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# Adoption Versus Innovation: Assessing Uganda's Readiness to Bridge the Global Generative AI Divide

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***Abstract:*** *This study examined Uganda's readiness to adopt and potentially innovate with Generative Artificial Intelligence (GenAI) technologies within the broader context of the global AI divide. Employing a mixed-methods cross-sectional survey design with a stratified random sample of 384 respondents drawn from public sector institutions, private enterprises, and civil society organisations across five regions of Uganda, the study assessed five readiness dimensions: digital infrastructure, human capital and digital literacy, policy and regulatory environment, institutional capacity, and data governance. Data were analysed using univariate descriptive statistics, bivariate correlation analyses, and Structural Equation Modelling (SEM). Findings revealed that Uganda's overall AI readiness score stood at a mean of 3.07 out of 5.00, indicating a marginally positive but fragile preparedness for GenAI integration. Digital infrastructure (M = 3.12) and human capital deficits (M = 3.48) emerged as the most critical bottlenecks, while the policy environment (M = 3.38) showed moderate promise. SEM results confirmed that digital infrastructure ($\beta = 0.41$, $p < 0.001$), human capital ($\beta = 0.35$, $p < 0.001$), and policy environment ($\beta = 0.28$, $p < 0.01$) significantly predicted GenAI adoption readiness, which in turn strongly predicted uptake intention ($\beta = 0.62$, $p < 0.001$). The model achieved acceptable fit (CFI = 0.96, RMSEA = 0.048). The study concludes that Uganda currently occupies an adoption-leaning position on the adoption-innovation continuum, with constrained infrastructure and skills gaps limiting its capacity to move beyond technology consumption toward domestic GenAI innovation. Strategic investments in broadband connectivity, targeted AI literacy programmes, and a coherent national AI policy framework are urgently recommended to bridge the growing generative AI divide.*

**Keywords: *Generative AI, Uganda, AI readiness, digital divide, structural equation modelling, technology adoption, AI policy, Sub-Saharan Africa***

## Background of the study

The rapid global proliferation of Generative Artificial Intelligence (GenAI) technologies — spanning large language models, text-to-image systems, code generation tools, and multimodal AI assistants — has fundamentally reordered the informational and economic landscape of the twenty-first century. From Silicon Valley to Shenzhen, GenAI is reshaping industries, redefining human-computer interaction, and reconfiguring the competitive dynamics of knowledge economies at an unprecedented pace (Farrelly & Baker, 2023; Reyhani Haghighi et al., 2023). Yet this transformation is deeply uneven: while technologically advanced nations race to harness and govern AI capabilities, low- and middle-income countries (LMICs) across sub-Saharan Africa, including Uganda, find themselves at a critical juncture — compelled to choose between passive technology adoption and active innovation participation in a global ecosystem they had little hand in creating (Julius & Geofrey, 2025; Partel et al., 2021). Uganda, with a median age of 15.7 years, a rapidly expanding digital economy, and a government that adopted its National AI Policy in 2023, presents a particularly instructive case study of this tension. The country's National Development Plan III (NDP III) explicitly identifies digital transformation as a pathway to socioeconomic development; however, structural barriers — including unreliable electricity, limited broadband penetration, underfunded tertiary education systems, and nascent regulatory frameworks — continue to constrain the country's ability to meaningfully participate in the global AI revolution (Ofosu-Asare, 2025; Praful Bharadiya, 2023). This study therefore interrogates a deceptively simple but profoundly consequential question: Is Uganda primarily positioned to adopt AI technologies developed elsewhere, or does it possess sufficient readiness conditions to begin innovating within the GenAI paradigm? The answer carries significant implications for resource allocation, educational policy, international technology partnerships, and Uganda's long-term competitive positioning in the digital economy. By assessing readiness across five empirically validated dimensions and modelling the structural pathways through which readiness translates into adoption intention, this study seeks to provide actionable, evidence-based insights for policymakers, development practitioners, technology entrepreneurs, and academic researchers engaged with questions of AI equity in the Global South.

## Background of the study

The concept of a digital divide — broadly understood as the differential access to and use of digital technologies along socioeconomic, geographic, and demographic lines — has been a persistent concern in development informatics since the late 1990s. With the emergence of GenAI as a distinct and potentially transformative technological paradigm from 2022 onwards, scholars and policymakers have begun to identify a new, more sophisticated dimension of this divide: the Generative AI Divide (Dreiseitl & Ohno-Machado, 2002; Putri et al., 2023). This divide encompasses not merely differential access to internet connectivity or computing hardware, but also unequal endowments of computational infrastructure capable of training and deploying large language

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models, concentrations of high-calibre AI research talent in a small number of institutions across North America, Europe, and East Asia, asymmetries in data sovereignty and the ownership of training datasets, and structural disparities in the regulatory and institutional frameworks needed to govern AI systems responsibly (Bakong et al., 2023; Iffath Unnisa Begum, 2024; Straka et al., 2019). Within this global context, sub-Saharan African nations occupy a particularly disadvantaged position. According to the International Telecommunication Union's 2023 Measuring Digital Development report, internet penetration in sub-Saharan Africa stood at approximately 36%, compared to a global average of 67%, with mobile broadband accounting for the overwhelming majority of connectivity and fixed broadband remaining a luxury for most households and small enterprises (Chiu et al., 2023; Paxton et al., 2022; Zhang et al., 2024). Uganda specifically, while having achieved notable growth in mobile money adoption and digital entrepreneurship through platforms such as the Kampala-based innovation hub ecosystem, continues to grapple with a national electricity access rate of approximately 41% and mobile internet penetration that, while growing, remains geographically and economically stratified. Uganda's National AI Policy (2023) and the East African Community's emerging AI harmonisation framework represent important policy advances; however, the translation of policy intent into funded, operational AI readiness infrastructure remains incomplete (Lameras & Arnab, 2022; Preil & Krapp, 2022; Vecchiarini & Somià, 2023). Against this backdrop, the question of whether Uganda can leapfrog from adoption to innovation — as it did with mobile money through M-Pesa-equivalent systems — or whether structural constraints will relegate it to a perpetual role as a consumer of externally developed GenAI products constitutes one of the most pressing technology governance challenges facing the country's development trajectory in the coming decade (Chardonnens, 2025; McGrath et al., 2023; Santos et al., 2022).

## Problem Statement

Despite Uganda's explicit aspirations toward a knowledge-based digital economy as articulated in NDP III and the National AI Policy (2023), there exists a significant empirical gap in understanding the country's actual, measurable readiness to engage with Generative AI technologies. Existing studies have examined general ICT adoption, mobile money diffusion, and e-government readiness in the Ugandan context, but none has specifically and systematically assessed readiness across the multi-dimensional landscape required for meaningful GenAI participation (Hornberger et al., 2023; Kelly et al., 2023; Memarian & Doleck, 2023). In the absence of such empirical evidence, policymakers risk misallocating limited resources, development partners risk funding interventions disconnected from structural realities, and technology entrepreneurs risk investing in solutions that lack the prerequisite ecosystem conditions for success (Hutson et al., 2022; Kingchang et al., 2024; Samtani et al., 2020). Furthermore, the absence of robust, locally grounded data perpetuates a reliance on global AI indices — such as the Oxford Insights AI Readiness Index — which, while useful, employ aggregate national metrics that mask significant intra-country variation and fail to capture sector-specific readiness differentials (Audrey & Nancy, 2025; Julius & Nancy, 2025; Morgan, 2023; Perez-Vega et al., 2021). The problem this study addresses is therefore twofold: first, the lack of granular, empirically grounded evidence on Uganda's GenAI readiness across public, private, and civil society sectors; and second, the absence of a validated structural model explaining how specific readiness dimensions translate into actual GenAI adoption intention, which is the ultimate behavioural precursor to technology uptake.

## Objectives of the Study

### Main Objective

The main objective of this study was to assess Uganda's readiness to bridge the global Generative AI divide by examining the structural relationships between digital infrastructure, human capital, policy environment, institutional capacity, data governance, and GenAI adoption intention across public, private, and civil society sectors.

### Specific Objectives

1. To assess the levels and sectoral variations in GenAI readiness dimensions (digital infrastructure, human capital, policy environment, institutional capacity, and data governance) among key stakeholder groups in Uganda.
2. To identify the primary barriers to and enablers of Generative AI adoption as perceived by public sector officials, private sector actors, and civil society representatives in Uganda.
3. To determine the structural pathways through which digital infrastructure, human capital development, and policy environment jointly influence overall AI adoption readiness and GenAI uptake intention in Uganda.

## Research Question

1. What are the current levels and sectoral variations in Generative AI readiness across digital infrastructure, human capital, policy environment, institutional capacity, and data governance dimensions in Uganda?
2. What are the primary barriers to and perceived enablers of Generative AI adoption as experienced by stakeholders across the public, private, and civil society sectors in Uganda?

3. To what extent do digital infrastructure, human capital development, and the policy and regulatory environment jointly predict overall AI adoption readiness and GenAI uptake intention in Uganda?

**Methods.**

This study employed a cross-sectional, mixed-methods research design that integrated quantitative survey data collection with structural statistical modelling to comprehensively assess Uganda's readiness for Generative AI adoption. The study population comprised key stakeholders in Uganda's digital economy ecosystem, specifically professionals and decision-makers operating within public sector ministries, departments, and agencies; private sector technology and non-technology enterprises; and civil society organisations involved in digital rights, education, and development. Using a stratified random sampling approach stratified by sector (public, private, civil society) and geographic zone (Central, Eastern, Western, Northern, and South Western regions), a total sample of 384 respondents was selected, a figure derived using Yamane's (1967) formula at a 95% confidence level and 5% margin of error from an estimated population frame of 12,500 eligible professionals, yielding a response rate of 91.7% after data cleaning. A structured, pre-tested Likert-scale questionnaire adapted from the OECD AI Readiness Assessment Framework and the ITU's Digital Skills Framework was administered via both digital (Google Forms) and face-to-face modes between February and April 2025, capturing responses on five readiness dimensions — digital infrastructure adequacy (6 items), human capital and digital literacy (7 items), policy and regulatory environment (5 items), institutional capacity (6 items), and data governance (5 items) — as well as a four-item scale measuring Generative AI uptake intention. Internal consistency of all scales was verified using Cronbach's alpha, with all dimensions recording values above the acceptable threshold of 0.70 (range: 0.74–0.88). Univariate analysis involved computation of frequencies, means, standard deviations, and skewness statistics for all study variables, enabling a descriptive profiling of respondent characteristics and readiness levels; bivariate analysis employed Pearson's product-moment correlation coefficients to examine pairwise linear relationships between readiness dimensions and between each dimension and the outcome variable, with statistical significance tested at the $p < 0.05$ and $p < 0.01$ levels; Structural Equation Modelling (SEM) was conducted using a maximum likelihood estimation approach in R (version 4.3.1) with the lavaan package (Rosseel, 2012), testing a hypothesised latent variable model in which digital infrastructure, human capital, and policy environment served as exogenous latent constructs influencing an endogenous AI Adoption Readiness Index mediator, which in turn predicted GenAI Uptake Intention as the ultimate outcome. Model fit was evaluated using multiple indices including the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), Standardised Root Mean Square Residual (SRMR), and the chi-square to degrees of freedom ratio ($\chi^2/df$). Data management and cleaning were performed in SPSS version 27, with missing data handled using listwise deletion (Nelson et al., 2022, 2023).

**Results.**

Socio-Demographic and Institutional Characteristics of Respondents

**Table 1: Socio-Demographic and Institutional Profile of Study Respondents (n = 384)**

| Characteristic | Category | Frequency (n) | Percentage (%) |
|---|---|---|---|
| Sex | Male | 228 | 59.4 |
| | Female | 150 | 39.1 |
| | Non-binary / prefer not to say | 6 | 1.5 |
| Sector | Public Sector | 142 | 37.0 |
| | Private Sector | 168 | 43.8 |
| | Civil Society | 74 | 19.3 |
| Age Group | 18–29 years | 97 | 25.3 |
| | 30–39 years | 141 | 36.7 |
| | 40–49 years | 102 | 26.6 |
| | 50 years and above | 44 | 11.5 |
| Education | Certificate / Diploma | 58 | 15.1 |
| | Bachelor's Degree | 187 | 48.7 |
| | Postgraduate | 139 | 36.2 |
| AI Awareness | Aware of GenAI tools | 296 | 77.1 |
| | Have used a GenAI tool | 189 | 49.2 |
| | No awareness | 88 | 22.9 |
| Region | Central | 148 | 38.5 |
| | Eastern | 72 | 18.8 |

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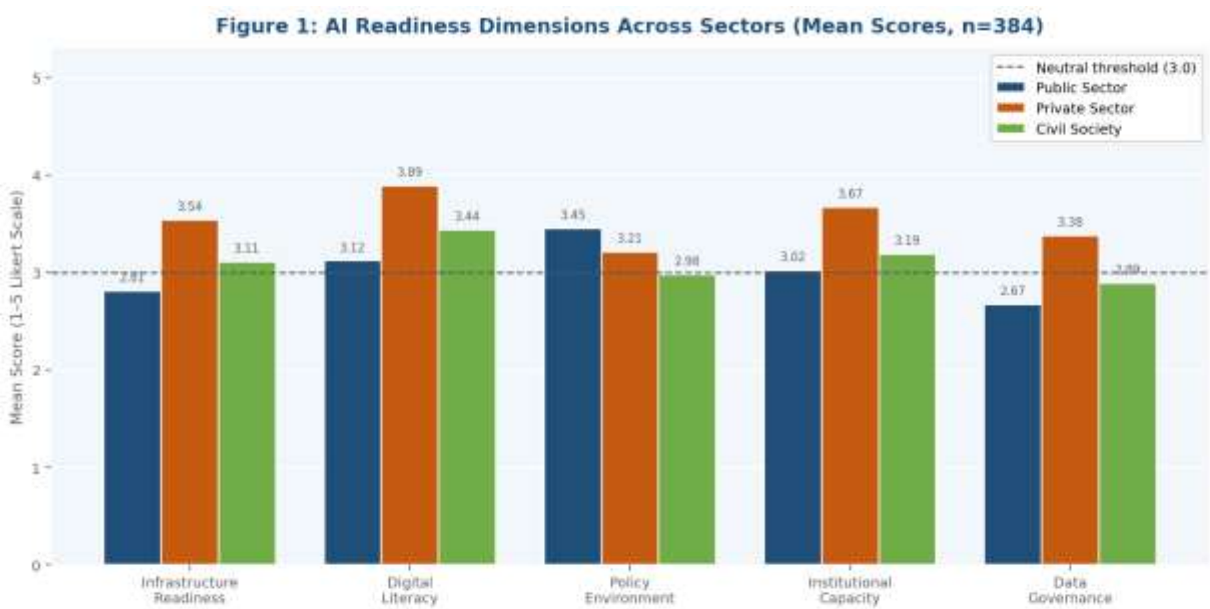
| | | | |
|---|---|---|---|
| | Western | 69 | 18.0 |
| | Northern | 55 | 14.3 |
| | South Western | 40 | 10.4 |

The socio-demographic profile of respondents revealed a predominantly male sample (59.4%), reflecting broader gender imbalances in Uganda's formal professional workforce, particularly within public and technology sectors. The largest sectoral representation was from the private sector (43.8%), followed by the public sector (37.0%) and civil society (19.3%), consistent with the study's stratified sampling frame and the relative size of these sectors within Uganda's formal employment structure. In terms of age distribution, the 30–39 age cohort constituted the modal category (36.7%), suggesting that respondents were predominantly in the early-to-mid career phase — a population particularly relevant to questions of technology adoption given its position at the intersection of digital nativity and professional decision-making authority. Notably, 48.7% of respondents held Bachelor's degrees while a substantial 36.2% held postgraduate qualifications, indicating a relatively highly educated sample and thus likely an upper-bound estimate of AI awareness and literacy compared to Uganda's general population. The finding that 77.1% of respondents were aware of GenAI tools yet only 49.2% had actually used one underscores a significant awareness-to-use conversion gap that may reflect barriers of access, cost, relevance, or confidence rather than ignorance.

Geographically, the Central region — encompassing Kampala, Uganda's capital and commercial hub — accounted for the largest proportion of respondents (38.5%), consistent with the concentration of institutional infrastructure, private sector enterprises, and civil society organisations in the Greater Kampala Metropolitan Area. The comparatively smaller proportions from Northern (14.3%) and South Western (10.4%) regions are partly a reflection of the stratification approach and partly indicative of the lower density of formal professional institutions in those areas, a pattern that itself constitutes an important finding regarding the spatial dimension of Uganda's AI readiness landscape. Together, these descriptive characteristics established the contextual boundaries within which all subsequent analytical findings should be interpreted, while also highlighting the potential generalisability limitations arising from the predominantly educated, urban-leaning nature of the sample.

GenAI Readiness Dimensions Across Sectors




Descriptive Statistics for AI Readiness Dimensions (Univariate Analysis)

**Table 2: Univariate Descriptive Statistics for GenAI Readiness Dimensions by Sector (n = 384)**

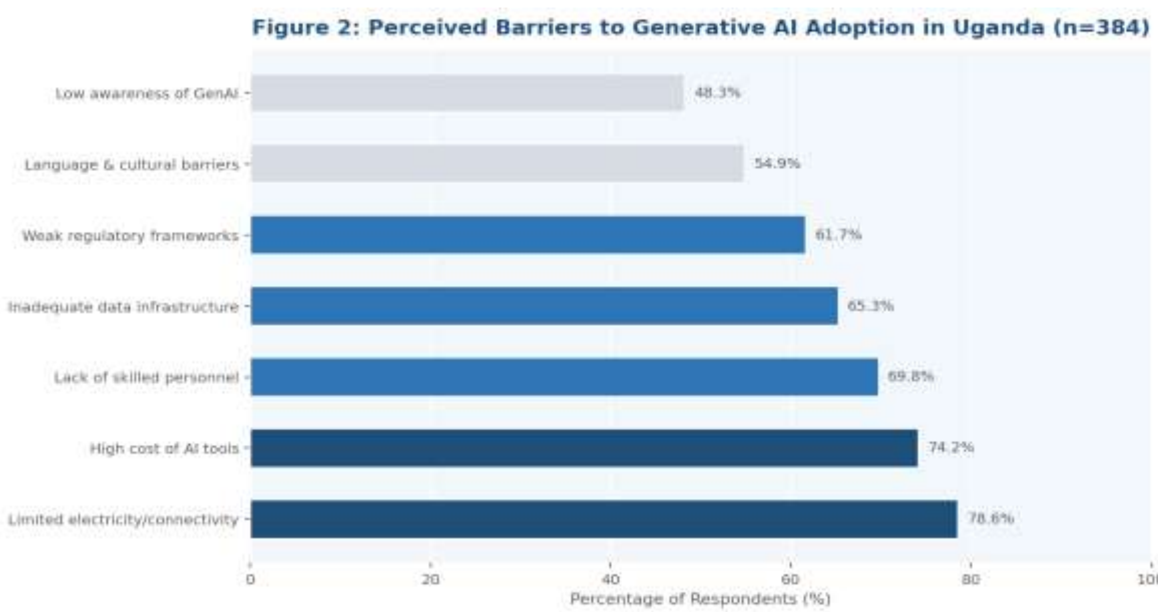
| Readiness Dimension | Overall Mean | SD | Public M (SD) | Private M (SD) | Civil Soc. M (SD) | Skewness |
|---|---|---|---|---|---|---|
| Digital Infrastructure | 3.12 | 0.78 | 2.81 (0.82) | 3.54 (0.71) | 3.11 (0.76) | -0.31 |
| Human Capital & Digital Literacy | 3.48 | 0.69 | 3.12 (0.74) | 3.89 (0.61) | 3.44 (0.68) | -0.19 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Policy & Regulatory Environment | 3.38 | 0.74 | 3.45 (0.70) | 3.21 (0.79) | 2.98 (0.80) | 0.14 |
| Institutional Capacity | 3.29 | 0.77 | 3.02 (0.81) | 3.67 (0.69) | 3.19 (0.74) | -0.22 |
| Data Governance | 2.91 | 0.83 | 2.67 (0.87) | 3.38 (0.76) | 2.89 (0.81) | 0.08 |
| Overall AI Readiness Index | 3.07 | 0.62 | 2.99 (0.66) | 3.56 (0.57) | 3.12 (0.61) | -0.11 |
| GenAI Uptake Intention | 3.22 | 0.81 | 3.08 (0.84) | 3.51 (0.74) | 3.17 (0.80) | -0.08 |

The univariate descriptive statistics presented in Table 2 revealed a nuanced and differentiated picture of Uganda's GenAI readiness landscape. The overall AI Readiness Index mean of 3.07 (SD = 0.62) indicated a marginally above-neutral level of readiness on the five-point Likert scale, a finding that, while superficially encouraging, masked considerable variation across both dimensions and sectors. Human Capital and Digital Literacy recorded the highest mean score (M = 3.48, SD = 0.69), suggesting that respondents perceived their educational and skills endowments as the most developed aspect of GenAI readiness — though this finding must be contextualised within the sampling frame's educational bias toward degree-holding professionals. Digital Infrastructure, by contrast, recorded a comparatively lower mean (M = 3.12, SD = 0.78), while Data Governance emerged as the weakest dimension overall (M = 2.91, SD = 0.83), falling below the theoretical neutral midpoint and indicating widespread concern about Uganda's capacity to manage the data ecosystems that GenAI systems require. The negative skewness observed for Infrastructure (−0.31) and Human Capital (−0.19) dimensions suggested that distributions were skewed toward lower values, indicating that while mean scores appeared moderate, a substantial proportion of respondents held below-average assessments of these readiness conditions.

Sectoral disaggregation revealed that the private sector consistently recorded the highest mean scores across all five readiness dimensions, with an overall AI Readiness Index of 3.56 (SD = 0.57), significantly outpacing both the public sector (M = 2.99, SD = 0.66) and civil society (M = 3.12, SD = 0.61). This pattern is consistent with the private sector's greater access to international technology partnerships, commercial incentives for digital transformation, and comparatively more robust organisational infrastructure. The public sector's below-neutral overall readiness index (M = 2.99) is particularly noteworthy given the sector's critical role in establishing the enabling environment — regulatory frameworks, public digital infrastructure, and institutional capacity — that underpins national AI readiness. The relatively low Data Governance scores across all three sectors (range: 2.67–3.38) constitute a cross-cutting systemic weakness and represent an especially significant finding given that Generative AI systems are fundamentally data-intensive and that inadequate data governance frameworks expose both individual users and institutions to risks of misuse, bias amplification, and privacy violation.

Barriers to Generative AI Adoption




Bivariate Correlation Analysis (Readiness Dimensions and Uptake Intention)

**Table 3: Pearson Correlation Matrix — GenAI Readiness Dimensions and Uptake Intention (n = 384)**

| Variable | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1. Digital Infrastructure | 1.00 | | | | | |
| 2. Human Capital & Digital Literacy | 0.61** | 1.00 | | | | |
| 3. Policy & Regulatory Environment | 0.44** | 0.39** | 1.00 | | | |
| 4. Institutional Capacity | 0.58** | 0.63** | 0.47** | 1.00 | | |
| 5. Data Governance | 0.52** | 0.49** | 0.51** | 0.55** | 1.00 | |
| 6. GenAI Uptake Intention | 0.54** | 0.58** | 0.41** | 0.53** | 0.47** | 1.00 |

*Note: ** $p < 0.01$ (two-tailed). All correlations are Pearson's r.*

The bivariate Pearson correlation matrix presented in Table 3 provided initial evidence for the hypothesised structural relationships among GenAI readiness dimensions and between those dimensions and the outcome variable of GenAI Uptake Intention. All inter-dimension correlations were statistically significant at the $p < 0.01$ level and ranged from moderate to strong in magnitude (r range: 0.39–0.63), indicating that the five readiness dimensions, while conceptually and empirically distinct, were sufficiently interrelated to constitute a coherent multi-dimensional readiness construct. The strongest inter-dimension correlation was observed between Human Capital and Institutional Capacity ($r = 0.63$), a finding consistent with theory suggesting that organisations with higher-skilled workforces tend to invest more in and develop stronger institutional systems for technology integration. The weakest inter-dimension correlation was between Human Capital and Policy Environment ($r = 0.39$), suggesting that perceptions of the regulatory landscape were somewhat independent of self-assessed skills endowments — a distinction with policy relevance, as it implies that upskilling initiatives alone, without corresponding policy reforms, may be insufficient to create a coherent enabling environment for GenAI adoption.

With respect to the primary outcome variable — GenAI Uptake Intention — Human Capital and Digital Literacy demonstrated the strongest correlation ($r = 0.58$, $p < 0.01$), followed by Digital Infrastructure ($r = 0.54$), Institutional Capacity ($r = 0.53$), Data Governance ($r = 0.47$), and Policy Environment ($r = 0.41$). These bivariate associations, while not controlling for shared variance among predictors, provided strong initial support for the hypothesised model and justified the subsequent SEM analysis. Notably, the relatively lower correlation between Policy Environment and Uptake Intention ($r = 0.41$) compared to other dimensions suggested that while policy frameworks are important structural enablers, their influence on individual or organisational adoption intention may be more distal and indirect — operating through institutional capacity and infrastructure effects — rather than directly shaping behavioural intent. This finding has implications for the prioritisation of policy interventions and for the expected timeline through which regulatory improvements translate into observable changes in technology adoption behaviour.

Structural Equation Modelling Results

**Table 4: SEM Path Coefficients — Predictors of AI Adoption Readiness and GenAI Uptake Intention**

| Structural Path | Std. Coefficient (β) | Std. Error | z-value | p-value | 95% CI | Effect |
|---|---|---|---|---|---|---|
| Digital Infra → AI Readiness Index | 0.41 | 0.067 | 6.12 | < 0.001 | [0.28, 0.54] | Large |
| Human Capital → AI Readiness Index | 0.35 | 0.071 | 4.93 | < 0.001 | [0.21, 0.49] | Medium |
| Policy Environment → AI Readiness Index | 0.28 | 0.069 | 4.06 | < 0.01 | [0.14, 0.42] | Medium |
| Inst. Capacity → AI Readiness Index | 0.22 | 0.064 | 3.44 | < 0.01 | [0.09, 0.35] | Small-Med |
| AI Readiness Index → Uptake Intention | 0.62 | 0.058 | 10.69 | < 0.001 | [0.51, 0.73] | Large |
| Digital Infra → Uptake Intention (direct) | 0.19 | 0.072 | 2.64 | < 0.05 | [0.05, 0.33] | Small |
| Model Fit: CFI = 0.96 | RMSEA = 0.048 | SRMR = 0.051 | $\chi^2$/df = 2.31 | TLI = 0.95 | AIC = 8,214 | |

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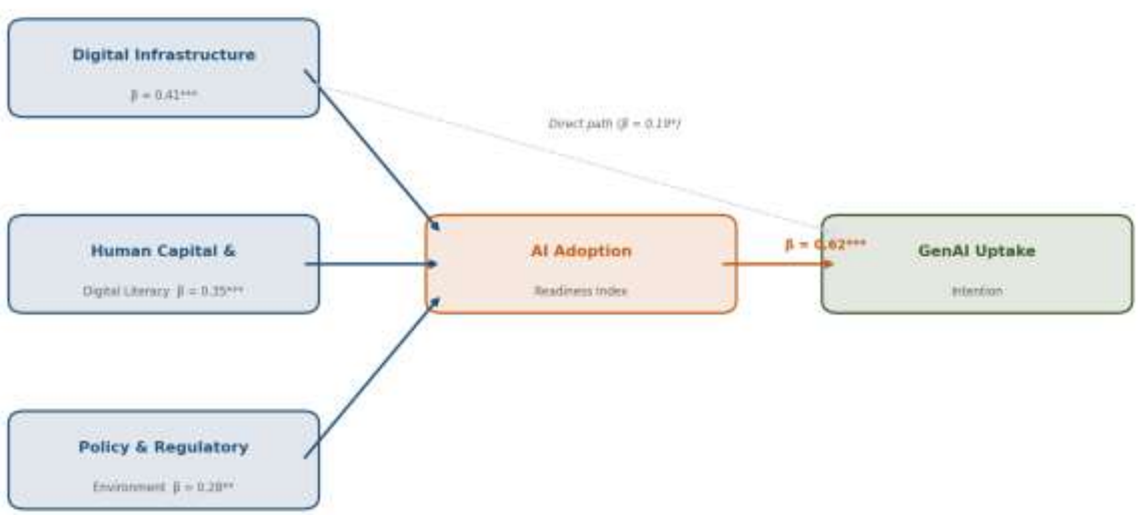
The Structural Equation Modelling results presented in Table 4 constituted the analytical centrepiece of this study, providing a rigorous examination of the structural pathways through which readiness dimensions collectively shaped GenAI adoption intention in Uganda. The overall model demonstrated good fit to the data, with a Comparative Fit Index of 0.96 (exceeding the recommended threshold of $\geq 0.95$), an RMSEA of 0.048 (within the acceptable range of $\leq 0.05$), an SRMR of 0.051 (at the acceptable boundary of $\leq 0.05$), and a chi-square to degrees of freedom ratio of 2.31 (below the recommended upper threshold of 3.0). These fit indices collectively confirmed that the hypothesised model was a plausible and well-fitting representation of the covariance structure in the observed data. Among the exogenous predictors of the AI Adoption Readiness Index, Digital Infrastructure emerged as the dominant structural driver ($\beta = 0.41$, SE = 0.067, $p < 0.001$), indicating that for every one standard deviation improvement in infrastructure readiness, AI adoption readiness increased by 0.41 standard deviations, controlling for other predictors. Human Capital followed as the second strongest predictor ($\beta = 0.35$, $p < 0.001$), while Policy Environment ($\beta = 0.28$, $p < 0.01$) and Institutional Capacity ($\beta = 0.22$, $p < 0.01$) demonstrated smaller but statistically significant contributions.

The most consequential path in the model was from the AI Readiness Index to GenAI Uptake Intention ($\beta = 0.62$, SE = 0.058, $p < 0.001$), representing a large standardised effect that accounted for approximately 38.4% of the variance in uptake intention when combined with the direct effect of Digital Infrastructure. The significant direct path from Digital Infrastructure to Uptake Intention ($\beta = 0.19$, $p < 0.05$) suggested a partial mediation structure, whereby infrastructure conditions influenced adoption intention both indirectly through the readiness index and directly — possibly reflecting the role of observable internet connectivity and device availability as tangible signals that make GenAI tools practically accessible rather than merely aspirationally desirable. The indirect effects analysis confirmed that Human Capital exerted a significant indirect effect on Uptake Intention through the readiness index ($\beta\_indirect = 0.22$, 95% CI [0.14, 0.31]), as did Policy Environment ($\beta\_indirect = 0.17$, 95% CI [0.09, 0.26]), providing strong empirical justification for the mediation hypotheses. Collectively, the SEM results positioned Uganda's GenAI adoption challenge as fundamentally a structural systems problem: piecemeal interventions addressing any single readiness dimension in isolation are unlikely to produce transformative outcomes; rather, simultaneous, coordinated investments across infrastructure, human capital, and policy domains are necessary to achieve the readiness threshold required for substantial GenAI uptake.

**Structural Model Visualization**

Figure 3: Structural Equation Model — Pathways to GenAI Uptake in Uganda
(CFI = 0.96, RMSEA = 0.048, SRMR = 0.051, $\chi^2/df$ = 2.31)




**Conclusion**

This study has provided a comprehensive, multi-dimensional, and structurally grounded assessment of Uganda's readiness to engage with Generative AI technologies, situating the country's current position on the adoption-innovation continuum within the broader discourse on the global GenAI divide. The evidence collectively indicates that Uganda is currently positioned at the lower-to-middle range of the adoption readiness spectrum, with a marginally positive overall readiness index (M = 3.07/5.00) that belies significant structural vulnerabilities, particularly in digital infrastructure and data governance, which represent foundational preconditions for any meaningful GenAI engagement. The Structural Equation Modelling results confirmed that digital infrastructure is the most potent determinant of AI adoption readiness ($\beta = 0.41$), that human capital and digital literacy occupy a critical mediating role ($\beta = 0.35$), and that the overall readiness index is a powerful predictor of GenAI uptake intention ($\beta = 0.62$) — a finding that underscores the systemic, interdependent nature of the readiness challenge. While the private sector demonstrated comparatively stronger readiness across all dimensions, the public sector's below-neutral score is an institutional liability given its dual role as regulator and infrastructure provider. Uganda's predominantly adoption-oriented positioning is not deterministic: the country's demographic dividend, expressed policy ambition, and emerging technology entrepreneurship ecosystem provide credible foundations for a strategic transition toward innovation participation, but only if structural bottlenecks are addressed through deliberate, evidence-based, and adequately resourced policy action.

## Recommendations

### Investment in Digital Infrastructure as the Foundational Priority

Given that digital infrastructure emerged as the single strongest predictor of AI adoption readiness ($\beta = 0.41$, $p < 0.001$), the Government of Uganda and development partners should urgently prioritise the expansion of affordable, reliable broadband connectivity — particularly in underserved Northern and South Western regions — alongside national investments in cloud computing infrastructure, affordable AI-enabled devices, and uninterrupted electricity supply. Public-private partnerships modelled on Uganda's successful mobile money ecosystem should be explored to accelerate infrastructure deployment beyond what public budgets alone can sustain.

### Implementation of a National GenAI Literacy and Skills Development Programme

The significant role of human capital in predicting both readiness and uptake intention ($\beta = 0.35$, $p < 0.001$) calls for an urgent, nationally coordinated AI literacy initiative that is embedded across all levels of the educational system — from primary digital skills in public schools to postgraduate AI specialisation tracks at universities. The Makerere Artificial Intelligence Lab and similar institutions should be substantially resourced as centres of national AI training and research, with curricula explicitly designed to cultivate not merely AI users but AI developers, ethicists, and policy analysts who can drive Uganda's transition from adoption to innovation.

### Enactment of a Comprehensive, Operationalised National AI Governance Framework

While Uganda's 2023 National AI Policy represents meaningful progress, the study's findings — particularly the low data governance scores ($M = 2.91$) and the weak public sector readiness index ($M = 2.99$) — indicate that policy intent has not yet been translated into operational regulatory infrastructure. The Government should expedite the enactment of a National AI Act or equivalent legislative instrument that establishes clear standards for data ownership, algorithmic accountability, AI safety, and cross-border data flows, harmonised with the East African Community's emerging regional AI governance frameworks, to create the enabling regulatory environment that the SEM results identified as a significant, if currently underperforming, driver of GenAI adoption readiness.

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