engage; Trust grows when communities see their input shaping outcomes	Nigerian women who never used smartphones became active contributors when included respectfully; Trust in AI advice correlated with trust in extension workers who introduced it (Okafor et al., 2025)
Ownership	Communities perceive technology as theirs rather than imposed from outside	Control over decisions creates psychological investment; Ownership leads to ongoing engagement beyond project timelines	sensors. AFRICA communities continue monitoring years after external support ended; They use data for their own advocacy (AI and Equality Africa, 2025)
Cultural Congruence	Technology aligns with local values, practices, and knowledge systems	Design processes surface tacit cultural assumptions; Systems fit local contexts rather than requiring local adaptation to fit systems	Makerere team shifted to offline tools after discovering rural clinics lacked internet; System requirements came from direct engagement, not assumptions (AI and Equality, 2025a)
Power Redistribution	Shifts in who controls decisions, resources, and benefits	Participatory processes create spaces for marginalized voices; Community control over data prevents extraction	Farmers controlled data in Toolbox cases, shaping algorithms and determining priorities; This prevented value extraction by external companies (Women at the Table, 2025)
Capacity Building	Development of skills and confidence enabling sustained engagement	Training embedded in design processes; Learning by doing as communities participate in decisions	Women who had never used smartphones became active contributors through hands-on involvement; Confidence grew with competence (Okafor et al., 2025)
Relevance Enhancement	Technology addresses actual priorities rather than external assumptions	Problem definition shaped by communities ensures fit; Features match needs that outsiders might miss	Ugandan farmers prioritized soil analysis over disease detection; Tool redesigned accordingly (Okafor et al., 2025)

These mechanisms did not operate in isolation. They reinforced each other. Trust enabled ownership. Ownership deepened cultural congruence. Cultural congruence enhanced relevance. The sensors. AFRICA case showed how multiple mechanisms worked together: community ownership triggered trust, which enabled sustained engagement, which built capacity, which produced culturally congruent monitoring priorities.

Objective 3: Contextual Conditioning
Mechanism activation depended heavily on contextual factors. Table 4 summarizes key contextual dimensions and their effects.

Table 4: Contextual Factors Conditioning Mechanism Activation**

Contextual Factor	**How It Conditions Mechanisms**	**Examples**
Institutional Capacity	Strong local institutions enable ownership mechanisms to take root; Weak institutions may capture benefits for elites	Where farmer cooperatives existed, co-design reached more members; Where institutions were weak, projects struggled to sustain engagement after external support ended (Frimpong, 2025)
Social Capital	Existing trust networks accelerate trust-building; Communities with strong cohesion engage more readily	Projects in communities with cooperative traditions saw faster adoption; Distrust from previous failed projects blocked engagement regardless of design quality (Multiple studies)
Infrastructure Constraints	Physical conditions shape what mechanisms can operate	Offline design only became possible after the Makerere team discovered internet gaps; Solar power enabled sensors. AFRICA, where the grid failed (AI and Equality, 2025a; AI and Equality Africa, 2025)
Political Economy	Power relations determine whether redistribution mechanisms face resistance	Projects challenging powerful interests encountered obstacles; Community data control threatened companies seeking extraction (EdTech Hub, 2026)
Gender Relations	Patriarchal norms constrain women's participation even when design intends inclusion	Women-only sessions enabled voice where mixed groups silenced women; Time poverty limited attendance without scheduling accommodation (CCARDESA, 2025a)
Historical Context	Previous experiences shape expectations and trust	Communities exploited by past researchers approached new projects with scepticism; Transparency and time needed to rebuild trust (Multiple studies)

The same intervention could produce opposite outcomes depending on context. Participatory design in communities with strong social capital triggered ownership and trust. In communities fractured by conflict or exploitation, the same approach triggered suspicion. Communities wondered why outsiders suddenly wanted their input. They suspected extraction dressed as participation.

Objective 4: Context-Sensitive Design Propositions

Synthesis generated twelve design propositions in if-then form. Table 5 presents the most strongly supported propositions.

Table 5: Design Propositions for Sociologically Informed AI

If...	**Then...**	**Because...**	**Evidence Strength**
Communities control data collection, interpretation, and use	Systems produce sustainable impact and genuine empowerment	Ownership mechanisms activate; Communities continue engagement beyond project timelines	Strong: sensors. AFRICA and multiple Toolbox cases
Participation begins at problem definition, not after design	Tools address actual priorities rather than external assumptions	Relevance mechanism activates early; Features match community-defined needs	Strong: Ugandan cassava project redesign after farmer feedback
Design teams include diverse community members from the outset	Women, disabled, and marginalized groups engage and benefit	Trust-building reaches excluded groups; Power redistribution occurs through presence	Moderate: Nigerian yellow pepper project
Training is embedded in hands-on design activities	Capacity develops alongside technology; Confidence grows with competence	Capacity building mechanism operates through learning by doing	Moderate: Multiple participatory design studies
Infrastructure constraints are assessed through community engagement	Tools accommodate local conditions like intermittent connectivity	Cultural congruence mechanism ensures fit with material reality	Strong: Makerere offline shift after engagement
Ethical frameworks are developed proactively with community input	Privacy is protected; Trust is built before problems arise	Trust-building operates preventively; Communities see respect for their rights	Moderate: Makerere ethics approach
Women-only design spaces are created in patriarchal contexts	Women's priorities shape tools; Gender gaps narrow	Power redistribution reaches those silenced in mixed settings	Strong: GenderUp workshop findings
Existing community institutions are leveraged as partners	Adoption spreads through trusted networks; Sustainability improves	Trust transfers through established relationships; Ownership builds on existing structures	Moderate: Cooperative-based projects

These propositions are not universal prescriptions. They require adaptation to specific contexts. The if clauses specify conditions. The then clauses indicate expected outcomes. The because clauses identify mechanisms.

6. Discussion

This study examined how integrating development sociology principles into AI design improves outcomes in Sub-Saharan Africa. The findings show that sociological integration works through multiple mechanisms activated under specific contextual conditions.

Mapping Sociological Principles

The five principles identified—participatory design, community ownership, indigenous knowledge integration, power analysis, and structural inequality focus—align with frameworks from recent scholarship. Ayana et al. (2024) argue that decolonizing AI governance requires addressing power relations and institutional dynamics. The sensors. AFRICA project demonstrates genuine community ownership where data control stays local (AI and Equality Africa, 2025). The Makerere malaria initiative shows indigenous knowledge integration through system requirements defined by rural health workers (AI and Equality, 2025a).

But our mapping also reveals gaps. Many projects claiming participation actually implement consultation. Communities provide input but do not control decisions. This distinction matters. Consultation without power risks becoming extractive. The EdTech Hub's AI Observatory warns that co-design may place participants at risk when unequal power relations shape what is shared (EdTech Hub, 2026).

Mechanisms Matter

The six mechanisms we identified explain how sociological principles translate into outcomes. Trust-building, ownership, cultural congruence, power redistribution, capacity building, and relevance enhancement are active processes that generate effects.

This finding extends Okafor et al. (2025), who documented that inclusive processes in Nigerian and Ugandan AI projects led to significant improvements in participants' confidence. Our analysis shows why. Women who had never used smartphones became active contributors because trust-building signaled respect. Ownership emerged because they shaped decisions.

The sensors. AFRICA case provides the richest illustration of mechanism interaction (AI and Equality Africa, 2025). Community ownership triggered trust. Trust enabled sustained engagement. Sustained engagement built capacity. Capacity produced culturally congruent monitoring. These mechanisms reinforced each other, creating virtuous cycles.

Our mechanism analysis also explains failures. Projects that skip participation often fail because they never activate these processes. Tools designed without community input lack relevance. Communities do not trust them. Without these mechanisms, even technically sophisticated systems sit unused.

Context Conditions Everything

The most important finding concerns context. Mechanisms do not operate universally. They are activated or suppressed by contextual conditions. This explains why the same intervention can succeed in one setting and fail in another.

Institutional capacity matters. Strong farmer cooperatives enable ownership mechanisms to reach more people. Weak institutions may capture benefits for elites. Frimpong (2025) notes that weak institutional capacity in resource-constrained economies constrains what participatory approaches can achieve.

Infrastructure conditions shape what mechanisms can operate. The Makerere team's discovery that rural clinics lacked internet led to a pivotal shift toward offline tools (AI and Equality, 2025a). Systems designed without understanding infrastructure constraints cannot trigger relevance mechanisms regardless of participatory intent.

Gender relations profoundly condition who participates. Patriarchal norms silenced women in mixed groups. Women-only spaces enabled voice. The GenderUp methodology helps teams anticipate who might be excluded when innovations scale (CCARDESA, 2025a).

Historical context shapes expectations. Communities exploited by previous researchers approached new projects with scepticism. Trust-building required more time and transparency.

The AI & Equality Toolbox embeds human rights principles precisely to guard against extractive dynamics (Women at the Table, 2025).

Implications for Theory

For development sociology, the findings demonstrate the field's relevance to contemporary technology debates. Concepts like power, participation, and structural inequality are essential tools for understanding why AI succeeds or fails.

For science and technology studies, the findings show how technologies carry social meanings shaped by design processes. The Makerere team did not just build a tool. They built relationships, trust, and capacity through how they designed.

For participatory development theory, our mechanism analysis provides explanatory depth. We move beyond normative arguments for participation toward explanatory accounts of its effects through trust, ownership, and relevance.

Implications for Practice

Several practical implications follow.

First, participatory design must be genuine, not tokenistic. Communities should control decisions, not just provide input. The sensors. AFRICA model of community ownership should guide practice.

Second, context assessment is essential before intervention design. Infrastructure constraints, institutional capacity, gender relations, and historical context condition what mechanisms can operate.

Third, gender inequality requires active intervention. Women-only spaces, scheduling accommodations, and female trainers can enable participation that mixed settings block. The GenderUp methodology provides tools for anticipating and addressing exclusion (CCARDESA, 2025a).

Fourth, ethical frameworks must be developed proactively with community input. The Makerere team's collaborative approach to ethics, focusing on anonymization and evidence-based impact demonstration, built trust while protecting privacy (AI and Equality, 2025a).

Fifth, capacity building should be embedded in design processes, not added as separate training. Learning by doing builds both skills and confidence, creating sustainability.

Limitations

This study has limitations. The synthesis depends on available literature, which may over-represent successful cases. Unsuccessful interventions are less likely to be published. The focus on English, French, and Portuguese sources may exclude relevant evidence in African languages. Contextual variation across Sub-Saharan Africa means findings may not apply uniformly. Despite these limitations, the systematic application of the CIMO framework provides robust explanatory insight.

7. Conclusion

Summary of Findings

This study set out to explain how and why integrating development sociology principles into AI-driven poverty interventions improves outcomes in Sub-Saharan Africa. Through realist synthesis of 68 studies across agriculture, health, finance, and governance sectors, we generated several key findings.

First, sociological principles documented in practice include participatory design, community ownership, indigenous knowledge integration, power analysis, and a structural inequality focus. Genuine participation where communities control decisions differs fundamentally from consultation where input is sought, but power is retained.

Second, these principles operate through six generative mechanisms: trust-building, ownership, cultural congruence, power redistribution, capacity building, and relevance enhancement. These mechanisms interact and reinforce each other. The sensors. AFRICA case shows how

community ownership triggered trust, which enabled sustained engagement, which built capacity, which produced culturally congruent monitoring (AI and Equality Africa, 2025).

Third, mechanism activation depends heavily on contextual conditions. Institutional capacity, social capital, infrastructure constraints, political economy, gender relations, and historical context all shape whether and how mechanisms operate.

Fourth, these findings translate into twelve context-sensitive design propositions in if-then form. These propositions connect intervention choices to expected outcomes through identified mechanisms, providing actionable guidance.

Contribution to Knowledge

This study makes several contributions. It addresses a gap identified by multiple scholars. Most AI research in development contexts focuses on technical performance or adoption metrics. We provide explanatory insight into how social processes shape outcomes. The IDRC's call for rigorous, context-specific data on AI's socioeconomic effects in Africa reflects the urgency of this need (IDRC, 2025).

The study extends understanding of participatory development in technology contexts. Previous research documented that inclusion matters. Our mechanism analysis shows how it matters, moving beyond normative arguments toward explanatory accounts.

The findings contribute to decolonizing AI discourse. Ayana et al. (2024) argue that decolonizing AI governance requires attention to power relations and institutional dynamics. Our analysis shows what this looks like in practice. Community data ownership, indigenous knowledge integration, and power redistribution are concrete mechanisms that produce equitable outcomes.

The study also contributes to emerging frameworks for equitable AI in Africa. The AI & Equality Toolbox, the GenderUp methodology, and sensors. AFRICA model provides tested approaches that our synthesis validates and extends (Women at the Table, 2025; CCARDESA, 2025a; AI and Equality Africa, 2025).

Implications for Policy

For policymakers developing AI strategies, several implications follow.

First, policies should require genuine community participation, not just consultation. Participation standards should specify who participates, at what stages, and with what decision-making authority.

Second, data governance frameworks should prioritize community ownership. When communities control data, they use it for their own advocacy and development. Policies should enable this rather than facilitating extraction.

Third, gender equality requires explicit attention. Policies should require gender analysis at all stages of AI development and deployment.

Fourth, infrastructure investment must accompany technology deployment. Sophisticated tools cannot function without basic infrastructure. Policies should coordinate technology and infrastructure development.

Fifth, capacity building should be embedded in AI initiatives. Learning by doing builds sustainable skills. Policies should fund extended engagement, not just technology delivery.

Implications for Practice

For practitioners designing AI interventions, several recommendations emerge.

Start with context assessment. Understand infrastructure constraints, institutional capacity, gender relations, and historical context before designing anything.

Involve communities from the beginning. Problem definition should be shaped by those who experience problems.

Create spaces for marginalized voices. Women-only sessions, accommodations for persons with disabilities, and attention to language barriers enable participation that mixed groups block.

Build for local conditions. Offline functionality, solar power compatibility, and multi-network SIM cards ensure tools work where infrastructure is weak.
Embed ethical reflection throughout. Develop data governance frameworks with community input before collecting data.
Sustainability plan. Ownership requires that communities can continue after external support ends.

Implications for Research

For researchers, several directions merit attention. Longitudinal studies could track how the mechanism activation evolves. Cross-context comparisons could test how contextual factors condition mechanism effectiveness. Action research could implement and refine design propositions in real-world settings.
Research should also examine unsuccessful cases. Understanding why mechanisms fail to activate is as important as understanding why they succeed. Studies of specific sectors could identify whether mechanisms operate differently in agriculture, health, finance, and governance. Research on data governance and ownership is particularly urgent as AI systems proliferate.

Concluding Reflection

Artificial intelligence will not transform African development by itself. The technology works when it meets certain conditions: genuine community participation, attention to context, integration of local knowledge, and redistribution of power. Without these, AI risks becoming another tool for extraction, benefiting outsiders while leaving local communities behind.
The sensors. AFRICA project shows a different path. Communities own their data. They decide what to monitor and how to use the findings. The technology serves their purposes, not the purposes of distant funders or companies. This is practical recognition that sustainable impact requires ownership, and ownership requires control.
Development sociology provides the concepts for understanding these dynamics. Power, participation, inequality, context—these are not abstract academic concerns. They are the practical realities that determine whether technology helps or harms. The challenge now is to embed these insights into how AI gets built, funded, and governed across Sub-Saharan Africa. The goal should not be technology adoption for its own sake. The goal should be technology that enables communities to solve their own problems, on their own terms, with their own priorities. Achieving that goal requires putting development sociology at the center of AI design, not at the margins. The evidence is clear. When communities participate genuinely, when they control their data, when their knowledge shapes design, outcomes improve. The question is whether funders, policymakers, and developers will act on this evidence.

References

Adamu, M., & Nkwo, M. (2023). AI in Africa: Preliminary notes on design and adoption. *Diid Disegno Industriale Industrial Design*, 80, 44-57. https://doi.org/10.30682/diid8023d

AI and Equality Africa. (2025). 5 lessons from sensors.AFRICA: How community-centered AI actually works. *AI and Equality Africa Toolbox*. https://africa.aiequalitytoolbox.com/5-lessons-from-sensors-africa-how-community-centered-ai-actually-works/

AI and Equality. (2025, November 12). AI for equitable health: The Makerere blueprint for context-aware system requirements. *AI and Equality Toolbox*. https://aiequalitytoolbox.com/ai-for-equitable-health-the-makerere-blueprint-for-context-aware-system-requirements/

Akpudo, U. E., Effoduh, J. O., Kong, J. D., & Gao, Y. (2024). Unveiling AI concerns for Sub-Saharan Africa and its vulnerable groups. *International Conference on Intelligent and Innovative Computing Applications*. https://doi.org/10.59200/ICONIC.2024.007

Ayana, G., Dese, K., Daba Nemomssa, H., Habtamu, B., Mellado, B., Badu, K., & Kong, J. D. (2024). Decolonizing global AI governance: Assessment of the state of decolonized AI governance in Sub-Saharan Africa. *Royal Society Open Science*, 11(8), 231994. https://doi.org/10.1098/rsos.231994

Centre for Coordination of Agricultural Research and Development for Southern Africa. (2025a, June 20). From equality to equity: *World Bank-led workshop sparks gender-smart innovation pathways for resilient agriculture in Eastern and Southern Africa. CCARDESA*. https://ccardesa.org/equality-equity-world-bank-led-workshop-sparks-gender-smart-innovation-pathways-resilient

EdTech Hub. (2026, January 21). How might low- and middle-income countries co-design solutions that align with education priorities and ethics? *AI Observatory Waypoints and Signals* Issue 29. https://edtechhub.org/2026/01/21/ai-observatory-waypoints-and-signals-issue-29/

Frimpong, V. (2025). Artificial intelligence investment in resource-constrained African economies: Financial, strategic, and ethical trade-offs with broader implications. *World*, 6(2), 70. https://doi.org/10.3390/world6020070

Hassan, Y. (2025). Machine learning as a state-building experiment: AI and development in Africa. In *The Oxford handbook of the sociology of machine learning*. *Oxford University Press*. https://stppstage.fordschool.umich.edu/news/2025/hassan-ai-power-and-decolonial-possibility-africa

International Development Research Centre. (2025). Frequently asked questions: Call for concept notes: Socio-economic impacts of artificial intelligence in Africa. *IDRC*. https://idrc-crdi.ca/en/topics/development?page=4

Makumbirofa, S. (2025). Leveraging economic policy for equitable and just AI in Africa. *Research ICT Africa*. https://researchictafrica.net/research/leveraging-economic-policy-for-equitable-and-just-ai-in-africa/

Observatory on Digital Communication. (2025, June 18). Bridging the rural-urban gap: The role of AI. *OCCAM*. https://www.occam.org/post/bridging-the-rural-urban-gap-the-role-of-ai

Ofori-Addo, D. L. (2024). Essays on the socioeconomic determinants and impact of information and communications technology in Sub-Saharan Africa *[Doctoral dissertation, George Mason University]*. *ERIC*. https://www.fachportal-paedagogik.de/en/literatur/vollanzeige.html?FId=eric_ed670516

Okafor, C., Nnamdi, E., & Ibrahim, Z. (2025). An integrated approach to gender equality, diversity, and inclusion in the development of artificial intelligence tools in agriculture and food system in Africa. *AI & Society.* Advance online publication. https://link.springer.com/article/10.1007/s00146-025-02722-y

Purkayastha, S., et al. (2025). Participatory design for AI-embedded artifacts: The case of ECEB app design to fostering ownership. *Studies in Health Technology and Informatics*, 329, 1307-1311. https://pubmed.ncbi.nlm.nih.gov/40776068/

The Reporter Ethiopia. (2025, June 7). Critical piece of the puzzle in AI. *The Reporter Ethiopia*. https://www.thereporterethiopia.com/45498/

Women at the Table. (2025, November 12). AI & Equality African Toolbox. *Women at the Table*. https://www.womenatthetable.net/project/ai-equality-african-toolbox/

Wongibeh Adunimay, A. (2025). Unexplored tool for sustainable development: Can artificial intelligence promote good health and well-being in Africa? *The Round Table*, 114(6). https://www.tandfonline.com/doi/full/10.1080/00358533.2025.2561726

World Bank. (2025, October 17). AgriConnect—Farms, firms, and finance for jobs. *World Bank Live*. https://live.worldbank.org/en/event/2025/annual-meetings-agriconnect-farms-firms-finance-for-jobs