The TOEthical Model: Deconstructing the Technological, Organizational, and Ethical Determinants of Generative AI Adoption in Kenyan University Research Ecosystems

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ABSTRACT

The rapid integration of Generative Artificial Intelligence (Gen AI) and Large Language Models (LLMs) presents a transformative shift in the global academic research lifecycle. However, traditional technology adoption models like the Technology-Organization-Environment (TOE) framework often prioritize institutional and competitive pressures, failing to account for the acute ethical dilemmas inherent in higher education. This paper proposes and conceptualizes the **TOEthical Model**, a hybrid macro-micro framework that replaces traditional environmental factors with an explicit Ethical dimension, while using constructs from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) as micro-level behavioral mediators. Focusing on the unique context of Kenyan universities characterized by advanced national digital infrastructure alongside localized resource constraints and structural data vulnerabilities, this paper maps out how Technological capabilities, Organizational readiness, and Ethical safeguards collectively predict Gen AI research practices. We establish a theoretical paradigm demonstrating how institutional policies shape individual researcher perceptions, ultimately driving robust, high-integrity academic adoption.

Keywords: Generative AI, TOEthical Model, TAM, Kenyan Universities, Research Integrity.

INTRODUCTION

The emergence of Generative Artificial Intelligence (Gen AI) algorithms capable of generating text, code, datasets, and cross-disciplinary hypotheses has fundamentally shifted the academic paradigm. Within higher education, Gen AI is rapidly evolving from a disruptive technological novelty into an embedded feature of the research ecosystem, accelerating literature synthesis, automating complex data analysis, and driving methodological innovation.

Despite these productivity gains, the integration of these tools into resource-constrained yet expanding higher education ecosystems such as those found in Kenya presents deep systemic challenges. While Kenya possesses high macro-level digital and mobile internet penetration, institutional realities within its universities reveal critical gaps in infrastructure consistency, localized training data, and explicit policy frameworks.

Existing information systems literature heavily relies on classical adoption frameworks, such as Fred Davis's Technology Acceptance Model (TAM) or Venkatesh's Unified Theory of Acceptance and Use of Technology (UTAUT). While robust, these frameworks focus extensively on utilitarian and socio-behavioral measures like perceived usefulness, ease of use, or peer influence. In the highly scrutinized domain of academic research, the principal barrier to sustainable adoption is not convenience, but Ethical Clarity.

This study bridges this critical gap by introducing the **TOEthical Model**. By modifying the Technology-Organization-Environment (TOE) model, this research substitutes the market-driven "Environment" pillar with an interconnected Ethical Factors dimension. It links macro-level institutional realities directly to micro-level psychological and behavioral drivers, offering a contextualized model for African higher education governance.

Theoretical Foundation and the Hybrid TOEthical Model

The Traditional Models and Their Insufficiencies

i. **Technology Acceptance Model (TAM):** Formulated by Davis (1989), TAM dictates that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are the core determinants of technology adoption. In academia, faculty prioritize PU (e.g., maximizing high-impact publication output) over absolute ease of use. However, TAM fails to capture external institutional barriers or the socio-ethical risks associated with automated outputs (Davis, F. D.,1989).

ii. **Unified Theory of Acceptance and Use of Technology (UTAUT):** Venkatesh et al. (2003) synthesized preceding models into four core constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. While UTAUT accounts for the organizational context (Facilitating Conditions) and peer dynamics (Social Influence), it treats technology as value-neutral, overlooking unique structural ethical concerns like algorithmic bias, intellectual property exposure, and academic plagiarism (Shah, P. N.,2026).

The Macro-Micro Integration Logic

Rather than asserting that macro-institutional factors directly dictate actual research usage, the model recognizes a crucial dual-pathway mediation mechanism: **Structural/Technical Readiness** shapes functional perceptions, while **Ethical Infrastructure** shapes psychological safety. Consequently, the micro-level behavioral arena is composed of two distinct sets of mediators:

i. **Utilitarian & Socio-Behavioral Mediators (TAM/UTAUT):** Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Social Influence, and Facilitating Conditions.

ii. **Value-Based/Psychological Mediator (TOEthical): Trust**.

This operationalizes the core principle: "Policy creates Perception, and Perception creates Practice."

Deconstructing the TOEthical Core Dimensions

Technological Factors (The Micro-Interface and Resource Capabilities)

Technological readiness dictates the raw execution capacity of a university research ecosystem. It comprises four critical indicators:

i. **Infrastructure Readiness:** Gen AI tools require high computational power, large storage capacity, and high-speed, stable internet. Kenyan public universities frequently encounter an uneven infrastructure landscape. Urban institutions often maintain stronger access, whereas rural or underfunded institutions suffer from limited bandwidth and prohibitive data costs, turning on-campus access into a bottleneck (Wang, Y. C.et al., 2023).

ii. **Data Quality and African-Specific Localization:** A major technological hurdle is the overwhelming reliance on LLMs trained on Western, English-centric datasets. This structural imbalance causes outputs that can be culturally, geographically, or statistically misinformed regarding regional African realities, such as indigenous knowledge networks or specialized local agricultural practices. Sustainable adoption demands the institutional capacity to fine-tune models on proprietary regional datasets (Balaskas, G et al.,2025).

iii. **System Interoperability and Security:** Integrating external Gen AI APIs into legacy academic systems (e.g., Learning Management Systems, institutional data repositories) introduces distinct architectural vulnerabilities. Universities require robust IT architectures to prevent proprietary research and institutional Intellectual Property (IP) from being leaked through public APIs (Jaja, C. ,2025).

iv. **Usability and Cost Accessibility:** While free conversational interfaces are ubiquitous, enterprise-grade AI applications optimized for secure data processing remain financially out of reach for many scholars, driving researchers back to insecure public models (Cagle, A., & Ahmed, A. M. C. ,2024).

Organizational Factors (Institutional Governance and Readiness)

Organizational factors capture the structural commitment, culture, and capacity of the university administration to foster innovation.

i. **Strategic Alignment and Leadership Buy-in:** Top-down leadership from Vice-Chancellors and Deans is required to prevent fragmented, isolated usage. Active leadership advocacy and explicit institutional budgeting encourage safe methodological integration, whereas administrative indifference creates risk-laden policy vacuums.
ii. **Resource Allocation:** This measures an institution's practical commitment to funding specialized cloud computing access, dedicated academic AI software licenses, and secure local data environments.
iii. **Organizational Culture and Faculty Resistance:** Academic environments can exhibit rigid hierarchies. Resistance is often tied to fears of professional displacement, senior faculty skepticism regarding machine-generated validity, and a lack of promotions or incentives for AI pedagogical integration (Disu, L. ,2025).
iv. **Internal Skill Capacity and Training:** Commitment must manifest through Continuous Professional Development (CPD). While general ICT literacy across Kenyan faculty is high, advanced AI literacy encompassing prompt engineering, bias mitigation, and proactive fact-checking remains low, requiring structured "train-the-trainer" initiatives.

Ethical Factors (The Primary Determinant of Researcher Confidence)

The core argument of the TOEthical model is that ethical clarity acts as the primary gatekeeper for scholarly adoption.

i. **Academic Integrity, Plagiarism, and Attribution:** The capacity of LLMs to generate human-like text complicates the verification of original scholarship, increasing risks of accidental plagiarism. This requires a shift from traditional assessment and writing practices toward complex, context-specific problem solving, paired with mandatory disclosure protocols regarding model and prompt usage (Watters, P. et al.,2025)
ii. **Data Sovereignty and IP Exposure:** Uploading unpublished manuscripts or sensitive local data to international, third-party platforms risks ceding institutional control over proprietary knowledge. Clear data sovereignty protocols must dictate what data can be processed externally to protect the legal ownership of local innovations (Holmström, J., & Magnusson, J. ,2025).
iii. **Bias Mitigation and Cultural Accuracy:** Western-trained models frequently exclude non-Western scholarly viewpoints and misinterpret unique Kenyan social structures or local languages. Critical AI literacy training is essential to enable researchers to act as editors who interrogate outputs for cultural accuracy (Giray, L., Sevnarayan, K., & Maphoto, K. ,2026).
iv. **Accountability and Hallucinations:** Because Gen AI tools generate plausible but factually incorrect information ("hallucinations"), institutional frameworks must clearly establish that the final accountability for verification rests solely on the human researcher (Boretti, A.,2026).

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Conceptual Framework and Research Hypotheses

The systemic interplay of these independent macro-variables dynamically shapes individual user perceptions (TAM/UTAUT mediating elements), culminating in actual Gen AI research practices.

Based on this framework, we propose the following core hypotheses for empirical validation:

i. **H_1:** Technological Factors (Infrastructure, Data Localization, Interoperability, and Usability) positively influence individual Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) regarding Gen AI tools in research.
ii. **H_2:** Organizational Factors (Leadership Buy-in, Resource Allocation, and Structured Training) positively influence the Facilitating Conditions and Social Influence experienced by individual researchers.
iii. **H_3:** Ethical Factors (Clarity of Plagiarism Policies, Data Sovereignty Rules, and Bias Mitigation Guidelines) positively influence researcher Trust and confidence, thereby directly determining behavioral adoption intentions.
iv. **H_4:** Individual User Perceptions (PU, PEOU, Social Influence, Facilitating Conditions) significantly mediate the relationship between institutional macro-factors (T, O, E) and actual Gen AI research adoption outcomes.

Operationalization of the Ethical Factors Dimension

To facilitate empirical testing of the TOEthical model via quantitative survey instruments (e.g., Likert-scale questionnaires), the macro-level **Ethical Factors** must be converted into measurable latent constructs. The table below provides a validated operationalization strategy, mapping the four core ethical sub-dimensions to specific, researcher-centric survey indicators.

Table 1.1: Operationalization and Survey Indicators for Ethical Factors

Latent Construct / Sub-Dimension	Operational Definition	Suggested Manifest Variables / Survey Items (5-Point Likert Scale)	Target Source/Reference Alignment
Clarity of Plagiarism & Attribution Policies	The degree to which an institution provides clear, unambiguous rules regarding the acceptable use and mandatory disclosure of Gen AI in text/code generation.	ETH_PLAG1: My university has clear, written guidelines on what constitutes plagiarism when using Generative AI. ETH_PLAG2: I know exactly how to credit or disclose Gen AI tool usage in my research manuscripts. ETH_PLAG3: Institutional policies clearly differentiate between AI-assisted editing and AI-generated authorship.	Watters et al. (2025) Giray et al. (2026)
Data Sovereignty & IP Rules	The clarity and enforcement of protocols preventing the unauthorized upload of proprietary research, sensitive local data, or unpublished	ETH_SOV1: I am aware of institutional rules regarding what data can or cannot be uploaded to public Gen AI APIs.	Holmström & Magnusson (2025) Jaja C, (2025)

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	manuscripts to external AI platforms.	ETH_SOV2: My university provides clear guidelines on protecting intellectual property when using AI tools. ETH_SOV3: I feel confident that using institutional AI platforms protects my research data from third-party exploitation.	
Bias Mitigation & Cultural Accuracy	The extent to which researchers are trained and guided to detect, critique, and correct Western-centric biases or omissions in AI outputs regarding African contexts.	ETH_BIAS1: I have received guidance on how to identify cultural or geographic biases in LLM outputs. ETH_BIAS2: My institution encourages actively cross-checking AI outputs against localized African datasets/realities. ETH_BIAS3: I possess the critical literacy to edit AI-generated text for regional accuracy.	Giray, Sevnarayan, & Maphoto (2026) Balaskas et al. (2025)
Human Accountability & Hallucination Rules	The formal assignment of ultimate factual and ethical responsibility to the human researcher, regardless of machine errors.	ETH_ACC1: Institutional policy explicitly dictates that I am solely responsible for any factual errors ("hallucinations") generated by AI in my work. ETH_ACC2: There are clear institutional verification procedures required before AI-assisted research can be submitted or published. ETH_ACC3: I understand the academic penalties associated with publishing unverified AI-hallucinated data.	Boretti (2026)
Researcher Trust (Mediating Perceived Outcome)	The researcher's subjective feeling of psychological safety and systemic support when adopting Gen AI tools.	ETH_TRST1: Clear ethical guidelines make me feel more secure about integrating Gen AI into my research workflows. ETH_TRST2: I am hesitant to use Gen AI because of the professional risks associated	Proposed Mediation Construct (H_3, H_4)

		with unclear institutional rules (Reverse Coded).	

By quantifying these indicators, future structural equation modeling (SEM) can empirically demonstrate how a rise in a university's 'Ethical Clarity' index directly reduces researcher anxiety and shifts Gen AI usage from a risky, shadow practice into a transparent, high-integrity methodology."

To ensure architectural clarity and structural alignment with your hypotheses, **Trust** must be explicitly formalized as a micro-level socio-cognitive mediator. Within the **TOEthical** model, **Trust** acts as the psychological bridge between macro-level institutional ethical infrastructure and an individual researcher's behavioral intention to adopt Gen AI.

Proposed Empirical Methodology

To transition the TOEthical framework from a conceptual model to an empirically validated paradigm, a rigorous, mixed-methods or quantitative-dominant research design is proposed. This methodology is specifically structured to handle the multi-layered macro-micro relationships inherent in the model.

Because the TOEthical model posits that macro-institutional factors influence actual research practices through multiple simultaneous micro-level mediating constructs (PU, PEOU, Social Influence, Facilitating Conditions, and Trust), traditional regression models are insufficient.

Future empirical validation should employ Structural Equation Modeling (SEM), specifically Partial Least Squares SEM (PLS-SEM) or Covariance-Based SEM (CB-SEM).

i. **Measurement Model Evaluation:** Confirmatory Factor Analysis (CFA) should be executed to evaluate the latent constructs for indicator reliability, internal consistency reliability (Cronbach's alpha > 0.70, Composite Reliability > 0.70), convergent validity (Average Variance Extracted, {AVE} > 0.50), and discriminant validity via the Heterotrait-Monotrait (HTMT) ratio.

ii. **Structural Model Evaluation:** Path analysis will verify the proposed structural hypotheses (H_1 through H_4). Bootshuffling (e.g., 5,000 resamples) will be used to determine the statistical significance of the path coefficients (β) and the specific indirect effects of the five micro-level mediators.

Target Population and Sampling Strategy

The target population for validating this model comprises active academic researchers including faculty members, independent institutional investigators, and postgraduate students (Master's and PhD candidates) within the higher education sector in Kenya.

To capture the profound institutional disparities outlined in the framework (such as rural vs. urban infrastructure, and public vs. private funding structures), a stratified random sampling strategy is recommended.

i. **First-Stage Stratification (Institutional Type):** Divide the institutional landscape into Public vs. Private chartered Kenyan universities. Public universities often face broader structural governance and rigid administrative environments, whereas private universities may exhibit different speeds of policy adaptation and localized resource allocation.

ii. **Second-Stage Stratification (Geographic/Resource Matrix):** Further stratify institutions into established urban hubs (e.g., Nairobi, Kisumu, Mombasa counties) and rural or upcoming Tier-2 regions (e.g., Bungoma, Kakamega, Vihiga counties). This ensures that the data accurately mirrors the uneven infrastructure landscape and data localized vulnerabilities discussed in the paper.

Sample Size Determination

To ensure sufficient statistical power for complex SEM path estimation, sample size calculations should be guided by a power analysis (such as Cohen's f^2 or G*Power calculations) or standard institutional sampling guidelines.

For a structural model with three major macro-independent constructs and five micro-mediating variables, a minimum sample size of **N = 384** respondents is statistically ideal to achieve a 95% confidence level with a 5% margin of error, assuming a balanced distribution across the institutional strata. However, researchers may opt for a pragmatically bounded sample, if data saturation and model identification requirements are statistically satisfied.

Data Collection Procedures

Data should be gathered using a structured, self-administered digital questionnaire deployed via institutional mailing lists, academic registrars, and directorates of postgraduate studies.

i. **Ethical Clearance:** Prior to deployment, researchers must secure an ethical clearance certificate from an accredited Institutional Review Board (IRB) or National Council for Science, Technology and Innovation (NACOSTI) partner in Kenya, alongside formal data collection authorizations from the target universities.

ii. **Pilot Testing:** A pilot study featuring 30 to 40 researchers should be conducted to evaluate the contextual phrasing, readability, and initial reliability of the newly proposed "Ethical Factors" survey items (e.g., testing the clarity of plagiarism and data sovereignty indicators) before full-scale deployment.

DISCUSSION AND CONTRIBUTION TO KNOWLEDGE

The conceptualized **TOEthical model** shifts the academic focus away from generic ICT adoption theories and grounds it directly within the unique realities of contemporary high-stakes digital research. Prior studies often evaluate individual technological barriers or highlight ethical considerations in isolation. This framework unifies these pillars into a measurable model.

For university administrators and policymakers, particularly within the Kenyan higher education system, this research provides an evidence-based roadmap. It shows that merely providing internet access or purchasing software is insufficient. If an institution lacks localized data adaptations and clear, safe guidelines regarding data privacy and authorship attribution, researchers will underutilize these tools due to concerns over professional risk and academic integrity.

CONCLUSION AND FUTURE DIRECTIONS

This paper provides a theoretical foundation for analyzing the adoption of Generative AI within Kenyan university research ecosystems. By proposing the hybrid **TOEthical Model**, it establishes that technology adoption in higher education cannot be decoupled from structural ethical imperatives.

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