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Determinants of Artificial Intelligence Technologies Adoption in Kenyan Universities: A Case of United States International University-Africa

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ABSTRACT

Purpose: This study sought to carry out analysis of factors influencing AI adoption in the education sector and focused on AI adoption determinants at the United States International University-Africa. This study sought to determine the effect of technical capability, trust, relative costs and institutional readiness on AI adoption at USIU-A. The study was founded on technology acceptance models and focused on analysis of technical capability factors, trust, cost factors and institutional readiness factors.

Methodology: The study was guided by a cross-sectional research design and targeted students when collecting data since these are the main targets of AI in the university. A sample of 378 students were considered in the research. The study relied on structured questionnaires to collect data, and a Likert scale was used to code the responses. Data analysis involved coding into SPSS software, descriptive and inferential statistics including correlation and multiple regression analysis. Findings revealed that technical capability had a significant positive influence on AI adoption, explaining 25.5% of the variance. Trust factors such as privacy, reliability, and ethical use showed a weak but significant influence, accounting for 10.7%.

Findings: Relative costs had an overall insignificant effect, though data management costs showed a weak positive significance. Institutional readiness factors such as culture and policy readiness had weak positive relationships, while resource readiness showed a negative correlation, with the combined factors explaining 8.4% of AI adoption. The study concluded that while cost factors are less influential, technical infrastructure, trust, and institutional readiness play important roles in AI adoption.

Unique Contribution to Theory, Practice and Policy: The study recommends that USIU-A enhance AI adoption by promoting hands-on learning through workshops, pilot projects, and industry collaborations. It should partner with external organizations to access advanced technical resources and training. To build trust, the university should involve students in selecting AI tools and implement systems with clear accountability frameworks. Strategic AI adoption plans are essential, focusing on professional training, scalable platforms, and minimizing non-monetary costs. Finally, the institution should regularly review AI tools for compatibility and appoint visionary leaders to foster a culture of innovation and readiness.

Key Words: *Technical Capability, Trust, Relative Costs, Institutional Readiness, AI Adoption*

Background of the Study

In the digital economy, institutions of higher learning are actively exploring and adopting different technologies to enhance learning experiences (Amankwah, et al., 2024). Among these are Artificial Intelligence (AI) technologies such as intelligent tutoring and automated grading systems which are enabling educators to refine their pedagogical abilities, work against geographic and time limitations, and offer personalized services (Chivose, 2023). Students as well as using these tools to enhance their cognitive retention and learning and according to Alupo, Omeiza, and Vernon (2022), 99 percent of higher education institutions in the United States have initiated steps to integrate AI in teaching and learning. Despite this, Singla, et al., (2024) aver that the integration of AI in education is not without challenges which affect the pace of AI adoption such as insufficient funding and limited technological infrastructure. Understanding the factors that determine successful adoption of AI technologies is crucial to ensuring these institutions are better placed to integrate them in teaching.

Artificial intelligence technologies consist of units of machines that can be programed to achieve numerous cognitive tasks with the thinking of a human. Ouyang, Zheng, and Jiao (2022) explain that AI is a pillar of the industry 4.0 technologies that is central to facilitating technology-enabled teaching and learning and is integrated into education as artificial intelligence in education (AIED). Chen, Chen, and Lin (2020) remark that the use of AI in education is heavily reliant on collection, usage and processing of big data. Ouyang, Zheng, and Jiao (2022) detail numerous benefits to AI adoption such as reduced cost, improved time and process efficiency among new users. Ouyang, Zheng and Jiao (2022) confirm that in the education sector, automated assessment, performance prediction, resource recommendation, and improvement of learning experiences are the main functions of AI in universities. Salas-Pilco and Yang (2022) confirmed that intelligent analytics, image analytics, and assistive technologies are the main AI applications being integrated into higher learning institutions.

Statement of the Problem

Universities are leveraging emerging technologies to improve learning outcomes and enhance the learning experience (Ouma & Gitonga, 2023). Rana, et al., (2024) report that AI has provided new avenues for universities to facilitate learning within and beyond classroom settings, influencing four core areas in education; content generation, teaching methods, assessment, and communication. Students at the United States International University-Africa, have been actively engaging with AI, with Adika (2025) asserting that the school offers pre-university courses on AI application, regularly hosts AI roadshows, hackathons, and encourages students to explore the application of AI in various sectors. Despite these efforts and the benefits of AI integration, Chen, et al., (2020) report that globally, only 50 percent of all organizations have integrated AI solutions into at least one of their core functions. The Chegg (2024) Global Student Survey reports that less than 20 percent of universities in Kenya have integrated GenAI applications and among students, and that only 53 percent of Kenyan university students have utilized some form AI in the past year.

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Improving AI adoption requires understanding of the factors that determine AI readiness from the students' perspectives. Previous research into AI adoption in education settings reveals a host of factors unique to the technology or the adapter. Almusawi, et al., (2021) study found that teacher's readiness is the most significant determinant of an institution's use of AI, while Cabero-Almenara et al., (2024) confirmed that constructivist beliefs are the factors that impacts teachers' and students' willingness to adopt AI in education. Meanwhile, Wang, et al., (2023) identified a supportive environment as the most essential determinant of AI adoption while Rana, et al., (2024) found users' intention to use AI to be a factor of trust, social influence, effort expectancy, and performance expectancy. These findings, however, are contradict findings from Amankwah, et al., (2024) which found individual perceptions of their AI ability to influence use intention, and Chivose (2023) whose analysis revealed that the cost of accessing GenAI technologies is the most significant determinant of AI adoption. In the study by Koros et al., (2024), access to a skilled digital workforce has had significant impacts on AI adoption at the Kenya Medical Training College.

Despite being informative, various gaps emerged from the studies, with Almusawi, et al., (2021), Cabero-Almenara et al., (2024) and Wang, et al., (2023) providing information from developed economies which are more AI ready both technically and resource-wise. The findings may not represent Kenya's state. Moreover, Chen et al., (2020) adopted a secondary literature review method while the current study will collect primary data from actual AI users. Rana, et al., (2024) used SEM methods while the current will rely on linear regressions to determine the direction of causality. Amankwah, et al., (2024) also provided conceptual gaps as it only investigated the adoption of one AI tool while the current will examine multiple functional uses of AI. Locally, Chivose (2023), despite evaluating adoption of AI technologies in Kenyan universities limited their analysis to the patterns of use of ChatGPT only while the study by Koros et al., (2024) limited itself to AI adoption determinants at the Kenya Medical Training Collage. These studies do not inform of the determinant factors for the adoption of AI technologies at USIU. This study sought to fill this gap.

Objectives of the Study

i. To determine the effect of technical capability on the adoption of artificial intelligence technologies at the United States International University - Africa.
ii. To examine the effect of trust on the adoption of artificial intelligence technologies at the United States International University - Africa
iii. To establish the effect of relative costs on the adoption of artificial intelligence technologies at the United States International University - Africa
iv. To examine the effect of institutional readiness on the adoption of artificial intelligence technologies at the United States International University – Africa

Literature Review

Technical Capability and the Adoption of AI Technologies

Dong and Fan (2024) discern data processing capabilities, technical capability and fundamental resource capabilities as AI capabilities that determine an organization's ability to effectively integrate AI technologies into their operations. The researchers defined data processing capabilities as the organization's ability to collect, store, process, and utilize data in advancing organizational goals, technical competencies as the knowledge and skills needed to select, integrate and maintain AI systems, and fundamental resource capabilities as the accessibility of the infrastructure, hardware, personnel needed to effectively integrate AI systems.

Nguyen, Nguyen, and Dang (2022) note that AI capabilities improve firms' ability to apply advanced analytics and logic-based systems such as machine learning to explain events, support and automate decision-making, improving the firm's ability to acquire, transform and apply knowledge to advance organizational goals. The research by Nguyen, et al., (2022) used Structural Equation Modeling (SEM) in analysis of the critical determinants of AI adoption in Vietnam, collecting data from different sectors. The study was based on the TOE framework and DOI theory, and analysis results were that the despite AI acceptance being in the early stages, the management's AI knowledge, capability and support for AI technologies has significant effects on firms' ability to adapt AI technologies. Stronger managerial capability was associated with a conducive environment for AI adoption and improved organizational readiness for AI systems. However, the evidence was from multiple firms in different sectors. Additionally, it evaluated external environment factors from the TOE framework which are not included in the current study..

Confirming an increase in demand for and introduction of new AI products, Lin, Ho, and Yang (2022) used the unified theory of acceptance and use of technology (UTAUT) model in analysis of the factors determining the adoption of online learning product within Chinese schools. The study used regression methods in analysis and findings were that perceived entertainment and perceived risk had the most significant effect on user's intention to adapt AI-enabled online education systems, while social inference and effort expectancy exhibited minimal effects. These findings implied that modern users prefer tools that are enjoyable and free of risks to data and in the education field, free from inaccuracies.

Abaddi (2024) adopted the TOE framework in analysis of the factors influencing AI adoption among SMEs in Jordan, examining the moderating effects of innovation culture, employee digital skill level and market competition. The study used PLS-SEM models in analysis and results of the hypothesis testing revealed that while business innovativeness, management support, and technological infrastructure improved AI adoption intention, perceived costs have no significant effects. On the other hand, the firms' innovation culture, and employee digital skill level were found to have moderating effects on the relationships between the study variables. These moderator variables will be considered as independent variables under the modelling of the current study.

Ankamah, Gyesi, and Amponsah (2024) also revealed that awareness and understanding of AI platforms are key determinants of students' adoption intentions. The study sought after the perspectives of medical students and relied on structured questionnaires to collect data. Analysis revealed that while there was a high degree of knowledge of AI tools, AI use was limited to the use of Grammarly and ChatGPT which are low skill demand level platforms requiring minimal training and understanding. The study further confirmed that limited opportunities for training on AI-assisted technologies and costs associated with subscription-based tools were limiting students' use of more advanced tools that are currently permeating medical education.

The objective of Chepchirchir (2024) analysis was to identify the challenges and opportunities with AI adoption in Kenyan academic institutions. A mixed-methods approach was utilized in the study and through bibliometrics analysis and systematic literature review, it was ascertained that effective AI integration is highly dependent on the AI skills and competencies of the users. The study confirmed that these skills are essential to meeting the evolving needs of the job market and to keep pace with the rapid technological advancements in automated systems. The initial high investment cost, training and maintenance of AI systems was identified as a significant hindrance to AI adoption in Kenyan government institutions which were mandated to integrate AI tools under the county government Management Information Systems.

Trust and the adoption of AI Technologies

Choung, David, and Ross (2023) sought to understand the relationship between AI trust and AI acceptance behavior by applying path analysis on data collected from survey responses of college students. the study revealed two dimensions of trust that have strong influences on acceptance of AI in the United States. Path analysis results confirmed that human-like trust and functionality trust both have direct effects on intention to use AI. Moreover, the findings ascertained that functionality-related trust factors had greater effect on usage intention than human-centered trust factors. The study confirmed the value of trustworthy AI but from US users' perspectives.

An, et al. (2023) sought to model the factors determining teachers' intention to use AI tools in middle school teaching, focusing on English learners in K-12 level in China. The study sought after the teachers' perceptions, knowledge, and behavioral intention, and relied on the UTAUT model as a theoretical basis. Performance Expectancy, Social Influence and AI language technological knowledge were confirmed to directly affect adoption intention, while Effort Expectancy Facilitating Conditions and AI technological pedagogical knowledge had indirect effects. The study findings confirmed the importance of assuring teachers that AI tools are useful and can improve teachers' efficiency and quality. The study further added that increasing teachers' understanding of AI tools would reduce earners' anxiety which is a considerable inhibitor to students' use of AI tools.

A high degree of trust that ChatGPT is secure and useful was also confirmed to influence university students' intention to use ChatGPT in their academic research. Au (2023) used correlation methods in analysis of AI adoption patterns in Malaysian HEIs and it was ascertained that there exists an intricate relationship between supportive environments and trust in the tools and their adoption. The study confirmed that successful AI adoption requires effective institutional support, ethical awareness initiatives, and comprehensive policies to ensure responsible integration of AI based generative tools among university students. This study will not restrict itself to one tool but instead examine multiple use cases of AI. Despite significant improvements in AI adoption, AlGerafi, Zhou, Alfadda and Wijaya (2023) confirmed that the extent of integration into daily operations remains low and insufficient in research that sought after the factors influencing Chinee students' intentions to adopt AI-based robots in learning. The study was constructed on the Technology Acceptance Model and used PLS-SEM in analysis whose findings revealed that user's perceptions of the consistency, reliability, usability and ease of use AI have significant influences on acceptance of AI-based robots. The findings confirmed that students are more willing to use AI-based robots in education because they trust in the reliability of the technologies and believe that it would improve their reputation. Contrary to expectations, AI literacy had insignificant effects on the acceptance of AI tools.

Cukurova, Miao, and Brooker (2023) sought after the determinant factors influencing the integration of adaptive learning platforms in Swiss schools, relying on regression models in analysis. The findings of the research were that despite teachers' knowledge, confidence and the quality of the products being essential determinants, the ability of the systems to reduce workload, a high degree of teacher ownership, support and trust are key to increasing engagement with adaptive learning platforms. The study confirmed that it is essential for teachers and staff to trust and be able to defend the value of the platform to continually deploy them in daily operations.

Almaiah, et al., (2022) integrated the innovation diffusion theory in analysis of the factors influencing the adoption rate of AIA-based technologies for governmental purposes in the Gulf region, specifying the effect of user characteristics and technology-based features. Data analysis for the study involved PLS-SEM methods and findings were that while easy-to-use technologies are associated with a high degree or acceptance, the belief that the technology has relative advantages, is compatible and less complex, and has observable benefits directly impacts its adoption rate.

Zaragoza, Tula, and Corona (2024) deployed a qualitative methodology in analysis of the factors and effect of the adoption of automatic grammar checker, Grammarly in academic settings. The study contacted specialists and utilized interview schedules in analysis which revealed that while the tool has the potential to enhance writing quality, teachers were concerned that overreliance on the tool can have detrimental effects on learning outcomes, hindering the development of students' writing skills and academic independence. Moreover, according to the respondents, the tool also raises privacy concerns, especially since it processes sensitive or proprietary academic work using commercially available platforms. The study confirmed the necessity to accompany such tools with policies to streamline their use, promote academic integrity and foster critical thinking skills among students.

Relative Costs and the Adoption of AI Technologies

Radhakrishnan and Chattopadhyay (2020) analysis confirmed that companies that incur higher technology adoption costs have higher expectations and will unsubscribe from new technologies if they fail to offer reciprocate advantages. The study which carried out a literature analysis of determinants of AI adoption highlighted the user's trust, the technology's cost, social influence, performance expectancy, and prior experience as the main individual-level determinants of adoption of AI tools.

Cubric (2020) carried out systematic literature review of AI adoption determinants in business context, focusing primarily on technical and economic factors of AI adoption such as cost and productivity outcomes. The study evaluated findings from 30 papers that evaluated firms in different sectors and analysis results were that drivers of AI adoption are mostly economic, while barriers are technical (data, model relevance) and social (AI knowledge, job insecurity, safety and trust considerations). The study confirmed that addressing these associated costs would increase the effectiveness of AI adoption.

Confirming an increase in the use of technology platforms offering coach matching, administration of coaching sessions and e-coaching services, Terblanche and Cilliers (2020) sought after the determinant factors for the use of AI coaches. The study evaluated the AI chatbot use in different domains and used the UTAUT framework in guiding the objectives relying on SEM analysis. SEM regression findings revealed that performance expectancy, social influence and attitude are the main determinants of AI chatbot use intention, with the easy access to chatbots significantly impacting their continued use. The study limited itself to chatbots while the current will consider multiple AI cases used in universities.

Shahadat, Nekmahmud, Ebrahimi, and Fekete-Farkas (2023) used the TOE framework in analysis of the factors that influence the adoption of new technologies on their adoption in SMEs in developing economies. Purposive sampling was utilized and PLS-SEM used in analysis. The observations were that a host of factors relating to observability, perceived cost, complexity, and top management innovativeness and support are the main predictors of ICT adoption among SMEs. The study was based on SOEs, while the current study will focus on AI integration in institutions of higher learning.

Ezekiel and Akinyemi (2022) carried out analysis of the determinants of AI adoption at the University of Ibadan using data from lecturers and academic staff. The study used a survey style design and Pearson Product Moment Correlation in analysis whose findings revealed that while there is widespread belief that AI can be optimized for higher education learning and has the potential to reduce workload and increase learning interactivity, there was also a high degree of fear of job loss, loss of human interactions and increased vulnerability to loss of academic integrity. Moreover, there was agreement that effective AI integration requires access to confidential student data and significant capital outlay to implement and sustain. This study conceded that AI integration cost much more than existing learning modules.

Similar observations were made in Ghana where Nsoh, Joseph, and Adablanu (2023) evaluated the trends, opportunities and pitfalls for AI integration in university settings. The study confirmed that while AI has seen increased use cases such as adaptive learning, teaching evaluation, and virtual classrooms, privacy concerns, increased cost of implementation, and difficulty contracting AI-competent personnel to manage AI systems were identified as existing pitfalls to effective AI integration. The study findings implied that to make the most if AI, universities have to ensure lecturers can access the resources and infrastructure needed to actualize the implementation of AI systems.

Institutional Readiness and the Adoption of AI Technologies

Emhmed, et al. (2021) study sought after the effect of technical and organizational facilitating conditions of the use of ERP systems in Libyan universities, relying on the UTAUT model and PLS-SEM technique regression models in analysis. The study confirmed that the existence of IT infrastructure, IT unit professionalism, and IT vendors' professionalism are the technical facilitators of ERP adoption, while managerial support, HR-IT and financial capacity are the organizational specific ERP facilitators. Of these, IT infrastructure and managerial support were confirmed to have the most significant impacts on firms' intention to use ERP systems. These factors will be evaluated in relation to AI adoption instead of ERP adoption factors.

Perello-Marin (2022) used descriptive and inferential methods in analysis of the factors influencing the adoption of AI-based human resource management tools in business. The findings of the study revealed that AI integration in staffing, till management, and compensation, with compatibility with existing tools and infrastructure being identified as the most significant contributor of AI adoption in HR. Other identified factors for AI adoption were managerial support, the technology's relative advantage, and the existence of vendor partnership, while low complexity had negative effects on adoption intention. Organizations with an innovative culture were found to be better prepared to adopt AI in HR. This study focuses on AI integration in universities which have educational purposes.

Mafara and Abdullahi (2024) sought to determine the main impediments to AI adoption in education contexts, focusing on natural language processing, speech recognition, machine learning, expert system, robotics, vision and planning tools. The study used a literature review methodology and confirmed that pursuit of educational advantage is a critical driver, while institutional readiness is the most significant challenge. Many of the institutions lacked adequate infrastructure, reliable internet connectivity, relevant local language, content and data, curricula, and cultural contexts necessary to train and improve AI tools' ability to meet specific learning needs. Moreover, lack of stakeholder awareness on how to protect privacy and security in the digital environments were shown to contribute to increased institutional rejection.

Bakhadirov and Alasgarova (2024) used ordinary least squares regression equations in analysis of the factors influencing teacher's intention to use AI tools to achieve instructional purposes at private schools Azerbaijan. The study specified the effect of individual, technological, and

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institutional variables and analysis results revealed that the degree of teacher innovativeness and perceived AI usefulness significantly influenced AI use for educational purposes, while the user's perception of the tool's ease of use had no statistically significant effect. The presence of an innovative culture, supportive orientation and AI policies were shown to improve a schoolteacher's readiness to use AI in learning contexts.

Tjebane, Musonda, and Okoro (2022) focused on determining AI adoption in South Africa's construction sector, using a quantitative survey that collected data from industry experts and exploratory factor analysis. The findings of this study were similar to Hassan (2024) who confirmed that top management support, innovative organizational culture, competence-based development, and collaborative decision-making are essential factors determining organizations' readiness and willingness to use new technologies. Managerial IT capabilities, human AI knowledge and information management capabilities were linked with a high degree of the diffusion of AI innovations.

Hlongwane, Shava, Mangena, and Muzari (2024) sought to identify the challenges influencing higher education institution's ability to integrate AI technologies in higher education. The study used a qualitative research approach and a case study design that sourced data through interviews with university lecturers. A key factor limiting AI adoption was the lack of adequate amounts of data about individual students as well as limited organizational awareness of the potential of AI to improve education outcomes. Moreover, resistance due to increased perceptions of job insecurity, limited access to associated resources such as laptops, smartphones, and tablets, costly internet and connectivity issues as well as a dearth of AI system experts were also confirmed to limit widespread AI utilization in higher learning institutions in Tanzania. This study will focus on a Kenyan university.

Research Methodology

The study was guided by a cross-sectional research design and targeted students when collecting data since these are the main targets of AI in the university. A sample of 378 students were considered in the research. The study relied on structured questionnaires to collect data, and a Likert scale was used to code the responses. Data analysis involved coding into SPSS software, descriptive and inferential statistics including correlation and multiple regression analysis. The multiple regression model was;

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon$$

Where: α is the constant of the regression model, $\beta_1 - \beta_4$ are the coefficients of the independent variables, X_1 is the technical capability, X_2 is the trust, X_3 is the relative costs, X_4 is the institutional readiness, and ε represents the error term of the model.

Results

The research sought to obtain responses from 378 students drawn from USIU-Africa. Physical data collection was utilized due to the proximal access of respondents within the institution. The

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research was able to obtain a 75 percent response rate (n = 283) with 25 percent of sample respondents not engaging during the allowed study period.

Descriptive Findings

The descriptive findings for the adoption of AI at USIU-Africa indicate strong agreement on the use of AI-based tools, with a high mean (Mean = 4.265) for the adoption of AI learning management systems and a standard deviation of 0.751, suggesting moderate consistency in responses. The overall mean for the responses on relative costs and adoption of AI tools is high (Mean = 4.126), indicating general agreement among respondents that the costs associated with adopting AI tools are manageable and affordable for students. The overall standard deviation of 0.673 also indicated consistency in responses. In addition, the overall mean of statements under institutional readiness and adoption of AI was high (Mean = 4.159), suggesting strong agreement among respondents that the university has provided essential infrastructure, policies, and support for AI adoption. The overall standard deviation of 0.688 indicates consistency in responses.

Correlation between Technical Capability and Adoption of AI

The research adopted correlation analysis to determine the direction of association between the technical capability construct and adoption of AI. The findings are shown in Table 1

Table 1: Correlation between Technical Capability and Adoption of AI

			Adoption AI	Employee Technical	Resource Capability	Managerial Capability
Spearman's rho	Adoption AI	Correlation Coefficient	1.000			
		Sig. (2-tailed)	.			
	Employee Technical	Correlation Coefficient	.225**	1.000		
		Sig. (2-tailed)	.000	.		
	Resource Capability	Correlation Coefficient	-.192**	.232**	1.000	
		Sig. (2-tailed)	.001	.000	.	
	Managerial Capability	Correlation Coefficient	.155**	.269**	.049	1.000
		Sig. (2-tailed)	.009	.000	.409	.
		N	283	283	283	283

**. Correlation is significant at the 0.01 level (2-tailed).

The findings show a positive weak and positive association between employee technical capabilities (rh = .225**, Sig = .000), and managerial capability (rh = .155**, Sig = .009) and adoption of AI at USIU-Africa. The tests further indicated a weak negative and significant relation between resource capability (rh = -.192**, Sig = .001) and adoption of AI at USIU-Africa.

Further, a multiple linear regression was performed to determine the magnitude of effect of technical capability on the adoption of AI at USIU-Africa and summary results are shown below.

Table 2: Regression between Technical Capability and Adoption of AI

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.505[a]	.255	.247	.41858

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a. Predictors: (Constant) Managerial Capability, Resource Capability, Employee Technical Capability

The results demonstrated a coefficient of determination (R^2 = .255) which revealed that with other factors held constant, technical capabilities (managerial capability, resource capability, employee technical capability) have a positive effect (25.5 percent) on the adoption of AI at USIU-Africa.

Table 3: ANOVA Technical Capability and Adoption of AI

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	16.762	3	5.587	31.890	.000[b]
	Residual	48.883	279	.175		
	Total	65.645	282			

a. Dependent Variable: Adoption of AI

b. Predictors: (Constant) Managerial Capability, Resource Capability, Employee Technical

The ANOVA findings indicated F-calculated = 31.890, sig = .000 <.05 thus signifying there was a positive and significant relationship between technical capability and the adoption of AI at USIU-Africa.

Table 4: Regression Coefficient Technical Capability and Adoption of AI

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.294	.249		9.223	.000
	Employee Technical	.460	.054	.451	8.520	.000
	Resource Capability	-.120	.023	-.269	-5.108	.000
	Managerial Capability	.072	.034	.111	2.140	.033

a. Dependent Variable: Adoption AI

The regression coefficient for employee technical capability was (B_1 = .460, t = 8.520, sig = .000<.05) revealing a positive and significant effect of employee technical capability on the adoption of AI at USIU-Africa. On the second construct, resource capability the findings showed (B_2 = -.120, t = -5.108, sig = .000<.05) revealing a negative and significant effect on the adoption of AI at USIU-Africa. Lastly, the analysis showed a coefficient for managerial capability (B_3 = .072, t = -5.108, sig = .000<.05) confirming existence of a positive and significant effect of managerial capability on the adoption of AI at USIU-Africa.

Correlation between Trust and Adoption of AI

The research adopted correlation analysis to determine the direction of association between the trust construct and adoption of AI. The findings are shown in Table 5.

Table 5: Correlation between Trust and Adoption of AI

			Adoption AI	Privacy	Reliability	Ethical & Responsible
Spearman's rho	Adoption AI	Correlation Coefficient	1.000			

	Sig. (2-tailed)	.			
Privacy	Correlation Coefficient	.268**	1.000		
	Sig. (2-tailed)	.000	.		
Reliability	Correlation Coefficient	.286**	.259**	1.000	
	Sig. (2-tailed)	.000	.000	.	
Ethical& Responsible	Correlation Coefficient	.245**	.330**	.387**	1.000
	Sig. (2-tailed)	.000	.000	.000	.
	N	283	283	283	283

**. Correlation is significant at the 0.01 level (2-tailed).

From the correlation analysis there is an established weak positive and significant association between privacy (rh = .268**, Sig = .000); reliability (rh = .286**, Sig = .000); ethical and responsible use (rh = .225**, Sig = .000) and adoption of AI at USIU-Africa.

Regression between Trust and Adoption of AI

The research adopted a linear regression analysis to determine the strength of the relationship between trust adoption of AI at USIU-Africa.

Table 6: Regression between Trust and Adoption of AI

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.326[a]	.107	.097	.45850

a. Predictors: (Constant), Ethical Responsible, Privacy, Reliability

The analysis yielded a regression coefficient of .107. This indicated that holding other factors constant, trust has a positive effect adoption of AI at USIU-Africa. This implied that 10.7 percent of changes in adoption of AI at USIU-Africa were predicted by ethical and responsible use, privacy, and reliability.

Table 7 ANOVA between Trust and Adoption of AI

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.993	3	2.331	11.087	.000[b]
	Residual	58.652	279	.210		
	Total	65.645	282			

a. Dependent Variable: Adoption of AI
b. Predictors: (Constant) Ethical & Responsible, Privacy, Reliability

The findings of the ANOVA analysis yielded F-calculated = 11.087> (f-critical) and Sig = .000<.05. These results showed there is a positive and significant relationship between trust and the adoption of AI at USIU-Africa.

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Table 8: Regression Coefficient Trust and Adoption of AI

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.288	.361		6.334	.000
	Privacy	.222	.063	.221	3.509	.001
	Reliability	.165	.076	.143	2.168	.031
	Ethical & Responsible	.060	.093	.044	.639	.523

a. Dependent Variable: Adoption of AI

The analysis of the coefficients showed the first construct privacy yielded (B_1 = .222, t = 3.509, sig = .001<.05) revealing a positive and significant effect of trust on the adoption of AI at USIU-Africa. On the reliability construct, the findings showed (B_2 = 165, t = 2.168, sig = .031<.05) revealing a positive and significant effect on the adoption of AI at USIU-Africa. Findings for the ethical and responsible construct yielded (B_3 = .060, t = .639, sig = .523>.05) which confirmed a positive and insignificant effect of managerial capability on the adoption of AI at USIU-Africa.

Correlation between Relative Costs and Adoption of AI

The research adopted correlation analysis to determine the direction of relationship between the relative costs construct and adoption of AI.

Table 9 Correlation between Relative Costs and Adoption of AI

			Adoption AI	Acquisition	Maintenance Cost	Data Management
Spearman's rho	Adoption AI	Correlation Coefficient	1.000			
		Sig. (2-tailed)	.			
	Acquisition	Correlation Coefficient	-.022	1.000		
		Sig. (2-tailed)	.712	.		
	Maintenance Cost	Correlation Coefficient	.026	.130*	1.000	
		Sig. (2-tailed)	.662	.028	.	
	Data Management	Correlation Coefficient	.160**	.109	.167**	1.000
		Sig. (2-tailed)	.007	.067	.005	.
		N	283	283	283	283

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

The correlation tests revealed acquisition costs had a negative and insignificant relation (rh = -.022 Sig = .712) while maintenance costs had a positive and insignificant relation (rh = .026 Sig = .662) to adoption of AI at USIU-Africa. Analysis pointed to a weak positive and significant relation between data management costs adoption of AI at USIU-Africa (rh = .160** Sig = .007).

Regression between Relative Costs and Adoption of AI

The study further performed a multiple linear regression to determine the magnitude of effect of relative costs on the adoption of AI at USIU-Africa and summary results are shown below.

Table 10: Regression between Relative Costs and Adoption of AI

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.178[a]	.032	.021	.47731

a. Predictors: (Constant) Data Management, Acquisition, Maintenance Cost

The regression analysis produced a coefficient of determination (R^2=.032) which implied that relative costs predicted 3.2 percent of the changes in the adoption of AI at USIU-Africa. This showed that data management costs, acquisition costs, and maintenance costs can predict the adoption of AI at USIU-Africa.

Table 11 ANOVA Regression between Relative Costs and Adoption of AI

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.080	3	.693	3.044	.029[b]
	Residual	63.564	279	.228		
	Total	65.645	282			

a. Dependent Variable: Adoption of AI

b. Predictors: (Constant) Data Management, Acquisition, Maintenance Cost

The research further sought to determine the statistical significance of the relationship at a 5 percent significance level, and the findings indicated an F-value of 3.044 and Sig =.029<.05. This showed there is a positive and significant relationship between relative costs and the adoption of AI at USIU-Africa.

Table 12 Regression Coefficient Relative Costs and Adoption of AI

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.136	.399		7.859	.000
	Acquisition	.016	.064	.015	.243	.808
	Maintenance Cost	.051	.071	.045	.724	.470
	Data Management	.176	.069	.157	2.550	.011

a. Dependent Variable: Adoption of AI

On the analysis of coefficients, the first construct, acquisition costs produced values of (B_1 = .016, t = .243, sig = .000<.05) revealing a positive and insignificant effect of employee acquisition costs on the adoption of AI at USIU-Africa. Results of the second construct, maintenance costs, showed findings of (B_2 = .051, t = .724, sig = .470<.05) revealing a positive and insignificant effect on the

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adoption of AI at USIU-Africa. Lastly, the analysis showed a coefficient for data management costs of (B_3 = .176, t = 2.550, sig = .011<.05) confirming the existence of a positive and significant effect of data management costs on the adoption of AI at USIU-Africa.

Correlation between Institutional Readiness and Adoption of AI

The research adopted correlation analysis to determine the direction of relationship between the institutional readinesses constructs and adoption of AI.

Table 13 Correlation between Institutional Readiness and Adoption of AI

			Adoption AI	Resource Readiness	Culture Readiness	Policy Readiness
Spearman's rho		Correlation Coefficient	1.000			
		Sig. (2-tailed)	.			
	Resource Readiness	Correlation Coefficient	-.035	1.000		
		Sig. (2-tailed)	.558	.		
	Culture Readiness	Correlation Coefficient	.173**	.306**	1.000	
		Sig. (2-tailed)	.004	.000	.	
	Policy Readiness	Correlation Coefficient	.176**	.003	.171**	1.000
		Sig. (2-tailed)	.003	.956	.004	.
		N	283	283	283	283

**. Correlation is significant at the 0.01 level (2-tailed).

The correlation tests pointed to a negative association between resource readiness (rh = -.035 Sig = .558), a weak positive relation of culture readiness (rh = .173**, Sig = .004); and a weak positive relation of policy readiness (rh = .176**, Sig = .004) and adoption of AI at USIU-Africa.

Regression between Institutional Readiness and Adoption of AI

The study further performed a multiple linear regression to determine the magnitude of effect of institutional readiness on the adoption of AI at USIU-Africa and summary results are shown below.

Table 14 Regression between Institutional Readiness and Adoption of AI

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.290[a]	.084	.074	.46419

a. Predictors: (Constant) Policy Readiness, Resource Readiness, Culture Readiness

The regression analysis produced a coefficient of determination (R^2=*.084*) which implied that institutional readiness predicted 8.4 percent of the changes in the adoption of AI at USIU-Africa. This showed that policy readiness, resource readiness, culture readiness can positively predict the adoption of AI at USIU-Africa.

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Table 15 ANOVA Institutional Readiness and Adoption of AI

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	5.527	3	1.842	8.551	.000[b]
	Residual	60.117	279	.215		
	Total	65.645	282			

a. Dependent Variable: Adoption AI

b. Predictors: (Constant) Policy Readiness, Resource Readiness, Culture Readiness

The research further sought to determine the statistical significance of the relationship at a 5 percent significance level, and the findings indicated an F-value of 8.551 and Sig =.000<.05. This showed there is a positive and significant relationship between institutional readiness and the adoption of AI at USIU-Africa.

Table 16 Regression Coefficients Institutional Readiness and Adoption of AI

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.247	.418		5.382	.000
	Resource Readiness	.044	.071	.037	.614	.540
	Culture Readiness	.118	.068	.108	1.730	.085
	Policy Readiness	.293	.073	.236	3.999	.000

a. Dependent Variable: Adoption of AI

The regression coefficients yielded a value for resource readiness (B_1 = .044, t = .614, sig = .540>.05) revealing a positive and insignificant effect on the adoption of AI at USIU-Africa. Results of the second construct culture readiness showed (B_2 = .118, t = 1.730, sig = .085>.05) revealing a positive and insignificant effect on the adoption of adoption of AI at USIU-Africa. On the analysis of the third construct policy readiness (B_3 = .293, t = 3.999, sig = .000<.05) confirming existence of a positive and significant effect of policy on the adoption of AI at USIU-Africa.

Determinants of Adoption of AI

The general objective of the research was to assess the determinants of the adoption of artificial intelligence technologies at the United States International University- Africa. The overall findings of the regression analysis are shown below.

Table 17 Regression Summary for Determinants of Adoption of AI

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.372[a]	.138	.126	.45103

a. Predictors: (Constant), Institutional Readiness, Technical Capability, Trust, Relative Costs

The findings above yielded a coefficient of determination (R^2 = .138) which revealed that with all other factors held constant; institutional readiness, technical capability, trust, and relative costs had a positive relationship with adoption of AI at USIU-Africa. The findings showed that jointly, the four drivers can determine 13.8 percent of the levels of adoption of AI at USIU-Africa.

Table 18 ANOVA Summary for Determinants of Adoption of AI

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9.091	4	2.273	11.172	.000[b]
	Residual	56.553	278	.203		
	Total	65.645	282			

a. Dependent Variable: Adoption AI
b. Predictors: (Constant) Institutional Readiness, Technical Capability, Trust, Relative Costs

The research further sought to determine the statistical significance of the relationship at a 5 percent significance level, and the findings indicated an F-value of 11.172 and Sig =.000<.05. This showed there is a positive and significant relationship between (institutional readiness, technical capability, trust, relative costs) and the adoption of AI at USIU-Africa.

Table 19 Regression Coefficients for Determinants of Adoption of AI

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.983	.528		1.863	.063
	Technical Capability	.090	.055	.093	1.652	.100
	Trust	.414	.088	.279	4.712	.000
	Relative Costs	-.069	.108	-.042	-.640	.523
	Institutional Readiness	.330	.110	.194	2.996	.003

a. Dependent Variable: Adoption of AI

The regression coefficient for technical capability was (B_1 = .090, t = 1.652, sig = .100>.05) revealing a positive and insignificant effect of technical capability on the adoption of AI at USIU-Africa. The analysis revealed a regression coefficient for trust was (B_2 = .414, t = 4.172, sig = .000<05) revealing a positive and significant effect of trust on the adoption of AI at USIU-Africa. The regression coefficient for relative costs was (B_3 = -.069, t = -.640, sig = .523>.05) revealing a negative and insignificant effect of relative costs on the adoption of AI at USIU-Africa. Further analysis showed a regression coefficient for institutional readiness was (B_4 = .330, t = 2.996, sig = .003<05) revealing a positive and significant effect of institutional readiness on the adoption of AI at USIU-Africa.

Conclusions

From the findings, the study concludes that an organization's technical capability has a positive and insignificant effect on the adoption of AI at USIU-Africa. As per the findings, the study concludes that trust factors have a positive and significant effect on the adoption of AI technologies at USIU-Africa, with trust factors of ethical and responsible use, privacy, and reliability potentially explaining up to 10.7 percent of changes in AI adoption.in addition, the study concludes that relative costs have insignificant effects on AI adoption at USIU-Africa. Finally, it can be concluded that institutional readiness factors of policy readiness, resource readiness, and culture readiness do not have significant effects on the adoption of AI at USIU-Africa, predicting up to 8.4 percent of the changes in AI adoption at the university.

Recommendations

The study recommends that to maximize the institution's ability to leverage AI in teaching and learning, the institution ensures it provides continuous professional development and training opportunities for all staff to upskill them and build expertise across different departments. Additionally, the study recommends that the university fosters trust-driven AI adoption by involving students in AI selection to ensure the adopted technologies address existing needs among students. The study also recommends that the university places more emphasis on non-cost factors such as increasing awareness of the available AI tools, as well as their advantages, perceived value and performance benefits. Lastly, the study recommends that the school ensures its policies and culture are relevant to the industry.

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