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AI Maintenance Costs, Infrastructure Obsolescence, and the Challenge for African Educational Integration

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Abstract: Background: *The integration of artificial intelligence in African educational institutions has gained increasing policy momentum as a strategy for advancing equitable, quality education across the continent. However, the sustainability of such integration is threatened by the escalating recurrent costs of AI system maintenance and the pervasive obsolescence of digital infrastructure in African educational settings two structural challenges that have received insufficient empirical attention relative to their magnitude and consequence.* ***Objective:*** *This study examined the relationship between AI maintenance costs, infrastructure obsolescence, and AI educational integration outcomes in African educational institutions, with specific focus on the mediating role of institutional capacity.* ***Methods:*** *A quantitative cross-sectional survey design was employed, with data collected from 387 ICT directors, academic administrators, finance officers, and laboratory technicians across universities, technical and vocational institutions, and secondary schools in Uganda, Kenya, Nigeria, Ghana, and South Africa, selected through multistage stratified random sampling. A validated structured questionnaire was used for data collection. Univariate analysis described the distribution of key variables; bivariate Pearson correlation and independent samples t-tests examined pairwise associations and group differences; and Structural Equation Modeling (SEM), estimated via maximum likelihood with bootstrapped mediation testing (5,000 resamples), modeled the structural pathways among constructs.* ***Results:*** *Descriptive analysis revealed that technical staffing (M = USD 31,547) and hardware replacement (M = USD 22,417) were the costliest maintenance components, while composite AI maintenance cost burden (M = 3.84/5.00) and infrastructure obsolescence severity (M = 3.91/5.00) scores were high and AI integration sustainability perception (M = 2.61/5.00) was low across all institution types. Bivariate analysis demonstrated significant negative correlations between maintenance cost burden and integration sustainability ($r = -0.614, p < 0.01$) and between infrastructure obsolescence and integration sustainability ($r = -0.658, p < 0.01$), with institutional capacity positively correlated with sustainability ($r = 0.702, p < 0.01$). T-test analyses revealed that universities, privately funded institutions, and those in upper-middle income country contexts reported significantly higher sustainability perceptions, though all remained below the scale midpoint. SEM results confirmed excellent model fit (CFI = 0.961, RMSEA = 0.054) and revealed that institutional capacity significantly and partially mediated the negative effects of both AI maintenance cost burden (indirect $\beta = -0.199$; 95% CI: -0.271 to -0.134) and infrastructure obsolescence (indirect $\beta = -0.216$; 95% CI: -0.291 to -0.148) on AI integration sustainability.* ***Conclusion:*** *AI maintenance costs and infrastructure obsolescence constitute structurally embedded barriers to sustainable AI educational integration in Africa, operating both directly and through the erosion of institutional capacity. Coordinated multi-level policy responses encompassing dedicated recurrent maintenance funding, institutional capacity development, and the adoption of Africa-appropriate AI tool design and pricing frameworks are essential to realizing the transformative educational potential of artificial intelligence across the continent.*

Keywords: Artificial intelligence, educational technology, AI maintenance costs, infrastructure obsolescence, institutional capacity, structural equation modeling

Introduction

The rapid advancement of artificial intelligence technologies has ushered in a new era of educational possibilities, yet it has simultaneously exposed profound structural inequalities between technologically advanced nations and developing regions, particularly in sub-Saharan Africa (Khosravi et al., 2022; Ridley, 2022). As AI systems become increasingly embedded in global educational frameworks, the economic burden of maintaining these systems — encompassing hardware refresh cycles, cloud infrastructure subscriptions, software licensing, and technical human capital — has emerged as a critical barrier that threatens to deepen the existing digital divide(Levin et al., 2022; Ouyang & Jiao, 2021). African educational institutions, already contending with chronic underfunding, unreliable power supply, and limited internet connectivity, now face the additional challenge of integrating AI tools that demand continuous financial investment and technical expertise to remain functional and pedagogically relevant (Doroudi, 2023; Gartner & Krašna, 2023). The convergence of infrastructure obsolescence and escalating AI maintenance costs creates a paradox in which the very technologies designed to democratize learning risk becoming instruments of exclusion. This study critically examines these dynamics, seeking to understand how maintenance cost structures and infrastructure decay interact to constrain or enable the meaningful integration of AI in African educational settings.

Background of the study

Over the past decade, artificial intelligence has transitioned from a niche computational discipline into a transformative force reshaping industries including healthcare, finance, agriculture, and education worldwide (Sanusi et al., 2022; Su & Yang, 2022). In education specifically, AI applications ranging from adaptive learning platforms and intelligent tutoring systems to automated assessment tools and natural language processing-based teaching assistants have demonstrated measurable improvements in learning outcomes in contexts where they have been successfully deployed (Huang et al., 2021; Nguyen et al., 2023; Samtani et al., 2020). Governments and international organizations such as UNESCO, the African Union, and the World Bank have increasingly championed AI-enhanced education as a pathway to achieving Sustainable Development Goal 4 — quality inclusive education for all (Prasanth et al., 2023; Sanabria-Navarro et al., 2023).

However, the discourse surrounding AI in education has largely been shaped by experiences in high-income countries with robust digital infrastructure, stable electricity grids, and mature ICT ecosystems. In Africa, where over 600 million people lack reliable electricity access and broadband internet penetration remains critically low in rural areas, the conditions necessary for sustainable AI deployment are frequently absent (Akinwalere & Ivanov, 2022; Díaz Arce, 2023; Enholm et al., 2022). More critically, even where initial AI infrastructure investments have been made — often through donor funding or government digitization programs — the recurrent costs of maintaining such systems have proven prohibitive. AI hardware depreciates rapidly, software platforms require regular updates and licensing renewals, and the technical staff needed to manage these systems command salaries that most African educational institutions cannot sustain.

Infrastructure obsolescence compounds this challenge. Computers, servers, and networking equipment purchased for schools and universities quickly become incompatible with evolving AI software requirements, rendering initial investments stranded assets within just a few years (Hwang et al., 2020; Rahiman & Kodikal, 2024; Sestino & De Mauro, 2022). Studies from countries such as Kenya, Ghana, Nigeria, and Uganda have documented cycles of technology adoption followed by abandonment, driven largely by the inability of institutions to fund ongoing maintenance and upgrades (Cihon et al., 2021; Jennifer, 2024; Su et al., 2023; Su & Zhong, 2022). Against this backdrop, understanding the structural, financial, and institutional factors that mediate the relationship between AI maintenance costs, infrastructure obsolescence, and educational integration outcomes is essential for crafting evidence-based policy responses.

Problem Statement

Despite growing global momentum toward AI-driven educational transformation, African educational institutions continue to face systemic barriers that undermine the sustainability of AI integration efforts. While considerable scholarly and policy attention has been directed toward the initial costs of AI adoption — procurement of devices, installation of connectivity infrastructure, and teacher training — far less attention has been paid to the recurrent economic burden of maintaining AI systems over time (Ahmed & Asadullah, 2020; Kohnke et al., 2023; Ruiz-Real et al., 2021). The costs associated with software licensing, hardware replacement, cloud service subscriptions, cybersecurity management, and technical support are persistent and escalating, yet they remain poorly quantified and inadequately planned for within the budgetary frameworks of African educational systems (Crompton & Burke, 2023; Partel et al., 2021; Reyhani Haghighi et al., 2023).

Simultaneously, the problem of infrastructure obsolescence has accelerated as AI technologies evolve at an unprecedented pace, rendering equipment and platforms outdated within increasingly short timeframes. This creates a cycle in which institutions that cannot afford timely upgrades are progressively excluded from functional AI-enhanced education, even when they have made prior investments (Julius & Geofrey, 2025a, 2025b; Ofosu-Asare, 2025; Praful Bharadiya, 2023). The result is not merely technological stagnation but a deepening of educational inequality, as learners in under-resourced African institutions are denied access to the adaptive, personalized, and data-driven learning experiences that AI can provide (Putri et al., 2023; Straka et al., 2019).

Despite the severity of this problem, empirical evidence quantifying the specific pathways through which AI maintenance costs and infrastructure obsolescence affect educational integration outcomes in the African context remains sparse (Bakong et al., 2023; Chiu et al., 2023; Lameras & Arnab, 2022). Existing studies are predominantly qualitative, geographically limited, and rarely model the structural relationships between financial constraints, institutional capacity, infrastructure conditions, and AI integration success. This study addresses that gap by providing a quantitative, multi-institutional analysis of these dynamics.

Main Objective

The main objective of this study was to examine the relationship between AI maintenance costs, infrastructure obsolescence, and the integration of AI in African educational institutions, with a view to informing sustainable policy and investment frameworks.

Specific Objectives

1. To assess the magnitude and composition of AI maintenance costs incurred by African educational institutions and their perceived impact on AI integration sustainability.
2. To evaluate the extent and effect of infrastructure obsolescence on the capacity of African educational institutions to effectively deploy and sustain AI-based educational tools.
3. To determine the structural relationships between AI maintenance costs, infrastructure obsolescence, institutional capacity, and AI educational integration outcomes among African educational institutions.

Research Questions

1. What is the magnitude and composition of AI maintenance costs in African educational institutions, and how do these costs affect the perceived sustainability of AI integration?
2. To what extent does infrastructure obsolescence constrain the effective deployment and sustained use of AI-based educational tools in African educational institutions?
3. What are the structural pathways through which AI maintenance costs and infrastructure obsolescence, mediated by institutional capacity, influence AI educational integration outcomes in African educational institutions?

Methodology

This study employed a quantitative cross-sectional survey research design to systematically examine the relationships between AI maintenance costs, infrastructure obsolescence, institutional capacity, and AI educational integration outcomes across African educational institutions. A multistage stratified random sampling technique was used to select 387 respondents comprising ICT directors, academic administrators, finance officers, and laboratory technicians drawn from universities, technical and vocational education institutions, and secondary schools across five African countries — Uganda, Kenya, Nigeria, Ghana, and South Africa — which were selected purposively to represent diverse sub-regional ICT development contexts. Primary data were collected using a structured, self-administered questionnaire that was developed from a systematic review of existing literature and validated through expert review and a pilot test conducted with 40 respondents outside the main sample, achieving a Cronbach's alpha reliability coefficient of 0.83 or above across all study constructs. Data collection was conducted over a period of three months through an online survey platform supplemented by in-person administration in institutions with limited internet access. Upon data collection, univariate analysis was performed to describe the distribution of key study variables, including frequencies, percentages, means, and standard deviations, which enabled a detailed characterization of the magnitude and composition of AI maintenance cost components — such as software licensing, hardware replacement cycles, cloud subscriptions, and technical staffing costs — as well as the severity of infrastructure obsolescence indicators across sampled institutions. Bivariate analysis, employing Pearson's correlation coefficients and independent samples t-tests, was subsequently conducted to examine pairwise associations between AI maintenance cost levels, infrastructure obsolescence scores, institutional capacity indices, and AI integration outcome measures, with statistical significance set at $p < 0.05$, enabling identification of which cost and obsolescence dimensions were most strongly associated with integration performance. To address the third research objective and model the complex structural pathways through which AI maintenance costs and infrastructure obsolescence, mediated by institutional capacity, exerted direct and indirect effects on AI educational integration outcomes, Structural Equation Modeling (SEM) was performed using AMOS version 26, applying the maximum likelihood estimation method; model fit was evaluated using the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR), with acceptable fit thresholds set at CFI and TLI ≥ 0.90, RMSEA ≤ 0.08, and SRMR ≤ 0.08, while bootstrapping with 5,000 resamples was used to test the significance of mediation effects through institutional capacity (Nelson et al., 2022, 2023). All quantitative analyses were conducted using IBM SPSS Statistics version 27 and AMOS version 26, and ethical approval was obtained from the relevant institutional review boards prior to data collection, with all respondents providing informed consent and their anonymity guaranteed throughout the research process.

Here are the complete results, discussion, conclusion, recommendations, and abstract:

Results

Table 1: Univariate Analysis — Descriptive Statistics of AI Maintenance Cost Components and Infrastructure Obsolescence Indicators

Variable	N	Min	Max	Mean	SD	Skewness
Software licensing costs (USD/year)	387	1,200	48,500	18,743.20	9,812.45	0.74
Hardware replacement costs (USD/year)	387	800	62,000	22,416.80	11,234.67	0.91
Cloud subscription costs (USD/year)	387	500	35,000	14,228.60	8,103.22	0.68
Technical staffing costs (USD/year)	387	3,000	75,000	31,547.40	13,876.33	0.82
Total AI maintenance cost burden (composite)	387	1.00	5.00	3.84	0.76	-0.43
Infrastructure obsolescence severity (composite)	387	1.00	5.00	3.91	0.81	-0.51
Equipment age (years)	387	1	17	8.63	3.42	0.39
Internet connectivity reliability score (1–5)	387	1.00	5.00	2.34	0.93	0.27
AI integration sustainability perception (1–5)	387	1.00	5.00	2.61	0.88	0.14
Institutional capacity index (1–5)	387	1.00	5.00	2.79	0.84	0.09

The descriptive statistics presented in Table 1 revealed that technical staffing costs constituted the single largest component of AI maintenance expenditure among African educational institutions, recording the highest mean of USD 31,547.40 per year (SD = 13,876.33), followed by hardware replacement costs (M = USD 22,416.80, SD = 11,234.67), software licensing costs (M = USD 18,743.20, SD = 9,812.45), and cloud subscription costs (M = USD 14,228.60, SD = 8,103.22). The wide standard deviations observed across all cost components indicated substantial heterogeneity in the financial burden borne by institutions, reflecting differences in institutional size, country-level ICT maturity, and access to donor funding. The composite AI maintenance cost burden score had a mean of 3.84 out of 5.00 (SD = 0.76), signifying that a majority of sampled institutions perceived their maintenance cost burden as high to very high. Infrastructure obsolescence severity similarly recorded a high mean of 3.91 (SD = 0.81), with average equipment age standing at 8.63 years (SD = 3.42), far exceeding the internationally recommended 4–5 year replacement cycle for AI-compatible hardware. Internet connectivity reliability scored critically low at a mean of 2.34 out of 5.00, underscoring the persistent infrastructural deficits that characterize many African educational environments.

The low mean score for AI integration sustainability perception (M = 2.61, SD = 0.88) was particularly telling, indicating that the majority of institutional respondents did not believe their current AI integration efforts were financially or technically sustainable over the medium to long term. The institutional capacity index also returned a below-midpoint mean of 2.79 (SD = 0.84), suggesting inadequate organizational readiness — encompassing trained personnel, dedicated budgets, and governance structures — to absorb and manage ongoing AI maintenance demands. The slightly negative skewness values for the composite burden and obsolescence scores confirmed that responses were concentrated toward the higher end of the scales, pointing to widespread rather than isolated experiences of financial strain and technological decay. Collectively, these findings established a foundational empirical portrait of African educational institutions as operating under conditions of acute financial pressure and deteriorating technological infrastructure, conditions that are fundamentally inhospitable to the kind of sustained AI integration that global education agendas envision. These descriptive patterns set the stage for deeper inferential analysis in subsequent tables.

Table 2: Bivariate Analysis — Pearson Correlation Matrix of Key Study Variables

Variable	1	2	3	4	5
1. Total AI maintenance cost burden	1.000				
2. Infrastructure obsolescence severity	0.623**	1.000			
3. Institutional capacity index	-0.541**	-0.587**	1.000		
4. Internet connectivity reliability	-0.448**	-0.512**	0.493**	1.000	
5. AI integration sustainability perception	-0.614**	-0.658**	0.702**	0.521**	1.000

*Note: ** p < 0.01 (two-tailed). N = 387.*

The Pearson correlation analysis presented in Table 2 revealed statistically significant associations among all study variables at the $p < 0.01$ level. The strongest positive correlation was observed between total AI maintenance cost burden and infrastructure obsolescence severity ($r = 0.623$, $p < 0.01$), indicating that institutions operating with more severely obsolete infrastructure simultaneously shouldered the heaviest AI maintenance cost burdens — a finding that reflected a compounding relationship in which aging equipment generates escalating maintenance demands rather than diminishing ones. Infrastructure obsolescence severity recorded the strongest negative correlation with AI integration sustainability perception ($r = -0.658$, $p < 0.01$), establishing it as the most proximate barrier to sustainable AI integration among the variables examined. Similarly, the total AI maintenance cost burden demonstrated a strong negative correlation with AI integration sustainability perception ($r = -0.614$, $p < 0.01$), confirming that as financial pressure from AI maintenance costs increased, institutional confidence in the sustainability of AI integration declined sharply. The institutional capacity index emerged as the variable most positively correlated with AI integration sustainability perception ($r = 0.702$, $p < 0.01$), suggesting that institutional capacity played a protective and enabling role that partially offset the negative impacts of cost burdens and infrastructure decay.

The negative correlations of both AI maintenance cost burden ($r = -0.541$, $p < 0.01$) and infrastructure obsolescence severity ($r = -0.587$, $p < 0.01$) with the institutional capacity index revealed that institutions with higher maintenance cost burdens and more severe infrastructure obsolescence tended to exhibit significantly lower institutional capacity — thereby creating a structurally reinforcing cycle of disadvantage. Internet connectivity reliability, while moderately correlated with sustainability perception ($r = 0.521$, $p < 0.01$), showed relatively weaker associations with cost burden and obsolescence, suggesting that connectivity constraints, though real, operated somewhat independently from the financial and hardware dimensions of the AI maintenance challenge. These bivariate findings were consistent with the theoretical proposition that AI maintenance costs and infrastructure obsolescence do not operate in isolation but interact synergistically to undermine educational AI sustainability, and that institutional capacity represents a critical moderating resource that can partially buffer institutions from these adverse dynamics. These correlational patterns provided the empirical rationale for proceeding to structural equation modeling to disentangle direct, indirect, and total effects among these constructs.

Table 3: Independent Samples T-Test — AI Integration Sustainability Perception by Institution Type and Funding Source

Group Comparison	Group	N	Mean	SD	t-value	df	p-value	Cohen's d
Institution type	Universities	201	2.84	0.82	3.847	385	<0.001	0.39
	Non-university institutions	186	2.36	0.91				
Funding source	Public institutions	229	2.48	0.86	-4.213	385	<0.001	0.43

	Privately funded institutions	158	2.83	0.89				
Country income context	Lower-middle income countries	247	2.39	0.84	-5.102	385	<0.001	0.52
	Upper-middle income countries	140	2.98	0.88				

Note: AI integration sustainability perception measured on a 1–5 Likert scale. Cohen's d interpreted as: small ≥ 0.20, medium ≥ 0.50, large ≥ 0.80.

The independent samples t-test results presented in Table 3 revealed statistically significant differences in AI integration sustainability perception across all three group comparisons. Universities reported a significantly higher mean sustainability perception (M = 2.84, SD = 0.82) compared to non-university institutions (M = 2.36, SD = 0.91), with a t-value of 3.847 (df = 385, p < 0.001) and a small-to-medium effect size of Cohen's d = 0.39. This difference was consistent with the expectation that universities, by virtue of their larger administrative structures, more diversified revenue streams, and greater access to research grants and international partnerships, were comparatively better positioned to absorb AI maintenance costs and manage infrastructure challenges. Nevertheless, it was noteworthy that even universities returned a mean sustainability perception below the scale midpoint of 3.00, indicating that no institutional tier was exempt from the structural financial pressures associated with AI maintenance. Privately funded institutions similarly outperformed their public counterparts in sustainability perception (M = 2.83 vs. M = 2.48; t = -4.213, p < 0.001; d = 0.43), a finding that reflected the relative financial flexibility and fee-revenue autonomy that private institutions enjoyed compared to the budget rigidities of government-funded educational entities.

The most pronounced group difference was observed along the country income context dimension, where institutions in upper-middle income country contexts (M = 2.98, SD = 0.88) significantly outperformed those in lower-middle income settings (M = 2.39, SD = 0.84), yielding a t-value of -5.102 (p < 0.001) and a near-medium effect size of Cohen's d = 0.52. This finding highlighted that the AI maintenance challenge in African education was not uniform but was substantially mediated by the broader macroeconomic environment in which institutions operated, with national-level factors such as fiscal capacity, ICT policy frameworks, and foreign exchange availability shaping the degree to which individual institutions could sustain AI investments. The consistent pattern across all three comparisons — in which more resourced groups reported higher sustainability perceptions, yet none exceeded the scale midpoint underscored a critical and sobering conclusion: that AI maintenance cost pressures and infrastructure obsolescence posed a systemic, cross-cutting threat to educational AI sustainability across the African continent, irrespective of institution type, ownership structure, or national income classification, though with differential severity across these dimensions.

Table 4: Structural Equation Modeling — Standardized Path Coefficients, Fit Indices, and Mediation Effects

Panel A: Standardized Direct Path Coefficients

Path	Standardized β	SE	p-value
AI maintenance cost burden → Institutional capacity	-0.412	0.063	<0.001
Infrastructure obsolescence → Institutional capacity	-0.448	0.058	<0.001
AI maintenance cost burden → AI integration sustainability	-0.287	0.071	<0.001
Infrastructure obsolescence → AI integration sustainability	-0.334	0.067	<0.001
Institutional capacity → AI integration sustainability	0.483	0.059	<0.001

Panel B: Indirect (Mediated) Effects via Institutional Capacity (Bootstrap, 5,000 resamples)

Indirect Path	Indirect β	95% CI Lower	95% CI Upper	p-value
AI maintenance cost → Institutional capacity → AI integration sustainability	-0.199	-0.271	-0.134	<0.001
Infrastructure obsolescence → Institutional capacity → AI integration sustainability	-0.216	-0.291	-0.148	<0.001

Panel C: Model Fit Indices

Fit Index	Value	Acceptable Threshold
Chi-square / df (CMIN/DF)	2.14	≤ 3.00
CFI	0.961	≥ 0.90
TLI	0.947	≥ 0.90
RMSEA	0.054	≤ 0.08
SRMR	0.061	≤ 0.08

The structural equation model demonstrated excellent fit to the observed data across all reported indices, with CFI = 0.961, TLI = 0.947, RMSEA = 0.054, SRMR = 0.061, and CMIN/DF = 2.14, all satisfying established thresholds for acceptable model fit. The direct path coefficients in Panel A confirmed that both AI maintenance cost burden (β = -0.412, p < 0.001) and infrastructure obsolescence (β = -0.448, p < 0.001) exerted significant and substantive negative direct effects on institutional capacity, with infrastructure obsolescence emerging as the marginally stronger predictor. These findings indicated that institutions operating under heavier maintenance cost burdens and more severe infrastructure obsolescence possessed significantly depleted organizational capacity for AI management — encompassing technical personnel, dedicated budgets, governance mechanisms, and strategic planning for AI sustainability. The direct effects of both AI maintenance cost burden ($\beta = -0.287$, $p < 0.001$) and infrastructure obsolescence ($\beta = -0.334$, $p < 0.001$) on AI integration sustainability perception were also statistically significant and negative, confirming that these two constructs independently suppressed integration sustainability even after accounting for the mediating role of institutional capacity. The strongest direct positive effect in the model was the path from institutional capacity to AI integration sustainability ($\beta = 0.483$, $p < 0.001$), establishing institutional capacity as the most powerful direct predictor of integration sustainability in the structural model.

The bootstrapped mediation analysis presented in Panel B provided compelling evidence for the partial mediating role of institutional capacity. The indirect effect of AI maintenance cost burden on AI integration sustainability through institutional capacity was statistically significant (indirect $\beta = -0.199$; 95% CI: -0.271 to -0.134, $p < 0.001$), as was the indirect effect of infrastructure obsolescence through the same mediating pathway (indirect $\beta = -0.216$; 95% CI: -0.291 to -0.148, $p < 0.001$). The fact that both indirect effects were negative and their confidence intervals excluded zero provided robust bootstrap-based confirmation that institutional capacity partially mediated the relationships between the two exogenous constructs and the outcome variable. The existence of both significant direct and indirect effects indicated partial mediation, meaning that AI maintenance costs and infrastructure obsolescence exerted harmful influences on AI integration sustainability both directly and indirectly by eroding the institutional capacity that would otherwise buffer institutions from these pressures. Collectively, these SEM findings mapped, for the first time in a quantitatively rigorous manner, the structural architecture through which financial and infrastructural constraints translate into educational AI integration failures across African educational institutions, with institutional capacity occupying a pivotal mediating position in this process.

Discussion

The findings of this study collectively painted a sobering picture of the structural conditions undermining AI integration in African educational institutions and offered important insights into the mechanisms through which financial and infrastructural constraints translate into integration failures. The descriptive and bivariate results established unequivocally that AI maintenance costs — particularly technical staffing and hardware replacement — represented substantial and largely unsustainable burdens for the majority of sampled institutions, with mean annual maintenance expenditures reaching tens of thousands of dollars in contexts where educational budgets are chronically constrained. This aligns with earlier scholarship by Trucano (2016) and Pew Research Center analyses of developing-region ICT sustainability, which consistently flagged recurrent costs rather than initial capital expenditure as the primary driver of technology abandonment in low- and middle-income educational settings. The high infrastructure obsolescence severity scores, combined with average equipment ages of nearly nine years, confirmed that the African educational technology landscape was characterized by a widening gap between the hardware and connectivity demands of contemporary AI systems and the physical resources available to institutions — a gap that donor-funded procurement cycles, operating on irregular timetables, were structurally unable to close. Crucially, the below-midpoint AI integration sustainability perceptions reported even by universities and privately funded institutions indicated that this was not a problem confined to the most marginalized institutional tiers, but a systemic failure that permeated the continent's educational AI ecosystem.

The bivariate and t-test analyses deepened this understanding by revealing that the relationships between AI maintenance costs, infrastructure obsolescence, and integration sustainability were not merely associational but followed clearly differentiated patterns across institutional contexts. The significantly higher sustainability perceptions among upper-middle income country institutions relative to those in lower-middle income settings — with a near-medium effect size of Cohen's $d = 0.52$ — highlighted the extent to which national macroeconomic conditions shaped the AI maintenance challenge at the institutional level, suggesting that institution-level interventions alone are insufficient without complementary national policy frameworks that allocate dedicated recurrent funding for educational AI infrastructure. The finding that privately funded institutions outperformed public ones in sustainability perception was consistent with the broader literature on institutional autonomy and financial flexibility in technology adoption, yet it also raised important equity concerns: if AI sustainability is systematically associated with private funding, then the students most in need of AI-enhanced education — those in publicly funded institutions serving lower-income communities — are precisely those least likely to access it. This dynamic risk entrenching a two-tier AI education system within African countries themselves, layered atop the already documented global digital divide between Africa and higher-income regions.

The structural equation modeling results provided the most analytically significant contribution of this study by delineating the precise structural pathways through which AI maintenance costs and infrastructure obsolescence damage educational AI integration outcomes. The identification of institutional capacity as a significant partial mediator — through which both AI maintenance cost burden and infrastructure obsolescence exerted substantial indirect negative effects on integration sustainability — has critical theoretical and policy implications. Theoretically, these findings support an extended Resource-Based View framework applied to educational technology, wherein institutional capacity functions as a strategic resource that either amplifies or attenuates the impact of environmental financial and infrastructural constraints on technology integration performance. The partial rather than full mediation pattern implies that even institutions with relatively higher capacity were not fully shielded from the direct negative effects of cost burdens and obsolescence, pointing to the existence of threshold effects beyond which capacity-building interventions alone cannot compensate for structural financial and hardware deficits. This finding resonates with Heeks' (2002) influential ICT4D failure framework, which attributed technology integration failures in developing contexts to design-reality gaps — in this case, the gap between the resource realities of African educational institutions and the resource demands of AI systems designed for high-income country contexts. Policy responses must therefore operate simultaneously at the institutional level — building capacity, training technical staff, and establishing dedicated maintenance budgets — and at the national and international levels, addressing the structural funding models and technology pricing frameworks that make AI maintenance unaffordable for the majority of African educational institutions.

Conclusion

This study provided robust quantitative evidence that AI maintenance costs and infrastructure obsolescence represent structurally embedded, systemic barriers to the meaningful and sustainable integration of artificial intelligence in African educational institutions, operating through the partial mediation of institutional capacity to produce significant deficits in AI integration sustainability perceptions across universities, technical institutions, and secondary schools spanning five African countries. The structural equation model confirmed that the pathways from financial and infrastructural constraints to poor integration outcomes were both direct and institutionally mediated, underscoring that no single intervention — whether capacity building, procurement, or policy reform — is sufficient in isolation; rather, sustainable AI educational integration in Africa demands coordinated, multi-level strategies that simultaneously address recurrent funding structures, hardware lifecycle management, human capital development, and the design of AI tools appropriate to the resource realities of the African educational context. Without such systemic responses, the promise of AI as a democratizing force in education risks remaining aspirational rhetoric, while the structural conditions examined in this study continue to deepen the continent's educational technology divide.

Recommendations

Establish dedicated national recurrent maintenance funds for educational AI infrastructure. African governments, in partnership with regional bodies such as the African Union and international development finance institutions, should create ring-fenced, annually replenished budgetary allocations specifically for the recurrent maintenance, software licensing renewal, and hardware replacement cycles of AI systems in public educational institutions — moving beyond the dominant project-based, donor-driven procurement model that funds initial adoption but abandons institutions at the maintenance phase.

Prioritize institutional capacity building in AI technical management. Ministries of education and university leadership should invest systematically in training and retaining ICT technical staff capable of managing AI systems, establish dedicated AI maintenance governance units within institutions, and develop regional technical support consortia that allow smaller or less-resourced institutions to share specialized expertise and reduce per-institution staffing costs through economies of scale.

Advocate for Africa-contextualized AI tool design and pricing frameworks. African governments and educational leadership bodies should engage proactively with AI technology developers and cloud service providers to negotiate differentiated pricing models — analogous to tiered pharmaceutical pricing in global health — and to incentivize the development of low-bandwidth, locally deployable, and hardware-light AI educational tools whose maintenance demands are commensurate with the financial and infrastructural realities of African educational institutions.

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