

SMALL AI AS A FRUGAL INNOVATION: DESIGN FIT, TECHNOLOGY ADOPTION, AND SOCIO-ECONOMIC OUTCOMES IN KENYA AND GHANA

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ABSTRACT

This study evaluates how Small AI design fit influences technology adoption and socio-economic outcomes across agriculture, education, and small businesses in developing markets. Grounded in Frugal Innovation Theory, we adopted an explanatory sequential mixed-methods design combining a survey of 384 end-users in Kenya and Ghana with four embedded qualitative case studies. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), we find that Small AI design-fit — offline capability, low-cost hardware compatibility, and local language adaptation — has a strong direct effect on socio-economic impact ($\beta = 0.38, p < 0.001$) and adoption intensity ($\beta = 0.42, p < 0.001$). Digital readiness and perceived trust significantly mediate these relationships.

Institutional support positively moderates the link ($\beta = 0.16, p < 0.01$). Integrating AI into familiar low-tech channels reduces adoption barriers. Tailoring AI to local infrastructure constraints thus offers a scalable pathway to inclusive digital development.

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1. INTRODUCTION

Artificial intelligence is increasingly influencing economic activity and organizational processes. Businesses increasingly use AI to automate operations and provide tailored services and products at scale (Rane et al., 2024). However, a dominant AI development paradigm relies on large datasets and substantial computational resources. This resource-intensive paradigm may reinforce existing disparities in access to advanced AI capabilities between high-resource and resource-constrained settings (Nour et al., 2026). Many AI systems are developed for environments with reliable electricity, high-speed internet access, substantial computing capacity, and secure data infrastructure. These constraints are especially relevant in sectors such as

agriculture, basic education, primary health care, and microenterprise, where digital services may offer substantial potential value. Many such contexts are located in the Global South and remain underrepresented in mainstream AI development and deployment research. The mismatch between resource-intensive AI systems and constrained deployment environments motivates the concept of “Small AI. Small AI refers to computationally efficient, task-specific models designed for constrained hardware and intermittent or absent connectivity (Liu et al., 2025). Such systems may operate on low-cost devices and interact through channels such as SMS, USSD, basic smartphones, or WhatsApp-based applications. (Lee & Ahn 2026; Kim & Qiang 2025). Whereas large-scale AI systems often emphasize broad generalization, Small AI

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systems are typically task-specific, energy-efficient, and designed for constrained environments.

Although interest in resource-efficient AI applications is growing and several deployments have been reported, there remains limited cross-sector evidence on which Small AI design characteristics are associated with wider use and socio-economic outcomes (Al-Husseini & Al-Khalili, 2025). Much of the literature consists either of high-level macroeconomic analyses with limited user-level data (Gikunda 2024) or of single-sector, single-application case studies (von Braun & Baumüller 2021). To address this gap, this paper examines the following research question: To what extent are Small AI design fit characteristics associated with adoption intensity and socio-economic outcomes in resource-constrained settings and how are these relationships mediated by digital readiness and perceived trust and moderated by institutional and sectoral conditions?

To address this research question, the study pursues the following objectives:

1. To assess the relationships between Small AI design-fit characteristics and both adoption intensity and socio-economic outcomes.
2. To examine the mediating role of digital infrastructure readiness and perceived trust in the relationship between Small AI design-fit and socio-economic impact.
3. To assess how sector context and public-private institutional support moderate the relationship between Small AI design-fit and technology adoption.
4. To triangulate quantitative empirical findings with qualitative evidence from real-world Small AI deployments in Sub-Saharan Africa.

Combining Frugal Innovation Theory (Radjou et al., 2012), the TOE framework (Tornatzky & Fleischer, 1990), and the Diffusion of Innovations theory (Rogers, 2003), this study offers three significant contributions. First, the study develops an empirically grounded

integrative framework for Small AI within information systems and development research. Second, the study evaluates the proposed relationships using survey data from 384 end users in Kenya and Ghana, supplemented by evidence from embedded cases. Third, the study derives design and implementation implications for technology developers, nongovernmental organizations (NGOs), and policymakers working on inclusive AI deployment and the digital divide.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 The Small AI Paradigm versus The Big AI Paradigm

A major trajectory in contemporary AI emphasizes parameter scale, large datasets, and cloud-based computation. Contemporary general-purpose foundation models may contain hundreds of billions of parameters. Such models may require dedicated GPU clusters and high-capacity data-center infrastructure (Vlachos et al., 2026). While these models have shown impressive multi-modal capabilities, their operational requirements can create access barriers in resource-constrained economies (Katende, 2025).

The Small AI paradigm emphasizes algorithmic efficiency through model compression (quantization, pruning, distillation) and optimization for specific tasks and edge deployment (Kim & Qiang, 2025). Small AI models may range from millions to billions of parameters and can, depending on architecture, be deployed on low-cost devices or edge servers with minimal power and bandwidth requirements. The structural characteristics of Big AI and Small AI are summarized in Table 1.

Table 1. Structural comparison between Big AI and Small AI paradigms

Dimension	Big AI Paradigm	Small AI Paradigm
Compute Architecture	Hyper-scale cloud data centers, high-end GPUs	Edge devices, low-cost smartphones, localized micro-servers
Connectivity Need	Continuous high-speed, low-latency broadband	Offline-first operation, asynchronous synchronization, intermittent connectivity, and low bandwidth
Power Dependency	Uninterrupted high-voltage grid supply	Battery-powered devices, solar micro-grids, low-energy sleep modes
Data Requirements	Trillion-token multi-domain internet crawls	Small, domain-specific, curated local datasets
Interface Channels	Dynamic web interfaces, high-bandwidth apps	SMS, USSD, WhatsApp, voice interfaces in local languages or dialects
Primary Design Goal	Broad generalization and emergent reasoning	Task-specific accuracy, resource efficiency, context-fit

2.2 Literature Synthesis and Identified Research Gap

A review of recent literature (2021–2026) suggests two broad streams relevant to this study. The first stream comprises macro-level policy analyses. Researchers in this stream study various Global South countries to understand national readiness, governance, and digital infrastructural gaps concerning AI (Gikunda, 2024; World Bank, 2026). Although these studies contribute to a body of knowledge that enables development of strategies, such studies typically provide limited insight into micro-level end-user adoption and the role of specific design characteristics. The second stream consists of isolated empirical studies of individual applications. For instance, von Braun and Baumüller (2021) studied local yield and cost improvements of integrated low-cost robotics and agricultural advisory systems. However, the study did not examine cross-domain generalizability. Similarly, recent empirical agricultural chatbot studies (e.g., Digital Green's Farmer Chatbot and iSDA Virtual Agronomist) and educational tools (e.g., Ghana's "Rori" WhatsApp Math Tutor) reported context-specific benefits but did not provide a cross-sector framework for examining how resource-efficient design characteristics relate to adoption and socio-economic outcomes. (Kim & Qiang, 2025; Lee & Ahn, 2026).

As it stands, there is a clear gap in the existing research: *Existing studies provide limited cross-sector evidence on how specific Small AI design-fit characteristics are associated with adoption intensity and socio-economic outcomes, particularly through mediating and moderating mechanisms. This gap is exactly what this study seeks to fill.*

2.3 Theoretical Grounding

The three theoretical perspectives provide complementary foundations for the conceptual framework.

1. Frugal Innovation Theory (Radjou et al., 2012; Schumacher, 1973): Within the domain of frugal innovation, frugal innovation emphasizes the careful use of scarce resources to develop high-value, accessible solutions. When discussing AI, Small AI should not be interpreted simply as an inferior form of large-scale AI. Rather, the concept emphasizes deliberate design choices that address resource and accessibility trade-offs while improving contextual fit.
2. Technology-Organization-Environment (TOE) Framework (Tornatzky & Fleischer, 1990): In the TOE framework, technology adoption depends on the interaction of technological, organizational, and environmental conditions (Small AI design), the organizational and personal factors (digital literacy, the availability

of hardware), and the environment (the stability of the infrastructure and the degree of institutional support).

Diffusion of Innovations Theory (Rogers, 2003): Rogers (2003) identifies innovation attributes such as relative advantage, compatibility, and complexity as important determinants of adoption. From this perspective, appropriately designed Small AI reduce complexity and, in combination with design fit, serve to increase user confidence and the level of intensity of adoption.

3. CONCEPTUAL MODEL AND HYPOTHESIS DEVELOPMENT

3.1 Conceptual framework

Based on the theoretical synthesis, we develop a conceptual model linking Small AI design-fit characteristics (Independent Variable) to Adoption Intensity and Socio-Economic Impact (Dependent Variables). Digital Infrastructure & Literacy Readiness and Perceived Trust are considered to be mediators in this relationship, while Sector Context and Public-Private Institutional Support are modeled as moderators of these relationships. Conceptual model is presented on Table 2.

Table 2: Conceptual model

Overall conceptual research model full diagram	
Independent variable (IV): Small AI design fit characteristics	
➤ Offline / Low-Bandwidth functionality	➤ Local-language & Cultural Adaptation
➤ Low Computational & Hardware Requirements	➤ Integration with Low-Tech Channels (SMS, USSD, WhatsApp)
↓ Direct effect: H1a, H1b ↓	
Dependent variables (DV): Adoption Intensity & Socio-Economic Impact	
➤ Adoption Intensity: frequency, scope, depth of usage	➤ Socio-Economic Impact: productivity, yield, revenue, learning
Mediating variables (mediating effects: H2a, H2b)	Moderating variables (moderating effects: H3a, H3b)
➤ Infrastructure & Literacy Readiness	➤ Sector Context (agri/edu/small business)
➤ Perceived Trust & Usefulness	➤ Institutional Support

3.2 Hypotheses Development

3.2.1 Direct Effects of Small AI Design-Fit

AI use in resource-constrained settings may be facilitated by systems that operate offline, run on low-cost devices, support local languages, and integrate with familiar messaging channels such as SMS and WhatsApp. (Katende, 2025; Kim & Qiang, 2025). When AI systems are better aligned with local infrastructure, users may face fewer operational barriers, which may be associated with improved efficiency and economic outcomes. (Rogers, 2003).

- **H1a:** Small AI design-fit characteristics have a significant positive direct effect on adoption intensity.
- **H1b:** Small AI design-fit characteristics have a significant positive direct effect on socio-economic impact.

3.2.2 Mediating Roles of Digital Readiness and Perceived Trust

Although low-cost AI tools may reduce some resource barriers, adoption ultimately depends on users' capacity and willingness to engage with the technology. More specifically, adoption depends on users' operational capacity (digital literacy, basic phone connectivity) and their psychological acceptance of the technology (perceived usefulness and trust). From a TOE perspective, adoption is more feasible when users and organizations have adequate technological resources and when the surrounding environment provides sufficient support. (Tornatzky & Fleischer, 1990). A resource-efficient, familiar interface may reduce perceived complexity and increase users' confidence in system recommendations (Lee & Ahn, 2026). Higher perceived trust may, in turn, be associated with greater adoption intensity and more favorable reported outcomes.

- **H2a:** Digital infrastructure and literacy readiness significantly mediate the relationship between Small AI design-fit and socio-economic impact.
- **H2b:** Perceived trust and usefulness significantly mediate the relationship between Small AI design-fit and adoption intensity.

3.2.3 Influence of Institutional Support and Sector Context

The relationship between Small AI adoption and socio-economic outcomes does not occur independently of the institutional environment. Institutional support from public and private actors can provide complementary resources, training, and operational legitimacy. (von Braun & Baumüller, 2021). Sectoral characteristics (for example, seasonal agricultural cycles and the operating patterns of microbusinesses) may also create different requirements for technological tools.

- **H3a:** Public-private institutional support positively moderates the relationship between Small AI design-fit and socio-economic impact,

such that the relationship is stronger under high institutional support.

- **H3b:** Sector context (agriculture, education, small business) significantly moderates the effect of Small AI design-fit on adoption intensity.

4. METHODOLOGY

4.1 Research Design

An explanatory sequential mixed-methods design (QUAN → qual) was adopted for this study. The quantitative phase involved survey data collected to test the structural model and hypotheses. The subsequent qualitative phase examined four established Small AI initiatives in Sub-Saharan Africa as embedded cases.

4.2 Target Population and Sample Selection

The target population comprised end users (smallholder farmers, primary/secondary teachers, and micro/small entrepreneurs) who were using Small AI solutions in Kenya and Ghana were selected as study contexts because of their active digital-innovation ecosystems, relatively high mobile-phone penetration, and persistent infrastructure constraints in some rural areas. The minimum sample size was calculated using Cochran (1977) formula for an unknown population: Sample size determination followed Cochran (1977) formula for unknown populations:

$$n = \frac{z^2 \cdot P \cdot (1 - P)}{e^2}$$

Setting $Z=1.96$ (95% confidence level), $p = 0.50$ (maximum variability), and margin of error $e=0.05$ yielded a minimum target sample of 384 respondents. Using a stratified random sampling strategy across the three sectors (Agriculture, Education, Small Business) in semi-urban and rural regions, the study distributed 450 questionnaires. A total of 384 fully completed and valid responses were retained for analysis, matching the target sample requirement ($N=384$).

4.3 Embedded Qualitative Cases

To triangulate the survey results, four active Small AI initiatives were analyzed as embedded case studies:

1. **Digital Green (Farmer Chatbot):** An AI-driven advisory tool reported to reach more than 460,000 farmers through multilingual WhatsApp and voice interfaces.
2. **iSDA Virtual Agronomist:** A hyper-local crop-recommendation system operating through WhatsApp and reported to cover approximately 350,000 plots in seven African countries.
3. **Rori (Rising Academies):** A localized, WhatsApp-based AI mathematics tutor serving

learners in West Africa at an estimated annual cost of US\$5 per student.

4. **Farmerline (Darli AI):** WhatsApp/voice-based agricultural credit scoring and agronomic advisory assistant operating in indigenous Ghanaian languages.

4.4 Measurement Instrument and Reliability

Survey items were adapted from validated scales in the information systems literature (Rogers, 2003; Tornatzky & Fleischer, 1990) and tailored to the Small AI context. All latent constructs were measured using five-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree). A pilot study (n=40) confirmed instrument clarity and internal consistency, with Cronbach's alpha values exceeding the 0.70 threshold across all subscales.

4.5 Data Analysis Strategy

Quantitative data were analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4 and IBM SPSS Statistics 28. PLS-SEM was chosen due to its suitability for complex predictive models containing mediating and moderating relationships, as well as its suitability for complex predictive models and its performance with non-normally distributed data, which are common in field surveys (Hair et al., 2017). The bootstrapped indirect effects (5,000 bootstrap resamples) were evaluated to test mediation hypotheses, while multi-group analysis (MGA) and interaction terms were used for moderation testing.

Table 3: Cross-Case Synthesis of Analyzed Small AI Deployments in Sub-Saharan Africa

Deployment / Initiative	Target Sector	Primary Low-Tech Interface	Key Small AI Architectural Innovations	Documented Scale & Reach	Primary Reported Socio-Economic Outcome
Digital Green Chatbot	Agriculture	WhatsApp, Multilingual Voice	Compressed NLP model, localized voice-to-text in native dialects	~460,000 farmers & extension workers	15–22% yield increase via timely pest management
iSDA Virtual Agronomist	Agriculture	WhatsApp	Downscaled satellite-to-soil mapping algorithms, offline prediction	~350,000 agricultural plots	20% reduction in fertilizer costs, improved farm profits
Rori (Rising Academics)	Basic Education	WhatsApp	Low-bandwidth text AI, micro-tutoring logic, dynamic feedback	Thousands of West African learners	Learning gains equivalent to +1 extra year of schooling (~\$5/student/yr)
Farmerline (Darli AI)	Small Business / Agri	WhatsApp, SMS, Voice	Local-language credit scoring engine, micro-loan risk assessment	~200,000 smallholders & agri-vendors	35% faster credit approval, increased micro-loan access

Source: Author synthesis based on institutional data, Kim & Qiang (2025), and case documentation.

5. CONTEXTUAL CASE ANALYSIS OF REAL SMALL AI DEPLOYMENTS

To ground the empirical findings in operational realities, Table 3 synthesizes the four embedded Small AI deployments evaluated in this study.

The cross-case synthesis suggests three recurring patterns:

1. **Channel Familiarity Minimizes Friction:** Embedding AI capabilities in channels such as WhatsApp or SMS may reduce the need for separate app downloads and allow users to rely on familiar communication services.
2. **Local-Language Voice Capabilities May Improve Accessibility:** Text-only interfaces may create barriers for some users with limited literacy. Integrating compressed speech-to-text engines in native dialects (e.g., Twi, Swahili) may broaden accessibility.

Hybrid Human-AI Workflows Build Trust: Case evidence suggests that pairing AI tools with local human-

support networks may strengthen trust and operational continuity, consistent with the proposed role of institutional support.

6. EMPIRICAL RESULTS

6.1 Sample Demographic Profile

Table 4 summarizes the demographic characteristics of the 384 quantitative survey respondents in Kenya and Ghana.

6.2 Measurement Model Assessment

The measurement model was evaluated for reliability, convergent validity, and discriminant validity. As detailed in Table 5, all composite reliability (CR) and Cronbach's alpha (α) values exceeded 0.70.

Table 4: Demographic Profile of Survey Respondents (N=384)

Characteristic	Category	Frequency (n)	Percentage (%)
Country	Kenya	204	53.1
	Ghana	180	46.9
Sector Context	Agriculture (Smallholders)	162	42.2
	Education (Teachers/Students)	114	29.7
	Small Business / Micro-entrepreneurs	108	28.1
Primary Device	Basic Feature Phone (SMS/USSD)	78	20.3
	Entry-level smartphone (<\$100)	246	64.1
	Mid- or high-tier smartphone	60	15.6
Primary Connectivity	Intermittent / Edge / 2G-3G	258	67.2
	Stable Broadband / 4G-5G	126	32.8
Gender	Male	210	54.7
	Female	174	45.3

Average variance extracted (AVE) values exceeded the 0.50 threshold, establishing convergent validity (Hair et al., 2017; Henseler et al., 2015). Discriminant validity

was assessed using the heterotrait-monotrait (HTMT) ratio, with all reported pairwise values below 0.85.

Table 5: Measurement Model Evaluation: Validity and Reliability Assessment

Construct	Indicator Items	Factor Loading Range	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Small AI Design-Fit (SDF)	SDF1 - Offline Function	0.78 – 0.86	0.84	0.89	0.62
	SDF2 – Low Hardware Requirements				
	SDF3 - Local Dialect Fit				
	SDF4 - WhatsApp/SMS Integration				
Digital Readiness (DR)	DR1 - Connectivity Access	0.74 – 0.82	0.81	0.87	0.58
	DR2 - Device Affordability				
	DR3 - Digital Literacy				
Perceived Trust (PT)	PT1 - Output Reliability	0.79 – 0.88	0.86	0.90	0.65
	PT2 - Perceived Usefulness				
	PT3 – Trust in Cultural Fit				
Institutional Support (IS)	IS1 - Local NGO Training	0.75 – 0.83	0.79	0.86	0.56
	IS2 - Government Extension				
Adoption Intensity (AI)	AI1 - Usage Frequency	0.81 – 0.89	0.88	0.92	0.68
	AI2 - Usage Diversity				
Socio-Economic Impact (SEI)	SEI1 - Productivity Gain	0.82 – 0.91	0.90	0.93	0.71
	SEI2 - Income/Revenue Increase				
	SEI3 - Cost Reduction				

6.3 Structural Model Assessment and Hypotheses Testing

6.3.1 Direct Path Analysis

PLS-SEM path analysis was conducted with 5,000 bootstrap resamples to evaluate structural relationships.

The direct paths shown in Table 6 indicate statistically significant positive relationships. Small AI design fit is positively associated with both adoption intensity ($\beta=0.42$, $t=8.64$, $p<0.001$) and Socio-Economic Impact ($\beta=0.38$, $t=7.92$, $p<0.001$), supporting **H1a** and **H1b**.

Table 6: Structural Model Direct Path Coefficients

Hypothesis	Structural Path	Path Coefficient (β)	Standard Error (SE)	t-Statistic	p-Value	Decision
H1a	Small AI Design-Fit → Adoption Intensity	0.42	0.049	8.64	<0.001	Supported
H1b	Small AI Design Fit → Socio-Economic Impact	0.38	0.048	7.92	<0.001	Supported
	Digital Readiness → Socio-Economic Impact	0.26	0.042	6.19	<0.001	Supported
	Perceived Trust → Adoption Intensity	0.31	0.045	6.88	<0.001	Supported
	Adoption Intensity → Socio-Economic Impact	0.34	0.046	7.39	<0.001	Supported

Model Fit Indices: R^2 (Socio-Economic Impact) = 0.542; R^2 (Adoption Intensity) = 0.486; SRMR=0.048.

6.3.2 Mediation Analysis

Mediation hypothesis testing was conducted using bootstrapped indirect effect calculations (95% bias-corrected confidence intervals). As presented in Table 7, both reported indirect paths are statistically significant, providing evidence consistent with mediation; the classification of mediation should be based on the

corresponding direct effects. Digital Infrastructure & Literacy Readiness significantly mediates the path from Design-Fit to Socio-Economic Impact ($\beta=0.14$; 95% CI [0.08, 0.21]), supporting **H2a**. Perceived Trust significantly mediates the path from Design-Fit to Adoption Intensity ($\beta=0.18$; 95%CI [0.11, 0.25]), supporting **H2b**.

Table 7 Bootstrapped Indirect Effects for Mediation Analysis

Hypothesis	Indirect Path Linkage	Point Estimate (β)	Boot SE	95% CI Lower	95% CI Upper	Decision
H2a	Small AI Design Fit → Digital Readiness → SEI	0.14	0.033	0.08	0.21	Supported
H2b	Small AI Design-Fit → Perceived Trust → Adoption Intensity	0.18	0.036	0.11	0.25	Supported

6.3.3 Moderation Analysis

Moderation effects were tested using product-indicator interaction terms and Multi-Group Analysis (MGA). For **H3a**, the interaction term (Small AI Design-fit x Institutional Support) on Socio-Economic Impact was positive and statistically significant ($\beta=0.16$, $t=3.42$, $p=0.001$), supporting **H3a**. This pattern suggests that the association between Small AI design fit and socio-

economic outcomes may be stronger when institutional support is higher.

For **H3b**, Multi-Group Analysis across the three sector cohorts (Agriculture, Education, Small Business) revealed significant differences in path magnitude ($F(2,381)=4.12$, $p=0.017$), supporting **H3b**. The direct effect of Small AI design-fit on adoption intensity was strongest in the Agriculture cohort ($\beta=0.49$, $p<0.001$),

followed by Small Business ($\beta=0.41$, $p<0.001$) and Education ($\beta=0.33$, $p<0.001$). The qualitative evidence suggests that agricultural users faced substantial connectivity and literacy constraints, which may help explain the stronger observed association in that sector.

7. DISCUSSION

7.1 Interpretation of Findings

The reported quantitative results and case evidence are consistent with the paper's central argument. Specifically, Greater Small AI design fit was associated with higher adoption intensity and more favorable reported socio-economic outcomes in the study sample.

The key aspect of this finding is the substantial impact of Small AI designs fitted to local contexts on socio-economic outcomes ($\beta=0.38$). According to Frugal Innovation Theory (Radjou et al., 2012), limiting the design process by imposing certain constraints on it (i.e., allowing offline functionalities, limiting computing resources needed and applying local voice interface) makes it much easier for users to operate the technology. This essentially means that the technology adapts to the users rather than the users adapting to the complex cloud technology.

In addition, the mediation analysis results show that technical compatibility is not an independent variable, as it enhances trust and reduces the gap in infrastructure. For instance, Interactions through familiar, local-language channels may reduce perceived complexity and support trust, although these mechanisms should be interpreted cautiously. These findings extend Rogers' (2003) Diffusion of Innovations framework to the context of AI adoption in resource-constrained settings.

7.2 Contextualization with Prior Empirical Studies

The conclusions we've uncovered contribute to the field of research on artificial intelligence for development. Earlier works in macroeconomic approaches (for instance, Gikunda, 2024; World Bank, 2026) pointed to the lack of infrastructural development as a major impediment to AI deployment, while our discoveries indicate that simple yet effective architectural innovations (Small AI) can overcome this challenge. This finding is consistent with what Katende (2025) as well as Lee and Ahn (2026) have found. They also established that compact machine learning models proved to be very effective in resource-poor environments. However, this study, with its 384 respondents and the three sectors examined (Agriculture, Education and Small Business) offers greater validity to the argument regarding the influence of frugal principles in the field of artificial intelligence.

8. THEORETICAL AND PRACTICAL IMPLICATIONS

8.1 Theoretical Contributions

This study offers three main theoretical contributions to the information systems, development studies, and artificial intelligence literatures:

1. **Conceptualization of the Small AI Paradigm:** It provides a formal conceptualization of Small AI and an empirical evaluation of a context-oriented design-fit framework.
2. **Integration of Frugal Innovation with TOE:** The study creates an integrative framework as a combination of Frugal Innovation Theory and Technology-Organization-Environment model, which helps explore the nature of architectural frugality and how it contributes to the creation of both technical compatibility and environmental feasibility.
3. **Cross-Sectoral Empirical Validation:** It addresses a gap in the AI4D literature by providing multi-sector user-level evidence through delivering multi-sectoral empirical data (Agriculture, Education, Small Business) that moves beyond single-application case studies.

8.2 Practical and Managerial Implications

For technology developers, technology entrepreneurs, and policymakers, this study offers concrete guidelines:

- **For AI Developers & Tech Entrepreneurs:**
 1. *Prioritize Compressed, Task-Specific Architectures:* Where appropriate, prioritize resource-efficient techniques such as model distillation, quantization, and edge deployment rather than relying exclusively on computationally intensive cloud-based models.
 2. *Leverage Existing Messaging Ecosystems:* Deploy interfaces within dominant platforms (e.g., WhatsApp, SMS) rather than requiring standalone mobile applications.
 3. *Incorporate Local-Language Voice:* Integrate speech-based interfaces in relevant local languages or dialects to reduce literacy-related barriers.
- **For NGOs and Development Agencies:**
 1. *Build Hybrid Human-AI Support Networks:* Pair Small AI tools with agricultural extension agents, community health workers, and local teachers to enhance trust and operational continuity.
 2. *Invest in Digital Micro-Literacy:* Focus training programs on practical interaction skills with conversational

agents rather than general computer literacy.

- **For Policymakers and Donors:**

1. **Incentivize Localized AI R&D:** Direct public research funds toward localized, edge-based AI models tailored to national economic priorities.

Support Off-Grid Digital Infrastructure: Expand investments in solar-powered micro-grids and subsidies for low-cost devices which may strengthen the infrastructure conditions associated with digital readiness in the proposed model.

9. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

While this study provides empirical and contextual insights, several limitations should be noted:

1. **Geographic Scope:** Survey data were collected across two Sub-Saharan African economies (Kenya and Ghana). Although Kenya and Ghana provide important examples of digital ecosystems in East and West Africa, caution is warranted when generalizing findings to post-conflict zones or differing institutional contexts in Latin America or South Asia.
2. **Cross-Sectional Design:** The quantitative phase utilized cross-sectional survey data, limiting causal inference because variables were measured at a single point in time. Future

research should employ longitudinal panel designs to track the long-term trajectories of Small AI use and socio-economic outcomes

3. **Emerging Sector Contexts:** This study focused on agriculture, education, and small business. Future studies should extend this framework into primary healthcare (e.g., localized diagnostic assistants) and municipal service delivery

10. CONCLUSION

Resource-intensive AI development may reinforce existing digital disparities in emerging and resource-constrained markets. The findings suggest that context-adapted Small AI may offer a viable approach to AI deployment in resource-constrained settings. Designing AI tools around low-resource constraints may improve their accessibility to smallholder farmers, educators, and micro-entrepreneurs.

Empirical testing across 384 end-users in Kenya and Ghana, combined with embedded case evidence from leading regional initiatives, indicates that Small AI design fit is positively associated with adoption intensity and reported socio-economic outcomes. When supported by institutional networks and tailored to local sector dynamics, Small AI may contribute to more accessible and context-appropriate AI deployment in support of inclusive digital development.

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