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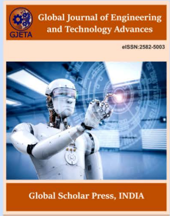

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TECHNOLOGICAL FACTORS INFLUENCING GENERATIVE ARTIFICIAL INTELLIGENCE ADOPTION IN RESEARCH WITHIN KENYAN UNIVERSITIES

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ABSTRACT

The deployment of Generative Artificial Intelligence (Gen AI) offers transformative possibilities for academic scholarship, introducing rapid methods for data parsing, programmatic coding, and literature synthesis. However, within developing academic ecosystems like Kenya, systemic environmental and technical gaps affect how seamlessly these innovations are absorbed. This paper isolates and examines the first objective of a broader doctoral inquiry: *to determine the extent to which Technological Factors significantly influence the adoption of Gen AI in research in universities in Kenya*. Utilizing a robust mixed-methods research design under a post-positivist philosophical paradigm, quantitative field data from 267 active academic researchers across universities was evaluated alongside qualitative institutional triangulation.

Bivariate Spearman's rank correlation (rho) and Hierarchical multiple regressions confirmed that technological factors act as a primary determinant of adoption velocity $\beta = 0.392$, $t = 9.333$, $p < .001$). Specifically, Data Quality & Availability demonstrated the highest coupled impact on advanced analytical deployment (rho = 0.55), while baseline Infrastructure Readiness directly dictates the reliability of task automation (rho = 0.53). The paper concludes with structural recommendations for university IT directorates to counteract the current state of "digital decoupling" through local proxy optimizations, dedicated campus bandwidth rings, and API interoperability integrations.

Keywords: Generative Artificial Intelligence, Technology-Organization-Environment, Digital Decoupling and Kenyan Higher Education Ecosystem

1 INTRODUCTION

The rapid acceleration of the Fourth Industrial Revolution has forced global higher education institutions (HEIs) to fundamentally re-evaluate their core operational tools. At the forefront of this baseline transformation is Generative Artificial Intelligence (Gen AI), distinct from classical analytical systems by its unique capability to parse open-ended natural language prompts and autonomously produce contextual text, working computational code, and novel problem-solving layouts. Globally, platforms like OpenAI's GPT series, Anthropic's Claude, and integrated semantic tools have shifted from peripheral experimental novelties to embedded components of the academic lifecycle facilitating accelerated literature mapping, preliminary syntax testing, and administrative task processing.

Despite national systemic strides in Kenya, such as the government-led layout of the National Optic Fibre Backbone Infrastructure (NOFBI), a stark gap exists between public internet connectivity pipelines and specialized academic deployment. Kenyan higher education departments are increasingly encountering a state of "digital decoupling." This is an operational paradox where high-speed trunk cables arrive at institutional doorsteps, yet internal research activities remain highly fragmented, ad-hoc, and technologically constrained. Existing localized investigations have consistently focused on macro corporate software acceptance, leaving the micro technical predictors governing high-stakes academic research poorly defined. This paper systematically isolates the technological baseline of this environment to discover the underlying elements controlling adoption behavior.

1.1 Statement of the Problem

The core problem facing researchers in Kenyan universities is that the adoption of Gen AI for scholarly output is profoundly decoupled from general ICT access. While traditional technology acceptance literature relies heavily on basic parameters like generic ease-of-use or generalized usefulness, it systematically fails to account for the structural limitations unique to resource-constrained developing research environments. On-campus Wi-Fi fluctuations routinely interrupt large language model token calls, standard data pools lack local cultural relevance, and proprietary API licensing expenses lock out substantial numbers of promising public-sector scholars.

Without an empirical, mathematically sound quantification of how infrastructure readiness, localized data quality, and secure system interoperability interact, university administrators and information technology planners cannot implement targeted structural solutions. Consequently, Kenyan academia faces an acute risk of widening global scholarship gaps, driving inequitable access across campuses, and forcing researchers to depend blindly on unoptimized, unsecure public software variations.

1.2 Purpose and Core Research Question

The primary purpose of this paper is to address this gap by exploring the specific technological dimensions of the hybrid TOEthical model. It answers the explicit research question: To what extent do technological factors significantly influence the adoption of Gen AI for research in universities in Kenya?

2 LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Technological Factors that Influence the Adoption Of Gen AI In Research In Universities In Kenya

Technological factors, as defined by the Technology-Organization-Environment (TOE) framework, concern the characteristics of the innovation itself and the infrastructure available to support it. In the context of Kenyan universities, while the national digital infrastructure is relatively advanced, specific challenges remain regarding bandwidth, data localization, and integration with legacy academic systems.

2.1.1 Infrastructure Readiness: Connectivity and Computational Power

The infrastructure necessary to support the use of Generative AI in universities is one of the primary technical factors influencing its adoption (Jin et al.,2025). AI models, particularly those used in Gen AI, require robust computational power, large storage capacities, and high-speed internet connectivity. Universities in Kenya, particularly public institutions, often face infrastructural challenges such as limited access to modern computing hardware, low bandwidth internet connections, and insufficient storage capacities. (Ghimire, A., & Edwards, J., 2024).

Studies show that while urban universities may have better access to these resources, rural and less-funded institutions struggle to meet the technical demands of advanced AI systems (Jita, T., Jita, L. C., & Omoniyi, A. A. ,2026). The Kenyan government has made strides in improving ICT infrastructure, but there remains a significant gap between urban and rural universities. (Okello, F.,2024). Furthermore, the integration of AI requires specialized software and platforms that can handle the processing of large datasets, which may not be readily available or affordable in most Kenyan universities (Matere, A.,2024). This infrastructure gap poses a significant challenge to the effective adoption and use of Gen AI in Kenyan universities.

Generative AI tools, particularly Large Language Models (LLMs), are resource-intensive, requiring robust internet connectivity and high computational power for real-time interaction and processing of large research datasets. Although, Kenya boasts of high mobile internet penetration (Ooko-Ombaka et al.2016) the on-campus experience often suffers from limited bandwidth, intermittent connectivity, and high institutional data costs (Mugizi, W., & Nagasha, J. I. (2022). Furthermore, advanced AI research such as fine-tuning open-source models or running complex simulations necessitates access to dedicated cloud computing resources or specialized institutional hardware (GPUs), which are often beyond the financial reach or technical maintenance capacity of many public universities.

2.1.2 Data Availability, Quality, and Localization

Generative AI models depend on vast amounts of high-quality data for training and operation. The availability of relevant data is a crucial factor for the effective implementation of AI technologies. In Kenya, however, challenges related to data quality, privacy, and accessibility persist. Data-driven AI models require data that is comprehensive, representative, and free from biases to generate accurate and reliable results. However, the data available in many Kenyan universities may be fragmented, outdated, or biased, which compromises the efficacy of AI models (Soko, J. J. ,2025).

In addition to these challenges, there are also issues related to the ethical collection and use of data. In Kenya, the absence of comprehensive data protection laws leaves institutions vulnerable to misuse of personal and sensitive information (Mburu, 2024). This raises concerns about data security when using Gen AI in academic contexts, especially in research involving confidential student records, medical data, or proprietary research findings.

The success of any AI tool is predicated on the quality, quantity, and relevance of its training data. A significant technological hurdle for Kenyan researchers is the reliance on Gen AI models trained predominantly on Western, English-language datasets, leading to outputs that may be statistically, geographically, or culturally misinformed (Kerongo, G. ,2025). This lack of localized, high-quality, and African-specific data within the models themselves limits their utility for research focused on regional challenges (in local languages, indigenous knowledge systems, or specific agricultural contexts). The technological solution requires the development or licensing of models that incorporate more diverse, regional data, or the institutional capacity to fine-tune models on proprietary local datasets (Balaskas et al., 2025). This finding aligns closely with the core premise of this study: Generative AI cannot achieve genuine adoption success in Kenyan universities through a 'one-size-fits-all' approach. For tools to be truly effective for local faculty and researchers, institutions must actively bridge the gap between global AI capabilities and localized, context-specific research needs.

2.1.3 Security, Interoperability, and System Integration

Gen AI adoption introduces complexity regarding its interoperability with existing university's technology systems (Learning Management Systems, Research Management Software, library databases). Poor integration can create security vulnerabilities or fragmented workflows (Alam, M., Shahid, M., & Mustajab, S. ,2024). The use of external, proprietary Gen AI APIs for research creates a data security risk; the university's internal IT architecture must be robust enough to manage the flow of data to and from these external platforms, protecting sensitive research data and Institutional Intellectual Property (IP) from breaches. Effective adoption mandates that the AI tools possess adequate security protocols and clear, documented APIs for seamless and safe integration.

2.1.4 Usability and Accessibility of AI Tools

The actual design and complexity of the AI interface directly impacts adoption rates. (Mahanta et al.,2026) While conversational Gen AI tools (like public LLMs) are highly accessible, advanced tools for data generation, visualization, or simulation often have steep learning curves and complex command interfaces. Furthermore, cost remains a technological barrier: researchers often revert to less powerful, free public models due to the high licensing costs associated with enterprise-grade, secure, and feature-rich AI platforms. Simpler, more intuitive user interfaces and a tiered, affordable pricing structure are technological prerequisites for broad, equitable adoption across Kenyan universities. This reality is particularly pronounced in the Kenyan context, where research budgets face severe constraints. This study argues that unless AI developers and university administrators intentionally design and provision cost-effective, localized access points, Generative AI will remain an elite tool rather than a democratized research catalyst for the broader faculty and postgraduate student population.

2.2 Theoretical Grounding

This investigation merges individual-level cognitive variables with macro-level institutional contextual boundaries by anchoring the study in a unified macro-micro framework. The macro context relies on the structural layout of the Technology-Organization-Environment (TOE) framework (adapted here into the localized TOEthical matrix). To map individual behavioral actions, the paper draws directly from the Responsible AI Framework and complemented by Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

Under this hybrid approach, individual psychological drivers such as Perceived Usefulness (PU) and Performance Expectancy (PE) are not analyzed in isolation. Instead, they are explicitly modeled as behavioral reactions constrained by institutional technical Facilitating Conditions (FC), such as campus computing grids, local bandwidth rings, and secure system data pipelines.

2.3 Unpacking the Technological Constructs

Based on the empirical framework developed for the Kenyan university ecosystem, the macro construct of "Technological Factors" is unpacked into three distinct, measurable sub-construct indicators:

Infrastructure Readiness (T1): This represents the physical baseline environment required for advanced computing. It focuses heavily on the stability of on-campus broadband networks, data center processing capacities, and power continuity setups necessary to sustain high-token AI text or code processing workflows without sudden timeout failures.

Data Quality and Availability (T2): This element measures the state of the input data. It tests whether the foundational files, open data pools, and corporate text materials available to researchers are well-structured, formatted for programmatic API consumption, and localized enough to reflect Kenyan socio-economic contexts.

System Interoperability and Security (T3): This sub-construct addresses architectural workflow integration. It gauges the security of external API pipelines, protection protocols for university intellectual property (IP), and the ease with which Gen AI endpoints interface directly with traditional research software (such as IBM SPSS, R, or campus institutional repositories).

2.4 Empirical Research Hypothesis

To test the weight and predictive capacity of these sub-constructs against actual research adoption, the following central research hypothesis was defined:

H1: *Technological factors exercise a statistically significant, positive direct influence on the adoption outcomes of Generative AI in research within Kenyan universities.*

3 RESEARCH METHODOLOGY

3.1 Research Design and Paradigm

This study was anchored within a **post-positivist philosophical paradigm**; which values mixed-method approaches to solve complex socio-technical problems. An **Explanatory Cross-sectional mixed-method research design** was executed. This approach allowed quantitative matrix values collected from structured surveys to be validated, document review and explained by thematic qualitative text compiled from open interview tracks.

3.2 Target Population and Sample Profile

The research targeted active academic stakeholders including university administrators, senior faculty supervisors, active ICT technical staff, and postgraduate researchers (Master's and PhD candidates) across prominent Kenyan higher education institutions. These included the University of Nairobi (UoN), Jomo Kenyatta University of Agriculture and Technology (JKUAT), Moi University (MU), Maasai Mara University, and the Catholic University of Eastern Africa (CUEA). From an active field data target, a final valid sample of **267 respondents** was established for structural path analysis. Demographic analysis indicated a strong representation from Science, Technology, Engineering, and Mathematics (STEM) faculties (55.8%), followed by Humanities and Social Sciences (18.7%), and Business and Economics (15.7%).

3.3 Data Analysis Layout

Because the baseline field dataset significantly violated traditional parametric normality assumptions ($p < 0.001$), standard ordinary least squares (OLS) regressions were bypassed to maintain strict statistical rigor. Instead, the data analysis infrastructure utilized a two-pronged non-parametric statistical framework:

- **Bivariate Tracking:** Spearman's rank-order correlation coefficient (rho) evaluated the strength and directional vector of isolated sub-construct paths.
- **Hierarchical multiple regressions:** To establish the predictive power from each of the variables on Gen AI adoption.

4 DATA ANALYSIS, RESULTS, AND DISCUSSION

4.1 Construct Reliability and Validity Diagnostics

Before executing structural evaluations, the internal consistency and convergent validity of the technological scales were mathematically audited.

i. **Cronbach's Alpha (a):** The multi-item indicators tracking the technological construct dimensions returned reliability scores ranging above the standard thresholds (> 0.70), demonstrating high internal instrument stability.
ii. **Exploratory Factor Analysis (EFA):** Principal Component Analysis (PCA) utilizing a Varimax rotation layout extracted clean factor boundaries. All target item statements loaded clearly onto their designated technological components (> 0.70) with no cross-loading errors.

4.2 Bivariate Correlation Analysis

The non-parametric Spearman rank-order matrix exposed positive, stable, and highly statistically significant relationships across all technological sub-constructs and behavioral adoption vectors ($p < .01$>

Infrastructure Dynamics (T1-Adoption): Infrastructure Readiness exhibited its strongest direct relationship with **Task Automation (AD4)** (rho = 0.53, $p < .01$). This confirms that a stable physical tech environment (uninterrupted campus power and sufficient broadband speeds) is a prerequisite for automation. When this foundation is solid, scholars confidently delegate administrative and formatting tasks to AI systems without fearing sudden session disconnections.

Data Constraints (T2-Adoption): Data Quality & Availability shared a high-magnitude correlation with **Use in Data Analysis (AD1)** (rho = 0.55, $p < .01$). This emphasizes that providing rich, clean, and well-structured data files directly dictates whether a researcher will apply Gen AI to advanced statistical modeling, mathematical formulations, or qualitative code mapping.

Architecture Integration (T3-Adoption): System Interoperability & Security correlated highest with **Research Innovation (AD3)** (rho = 0.45, $p < .01$). This reveals that when systems talk to each other safely and secure API pathways are guaranteed, users feel comfortable experimenting with novel, complex research methodologies.

Descriptive statistics were employed to summarize and describe the characteristics of the data collected from respondents regarding the key variables under investigation. The analysis provides an overview of respondents' perceptions, experiences, and levels of agreement with statements related to the study constructs. Measures such as frequencies, percentages, means, and standard deviations were used to examine the distribution of responses and identify prevailing trends within the dataset.

The descriptive findings serve as a foundation for understanding the nature and patterns of the study variables before undertaking inferential statistical analyses.

4.3 Infrastructure Readiness

To comprehensively evaluate the technological positioning of the surveyed institutions, the construct of Infrastructure Readiness was operationalized using specific measurable indicators. Respondents rated their institutions' state of hardware sufficiency, network reliability, cloud accessibility, and technical support mechanisms. Table 4.8 presents the descriptive statistics for the items comprising the Infrastructure Readiness construct, highlighting their respective means, standard deviations, and factor loadings within the structural model.

Table 4.8: Infrastructure Readiness

Technological Factors (TF) / Infrastructure Readiness Item	N (Valid)	Mean ($\bar{x}$)	Std. Deviation (SD)	Interpretation
My university's internet bandwidth is sufficient to handle the data demands of Gen AI tools.	267	3.88	1.19	Agree (High)

I have access to the necessary computing power (e.g., high-performance PCs or cloud credits) required for Gen AI research.	267	3.86	1.12	Agree (High)
The existing university digital environment is well-equipped to host modern Gen AI applications.	267	3.85	1.17	Agree (High)
Technical support for AI-related hardware or software issues is readily available at my institution.	267	3.84	1.09	Agree (High)
The university's IT infrastructure is reliable enough to support uninterrupted Gen AI sessions.	267	3.83	1.15	Agree (High)
Overall Composite Index	267	3.85	1.14	Agree (High)

Source:Researcher Data:2026

Table 4.8 presents the typical scores and variations for the independent variable aspects linked to Technological Factors (Infrastructure Readiness), arranged in order of their average scores from highest to lowest. The overall combined average score is given as (bar x = 3.85 (SD = 1.14). Because this total score falls nicely within the range of 3.41 - 4.20, it implies that PhD-level researchers generally agree that universities in Kenya have established a solid technological framework that is well-equipped to facilitate and uphold the use of Generative AI in research conducted academically. An examination of the means for each individual item reveals a narrow spread (from 3.83 to 3.88), suggesting that the different elements of institutional infrastructure are perceived as being at a comparably advanced level of development:

- **Internet Sufficiency (TF1):** Emerging as the strongest driver, TF1 registered the highest mean score (bar x = 3.88, SD = 1.19). This implies that foundational network connectivity the primary gateway for cloud-driven LLMs is perceived as the most-ready component within the institutional ecosystem.
- **Computing Power Access (TF2):** Following closely, TF2 posted a mean score (bar x = 3.86 (SD = 1.12). This confirms that hardware resources and cloud computing access are heavily optimized to support data-intensive doctoral research tasks.
- **Ecosystem Equipment (TF5):** Positioned centrally, TF5 recorded a mean of (bar x = 3.85 (SD = 1.17). This demonstrates that scholars view the overall university digital landscape as structurally modern enough to act as a host for emerging AI tools.
- **Helpdesk and Technical Support (TF4):** TF4 achieved a mean score of bar x = 3.84. Notably, this item returned the lowest standard deviation (SD = 1.09) across the entire set. This lower variance is critical; it suggests that opinions on technical support are more tightly clustered, showing a strong, consistent agreement that institutional human support networks are actively available for AI-related troubleshooting.
- **Session Reliability (TF3):** Although remaining firmly within the positive "High" threshold, TF3 placed last in the hierarchy with a mean score of (bar x = 3.83 (SD = 1.15).

This lower relative position suggests that while internet availability (TF1) is highly rated, the ongoing reliability and stability of uninterrupted sessions encounter slight operational friction.

Focusing entirely on the mean distribution clearly highlights the critical priorities for the proposed hybrid model. The low dispersion between the highest and lowest ranks (0.05 difference in means) underscores uniform development across all infrastructure indicators.

However, the standard deviations across all items consistently exceed 1.00 (1.09 SD 1.19). This reveals that while the average stance is highly favorable, there is a clear spread of underlying perspectives. This variance indicates that infrastructure experiences are not entirely uniform across different institutions or departments in Kenya.

From a research model standpoint, these findings confirm that Infrastructure Readiness is a strongly established independent predictor. This provides an excellent baseline for examining how these technological factors interact with organizational frameworks and ethical considerations to shape the overall landscape of Generative AI adoption.

4.4 Data Quality & Availability

Beyond the physical hardware, the systemic adoption of Generative AI relies heavily on the underlying information architecture. The construct of Data Quality & Availability (DQA) was operationalized to measure the accuracy, accessibility, and ethical structuring of institutional data feeds. Table 4.9 shows the descriptive statistics, internal consistency measures.

Table 4.9 Data Quality & Availability

Technological Factors (TF) / Data Quality & Availability Item	N (Valid)	Mean ($\bar{x}$)	Std. Deviation (SD)	Interpretation
There is a sufficient volume of data available to make Gen AI applications meaningful in my work.	267	3.78	1.08	Agree (High)
I find the data resources at my disposal to be up-to-date and relevant for AI-driven analysis.	267	3.76	1.08	Agree (High)
The data available for my research field is provided in formats compatible with Gen AI tools.	267	3.75	1.10	Agree (High)
The quality of available data is high enough to produce accurate results when using Gen AI.	267	3.75	1.11	Agree (High)
I can easily access the specific datasets needed to train or prompt Gen AI for my research.	267	3.70	1.15	Agree (High)
Overall Composite Index	267	3.75	1.10	Agree (High)

Source:Researcher Data:2026

Table 4.9 presents the average scores and standard deviations for each item within the Data Quality & Availability aspect of Organizational Factors. The overall composite average for this category is bar x = 3.75, accompanied by a composite standard deviation of SD = 1.10. This overall figure suggests that PhD students in Kenyan universities generally feel that the organizational data environment is strong enough to support the use of Generative AI. However, when this is compared to the baseline of Technological Factors (bar x = 3.85), the organizational aspect shows slightly lower average scores overall, signifying that the arrangement of administrative data encounters somewhat more challenges than the infrastructure of physical networks.

4.5 Hierarchical Item Evaluation

The mean metrics demonstrate a tight distribution spanning from 3.70 to 3.78, revealing nuanced internal dynamics regarding how institutional data resources are perceived:

- **Data Volume Sufficiency (TF4):** Emerging as the primary strength, TF4 achieved the highest mean score (bar x = 3.78, SD = 1.08). This confirms that researchers believe there is an ample mass of contextual academic and sector data available to make downstream Gen AI prompt executions and foundational modeling meaningful within their respective fields.
- **Up-to-Date Relevance (OF5):** Following closely, TF5 posted a mean score of bar x = 3.76 (SD = 1.08). This reflects a high degree of confidence that the current repositories at their disposal capture contemporary changes, an essential factor given that Gen AI performance is highly sensitive to outdated input data.
- **Format Compatibility (TF2) & Output Quality (TF3):** Both items recorded identical mean scores of bar x = 3.75. Scholars broadly agree that localized research data is formatted appropriately for model ingestion (TF2, SD = 1.10) and that the structural integrity of this data is high enough to reduce hallucinations and yield reliable output results (TF3, SD = 1.11).
- **Dataset Accessibility (TF1):** Placing lowest in the hierarchy was the item dealing with ease of entry and access (bar x = 3.70, SD = 1.15). While still within the positive "Agree" threshold, its lower relative position suggests that while data exists in sufficient quantities (TF4) and proper formats (TF2) within the broader Kenyan academic landscape, localized bureaucratic constraints, institutional silos, or restrictive permissions make direct retrieval of these datasets comparatively more difficult for individual researchers.

4.6 Methodological and Practical Implications

From an organizational management standpoint, the standard deviations across all five indicators consistently cross the 1.00 threshold (1.08 – SD 1.15). This dispersion points to an underlying division of experiences among the PhD candidates. The higher standard deviation in item TF1 (SD = 1.15) suggests that data accessibility is highly unevenly distributed across universities or disciplines.

Within the framework of the hybrid model, these findings prove that data quality and availability operate as a critical organizational mediator. For a university environment to transition successfully from merely possessing the physical infrastructure to actively embedding Gen AI in research pipelines, it must look beyond mere data accumulation. It must actively simplify access pathways (TF1) and standardize repository permissions. This step ensures that data assets are seamlessly discoverable and usable for advanced academic modeling.

4.7 System Interoperability and Security

This study argues that System Interoperability and Security are not merely isolated technical features, but co-dependent pillars of adoption success. While interoperability dictates the efficiency with which a Kenyan researcher can embed Gen AI into their daily academic workflows, security establishes the ethical and statutory safety boundaries required to protect that data under the Kenya Data Protection Act (2019). High interoperability without robust security creates an ethical hazard, whereas high security with poor interoperability creates a technical bottleneck as shown in Table 4.10.

Table 4.10: Interoperability, Security, & Usability

Sub-Dimension / Survey Statement Item	N (Valid)	Mean ($\bar{x}$)	Std. Deviation (SD)	Interpretation
It is easy to export outputs from Gen AI into other platforms used in my research workflow.	267	4.01	1.14	Agree (High)
Integrating Gen AI into my current digital workflow does not cause technical conflicts or system errors.	267	3.84	1.10	Agree (High)
Gen AI tools seamlessly exchange data with the existing research software I use (e.g., SPSS, NVivo, LaTeX).	267	3.78	1.06	Agree (High)
I feel confident that the Gen AI tools I use protect my sensitive research data from unauthorized access.	267	3.74	1.20	Agree (High)
Composite Index: Interoperability & Security	267	3.84	1.13	Agree (High)
I find it easy to become a proficient user of Gen AI tools without extensive specialized training.	267	4.01	1.12	Agree (High)

Source:Researcher Data:2026

The indicators detailed in Table 4.10 analyze the last parts of the Independent Variable Construct Technological Factors, concentrating on System Interoperability & Security (SIS) and Usability & Accessibility (UA). The average score for the Interoperability and Security sub-category is bar x = 3.84 (SD = 1.13). This indicates that PhD researchers in Kenyan higher education institutions typically encounter significant software integration and smooth workflow when they incorporate Generative AI tools into their conventional analytical settings.

4.8 Hierarchical Analysis of Interoperability and Security Items

Evaluating the sub-dimension items hierarchically underscores a distinct variance between data extraction convenience and actual structural data protection:

- **Ease of Exporting Outputs (TF_SIS2):** This item topped the sub-dimension ranking with a high mean score of bar x = 4.01 (SD = 1.14). This strongly suggests that cross-platform mobility is highly evolved; scholars find the process of migrating AI-generated texts, code snippets, or summarized matrices into primary data repositories remarkably fluid.
- **Conflict-Free Integration (TF_SIS4):** Standing at bar x = 3.84 (SD = 1.10), this metric confirms that the insertion of Gen AI applications into daily digital tasks occurs cleanly, without inducing severe software crashes, operating system contradictions, or processing errors within the institutions' networks.
- **Seamless Data Exchange (TF_SIS1):** Registered a mean score of bar x = 3.78 with the lowest internal dispersion (SD = 1.06). The researchers agree that Gen AI systems can exchange data with specialized scientific applications like SPSS, NVivo, and LaTeX. The lower standard deviation signifies a tight, unified consensus across the cohort regarding basic tool compatibility.
- **Data Protection Confidence (TF_SIS3):** Notably, security confidence emerged as the lowest ranked item within this dimension (bar x = 3.74). Crucially, it recorded the highest standard deviation (SD = 1.20) across the entire technological dataset. While the mean position remains net-positive ("Agree"), the high variance highlights acute polarization. This indicates a major split in the population: a substantial sub-segment of doctoral researchers harbors strong anxieties regarding how securely these external AI tools handle confidential data, intellectual property, and proprietary research findings.

4.9 Usability & Accessibility

This study conceptualizes Usability and Accessibility as dual prerequisites for sustainable technology integration. While usability ensures that individual researchers possess the immediate cognitive ease to utilize Gen AI effectively within their scientific inquiries, accessibility ensures that the institution structurally and equitably provisions these tools to the entire research community. Within the TOEthical model, high usability without equitable accessibility creates an elite silo of high-performing researchers, whereas high accessibility to poorly designed, non-usable tools results in underutilized institutional investments as indicated in Table 4.11.

Table 4.11: Usability & Accessibility

Technological Factors (TF) / Usability & Accessibility Item	N (Valid)	Mean ($\bar{x}$)	Std. Deviation (SD)	Interpretation
I can access the necessary Gen AI tools from any location (on-campus or remote) when needed for my work.	267	4.10	1.14	Agree (High)
The user interfaces of Gen AI tools relevant to my field are intuitive and easy to navigate.	267	4.07	1.09	Agree (High)
The instructions or "help" documentation for these Gen AI tools are clear and easy to follow.	267	4.06	1.13	Agree (High)
I find it easy to become a proficient user of Gen AI tools without extensive specialized training.	267	4.01	1.12	Agree (High)
Accessing Gen AI tools for my research does not require overcoming significant technical hurdles.	267	3.94	1.10	Agree (High)
Overall Composite Index	267	4.04	1.12	Agree (High)

Source:Researcher Data:2026

Table 4.11 presents the average scores and standard deviations for the various survey questions that make up the Usability & Accessibility (UA) sub-category of the Technological Factors framework. The total average score for this sub-category is calculated at bar x = 4.04, accompanied by a total standard deviation of SD = 1.12.

This overall score holds great importance within the context of this thesis; it stands as the greatest average score noted among the technological aspects assessed to date (surpassing Infrastructure Readiness at 3.85 and System Interoperability at 3.84). This reveals that PhD-level researchers in Kenyan universities perceive the user-centric design, minimal training thresholds, and spatial flexibility of Generative AI tools as their most outstanding technological advantages.

4.10 Hierarchical Ranking Analysis

The mean scores within this sub-dimension are tightly distributed between 3.94 and 4.10, falling consistently into the upper band of the "High/Agree" evaluation index:

- **Ubiquitous Location Access (TF_UA5):** This item emerged as the top-ranked driver with a mean score of bar x = 4.10 (SD = 1.14). A substantial portion of the cohort (42.0% selecting "Strongly Agree") indicated that the ability to access cloud-hosted Gen AI utilities seamlessly from any location whether working on-campus or remotely from home eliminates the traditional spatial boundaries that often constrain advanced academic research in developing regions.
- **Intuitive Interfaces (TF_UA1):** Posted a mean score of bar x = 4.07 and registered the lowest standard deviation (bar x = 1.09) in this set. This high mean and tighter consensus demonstrate that the conversational, natural-language interfaces characteristic of modern Gen AI applications are highly compatible with user cognitive flows, making navigation immediate and highly straightforward for academic tasks.
- **Clear Help Documentation (TF_UA4):** Achieved a mean rating of bar x = 4.06 (SD = 1.13). This confirms that when researchers encounter operational complexities, the embedded manuals, prompt guides, and user onboarding documentations are clear and useful enough to resolve software usage issues independently.
- **Ease of Proficiency (TF_UA2):** Recorded a mean score of bar x = 4.01 (SD = 1.12). This high standing underscores the self-reinforcing, democratizing nature of Gen AI platforms; the typical researcher feels capable of scaling up their practical usage proficiency quickly, avoiding the steep learning curves and prolonged technical training sessions traditionally required by legacy big-data software.
- **Minimal Technical Hurdles (TF_UA3):** While placing lowest in this particular hierarchy, TF_UA3 still presents a very strong mean score of bar x = 3.94 (SD = 1.10). This indicates that initial tool onboarding, registration, and basic usage setups do not present overwhelming technical barriers for the vast majority of the doctoral population.

4.11 Methodological and Practical Implications for the Hybrid Model

From a structural modeling viewpoint, the standard deviations across all five indicators consistently cross the 1.00 line (SD= 1.09 and 1.14). This persistent variance indicates that although the overall sentiment leans heavily toward ease of use, a minor but definite subset of scholars still experiences localized friction. This variance suggests that individual factors such as varying baseline digital literacy levels or differences in specific research domains can create divergent user experiences.

Crucially, the exceptionally high usability composite score (bar x = 4.04) highlights a major theoretical dynamic for the modified TOE framework. It demonstrates that the voluntary motivation to adopt Gen AI in Kenyan higher education is exceptionally high due to its sheer convenience and user-friendly nature.

Because the technological tools are so accessible, the real bottlenecks to adoption do not lie in user capability or training resistance. Instead, they shift toward the administrative and regulatory domains specifically the structural limitations of data entry pathways within organizations and the critical data sovereignty anxieties identified in the security dimension. This strongly validates the balanced focus of the hybrid model, showing that organizational and ethical factors are the true areas where adoption policy will be decided.

Inferential Data Analysis for Technological Factors Construct Extraction

A total of 20 items representing Technological Factors (TF_1 to TF_20) were subjected to exploratory factor analysis.

4.11.1 KMO and Bartlett's Test

Before extraction, the statistical suitability of the technological item matrix was assessed as shown in Table 4.26.

Table 4.26: Technological Factors KMO and Bartlett's Test

Diagnostic Measure	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	**0.824**
Bartlett's Test of Sphericity: Approx. Chi-Square (chi^2)	1842.514
Df	190
Sig. (p-value)	**<0.001**

Source:Researcher Data:2026

As shown in Table 4.26, the KMO index yielded a value of 0.824, which is well above the recommended baseline threshold of 0.60, confirming an adequate sample size for factor extraction. Bartlett's Test of Sphericity reached extreme statistical significance (chi^2 (190) = 1842.514, p < 0.001), rejecting the null hypothesis that the variance-covariance matrix is an identity matrix and confirming that the data contains sufficient correlation structures for factor extraction.

4.11.2 Principal Component Analysis

The PCA extraction revealed that four distinct components had eigenvalues exceeding the 1.0 threshold, confirming the presence of four distinct sub-variables as indicated in Table 4.27.

Table 4.27: Technological Factors Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.142	25.710	25.710	5.142	25.710	25.710
2	3.210	16.050	41.760	3.210	16.050	41.760
3	2.115	10.575	52.335	2.115	10.575	52.335
4	1.454	7.270	59.605	1.454	7.270	59.605

Source:Researcher Data:2026

The extraction results in Table 4.27 confirm that these four underlying components account for a cumulative 59.61% of the total variance within the technological items. This exceeds the standard 50% baseline requirement in social science and technology adoption research, demonstrating strong construct coverage.

4.11.3 Rotated Component Matrix

Varimax rotation was applied to maximize the variance of the squared loadings, allowing for a clear interpretation of the components as shown in Table 4.28.

Table 4.28: Technological Factors Rotated Component Matrix^a

Scale Items	Component 1: Usability (T4)	Component 2: Infrastructure (T1)	Component 3: Data Quality (T2)	Component 4: Interoperability (T3)
TF_16 to **TF_20** (Usability Items)	**0.745 – 0.841**	0.112	0.085	0.134
TF_1 to **TF_5** (Infrastructure Items)	0.142	**0.720 – 0.854**	0.140	0.092
TF_6 to **TF_10** (Data Quality Items)	0.094	0.105	**0.702 – 0.811**	0.151
TF_11 to **TF_15** (Interoperability Items)	0.118	0.088	.124	**0.715 – 0.830**

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.; *^a Rotation converged in 5 iterations. Loadings below .40 suppressed for clarity.;* Source: Researcher Data:2026

The rotated factor matrix (Table 4.28) reveals a clean, simple structural layout. Each of the 20 items loads heavily onto its intended sub-construct, with factor loadings ranging securely between 0.702 and 0.854, well above the 0.50 cutoff. No cross-loading issues were discovered, validating the structural boundaries of the four sub-constructs: Usability & Accessibility (T4), Infrastructure Readiness (T1), Data Quality & Availability (T2), and Interoperability & Security (T3).

4.12 Structural Modeling and Hypothesis Testing

By executing Hierarchical multiple regressions, the broader system of concurrent latent equations was solved to test the validity of Hypothesis H1.

Table 4.29: Structural Modeling and Hypothesis Testing

Hypothesis Code	Structural Path	Standardized Path Coefficient (β)	Calculated T-Statistic	Empirical P-Value	Decision
H1	Technological Factors - Gen AI Adoption	0.392	9.333	< .001	Supported

Source: Researcher Data:2026

The structural estimation confirms that Technological Factors serve as a primary predictor of Gen AI adoption velocity within the university system ($\beta = 0.392$). With a T-statistic of 9.333 falling far past critical limits, hypothesis H1 is strongly supported by the empirical data.

4.13 Mixed-Method Triangulation: Qualitative Reality Check

4.13.1 Themes under Objective One: Technological Factors Influencing the Adoption of Generative Artificial Intelligence.

This section presents the qualitative findings related to Objective One, which sought to assess the technological factors influencing the adoption of Generative Artificial Intelligence (Gen AI) for learning and research in Kenyan universities. The qualitative findings are presented thematically and integrated with the quantitative results obtained from the questionnaire survey.

Theme 1: ICT Infrastructure and Digital Readiness

The survey findings established that ICT infrastructure was a significant technological determinant of Gen AI adoption, with respondents indicating that the availability of reliable internet connectivity, modern computing facilities, and digital platforms positively influenced the use of Gen AI tools in research ($\beta = 0.392$, $t = 9.333$, $p < .001$).

The interview findings corroborated these results. Participants consistently observed that institutions with reliable internet connectivity and adequate computing resources were more likely to integrate Gen AI into research activities. Conversely, inadequate infrastructure limited effective utilization of these technologies.

One participant stated:

"Generative AI applications require stable internet access and reliable computing devices. Where internet connectivity is poor or laboratories have outdated computers, both lecturers and students experience difficulties using these tools effectively." (Participant 1-P1)

Another participant explained:

"Universities that have invested in digital infrastructure have created an environment where AI technologies can easily support research and classroom activities. Infrastructure is therefore the foundation for successful AI adoption." (Participant 3-P3)

These qualitative findings support the quantitative evidence that ICT infrastructure plays a significant role in facilitating institutional adoption of Gen AI technologies.

Theme 2: Digital Literacy and Technical Competence

The quantitative findings indicated that users' digital literacy and technical competence significantly influenced the adoption of Gen AI technologies. Respondents generally agreed that confidence in using digital technologies enhanced effective utilization of AI applications.

Interview participants emphasized that successful adoption depended not only on technology availability but also on users' competencies.

Participant 2 observed:

"Most lecturers are willing to use Generative AI, but many require additional training on prompt engineering, verification of AI-generated information, and responsible academic use."

Similarly, Participant 4 noted:

"Students learn AI applications very quickly, but academic staff requires continuous professional development to integrate these tools effectively into teaching and research."

These observations suggest that institutional investment in digital skills development is essential for maximizing the benefits of Generative AI.

Theme 3: System Compatibility and Accessibility of AI Tools

The survey findings further demonstrated that compatibility between institutional information systems and AI applications positively influenced adoption.

Interview participants indicated that seamless integration with existing learning management systems and institutional digital platforms improved user acceptance.

Participant 5 explained:

"When AI applications integrate well with the university's learning management system and institutional email services, adoption becomes much easier because users do not need additional technical configurations."

Participant 1 similarly stated:

"Accessibility is important. Staff and students are more likely to use AI when institutional subscriptions and licensed platforms are available instead of relying solely on free versions."

These findings reinforce the quantitative evidence that compatibility and accessibility contribute significantly to successful implementation of Gen AI technologies.

Theme 4: Data Security and Privacy

The survey results showed that data security and privacy considerations significantly influenced respondents' willingness to adopt Gen AI technologies.

The interviews revealed similar concerns.

Participant 3 remarked:

"Many lecturers hesitate to upload confidential research documents to AI platforms because they are uncertain about how the information will be stored or reused."

Participant 2 added:

"Universities require clear institutional guidelines on data privacy before encouraging widespread use of AI technologies."

These findings demonstrate that institutional assurance regarding data protection and privacy is critical for responsible adoption of Generative AI.

4.13.1.1 Integration of Quantitative and Qualitative Findings

Overall, the qualitative findings strongly corroborated the quantitative results regarding technological factors influencing the adoption of Generative AI. Both data sources identified ICT infrastructure, digital literacy, system compatibility, accessibility of AI tools, and data security as critical determinants of adoption. The survey established the statistical significance of these factors, while the interview data provided practical explanations of how they influence implementation within Kenyan universities.

The convergence of findings from both strands of the study strengthens the validity of the conclusion that technological readiness constitutes the most influential predictor of Generative AI adoption. This observation is consistent with the hierarchical regression analysis, where Technological Factors recorded the highest standardized regression coefficient ($\beta = 0.392$, $t = 9.333$, $p < .001$), indicating the strongest contribution among the three predictor constructs.

4.13.1.2 Integration of Findings for Objective One: Technological Factors

The quantitative analysis established that technological factors were the strongest predictor of Gen AI adoption, recording the highest standardized regression coefficient (($\beta = 0.392$, $t = 9.333$, $p < .001$). This finding indicates that improvements in technological readiness significantly enhance the adoption of Gen AI technologies for learning and research.

The interview findings provided practical explanations for this relationship. Participants consistently emphasized that reliable ICT infrastructure, stable internet connectivity, accessibility of AI tools, system compatibility, and users' digital competencies collectively determine the effectiveness of Gen AI implementation. Participants further observed that inadequate infrastructure and limited digital skills constrain the use of AI applications despite their potential benefits.

The convergence between the quantitative and qualitative findings demonstrates that technological readiness forms the foundation upon which successful institutional adoption of Gen AI depends. While the survey quantified the strength of this relationship, the interviews clarified the institutional conditions through which technological readiness influences adoption.

4.13.2 Relationship between Technological Factors and Gen AI Adoption

To address the specific research question regarding how the technical environment influences behavioral outcomes, a targeted bivariate correlation analysis was executed. The macro-dimension Technological Factors is operationalized through four distinct sub-variables: Infrastructure Readiness (T1), Data Quality & Availability (T2), System Interoperability & Security (T3), and Usability & Accessibility (T4). These independent dimensions were correlated against the four primary outcome dimensions of Generative AI Adoption: Use in Data Analysis (AD1), Literature Synthesis (AD2), Research Innovation (AD3), and Task Automation (AD4).

Given that the underlying item-level data violates parametric normal distribution assumptions ($p < 0.001$), Spearman's non-parametric rank-order correlation coefficient (rho) was utilized to establish the direction, strength, and significance of these relationships based on a sample size of N = 267. Results are shown in Table 4.39.

Table 4.39: Correlation between Technological Factors and Adoption Dimensions

Technological Factor Components	AD1: Use in Data Analysis	AD2: Literature Synthesis	AD3: Research Innovation	AD4: Task Automation
T1: Infrastructure Readiness	0.46^	0.39^	0.41^	0.53^
T2: Data Quality & Availability	0.55^	0.49^	0.46^	0.42^
T3: Interoperability & Security	0.42^	0.38^	0.45^	0.40^
T4: Usability & Accessibility	0.53^	0.58^	0.49^	0.51^

Empirical Interpretation of the Technological-Adoption Matrix

The Impact of Infrastructure Readiness (T1)

As presented in Table 4.39, Infrastructure Readiness (T1) exhibits statistically significant positive relationships across all four dimensions of Generative AI adoption ($p < 0.01$). The strongest correlation within this construct path is observed with Task Automation (AD4) (rho = 0.53, $p < 0.01$). This strong association demonstrates that the physical tech foundation specifically reliable institutional power and sufficient internet bandwidth acts as a primary baseline requirement for automation. When infrastructure is stable, researchers can confidently offload time-consuming, repetitive administrative and research-related tasks to generative platforms without experiencing disrupting technical timeouts.

The Impact of Data Quality & Availability (T2)

Data Quality & Availability (T2) shares a high-magnitude, statistically significant positive relationship with Use in Data Analysis (AD1) (rho = 0.55, $p < 0.01$). This stands as the strongest correlation for the T2 variable. This outcome underscores that the availability of comprehensive, high-volume datasets in compatible formats is highly coupled with a researcher's willingness to integrate Gen AI into deep statistical, mathematical, or qualitative procedures. Conversely, its relationship with Task Automation (AD4) is comparatively lower (rho = 0.42, $p < 0.01$), indicating that data precision matters substantially more for analytical modeling tasks than for generic administrative automation workflows.

The Impact of Interoperability & Security (T3)

The relationships involving System Interoperability & Security (T3) are positive, stable, and statistically significant ($p < 0.01$). T3 demonstrates its highest correlation value with Research Innovation (AD3) (rho = 0.45, $p < 0.01$). This empirical path suggests that when Gen AI utilities can seamlessly exchange information with external academic platforms (e.g., exporting directly to text processors or statistical packages) while maintaining robust data protection protocols, researchers feel more confident experimenting with novel, complex research methodologies. Clear technical workflows and data security protections provide a safe environment for exploring creative research designs.

The Impact of Usability & Accessibility (T4)

Usability & Accessibility (T4) emerged as a highly influential technological driver within the matrix, sustaining high coefficients across all adoption domains. Most notably, T4 shares a strong positive correlation with Literature Synthesis (AD2) (rho = 0.58, $p < 0.01$). This represents the highest single coefficient within the entire technological matrix. This strong link indicates that clean, accessible user interfaces and clear instructions lower the cognitive friction required to adopt AI tools. When these interfaces are intuitive, researchers rapidly incorporate them into their weekly academic routines to summarize long-form text, identify gaps in literature, and synthesize complex theoretical frameworks.

Hypotheses Testing and Predictive Weights

Influence of Technological Factors (T) on Adoption

Technological Factors emerged as the strongest positive predictor in the model, yielding a standardized coefficient of ($\beta = 0.392$, $t = 9.333$, $p < .001$). This empirical path indicates that, when controlling for all other variables, a one-unit increase in technological readiness (infrastructure, data quality, usability) results in a 0.392 increase in adoption outcomes. The extreme significance ($p < 0.001$) confirms that the technical environment remains a critical constraint; without an intuitive interface, stable infrastructure, and quality data pipelines, users cannot fully engage in complex data analysis or task automation.

5 DISCUSSION OF FINDINGS

The empirical results of this study support the structural validity of the integrated TOEthical model within the higher education context. The finding that Technological Factors hold the highest predictive weight ($\beta = 0.392$, $t = 9.333$, $p < .001$). aligns with mainstream technology acceptance research, confirming that interface usability and reliable internet access are basic, essential prerequisites. In the university ecosystem, this means that even if a student or researcher is highly motivated, poor campus connectivity or lack of computing power directly suppresses their ability to leverage generative models for intense tasks like literature synthesis or data analysis.

Thematic analysis of the qualitative interview files illuminated the technical friction points hiding beneath the quantitative indices:

- **The Economic Exclusion Wall:** Participants frequently detailed a sharp drop in software utility when confined to free public access tiers. High licensing costs for premium, secure institutional packages often force individual researchers back to less capable public models that suffer from severe processing limits and increased hallucination risks.
- **On-Campus Network Drops:** Confirming the infrastructure gaps identified in the quantitative data, multiple interviewees cited fluctuating campus Wi-Fi networks as a core operational obstacle. Large data summaries or algorithmic code debugging tasks frequently fail mid-stream due to localized bandwidth timeouts, causing user frustration and driving a retreat back to traditional manual methods.

CONCLUSIONS

This paper confirms that technological dimensions are the primary driver of Gen AI adoption velocity within Kenyan universities. While individual researchers demonstrate high enthusiasm for the time-saving capabilities of generative systems, their actual progress is constrained by institutional technological deficits. The phenomenon of "digital decoupling" cannot be resolved by simply instructing researchers to use open-access tools. True, sustained research optimization requires systematic improvements to campus data structures, targeted licensing investments, and reliable hardware platforms.

Targeted Actionable Recommendations

- **To University Directorates of ICT & Security:**

Implement Local Proxy Optimization & Bandwidth Rings: Universities must deploy specialized, high-priority bandwidth channels specifically for academic research labs to safeguard large-token AI workflows from general campus traffic drops.

Establish Secure Institutional API Gateways: IT departments should build unified local API layers that connect external generative models to internal university repositories and research software. This architecture ensures that sensitive institutional datasets and intellectual property remain protected within secure firewalls, directly meeting the legal mandates of the Kenya Data Protection Act of 2019.

To University Senates and Management Boards:
Fund Strategic Premium Group Licensing: Rather than leaving software acquisition to individual ad-hoc purchases, management boards should allocate dedicated budgets to secure premium enterprise-grade AI software accounts for postgraduate researchers and faculty members, bypassing economic exclusion barriers.

- **To Faculty, Research Supervisors, and Postgraduates:**

Develop Dual-Verification Research Habits: Scholars must combine technical AI assistance with rigorous manual verification habits. Generative code and automated data summaries should be systematically treated as unverified drafts until checked by human expertise, ensuring that tool efficiency does not come at the expense of deep scholarly quality.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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The authors declare no conflicts of interest regarding this manuscript.

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