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RESEARCH ARTICLE

Trust and AI Adoption for Mobile Learning in Higher Education: Evidence from Tanzanian Universities

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Abstract: Artificial intelligence (AI) is transforming practices across multiple domains, including education, where adaptive teaching methods are enhancing learning processes. This study examines whether trust influences AI acceptance in higher learning institutions (HLIs) in Tanzania. Using a quantitative approach based on structural equation modeling (SEM) with data from 215 respondents, we extended the Technology Acceptance Model (TAM) by integrating trust as an external variable. While the model was generally supported, perceived trust did not emerge as a significant predictor of behavioral intention to use AI in Tanzanian HLIs. These findings provide theoretical and policy insights for AI adoption in higher education and suggest avenues for future research.

Keywords: Artificial Intelligence, Technology Acceptance Model (TAM), mobile learning, higher education, Tanzania

1 Introduction

The increasing popularity of Artificial Intelligence (AI) applications and the related difficulties make research on integrating AI in education crucial. Teachers' fear of AI and emotional deficiencies in AI applications are among these challenges, while there are also ethical risks (Brandhofer & Tengler, 2024).

Currently, the majority of students in the Higher Learning Institutions (HLIs) worldwide use mobile phones and other digital technologies to facilitate the learning process (Lavidas et al., 2022). Various apps operate on mobile devices, facilitating AI capabilities, thereby providing further alternatives and mechanisms for teaching and learning. Applications such as AI mobile chatbots, Gemini, Siri, mobile learning platforms, high-end smartphones and other initiatives have significantly enhanced the learning process for the HLI's communities (Papadakis et al., 2023).

The influx of ubiquitous learning systems provides learners with an accommodating environment that supports individual preferences and learners' needs, accessible anywhere and at any time (Adewale et al., 2024). As students, instructors and supporting staff readjust to access information in the digital media, AI is essential as it offers more convenient, accessible and simplified alternatives.

Trust significantly influences user acceptance of AI in education, particularly in contexts where there is uncertainty about how AI systems function (Pérez-Jorge et al., 2025). The lack of trust can slow down or even prevent the adoption of AI tools in higher learning institutions (Pérez-Jorge et al., 2025). To support educational practices like assessment, personalization, and stakeholder engagement in the educational environment, it is necessary to communicate complex data insights to stakeholders effectively (Brandhofer & Tengler, 2024; Ritter & Koedinger, 2023).

AI text generators like ChatGPT have the power to drastically alter the educational landscape. Athanassopoulos et al. (2023) and Kavak (2024) discuss how ChatGPT can be used to support language instruction and foster a positive learning environment, particularly for students with a migrant or refugee background. While there are many advantages to using ChatGPT for good purposes, it is important to keep an eye on and address any negative effects and ethical issues to maintain a fair and productive learning environment (Kavak et al., 2024). It is therefore important to comprehend how educators view AI apps to overcome the obstacles presented by the growing popularity of these tools. This research investigates the factors which influence students and instructors in Higher learning institutions to use AI with a special focus on trust in its usage.

This paper has the following research objectives:
(1) To analyse how perceived trust influences the acceptance and usage of artificial intelligence in Tanzanian Higher Learning Institutions.
(2) To examine the relationships between perceived ease of use, perceived usefulness, attitude, and behavioural intention in the adoption of AI technologies in Tanzanian HLIs.
(3) To provide theoretical and policy insights into how trust and related factors affect the adoption of AI in higher education contexts, particularly in Tanzania.

In line with the objectives of the research, the following are the proposed research questions:
(1) To what extent does perceived trust have an impact on the acceptance and behavioural intention to use AI in Tanzanian Higher Learning Institutions?
(2) How do perceived ease of use and perceived usefulness affect users' attitudes and intentions towards AI adoption in Tanzanian HLIs?
(3) What theoretical and practical implications can be drawn for policy-making to enhance trust and acceptance of AI in higher education in Tanzania?

The remainder of this paper is organized as follows: The second section deals with aspects of technology acceptance. The third section discusses the context of Tanzanian higher learning, followed by section four, which defines Artificial Intelligence. Section five discusses the concept of trust in AI, followed by section six, which describes the formulation of hypotheses and design of the conceptual framework of the study. Section seven discusses the methodological details before discussing the results in section eight. Section nine provides a critical analysis and implications of the research, while and section section ten discusses the limitations of this research. Section eleven concludes this paper.

1.1 Acceptance of Technology

In certain contexts, the terms "technology acceptance" and "technology adoption" are equivalent. It is critical to differentiate between these two concepts. Adoption is the act of claiming something as one's own, whereas acceptance is the act of receiving something, according to the Oxford Dictionary (Oxford, 2009).

A user's adoption of technology starts when he learns about it and ends when he fully accepts it and incorporates it into his daily routine (Addotey-Delove et al., 2022). Users of technology should be free from external pressure and able to use it comfortably. In such cases, research is needed to determine and analyze the variables that might affect its application in various settings (Lavidas et al., 2022).

The factors influencing people's adoption of technology are explained by a variety of models found in the literature. To determine how factors impact people's intentions to utilize technology both now and in the future, these models look at the causal linkages between variables (Alsharida et al., 2021; Mushi, 2020).

1.2 Tanzanian Higher Learning Context

The Tanzanian Higher Learning Institutions (HLI) sector comprises Public universities like the University of Dar es Salaam (UDSM), University of Dodoma (UDOM) and the Nelson Mandela African Institute of Science and Technology (NM-AIST), Private universities or institutions like St. Augustine University of Tanzania (SAUT) and the International University of East Africa (IUEA) (Tanzania Commission for Universities (TCU), 2022). HLIs also include Vocational and Technical Education, focusing on vocational training, including the Institute of Finance Management (IFM) and College of Business Education, which offer specialized education aimed at developing technical skills required by various sectors like engineering, business, and healthcare (Tanzania Education and Training Policy (ETP), 1995).

The students in these institutions mostly own smartphones or gadgets which can assist them in assessing wireless materials for educational purposes. As AI becomes widely exposed to this community, its usage has no clear boundaries, especially taking into consideration assessment components which need grading on their performance. Therefore, trust in both instructors/lecturers and students becomes of much concern.

Trust in AI is influenced by social and cultural contexts. From a Tanzanian perspective, limited exposure to AI technologies may create scepticism (Pérez-Jorge et al., 2025). The concerns on ethics in terms of fairness, accountability, and inclusiveness are becoming increasingly significant in education, where vulnerable groups may be affected (Pérez-Jorge et al., 2025). Adding up the fact that there is a high population of people who are less informed about the new trends of technologies can also have an impact on how users trust AI in the context.

1.3 Artificial Intelligence

The introduction of revolutionary developments in machine learning, the availability of huge data, and the availability of reasonably priced computer power have all contributed to the recent period of rapid improvement in the field of artificial intelligence (AI) (Rodríguez-Ruiz et al., 2024). AI has been incorporated into many facets of our lives, such as self-driving cars and facial recognition technology, as a result of its rapid advancement (Shah et al., 2021). In addition to being a technological event, the spread of AI represents a societal change that is altering daily routines, the economy, and industry (Chita et al., 2023). More insights in the Tanzanian context show that AI results in enhanced assessment, time-saving, personalised learning, improved accessibility and detecting cheating in higher education (Mambile & Mwogosi, 2024).

The majority of businesses are expected to adopt AI at a rate of 75% in the near future, given the influence of digital transformation and global employability trends. This will lead to substantial changes, either by the creation of new roles or by the replacement of current ones (Velli & Zafiropoulos, 2024). The shift of many workers to higher-skilled professional categories necessitates the growth of entrepreneurial skills, the construction of a legislative framework, the promotion of open innovation, and international cooperation (Chita et al., 2023). Many continuous changes to lifestyles, social structures, conventions, curricula, and educational modalities will be brought about by technological upheaval (Harari, 2017).

Likewise, the field of education is not exempt from the revolutionary impact of artificial intelligence (Lampropoulos & Papadakis, 2025). AI incorporation into education has accelerated significantly, especially with intelligent tutoring systems (ITS). Once teacher-centred, these systems have since changed to be student-centric, accommodating different learning requirements and styles (Geroimenko, 2023). This has opened the door for the creation of cutting-edge AI tools.

The two main characteristics of AI systems are their adaptability and autonomy. While adaptation includes the potential to improve performance via experience, autonomy refers to the ability to carry out complex activities without constant instruction (Velli & Zafiropoulos, 2024). Learner-facing, teacher-facing, and system-facing are the three general categories into which educational AI technologies (EAIT) fall. By customising content and offering feedback, learner-facing tools like adaptive learning systems and personalised learning platforms directly assist students. Content recommendation engines and automated grading systems are examples of teacher-facing tools that support teachers in their teaching activities. Data analytics platforms and software for creating timetables are examples of system-facing solutions that assist educational institutions in managing and planning administrative duties (Velli & Zafiropoulos, 2024).

1.4 Trust in AI

Trust is among the key drivers for the successful adoption and use of technology (AI HLEG, 2018; Khan et al., 2021). Various studies have discussed how trust impacts the acceptance of various technologies in multiple contexts. Notable examples include Mushi (2024), who highlights trust's significant impact on e-government system adoption, and Khan et al. (2021). On the investigation of trust antecedents on social media usage by citizens and Edjys (2018) on trust aspects in using ICT in educational settings. Previous research shows that AI's tangibility, transparency, reliability, and immediacy behaviours in developing cognitive trust, was found to be associated with anthropomorphism, specifically for emotional trust (Glikson & Woolley, 2020).

Pedagogically, the teachers have recently been forced to adjust how the materials can effectively be delivered to learners, where the most recent examples and teaching materials becomes available online, resulting in simplicity in setting up examinations. Among the challenges of AI in higher education are cost and infrastructure, academic misconduct, data privacy and security, bias and ethical concerns and lack of human interaction (Mambile & Mwogosi, 2024).

Sociotechnically, AI can be perceived as a disruptive technology when it comes to other sociotechnical systems and society, where it encompasses adding new elements to energy systems, allowing, for example, forms of real-time trading of energy, or optimising energy delivery through the net (Akata et al., 2020; Mambile & Mwogosi, 2024). AI systems are also likely to disrupt social practices and institutions. For example, ChatGPT is currently disrupting existing practices of writing and education (Shidiq, 2023). Social media has already disrupted the functioning, but also the traditional understanding, of democracy (Mambile & Mwogosi, 2024), and social robots have challenged the distinction between human and non-human entities like robots (Nyholm, 2024).

Previous research shows that three out of five people (61%) are wary about trusting in artificial intelligence systems, reporting either ambivalence or an unwillingness to trust, according to a 2023 global study by KPMG that covered 17 nations. 39%, on the other hand, said they are willing to trust AI technologies. According to the majority (67%) of respondents, AI is accepted to a low to moderate degree. In all countries, only one-third of people say they are well-accepted (Gillespie et al., 2023).

The research also shows that managers, university graduates, and younger generations are more likely to feel good about AI systems and are more willing to trust and accept them (Gillespie et al., 2023). This implies that the AI systems are seen as more reliable by younger generations, particularly Millennials and Generation Z, who are also more tolerant and trusting of AI than earlier generations.

Nationwide, the impact of trust on AI is more noticeable in the USA and Australia. In Australia, for instance, 13% of older generations accept AI, compared to 34% of Gen Z and Millennials, and 25% of older generations trust it, according to Gen X and Millennials. China and South Korea, on the other hand, exhibit the opposite trend, with older generations having greater faith in AI than younger ones (Gillespie et al., 2023).

In an African perspective, factors such as previous experiences with AI, concerns about data privacy, system transparency, and the perceived fairness of AI-generated recommendations can play a huge role in shaping students' confidence in these technologies (James et al., 2025). These aspects are vital since they are core elements of implementing AI-driven education tools and may lead to resistance or low engagement among students.

The nature of AI usage involves searching for information from a wide range of sources. As a result, there are serious concerns about how users perceive risk, confidentiality of information and completeness when AI is used in educational settings, especially in higher learning environments. Among the initiatives which were introduced are the guidelines which were proposed to ensure trustworthy AI usage in educational settings in the European Union (AI HLEG, 2018). However, there is still a lack of similar research which can fit the context of the Tanzanian higher learning sector.

1.5 Hypotheses Formulation and Conceptual Framework Design

The philosophical perspective in this research is based on positivism (Creswell et al., 2003). In positivism, the main focus is to test the theory or truth. This research is therefore based on proposing hypotheses based on the experiences of previous research and the current state of the art. Since the majority of aspects involved in this research are mainly explained in individual acceptance of technology models, the theoretical model is based on an extension of the Technology Acceptance Model (TAM). Individual technology acceptance models/theories focus on explaining why users tend to accept or reject a particular technology under a particular usage context (Marchewka & Kostiwa, 2007). Such insights are explained in terms of factors, where the influencing relationships are tested for significance to determine whether there are influencing relationships between factors in a model (Venkatesh et al., 2003). In that case, TAM has the potential to be adopted to explain the concepts in this research.

Based on TAM, there are various factors which influence the user's decisions about when and how to use technology (Davis, 1989; Fishbein & Ajzen, 1975). In TAM, perceived usefulness (PU) and perceived ease of use (PEU) are two important predictors. PEU explains how much effort the system will save users, whereas PU shows whether the technology will enhance the user's ability to accomplish their work (Davis, 1989).

Similar research, which has extended TAM, has found that Perceived Usefulness (PU) and Perceived Ease of Use (PEU) tend to statistically influence Behavioural Intention (BI) (Davis, 1989; Mushi, 2020). In this regard, this research will also adopt these proven hypotheses:

H1: *Perceived Ease of Use (PEU) AI will positively influence the Perceived Usefulness (PU) in Tanzanian HLIs.*

Personal characteristics that represent feelings and understanding about a certain subject or topic, as well as positive or negative behaviour, are referred to as attitude (Al-Emran et al., 2016;

Fishbein & Ajzen, 1975). People's level of preference, their comprehension of the attitudinal object, and their goals and reactions to it are all related to their attitude, which is composed of affect, cognition, and behaviour in psychology (Mantle-Bromley, 1995). According to Al-Emran et al. (2016) and Fishbein and Ajzen (1975), attitude encompasses personal characteristics that show either positive or negative behaviour as well as a reflection of sentiments and knowledge toward a specific subject or topic. According to Mantle-Bromley (1995), people's degree of preference, their comprehension of the attitudinal object, and their intentions and reactions to it are all related to their attitude, which is composed of emotion, cognition, and behaviour.

According to Bruess (2003), attitudes have a significant impact on students' learning outcomes in the classroom, and research on the impact of attitudes on educational settings includes the use of instructional technology. Additionally, based on the case study at Bangkok University, Wangpipatwong (2008) demonstrates that students' views toward computers influence their intention and perception of using e-learning. Therefore, it is also possible to propose the following hypotheses:

H2: *Perceived Usefulness (PU) of AI will positively influence the Attitude towards using AI (ATT) in Tanzanian HLIs.*
H3: *Perceived Ease of Use (PEU) of AI will positively influence the Attitude towards using AI (ATT) in Tanzanian HLIs.*
H4: *The Attitude towards using AI will positively influence the Behaviour Intention (BI) in Tanzanian HLIs.*
H5: *The Behavioural Intention (BI) of using AI will influence their actual Usage (U) in Tanzanian HLIs.*

The propositions of hypotheses related to trust in the acceptance of AI follow the previous research. Trust is also discussed to be a subjective attitude that allows individuals to make a vulnerable decision (Chang et al., 2017; Zerilli et al., 2022). Chang et al. (2017) discuss how trust in technology can influence users to believe that using a device will achieve the desired goal by providing examples of asking Google Maps for directions to a restaurant and successfully arriving at the destination. In such regard, trust is proposed to have a significant use behaviour and has also been extended into technology acceptance models to predict behavioural intentions. For example, Choung et al. (2023) extended the TAM and found that trust positively influenced the perceived usefulness of AI. Therefore, this research proposes the following hypothesis:

H7: *Perceived Trust in AI will positively influence Perceived Usefulness (PU) in Tanzanian HLIs.*

In another study, trust was found to predict behavioural intentions to use artificial intelligence for iris scanning (Miltgen et al., 2013). The use of AI in Tanzanian HLIs can likely follow this trend, leading to the following hypothesis:

H6: *Perceived Trust in AI will positively influence behavioural intention to use it in Tanzanian HLIs.*

The derived hypotheses resulted in the conceptual framework for this research, depicted in Figure 1.

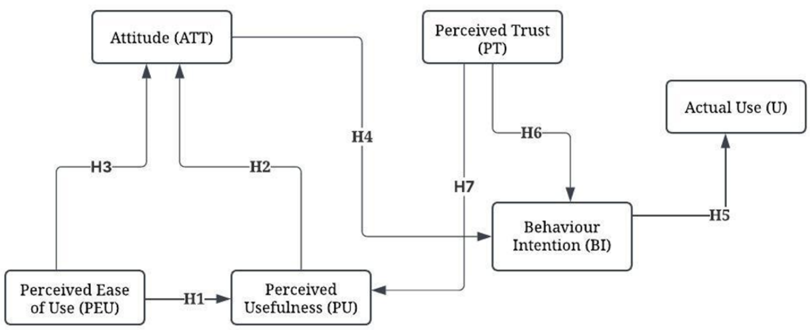

Figure 1 The conceptual framework of the research

2 Research Methodology

The population targeted comprised students, academic staff, and supporting staff in Tanzanian Higher Learning Institutions (HLIs). The baseline design used random sampling, where 234 questionnaires were distributed by hand and online. Random sampling was chosen to ensure that each potential respondent had an equal chance of being included in the survey, thereby reducing sampling bias and increasing the representativeness of the results. The sample was stratified to ensure that students, instructors (lecturers) and supporting staff are all included.

The sampling frame consisted of students, academic staff, and support staff within selected HLIs. Since most students and staff in Tanzanian universities are already familiar with various AI tools and applications, the target population was considered suitable for capturing perceptions of AI adoption and trust. The list of institutions was first identified, compiled and contacted followed by distributing questionnaires within their campuses. Every individual respondent encountered had an equal probability of being asked to participate in the survey. To maximise inclusivity, printed questionnaires were handed out directly to students and staff who were randomly selected on-site, while the questionnaire was also shared via online platforms, with links sent randomly to available contacts for the respondents with online access. The participation was entirely voluntary, and informed consent was obtained.

About 34 days were spent gathering the data. A 91.9% response rate was obtained from the 215 completed surveys out of the 234 that were sent. 92 males and 123 females made up the data set.

The inclusion of participants include having a current affiliation with a Tanzanian HLI as a faculty member, student, or supporting staff; , Age $\geq$ 18, be able to read English or Kiswahili, be able to provide and having a basic awareness of AI tools in education. When a participant failed such criteria, they were excluded from this research.

In regard to ethical considerations, all participants (students, faculty, and support staff from Tanzanian HLIs) were informed of the purpose of the research and the voluntary nature and that they have a right to withdraw at any time without problem. Since the collected information was on social perspectives on using technologies in the learning process, there were assumptions that there was minimal negative impact on the subjects.

To ensure accuracy, the surveys were translated from English to Kiswahili by linguistic experts because Kiswahili is Tanzania's official language. A second language expert then translated the Kiswahili version back into English to check for consistency between the original and final English translations.

In regard to the modality, while the majority of the questionnaires were distributed by hand, some were sent to the respondents online. In certain cases, further measures were taken to encourage respondents to set aside time to complete the questionnaires.

The survey form used in this study has twenty-six (26) items as shown in Table 1. A multiple-item Likert scale was used for assessments, following information systems research methodology (Tavakol & Dennick, 2011). In line with relevant earlier studies (Alsharida et al., 2021; Tavakol& Dennick, 2011), the Likert scale was used to measure the constructs, with 1 denoting "Strongly Disagree" and 5 noting "Strongly Agree". Every survey respondent spoke Swahili; thus, accurate translation was required to ensure the effective translation of survey forms from English into the dialect of Swahili. Thus, back translations were carried out, a method widely used in numerous cross-cultural surveys (Brislin, 1970).

Following descriptive analyses, the analysis was split into two stages: evaluations of the existing structural models and evaluations of the current measurement models. A one-step evaluation, which includes an assessment of the measurement model and a structural model, is not as good as this two-stage analytical technique (Burgess, 2001). The structural models define the relationships between the constructs, while the measurement models describe how the constructs are measured (Awang, 2015).

This study employed Structured Equation Modelling (SEM) and Partial Least Squares (PLS-SEM) for analysis (Awang, 2015). Chi-square (x^2), the Confirmatory Fit Index (CFI) for incremental fit, and the parsimonious fit were used to test the absolute fit in the case of model fitness.

3 Results and Discussions

As shown in Figure 2, the structural model, which included 26 measurement items and six constructs, was modelled in Smart PLS 4. Before moving on to additional analysis processes, it was subsequently examined for validity and reliability. As can be observed, every factor loading is higher than 0.5, suggesting that the model has satisfied the requirement for unidimensionality.

Table 1 Measurement items of the study

Construct	Item	Description	References
Perceived Ease of Use (PEU)	PEU1	AI applications are user-friendly	(Karaiskos et al. 2012)
	PEU2	It is easy to find information when using AI	(Byomire and Maiga, 2015)
	PEU3	It is easy to understand information in AI systems.	(Karaiskos et al. 2012)
	PEU4	My interaction with AI tools is clear and understandable	(Byomire and Maiga, 2015)
Perceived Usefulness (PU)	PU1	Using AI enables me to accomplish my work tasks quickly	(Byomire & Maiga, 2015)
	PU2	Using AI enhances my task effectiveness.	(Karaiskos et al. 2012)
	PU3	Using AI increases my productivity in accomplishing tasks.	(Karaiskos et al. 2012)
	PU4	Using AI provides me with the flexibility to accomplish tasks anywhere.	(Karaiskos et al. 2012)
	PU5	Using AI helps communicate with clients and colleagues in the workplace	(Davis et al. 1989)
	PU6	On using AI, my duties are done faster	(Brandhofer&Tengler, 2024)
Behaviour Intention (BI)	BI1	I plan to use AI to work in the future	(Karaiskos et al. 2012)
	BI2	The nature of my work will require me to use AI	(Pedersen, 2005)
	BI3	The AI will fit well with my work demands	(Pedersen 2005)
	BI4	I expect to use AI in the near future	(Karaiskos et al., 2012), (López-Nicolás et al., 2008)
Attitude	ATT1	Using AI is nice	(Al-Emran et al., 2016)
	ATT2	My use of AI is favourable.	(Fishbein &Ajzen, 1975)
	ATT3	I think it is valuable to use AI in performing my duties.	(Fishbein &Ajzen, 1975)
	ATT4	It feels trendy to use AI	(Al-Emran et al., 2016)
Actual Use (U)	U1	It has been a long time since I started to use AI in my work	(Byomire and Maiga, 2015)
	U2	Using AI helps finish work tasks during office hours.	(Kim, 2008)
	U3	I use AI frequently	(Davis et al. 1989)
	U4	Using AI helps communicate office matters with clients/colleagues/management.	(Davis et al. 1989)
Perceived Trust (PT)	PT1	Trust in AI applications is high	(Ejdys, 2018)
	PT2	With AI, it is safe to disclose personal information.	(Alzahrani et al., 2018)
	PT3	There are legislations against cybercrimes in using AI applications	(Khan et al., 2021)
	PT4	There is confidentiality in AI systems	(Glikson & Woolley, 2020)

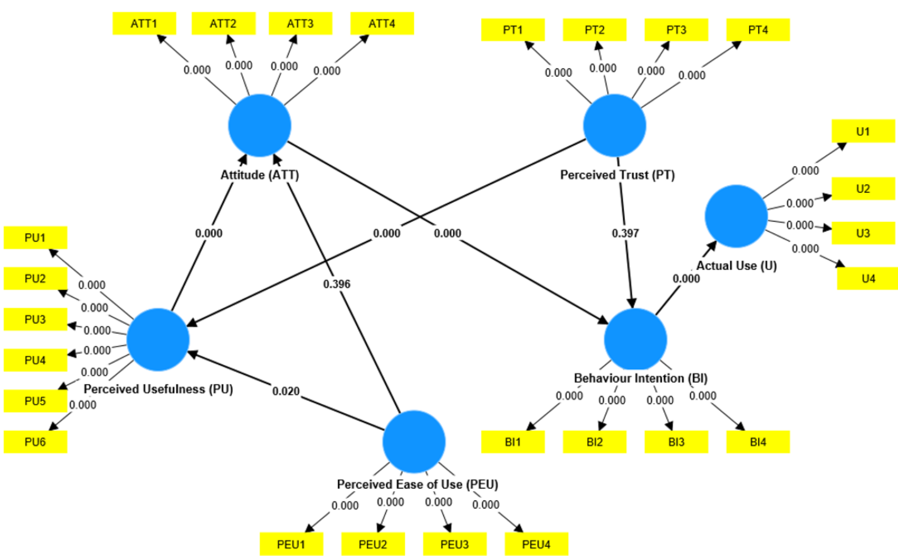

Figure 2 Structural model of the study

The construct reliability and validity parameters of the model are displayed in Table 2. It can be noted that all values of Cronbach's Alpha are above 0.5 and the Composite reliability (rho_c) is above 0.7, showing that the model is valid and reliable to produce results for path analysis.

Table 2 Construct reliability and validity parameters

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Actual Use (U)	0.867	0.910	0.860	0.618
Attitude (ATT)	0.880	0.885	0.880	0.649
Behaviour Intention (BI)	0.945	0.946	0.945	0.811
Perceived Trust (PT)	0.870	0.875	0.864	0.616
Perceived Ease of Use (PEU)	0.900	0.910	0.902	0.698
Perceived Usefulness (PU)	0.865	0.873	0.867	0.523

According to Table 3, the results of the Heterotrait-monotrait Ratio of Correlations (HTMT), which is used to assess discriminant validity, show that all values are less than 0.9, indicating that the model is dependable because each construct in the PLS path model has the strongest relationships with its indicators (Hair et al., 2022).

Table 3 Discriminant validity details

Path	Heterotrait-monotrait ratio (HTMT)
Attitude (ATT) -> Actual Use (U)	0.738
Behaviour Intention (BI) -> Actual Use (U)	0.547
Behaviour Intention (BI) -> Attitude (ATT)	0.827
Percceived Trust (PT) -> Actual Use (U)	0.654
Percceived Trust (PT) -> Attitude (ATT)	0.688
Percceived Trust (PT) -> Behaviour Intention (BI)	0.436
Perceived Ease of Use (PEU) -> Actual Use (U)	0.511
Perceived Ease of Use (PEU) -> Attitude (ATT)	0.642
Perceived Ease of Use (PEU) -> Behaviour Intention (BI)	0.653
Perceived Ease of Use (PEU) -> Perceived Trust (PT)	0.567
Perceived Usefulness (PU) -> Actual Use (U)	0.536
Perceived Usefulness (PU) -> Attitude (ATT)	0.882
Perceived Usefulness (PU) -> Behaviour Intention (BI)	0.754
Perceived Usefulness (PU) ->Percceived Trust (PT)	0.719
Perceived Ease of Use (PEU)->Perceived Usefulness (PU)	0.744

The analysis of how powerful the model is in testing the hypotheses was performed using Q^2 and the results are seen in Table 4. The results show that all values are above 0, indicating that the model is strong enough to be able to predict the relationship between the constructs.

Table 4 Q^2 predictive relevance

Construct	Q^2predict	RMSE	MAE
Actual Use (U)	0.126	1.007	0.685
Attitude (ATT)	0.323	0.911	0.666
Behaviour Intention (BI)	0.066	1.142	0.742
Perceived Ease of Use (PEU)	0.170	1.108	0.723
Perceived Usefulness (PU)	0.326	1.015	0.622

Table 5 displays the path analysis results, including all hypotheses and the corresponding p-values.

(1) The direct influence of Perceived Ease of Use on Perceived Usefulness (H1)

According to this study, people's opinions on AI's perceived usefulness would be directly impacted by how simple they thought it was to use. This has been supported by some studies on mobile phone technology use (Gallego et al., 2008; Mushi et al., 2017).

The study's results, which show that H1 was statistically significant, are shown in Table 5. This proves the validity of the hypothesis. Thus, this study suggests that employees' opinions of mobile phones' usefulness rose in tandem with their opinions of how simple they were to use. The results of Davis (1989) and Mushi (2024) support this hypothesis.

Table 5 Path analysis results

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Attitude (ATT) -> Behaviour Intention (BI)	0.824	0.806	0.115	7.153	< 0.001
Behaviour Intention (BI) -> Actual Use (U)	0.522	0.530	0.121	4.309	< 0.001
Perceived Ease of Use (PEU) -> Attitude (ATT)	0.126	0.124	0.148	0.848	0.396
Perceived Ease of Use (PEU) -> Perceived Usefulness (PU)	0.457	0.399	0.197	2.323	0.020
Perceived Trust (PT) -> Behaviour Intention (BI)	-0.099	-0.105	0.117	0.847	0.397
Perceived Trust (PT) -> Perceived Usefulness (PU)	0.395	0.431	0.106	3.742	< 0.001
Perceived Usefulness (PU) -> Attitude (ATT)	0.688	0.682	0.128	5.380	< 0.001

(2) The direct influence of Perceived Usefulness on the Attitude toward using AI (H2)

This research hypothesised that there would be a statistically significant association between perceived usefulness and attitude towards using AI in Tanzanian HLIs. The results of this research, as seen in Table 5, show that the hypothesis is significant, implying that the more they perceive that AI is useful to their activities it is the more significant the attitude of the users toward using AI becomes.

(3) Direct Influence of Perceived Ease of Use on Attitude (H3)

According to this study, it was hypothesised that the perceived ease of use would positively influence attitudes towards using AIs in Tanzanian HLIs. This hypothesis was rejected as seen in Table 5. This implies that the easier use of trust in using AI applications does not guarantee that there will be an influence on the intention of using AI in Tanzanian HLIs. The stakeholders and policymakers should therefore focus on other aspects of improving intention and usage more.

(4) Direct Influence of Behaviour Intention Actual Usage (H5)

This study predicted that the usage of AI in Tanzanian HLIs would be influenced by the intentions to use AI. This was based on previous studies where it was found that whenever people intend to use technology in a particular circumstance, they will end up using it (Byomire & Maiga, 2015; Davis, 1989; Mushi, 2020, 2024).

The results in Table 5 demonstrate that this study supports such a hypothesis. That means that the actual use of AI in Tanzanian HLIs is predicted by the intention to use technology. In other words, awareness of the appropriate usage of AI needs to be given to all HLI stakeholders to understand the positive roles of technology to increase their need to finally use it.

(5) Direct Influence of Attitude on Behaviour Intention (H4)

This research hypothesised that the attitude would predict the behavioural intention to use AI in the sense that the more there is a positive attitude towards using AI leads to more it influences their intention to use the technology.

As seen in Table 5, this hypothesis was supported. This means that attitude is a potential predictor of intention to use AI in Tanzanian HLIs. Enhancing the attitude to use AI will influence such people to use AI in the context.

(6) Direct Influence of Perceived Trust on Perceived Usefulness (H7)

In this research, it was hypothesised that if more people perceive that they have trust in the use of AI in performing their duties, their perception of their usefulness will also be elevated. As seen in Table 5, this hypothesis was supported. This finding implies that the more the users have put trust in the AI it is the more they believe that the systems are useful to them in performing teaching and learning activities in Tanzanian HLIs.

(7) Direct Influence of Perceived Trust on Behaviour Intention (H6)

This research hypothesised that the more people trust the AI applications it is the more they will intend to use them in the future. The results in Table 5 show that the hypothesis was rejected ($p = 0.397$). This implies that the trust has nothing to do with the intention to use AI in Tanzanian HLIs. This is against the previous research where this hypothesis was supported (Mitgen et. al, 2013).

The reason for this unique finding can be due to the fact that the majority of students, lecturers and supporting staff in Tanzanian HLIs already use AI-driven applications (e.g., translation tools, plagiarism checkers, ChatGPT). This practical exposure may reduce the need to evaluate AI systems on trust, as usage is driven more by usefulness and necessity than by trust considerations. Also, trust is likely to be taken for granted in academic settings, as users may assume that technologies introduced or widely available in universities are already vetted and safe. This implicit assumption means that trust does not consciously drive their behavioural intention, as it becomes a "background factor" rather than an active consideration.

Also, taking into consideration that the infrastructure is not a big problem for enabling AI applicability, the issue of trust is not a problem in this context. In Tanzania, other initiatives that ensure effective usage of AI in HLIs have to keep being in place across all stakeholders without trust as is not a potential factor of concern anymore.

3.1 Critical Analysis and Implications

One of the main challenges facing the adoption and acceptance of technologies in various contexts is trust. AI depends on a high volume of data to make informed decisions. In this case, users have to believe that the information provided by AI is legit. This research provides insights into such a perspective in which the predictors of intentions and usage are studied by extending a fundamental technology acceptance model. AI is continuing to expand its usage in various aspects of teaching and learning processes. As such, more users are beginning to utilise AI regardless of how much trust they have in the tools and applications.

This research calls for more training to be provided to stakeholders in reinforcing security practices on all possible aspects, only to provide more confident expectations among the users. The contributions of this research provide the necessary grounds for the preparation of more informed and reliable recommendations in the form of policies and legislation.

Implications of this research include that it provides evidence for Tanzanian higher learning institutions (HLIs) and policymakers to design AI adoption strategies that go beyond trust by emphasising training, perceived usefulness, and attitude formation, thereby helping decision makers identify where to invest resources. Also, trust was not a strong predictor of behavioural intention, suggesting that the universities should instead focus on capacity building, awareness workshops, and attitude enhancement for both students and staff to increase effective AI integration. Theoretically, this research study expands TAM by integrating perceived trust as an external construct, testing its relevance in the Tanzanian HLI context. While some hypotheses were rejected, this contributes to the theory by showing the boundary conditions under which trust may or may not be significant. In general, the extended TAM has failed to fully fit the context of the Tanzanian Higher Learning sector under the current situation.

Based on the results of this research, more specific recommendations for Tanzanian HLIs include the establishment of knowledge awareness centres which can provide continual training on how emerging technologies can shape teaching and learning processes at the institute. Also, there should be special interventions from the Tanzanian government that provide an enabling environment for AI inclusion in the teaching and learning while minimising its negative aspects as much as possible.

The findings of this research are much concerned with the utilisation of mobile learning in Tanzanian HLIs. The fact that the majority of Tanzanians owns smartphones, they mostly tend to deploy them for accessing materials for the learning process. This paper therefore provides a more informed theoretical contribution to the acceptance of AI in both mobile devices and other computing platforms. This research therefore provides necessary insights for a wide range of low-resource higher education contexts on the issues that matters in AI usage in the learning process.

This research also informs that trust was not found to be a strong predictor of AI usage, implying that societal attitudes and perceived usefulness are more central to AI adoption. This shifts the focus from fear and scepticism to practical value creation, influencing how communities embrace AI tools. In the education context, this research calls for HLIs to incorporate AI literacy and digital skills into their curricula so as to ensure both students and instructors gain practical experience and awareness of AI's usefulness in learning and research. In addition to that, there should be special capacity building for faculty where lecturers need targeted professional development to improve their confidence and attitudes toward AI, since attitude strongly predicts intention and usage.

3.2 Limitations

This research was limited to the context of the Tanzanian Higher Learning Institutions (HLIs). As a result, the findings may not be fully generalizable to other countries or even to different sectors within Tanzania, such as healthcare or government services. Also, the study is based on a cross-sectional design where data were only collected at a single point in time. This limits the ability to capture how perceptions of trust, usefulness, and attitudes toward AI may evolve as exposure and experiences change over time. This research depends on the survey responses, which may be subject to social desirability bias or inaccuracies in self-assessment. Respondents may have overstated their familiarity, trust, or usage of AI tools. While the research extended the Technology Acceptance Model (TAM) by including perceived trust, other important factors, such as cultural attitudes, ethical awareness, organisational readiness, or digital infrastructure availability, were not included and may influence AI adoption. Lastly, the findings are specific to the educational sector. Thus, their application to other contexts (e.g., healthcare, business, government) should be made cautiously until further studies are conducted.

4 Conclusion

This research provides insights into technology acceptance mainly focusing on AI in Tanzanian HLIs. The theoretical model was formulated by proposing the hypotheses before development based on extending the Technology Acceptance Model with perceived trust to understand how it features and impacts the acceptance of AI. The methodology involved 215 respondents from Tanzanian HLIs. Except for two hypotheses, the rest of them were all supported by the research. This research contributes a new perspective on the acceptance of AI in educational settings with a special focus on how trust fits in the context. This research has found that trust is not among the significant factors influencing intention to use AI in Tanzanian HLIs. Further research may focus on conducting more research on the success and challenges facing the adoption of AI in other contextual settings, such as in the healthcare and transportation sectors. Also, the future research can focus on a longitudinal design where various factors can be measured after intervals of periods of time.

Conflicts of Interest

The author declares no conflict of interest.

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