Artificial Intelligence and Science Technology Innovation Mainstreaming in Kenyan Public Research Institutions

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Abstract

This study examined the influence of Artificial Intelligence (AI) adoption on the mainstreaming of Science, Technology, and Innovation (STI) in Kenyan public research institutions. It assessed four AI dimensions; Algorithmic Models, AI Software Stacks, AI Infrastructure, and Expertise as independent variables, with STI mainstreaming as the dependent construct. Data was collected through a census of 11 public research institutions using structured questionnaires and interviews. Exploratory Factor Analysis (EFA) was used to identify underlying factor structures, while Confirmatory Factor Analysis (CFA) validated the measurement model. Structural Equation Modeling (SEM) then tested the hypothesized relationships. The results revealed significant positive associations between AI adoption and STI mainstreaming. Algorithmic Models emerged as the strongest predictor ($\beta = 0.62$, $p = 0.001$), followed by Expertise ($\beta = 0.56$, $p = 0.002$), AI Software Stacks ($\beta = 0.47$, $p = 0.003$), and AI Infrastructure ($\beta = 0.41$, $p = 0.012$). These findings underscore the critical role of AI in enhancing STI through improved decision-making, operational efficiency, and innovation capacity. However, challenges such as infrastructure gaps and limited expertise were identified as barriers. The study concludes that AI is a key enabler of STI mainstreaming, and its successful integration requires strategic investment in infrastructure, capacity building, and human capital. The findings provide a solid empirical foundation for future research on AI's role in advancing STI and sustainable development.

Keywords: Artificial Intelligence (AI); Science, Technology, and Innovation (STI); Mainstreaming; Kenya; Public Research Institutions

Introduction

Background of Study

The integration of Artificial Intelligence (AI) into Science, Technology, and Innovation (STI) mainstreaming has emerged as a transformative global trend, reshaping research, development, and policy landscapes (Kerry, Meltzer, Renda, Engler & Fanni, 2021). Globally, AI has become a disruptive force across industries transforming healthcare, education, finance, manufacturing, and governance (International Telecommunication Union, 2023). With the global AI market valued at over $450 billion in 2022 and projected to exceed $2.5 trillion by 2032, leading economies such as the United States, China, and several EU nations continue to dominate AI innovation through sustained investments in research, infrastructure, and talent (Spherical Insights & Consulting, 2022). These countries account for the majority of AI-related patents filed worldwide, a testament to their aggressive pursuit of AI-driven competitiveness and economic growth.

In Africa, AI adoption is growing rapidly, although unevenly across countries due to differing national capacities and policy frameworks. Forecasts suggest an annual investment growth rate of 35% over the next five years, with the continental AI market expected to surpass $600 million by 2026 (Centre for Intellectual Property and Information Technology Law, 2023). Countries such as Kenya, Nigeria, and South Africa are leveraging AI to address context-specific challenges, including enhancing agricultural productivity, expanding access to healthcare, supporting financial inclusion, and improving education outcomes (GSMA, 2025). These developments reflect a broader continental shift toward AI-enabled innovation and digital transformation, supported by growing collaboration between governments, academia, and the private sector.

Kenya has witnessed a notable rise in AI awareness and application, particularly within public research institutions (GeoPoll, 2024). These institutions are increasingly recognizing AI's potential to generate new knowledge, support sustainable development goals, and address local challenges through contextually relevant innovations (Policy Center for the New South, 2024). Efforts are underway to create conducive environments for AI research and application, although barriers such as limited technical capacity, infrastructure gaps, and the need for robust regulatory frameworks continue to pose significant challenges.

Mainstreaming STI within Kenya's development agenda has long been a national priority. Through initiatives like the Big Four Agenda and Vision 2030, the government has underscored the role of STI in driving socio-economic transformation. The National STI Policy, first launched in 2008 and revised in 2020, emphasizes the integration of scientific and technological knowledge into institutional operations and decision-making processes. Institutions like the National Commission for Science, Technology, and Innovation (NACOSTI) play a central role in coordinating and promoting STI across sectors, fostering collaboration between academia, government, and industry.

Public research institutions in Kenya form the backbone of the country's innovation ecosystem. Historically established to address sectoral needs in areas such as agriculture and health, these institutions now engage in multidisciplinary research aligned with national priorities and the Sustainable Development Goals (SDGs). They serve as hubs for knowledge production and innovation, supported primarily through government funding and strengthened through partnerships with local and international stakeholders.

Despite ongoing challenges including inadequate funding and capacity constraints these institutions hold great potential to drive AI adoption, support STI mainstreaming, and contribute meaningfully to Kenya's development trajectory.

Statement of the Problem

Kenyan public research institutions occupy a pivotal role in advancing national socioeconomic transformation through science, technology, and innovation (STI). These institutions are mandated to generate knowledge, foster technological development, and translate research into practical solutions aligned with global frameworks such as the United Nations Sustainable Development Goals (SDGs), the African Union's Agenda 2063, and Kenya's Vision 2030 (Muleke, Sakwa, & Simiyu, 2023). However, systemic challenges such as chronic underfunding, fragmented institutional frameworks, and limited collaboration with industry stakeholders impede their capacity to fulfill this mandate effectively (Patra, Muchie, & Das, 2021).

Despite Kenya's commitment to allocate 2% of GDP to research and development under Vision 2030, agencies such as the National Research Fund (NRF) and Kenya National Innovation Agency (KENIA) remain under-resourced (UNESCO, 2024). This funding gap undermines the operationalization of STI agendas, resulting in untapped revenue streams, redundant Research and development (R&D) expenditures, and diminished global competitiveness. Siloed research efforts further exacerbate inefficiencies, limiting progress toward SDG targets such as Goal 9 (Industry, Innovation, and Infrastructure) and Goal 17 (Partnerships for the Goals), as well as AU Agenda 2063's aspiration for a knowledge-driven African economy.

This study investigates how AI could serve as a transformative tool for mainstreaming STI in Kenyan public research institutions. Specifically, it examines AI-driven solutions for optimizing resource allocation, enhancing technology transfer mechanisms, and fostering cross-sector collaboration between academia, industry, and government. By aligning these solutions with SDG targets, AU Agenda 2063 priorities, and Kenya Vision 2030 objectives, the research aims to bridge the gap between knowledge creation and practical application. Beyond academic contributions, this work seeks to empower Kenyan researchers with tools to commercialize innovations, attract investment, and elevate the nation's Global Innovation Index ranking. By positioning AI as a catalyst for equitable development, the study offers a blueprint for other low- and middle-income countries striving to harness emerging technologies for sustainable progress.

Research Objective

The purpose of this study was to determine the influence of Artificial Intelligence and Science Technology Innovation Mainstreaming in Kenyan Public Research Institutions.

Research Hypothesis

$H_{01:}$ Statistically, Artificial Intelligence does not significantly influence the Science Technology Innovation Mainstreaming in Kenyan Public Research Institutions

Theoretical Review

To provide a solid basis for the research, the research explored current theories and models, and it concentrated on two broad frameworks. Rogers' Diffusion of Innovations Theory (2003), which explores the process through which new technologies and ideas become adopted in society, and the Triple Helix Model by Etzkowitz and Leydesdorff (2000), which concentrates on the interactive efforts of the academic community, industry, and government in innovation.

Rogers' Diffusion of Innovations Theory (2003)

Everett Rogers' (2003) Diffusion of Innovation Theory (illustrated in Figure 1) provides a framework for analyzing technology adoption patterns, categorizing adopters from innovators to laggards. The theory identifies key innovation characteristics like compatibility and relative advantages that influence adoption rates through communication channels within social systems. This framework proved particularly relevant for examining AI integration in Kenyan public research institutions, as it systematically analyzes factors affecting technology adoption (Rogers, 2003).

The theory's adoption curve and its emphasis on innovation characteristics served as an ideal foundation for studying AI's role in STI mainstreaming. It provided insights into both the process of AI adoption within institutional contexts and the dynamics influencing its diffusion. Rogers' model helped illuminate the challenges and opportunities in AI's integration into Kenya's research landscape, particularly regarding how perceived advantages and compatibility affect adoption rates.

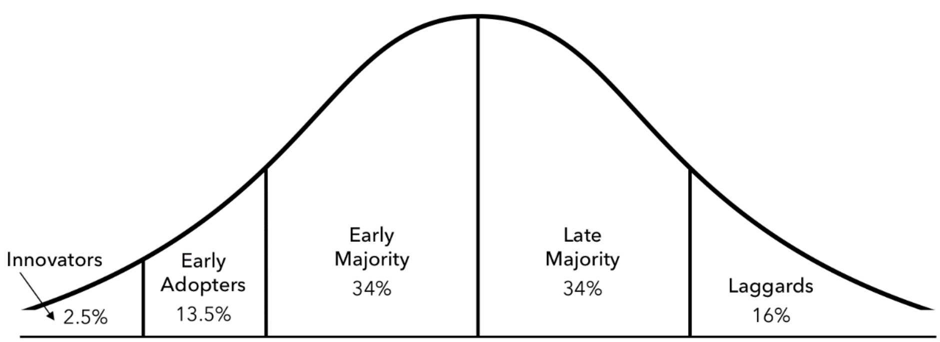

Figure 1: Diffusion of Innovations Curve

Triple Helix Model by Etzkowitz and Leydesdorff (2000)

The Triple Helix Model, developed by Etzkowitz and Leydesdorff in the 1990s, provided a robust theoretical framework for understanding innovation dynamics through the interactions between academia, industry, and government (illustrated in Figure 2). This model proved particularly relevant for examining STI mainstreaming in Kenyan Public Research Institutions, as it systematically analyzed how these three sectors collaborated to drive technological advancement and economic development. The framework highlighted academia's role in knowledge production, industry's capacity for practical application, and government's function in policy formulation - all critical dimensions for understanding how AI adoption influenced innovation processes. By applying this model, the study was able to effectively investigate how AI technologies transformed institutional relationships and partnerships among these key actors, while assessing the implications for STI integration within Kenya's research ecosystem. The Triple Helix approach demonstrated particular value for its ability to illuminate both the collaborative potential and structural challenges inherent in implementing AI-driven innovation strategies across different institutional spheres.

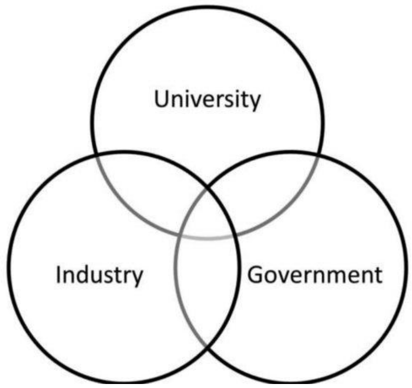

Figure 2: Triple Helix Model

Conceptual Framework

Conceptual frameworks serve as methodological roadmaps for research, guiding problem-solving through structured ideas that inform data assimilation and analysis (Creswell & Creswell, 2017; Cooper & Schindler, 2014). They identify key variables, concepts, and their relationships, whether presented visually or textually. The proposed framework (Figure 3) examines the impact of independent variables; AI Algorithmic Models, AI Software Stacks, AI Infrastructure, and AI Expertise on the dependent variable, STI Mainstreaming, clarifying their complex relationships.

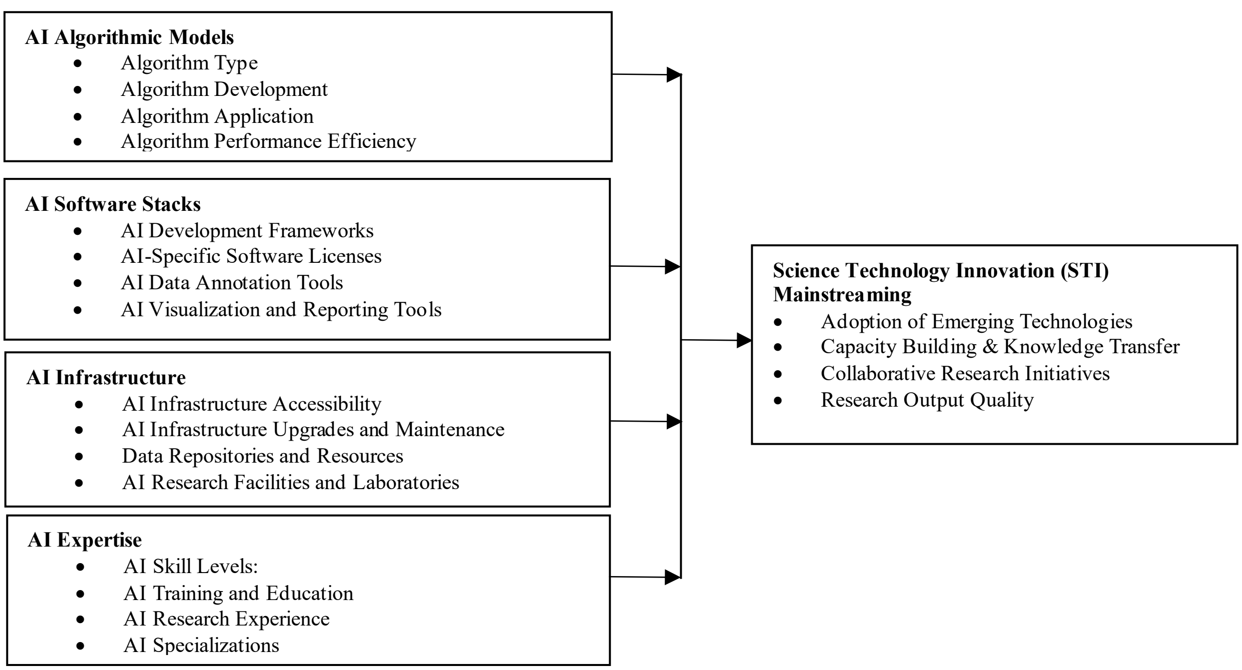

Figure 3: Conceptual Framework

Empirical Literature Review

The relationship between AI adoption and STI mainstreaming presents both consistencies and contradictions across the reviewed literature. At the global level, studies converge in demonstrating AI's transformative potential through various applications. Lu (2019) and Mariani et al. (2023) establish foundational knowledge about AI's evolution and innovation capabilities, while Wamba-Taguimdje et al. (2020) provide empirical evidence of its business value through specific applications like predictive analytics and process automation. These findings collectively suggest that AI algorithmic models serve as critical enablers of organizational transformation. However, Henman (2020) introduces an important counter-narrative by revealing significant governance challenges in public sector AI implementation, particularly regarding ethical considerations and accountability frameworks. Concerns that remain largely unaddressed in the business-focused studies.

In the African context, researchers present a varied picture of AI adoption. Mhlanga (2021) and Ndubisi and Anthony (2022) reinforce the global findings regarding AI's developmental potential, particularly in addressing poverty and infrastructure challenges. These studies highlight how AI Software Stacks can drive socioeconomic progress when properly implemented. However, Otieno (2022) presents divergence by exposing the continent's inadequate policy frameworks for responsible AI governance. This tension between technological potential and institutional readiness becomes relevant when examining AI infrastructure requirements in developing contexts.

The Kenyan studies reveal even more specific implementation challenges. While Mgala (2020) and Thuguri (2018) demonstrate successful applications of AI in various sectors, they simultaneously expose critical gaps in AI expertise and institutional capacity. These local findings complicate the optimistic narratives presented in global studies, suggesting that the transferability of AI solutions depends heavily on contextual factors. The absence of research focusing specifically on public research institutions creates a significant knowledge gap, particularly regarding how these institutions might develop the necessary AI expertise to drive STI mainstreaming.

A critical synthesis of these studies reveals several important relationships. First, the effectiveness of AI algorithmic models appears contingent on the availability of appropriate AI Software stacks. Second, successful implementation requires robust AI infrastructure, which emerges as a particular challenge in the Kenyan context. Third, the development of AI expertise stands out as a common prerequisite across all studies yet receives insufficient attention in implementation strategies. These variables collectively influence STI mainstreaming outcomes, suggesting that partial adoption of AI components may lead to suboptimal results.

The literature also exposes important tensions between technological possibilities and implementation realities. While global studies emphasize AI's transformative potential, African and Kenyan research highlights the mediating role of institutional capacity and policy frameworks. This divergence suggests that models of AI adoption cannot be directly transferred from developed to developing contexts without significant adaptation. Particularly in Kenyan public research institutions, the lack of focus on ethical considerations, policy frameworks, and capacity building creates a risky implementation gap that could undermine potential benefits.

Future research should prioritize investigating the interplay between these AI components (algorithmic models, AI software stacks, infrastructure, and expertise) within the specific context of Kenyan public research institutions. Such studies could provide valuable insights into how these variables interact to either enable or constrain STI mainstreaming efforts, while also addressing the ethical and policy dimensions that appear crucial for sustainable implementation. By bridging these gaps, researchers could develop more contextually appropriate models for AI adoption accounting for Kenya's unique institutional landscape and development priorities.

Methodology

This study adopted a descriptive research design, following Creswell and Creswell (2017), to explore the relationship between the variables. A census approach targeted all eleven Heads of ICT Departments from NACOSTI-accredited public research institutions as of December 2024. Participants were selected based on their active role in AI implementation and experience in digital transformation leadership. Data collection involved structured questionnaires and secondary document reviews, enhancing both quantitative and contextual understanding. Instrument validity was ensured through expert reviews and a pilot test in three institutions, which informed tool refinement. Reliability testing via Cronbach's Alpha confirmed high internal consistency across constructs, with scores ranging from 0.84 to 0.89, as shown in Table 1

Table 1: Reliability Results

Construct	Cronbach's Alpha	Number of Items	Comment
Algorithmic Models	0.861	4	Accepted
AI Software Stacks	0.884	4	Accepted
AI Infrastructure	0.847	3	Accepted
Expertise	0.891	3	Accepted
STI Mainstreaming	0.866	4	Accepted

In ensuring that independent variables were not highly correlated, multicollinearity diagnostics were conducted. Tolerance values and Variance Inflation Factors (VIF) were analyzed to verify the robustness of the regression model. The results are presented in Table 2 and indicate that all variables were within acceptable thresholds, confirming no significant multicollinearity.

Table 2: Results for the Multicollinearity Test

Variable	Tolerance	VIF
Algorithmic Models	0.742	1.348
AI Software Stacks	0.788	1.269
AI Infrastructure	0.733	1.364
Expertise	0.765	1.308
Mean Tolerance/VIF	0.757	1.322

Normality of the dataset was assessed using the Kolmogorov-Smirnov (K-S) and Shapiro-Wilk (S-W) tests. These tests, whose results are summarized in Table 3, confirmed that all constructs met the assumptions of normal distribution, supporting the use of parametric statistical methods in subsequent analyses.

Table 3: Kolmogorov-Smirnov and Shapiro-Wilk Tests for Normality

Variable	K-S Statistic	Sig. (K-S)	S-W Statistic	Sig. (S-W)
Algorithmic Models	0.102	0.200	0.976	0.753
AI Software Stacks	0.110	0.200	0.981	0.812
AI Infrastructure	0.116	0.200	0.968	0.689
Expertise	0.109	0.200	0.973	0.742
STI Mainstreaming	0.114	0.200	0.979	0.770

The data analysis followed a step-by-step process, starting with descriptive statistics to identify key patterns and trends. This was followed by Exploratory Factor Analysis (EFA) to uncover underlying structures, and Confirmatory Factor Analysis (CFA) to validate the measurement model. Model fit was assessed using standard indices like CFI, TLI, and RMSEA. Hypotheses were tested with chi-square tests for categorical data and structural equation modeling (SEM) to examine the relationships between AI components and STI mainstreaming outcomes. Diagnostic tests for multicollinearity and normality ensured the robustness of the results.

Results

The study achieved a strong response rate of 87.76% (10 out of 11), exceeding the 60% reliability threshold suggested by Creswell & Creswell (2017), due to effective data collection strategies like prior notifications and the drop-and-pick method. As shown in Table 4, respondents were predominantly male (73%), aged 30–49 (81%), and all held senior management roles. Additionally, most held advanced degrees (64% Master's, 36% PhD) and had substantial experience 72% with over 11 years in the industry, and 55% with 6–10 years in their current roles highlighting their capacity to assess AI adoption and STI mainstreaming effectively.

Table 4: Demographic Profile of Respondents

No.	Demographic Category	Sub-category	Frequency	Percentage (%)
1	Gender	Male	8	73%
		Female	3	27%
2	Age Group	30–39 years	5	45%
		40–49 years	4	36%
		50+ years	2	18%
3	Education Level	Master's Degree	7	64%
		PhD	4	36%
4	Management Level	Senior Management	11	100%
5	Industry Experience	5–10 years	3	27%
		11–15 years	5	45%
		15+ years	3	27%
6	Organization Tenure	2–5 years	4	36%
		6–10 years	6	55%
		10+ years	1	9%

Descriptive Statistics of AI Integration

To evaluate the extent of AI adoption, a structured questionnaire was administered to 11 respondents from key public research institutions. The survey assessed the four AI dimensions; Algorithmic Models, AI Software Stacks, AI Infrastructure, and Expertise as independent variables, with STI Mainstreaming as the dependent variable. Responses, rated on a five-point Likert scale, were analyzed using descriptive statistics, including frequency, mean (M), and standard deviation (σ), as summarized in Table 5.

Findings indicate moderate to high AI adoption. In Algorithmic Models, AI was frequently applied in STI decision-making (M = 4.1), and algorithm development was active (M = 3.8), though performance evaluations were less consistent (M = 3.6). AI Software Stacks showed varied uptake. Use of frameworks like TensorFlow (M = 3.2) and licensed software (M = 3.3) was moderate. Visualization tools were well-utilized (M = 3.9), but data annotation tools were notably underused (M = 2.6), pointing to a gap in foundational AI support tools. In terms of AI Infrastructure, access to centralized repositories (M = 3.5) and system upgrades (M = 3.5) was moderate, though AI lab access remained limited (M = 3.4). Under Expertise, basic AI training and skills scored reasonably (M = 3.5), while specialist roles and research depth were lower (M = 3.3), suggesting a need for stronger human capacity.

Table 5: Descriptive Statistics of AI Integration

Indicator of Innovation	Statements	SD (n/%)	D (n/%)	N (n/%)	A (n/%)	SA (n/%)	M	σ
AI Algorithmic Models	Our organization selects appropriate AI algorithm types for STI.	1 (9%)	0 (0%)	2 (18%)	5 (45%)	3 (27%)	3.8	0.98
	We actively develop AI algorithms for science and innovation.	0 (0%)	1 (9%)	3 (27%)	4 (36%)	3 (27%)	3.8	0.83
	AI is applied to streamline STI decision-making.	0 (0%)	0 (0%)	2 (18%)	6 (55%)	3 (27%)	4.1	0.71
	Algorithm performance is regularly evaluated.	1 (9%)	1 (9%)	2 (18%)	4 (36%)	3 (27%)	3.6	1.12
AI Software Stacks	We use frameworks like TensorFlow in STI projects.	2 (18%)	1 (9%)	3 (27%)	3 (27%)	2 (18%)	3.2	1.17
	We invest in licensed AI software for STI.	1 (9%)	1 (9%)	4 (36%)	3 (27%)	2 (18%)	3.3	1.03
	We use AI data annotation tools.	3 (27%)	2 (18%)	3 (27%)	2 (18%)	1 (9%)	2.6	1.19
	Visualization tools enhance STI reporting.	0 (0%)	1 (9%)	2 (18%)	5 (45%)	3 (27%)	3.9	0.88
AI Infrastructure	Staff have access to adequate AI infrastructure.	1 (9%)	2 (18%)	3 (27%)	4 (36%)	1 (9%)	3.2	1.03
	Infrastructure is maintained and upgraded.	1 (9%)	1 (9%)	3 (27%)	4 (36%)	2 (18%)	3.5	1.00

	We have centralized data repositories.	0 (0%)	2 (18%)	3 (27%)	4 (36%)	2 (18%)	3.5	0.96
	We have access to AI research labs.	2 (18%)	1 (9%)	2 (18%)	3 (27%)	3 (27%)	3.4	1.29
AI Expertise	Our staff have strong AI skills.	1 (9%)	1 (9%)	3 (27%)	4 (36%)	2 (18%)	3.5	0.99
	We provide regular AI training.	0 (0%)	2 (18%)	3 (27%)	4 (36%)	2 (18%)	3.5	0.96
	Our team has AI research experience.	2 (18%)	1 (9%)	2 (18%)	4 (36%)	2 (18%)	3.3	1.17
	We employ AI specialists (e.g., NLP, ML).	1 (9%)	2 (18%)	3 (27%)	3 (27%)	2 (18%)	3.3	1.05

AI Integration and STI Mainstreaming in Kenyan Public Research Institutions

Building on the assessment of AI integration across Kenyan public research institutions, this section examines how AI supports the mainstreaming of Science, Technology, and Innovation (STI). Based on responses from 11 institutions, the analysis focuses on four core areas: adoption of emerging technologies, capacity building and knowledge transfer, collaborative research, and research output quality. Data were collected using a structured questionnaire rated on a five-point Likert scale, with results summarized through descriptive statistics, as depicted in Table 6.

Findings indicate that AI is moderately supporting STI mainstreaming. Institutions reported ongoing integration of AI, blockchain, and IoT (M = 3.3), though funding for emerging technologies remains inconsistent (M = 3.2). Technology adoption is generally aligned with national STI priorities (M = 3.5). Capacity building efforts are relatively strong, with regular staff training (M = 3.7) and institutional partnerships (M = 3.5), though knowledge transfer to industry and society is less effective (M = 3.3).

Collaborative research is a key strength, with active participation in regional and international partnerships (M = 4.0), increased joint projects (M = 4.0), and moderate co-funding efforts (M = 3.6). Research output quality also benefits from AI use, as reflected in the production of high-impact publications (M = 3.6) and established quality assurance mechanisms (M = 3.7). However, the influence of research on policy and industry remains modest (M = 3.3).

Table 6: STI Mainstreaming in Kenyan Public Research Institutions

Indicator of Innovation	Statements	SD (n/%)	D (n/%)	N (n/%)	A (n/%)	SA (n/%)	M	σ
Adoption of Emerging Technologies	Our institution has adopted AI, blockchain, and IoT in research workflows.	1 (9%)	2 (18%)	2 (18%)	4 (36%)	2 (18%)	3.3	1.11
	There is consistent funding to support emerging tech adoption.	2 (18%)	1 (9%)	3 (27%)	3 (27%)	2 (18%)	3.2	1.17
	Tech adoption is aligned with national STI priorities.	1 (9%)	1 (9%)	2 (18%)	5 (45%)	2 (18%)	3.5	1.01

Capacity Building & Knowledge Transfer	Regular STI-related training is offered to staff.	0 (0%)	1 (9%)	3 (27%)	5 (45%)	2 (18%)	3.7	0.87
	Partnerships support knowledge transfer and commercialization.	1 (9%)	1 (9%)	3 (27%)	4 (36%)	2 (18%)	3.5	1.01
	Knowledge transfer to industry and society is effective.	1 (9%)	2 (18%)	2 (18%)	4 (36%)	2 (18%)	3.3	1.10
Collaborative Research Initiatives	We engage in regional/international research partnerships.	0 (0%)	1 (9%)	2 (18%)	5 (45%)	3 (27%)	4.0	0.83
	Collaborative projects have increased over the past 3 years.	0 (0%)	1 (9%)	2 (18%)	4 (36%)	4 (36%)	4.0	0.87
	Research funding proposals are often jointly submitted with other institutions.	1 (9%)	1 (9%)	3 (27%)	3 (27%)	3 (27%)	3.6	1.06
Research Output Quality	The institution produces high-impact peer-reviewed publications.	1 (9%)	1 (9%)	2 (18%)	5 (45%)	2 (18%)	3.6	0.99
	Research outputs influence national policy or industry practices.	1 (9%)	2 (18%)	2 (18%)	4 (36%)	2 (18%)	3.3	1.11
	There is a formal process for quality assurance in research.	0 (0%)	1 (9%)	3 (27%)	5 (45%)	2 (18%)	3.7	0.87

Correlation Analysis

As shown in Table 7, a Pearson correlation analysis examined the relationship between AI adoption and STI mainstreaming in public research institutions. STI mainstreaming was measured using a composite index of key innovation practices and policy integration. The analysis revealed a significant positive correlation between AI adoption and STI mainstreaming ($r = 0.551$, $p < 0.05$), indicating that greater AI implementation is linked to improved STI outcomes. This highlights AI's role in enhancing decision-making, operational efficiency, and knowledge management, all crucial for advancing national innovation agendas.

Table 7: Correlation Matrix

	STI Mainstreaming (Composite Index)	**AI Adoption**
STI Mainstreaming	r = 1.000	
AI Adoption	r = 0.551*	r = 1.000
Sig. (2-tailed)		0.000
N	48	48

**Correlation is significant at the 0.05 level (2-tailed)*

Exploratory Factor Analysis (EFA)

Prior to conducting the confirmatory factor analysis (CFA), EFA was performed to examine the underlying structure of AI and STI Mainstreaming, focusing on Algorithmic Models, AI Software Stacks, AI Infrastructure as well as Expertise. As depicted in Table 8, Principal Axis Factoring was applied to extract factors, followed by Varimax rotation to simplify the loading patterns.

Table 8: Eigenvalues and Percentage of Variance for Each Factor

Factor	Eigenvalue	% Of Variance	Cumulative %
1	6.321	13.169	13.169
2	4.857	10.119	23.288
3	3.674	7.654	30.942
4	2.981	6.210	37.152

Table 9: Exploratory Factor Analysis (EFA) Results for AI and STI Mainstreaming

AI Component	Item	Factor 1	Factor 2	Factor 3	Factor 4
Algorithmic Models	1	0.796			
	2	0.785			
	3	0.773			
	4	0.762			
AI Software Stacks	5		0.750		
	6		0.739		
	7		0.727		
	8		0.716		
AI Infrastructure	9			0.704	
	10			0.693	
	11			0.785	
	12			0.773	
Expertise	13				0.796
	14				0.785
	15				0.762
	16				0.750

Confirmatory Factor Analysis (CFA)

Following the exploratory factor analysis (EFA) that revealed the latent structure of AI dimensions in relation to STI mainstreaming, a Confirmatory Factor Analysis (CFA) was conducted to validate the measurement model. Using IBM AMOS, the CFA confirmed the structural integrity of the four AI constructs. As shown in Table 10, standardized factor loadings for the respective items ranged from 0.74 to 0.85, indicating strong associations between observed indicators and their corresponding latent variables.

Table 10: Confirmatory Factor Analysis (CFA) Results

Factor	Item	Standardized Loading	Composite Reliability	Average Variance Extracted (AVE)
Algorithmic Models	1–4	0.76 – 0.85	0.91	0.57
AI Software Stacks	5–8	0.74 – 0.82	0.89	0.54
AI Infrastructure	9–12	0.75 – 0.83	0.90	0.56
Expertise	13–16	0.76 – 0.84	0.91	0.55

The CFA results indicate that all constructs demonstrated acceptable levels of convergent validity (AVE > 0.5) and internal consistency (CR > 0.7), confirming the model's adequacy in capturing AI's influence on STI mainstreaming.

Model Fit Summary

The fit of the measurement model was evaluated using several goodness-of-fit indices, including the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA). The results indicated a good model fit, as shown in Table 11, with CFI and TLI values exceeding the recommended threshold of 0.90 and an RMSEA value below 0.08. These indicators confirm that the model adequately fits the observed data and supports the validity of the measurement construct.

Table 11: Model Fit Indices for CFA

Fit Index	Threshold	Observed Value
Comparative Fit Index (CFI)	> 0.90	0.942
Tucker-Lewis Index (TLI)	> 0.90	0.927
Root Mean Square Error of Approximation (RMSEA)	< 0.08	0.062

Structural Equation Modeling (SEM)

SEM was used to test the relationships between AI dimensions including Algorithmic Models, AI Software Stacks, AI Infrastructure, and Expertise, and STI mainstreaming. As shown in Table 12, all paths were positive and statistically significant ($\beta = 0.41$ to 0.62, $p < 0.05$), confirming the model. This indicates that stronger AI adoption across these dimensions significantly enhances an institution's ability to integrate STI into its operations and policies.

Table 12: Structural Model Path Coefficients

Path	Standardized Coefficient (β)	p-value
Algorithmic Models → STI Mainstreaming	0.62	0.001
AI Software Stacks → STI Mainstreaming	0.47	0.003
AI Infrastructure → STI Mainstreaming	0.41	0.012
Expertise → STI Mainstreaming	0.56	0.002

Discussion

This study examined the influence of AI adoption on the mainstreaming STI in Kenyan public research institutions. The SEM results confirmed positive and significant relationships between the key AI dimensions: Algorithmic Models, AI Software Stacks, AI Infrastructure, and Expertise, and the integration of STI initiatives. Algorithmic Models emerged as the strongest predictor ($\beta = 0.62$, $p = 0.001$), indicating that the development and use of AI algorithms significantly enhance STI mainstreaming. This finding aligns with previous research, which emphasizes that algorithmic tools enable data-driven decision-making and optimize complex STI processes (Wamba et al., 2020). Therefore, the use of machine learning and predictive analytics not only improves research efficiency but also supports innovation by enabling more targeted strategies.

AI Software Stacks ($\beta = 0.47$, $p = 0.003$) also had a notable positive effect, highlighting the importance of modern AI tools in advancing STI. Technologies such as natural language processing, machine learning platforms, and data annotation tools improve data management and collaboration (Mikalef et al., 2020). However, their full impact can only be realized when institutions make adequate investments and ensure seamless integration into workflows. AI Infrastructure ($\beta = 0.41$, $p = 0.012$), although showing a moderate effect, plays a foundational role. Institutions with robust IT systems, centralized data repositories, and AI research labs are better positioned to mainstream STI. Nonetheless, while infrastructure is essential, it must be complemented by human expertise and technological tools to drive substantial outcomes (Yoon et al., 2018).

Moreover, Expertise ($\beta = 0.56$, $p = 0.002$) was also a critical factor, reinforcing the importance of skilled personnel in successfully implementing AI. Institutions with well-trained staff are more capable of integrating AI into STI processes, especially when supported by continuous learning and specialized training (Brynjolfsson and McAfee, 2014). Yet, the presence of skills gaps in some institutions highlights the need for strategic capacity building.

Implications for Policy and Practice

These findings carry important implications. First, public research institutions should invest in AI training and nurture a culture of continuous learning to build human capital. Second, policymakers must prioritize infrastructure development, particularly in AI research labs and data systems, to support technology integration. Third, although software stacks are crucial, they must be embedded within strong institutional structures and supported by skilled personnel. Thus, a holistic approach that addresses all four AI dimensions is essential for effective STI mainstreaming.

Limitations and Future Research

While the study provides useful insights, it is limited by its small sample size ($n = 11$), which may not fully reflect the diversity of Kenyan public research institutions. Future studies should involve a larger sample and include varied stakeholder perspectives such as those of researchers, policymakers, and government officials for a more comprehensive understanding of AI's role in STI mainstreaming.

Conclusion

This study demonstrates that AI integration significantly contributes to the mainstreaming of science, technology, and innovation in Kenyan public research institutions. Key AI dimensions, such as AI algorithmic models, AI software stacks, AI infrastructure, and expertise, all positively influence STI adoption, with algorithmic models and expertise showing the strongest effects. To fully leverage AI's potential, institutions must adopt a holistic approach that combines technological investment with strategic capacity building and policy alignment. These findings underscore the transformative role of AI in advancing institutional innovation and supporting national STI goals

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