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The acceptance of Artificial Intelligence in Education: The role of Self-efficacy in Tanzanian Higher Learning Institutions

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ABSTRACT

Artificial Intelligence is currently transforming the way activities are done in various contexts. It has provided alternatives to most complex situations where information is well captured from different sources to enable effective decision-making. While numerous efforts are in place to ensure continual improvements in the sectors, some factors are likely to influence its acceptance and usage in higher learning institutions. This research explores such factors by adopting the Technology Acceptance Model while extending it with Self-Efficacy to assess its significance. This study employed a quantitative approach based on Structural Equation Modelling to analyse data collected in a survey with 179 respondents and an analysis using Smart PLS 4. Among others, the results show that Self-efficacy significantly impacts the Perceived ease of use of Artificial Intelligence tools in Tanzanian Higher Learning Institutions. This research has also provided a roadmap for effective regulatory and policy-making in the Tanzanian context and areas for further study.

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1 Introduction

The increasing popularity of Artificial Intelligence (AI) applications and the related difficulties make research on integrating AI in education crucial. AI adoption confronts several obstacles. Teachers' fear of AI and emotional deficiencies in AI applications are among these challenges, as are ethical risks related to privacy and security concerns arising from the use of big data in education, the potential alienation of students due to algorithmic recommendations, the exacerbation of educational inequality through the "digital divide," the risk of simplifying educational processes leading to behaviourism, and information cocooning through algorithmic recommendations [1]. Furthermore, there are substantial obstacles to integrating AI technology into educational processes and culture, and to support educational practices like these, it is necessary to effectively communicate the issues about the usage of AI in the context of education.

Recent research has indicated that there are significant obstacles to integrating AI technologies into educational processes and culture. To support educational practices like assessment, personalization, and stakeholder engagement in the educational environment, it is necessary to effectively communicate complex data insights to stakeholders [1, 2].

Artificial intelligence (AI) text generators like ChatGPT have the power to drastically alter the educational landscape. Athanassopoulos et al. [3] and Kavak [4] 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. AI can also assist with inclusion issues in general. 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 [4]. Therefore, it is 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 Self-efficacy.

Examples of models applied by researchers to explain technology acceptance include the Technology Acceptance Model (TAM) and the Unified Theory of Technology Acceptance and Use (UTAUT). Technology adoption in various industries, geographical locations, and firm sizes is explained by TAM and UTAUT [5, 6]. This study expands TAM with an extra structure that explains the service quality element before testing using Structural Equation Modeling (SEM) to construct a theoretical model [7].

The remainder of this paper is organized as follows: The second part deals with aspects of technology acceptance. The third section defines AI self-efficacy while section four discusses the hypotheses formulation and development of the theoretical model and section five discusses the methodological details. Section six presents and discusses the results while section seven provides a critical analysis and section eight is the conclusion of this paper.

2 Technology Acceptance and Adoption

The words "technology adoption" and "technology acceptance" are sometimes used interchangeably. It is important to distinguish between these two ideas. According to the Oxford Dictionary, acceptance is the act of receiving something, while adoption is the act of claiming it as one's own [8]. In this way, the factors that could influence a technology's use in a particular circumstance must be taken into account while determining whether to accept or reject it.

In a similar vein, the adoption of technology begins the moment a user becomes aware of it and concludes when he fully embraces it and integrates it into his everyday activities [9]. This suggests that adopting technology involves more than just accepting it. Technology users ought to be able to use it comfortably and without outside pressure. Therefore, studies must be conducted to identify and examine the factors that could influence its use in different contexts.

There are many models in the literature that explain the variables that affect people's acceptance of technology. In these models, the causal relationships between variables are examined to ascertain how they affect people's intentions to use technology now and in the future [10, 11]. Some models that explain technology acceptance at the individual level include the Theory of Planned Behavior (TPB) [12], the Theory of Rational Action (TRA) [13], The Theoretical Model of Acceptance and Use of Technology (UTAUT) [6] and the Technology Acceptance Model (TAM) [5].

3 AI Self-Efficacy

Bandura first proposed the idea of self-efficacy in 1977. It refers to a person's belief in their ability to perform a particular behaviour despite challenges [14]. Self-efficacy is an important consideration in models that aim to describe a particular behaviour since it influences behaviour both directly and indirectly through expectations [11, 14].

People with low self-efficacy may use AI tools more frequently to try to overcome their perceived inability to complete a task because they allow them to perform multiple tasks as a human would. Additionally, self-efficacy is linked to greater social adaptability [14], and recent research indicates that the use of AI in education has a negative impact on social adaptability [15]. Taken together, these findings suggest that the use of AI tools is associated with low self-efficacy.

Taking into consideration the existing studies in the area of the use of AI in teaching and learning contexts, it is now important to find out whether self-efficacy can be among the potential factors in the higher learning perspectives especially in Tanzania. This research performs this by extending the TAM with self-efficacy before testing it in the survey.

4 Hypotheses Formulation and Theoretical Model Design

This research builds on the Technology Acceptance Model (TAM), which suggests that when people are given technology, several factors influence their decisions about when and how to utilize it [5, 16]. Perceived utility (PU) and perceived ease of

H1b: Perceived Ease of Use (PEU) AI will positively influence the Perceived Usefulness (PU) in Tanzanian HLIs
H1c: Perceived Ease of Use (PEU) of AI will positively influence the Attitude towards using AI (ATT) in Tanzanian HLIs
H1d: Perceived Usefulness (PU) of AI will positively influence the Attitude towards using AI (ATT) in Tanzanian HLIs
H1e: Behavioural Intention (BI) of using AI will influence their actual Usage (U) in Tanzanian HLIs

H1f: The Attitude towards using AI will positively influence the Behaviour Intention (BI) in Tanzanian HLIs

use (PEU) are two important measures that form the basis of TAM. PEU explains how much effort the system will save users, whereas PU shows whether the technology will enhance or increase the user's ability to accomplish their work [5].

TAM has been effectively extended from several other models to study how various perspectives are involved in the effective use of technologies in specific environmental settings. Few of the previous studies that used TAM as a benchmark included the context of mobile phone self-efficacy in SMEs where among others, Perceived Usefulness (PU) and Perceived Ease of Use (PEU) tend to statistically influence the Behavioural Intention (BI) [11]. Because it has an indirect impact on the intention to acquire technology and, eventually, its use, PEU largely influences PU. Because this study uses extended TAM, the associations that were examined using TAM in previous studies that are comparable to this one are also used.

Concerning the context of self-efficacy on technology usage, there were previous studies in the context of mobile phone acceptance in SMEs [11]) and acceptance of e-government [17] where these factors have been found to have a significant impact on such technologies. From a philosophical perspective, this study is grounded in positivism, which is centred on formulating and testing hypotheses with the primary goal of testing the theory (truth). Notable previous research has found that self-efficacy tends to influence the Perceived Ease of Use of technologies [11, 17]) The following is the hypothesis concerning self-efficacy.

H1a: AI Self-Efficacy will positively influence Perceived Ease of Use (PEU) in Tanzanian HLIs

All of the TAM elements can be employed in this study because previous research has mostly concentrated on how AI is accepted in the Tanzanian Higher Learning Institutions. Thus, the following hypotheses are then proposed:

Attitude refers to personal features that depict either positive or bad conduct as well as a reflection of feelings and knowledge toward a particular concept or topic[13, 18]. In the psychology study, attitude is made up of affect, cognition, and behaviour upon which they relate to

People's degree of preference, their understanding of the attitudinal object, and their intentions and reactions to it, are in that order [19].

Research on the influence of attitude on educational settings includes the use of instructional technology, Bruess [20]where attitudes greatly impact how well students learn in the classroom. Furthermore, Wangpipatwong [21] confirms that students' attitudes regarding computers have an impact on their intention and perception of adopting e-learning, based on the case study at Bangkok University. As such, the following hypothesis can also be posited:

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

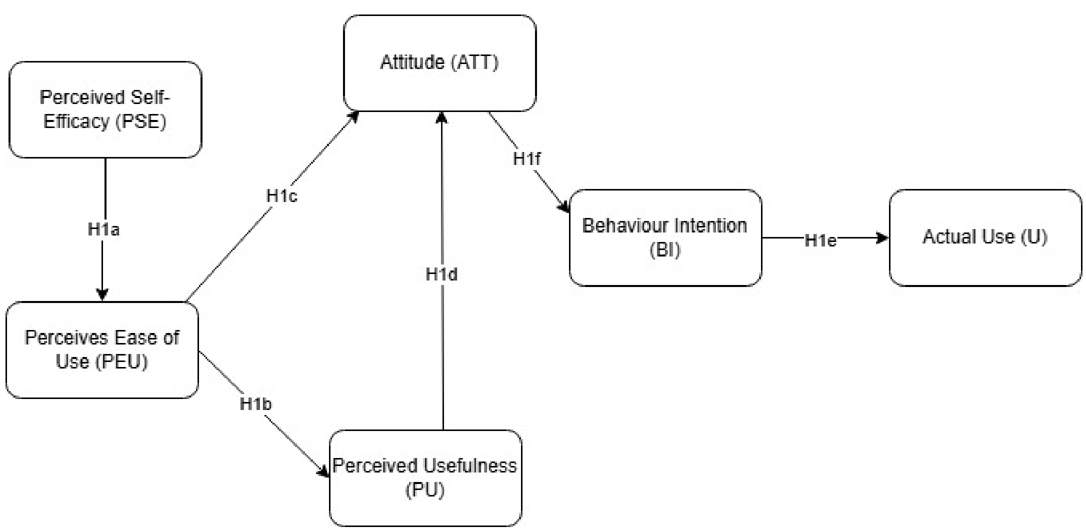

Figure 1: The conceptual framework of the research

5 Research Method

The study's sample consisted of Tanzanian participants who are students, instructors or supporting staff in higher learning Institutions. Since Kiswahili is Tanzania's official language, the surveys were translated from English to Kiswahili by linguistic specialists to guarantee accuracy. The Kiswahili version was then translated back into English by a second language specialist to see if the meanings of the original and final English versions were the same. Data collection took roughly 145 days. Out of the 179 questionnaires distributed, only 162 were filled out, resulting in a 90.5% response rate. The data collected consisted of 78 females and 84 males.

Since the majority of Tanzanian HLI students are aware of various AI tools and applications, a random sample technique was employed. Some of the questionnaires were delivered to the respondents online, while the rest were distributed by hand. In some instances, further efforts were undertaken to get participants to allocate time for filling out the surveys.

The survey form used in this study has twenty-six (26). A multiple-item Likert scale was used for assessments following information systems research methodology [22]. In line with relevant earlier studies [10, 22], the Likert scale was used to measure the constructs, with 1 denoting "Strongly Disagree" and 5 denoting "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 [23].

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. The structural models define the relationships between the constructs, while the measurement models describe how the constructs are measured [10, 24].

This study employed Structured Equation Modelling (SEM) and Partial Lease Square (PLS-SEM 4) for analysis [7]. The reliability of the questionnaire was evaluated using Cronbach's alpha, which has reasonable levels of alpha of 0.7 and lower as undesirable, and acceptable levels of alpha of 0.8 and higher as good [31, 32]. The Squared Mahalanobis Distance (D2) was used to evaluate the outliers [33]. Covariance and variance deviation from the centroid were investigated to evaluate the multivariate normality of the datasets [34]. In the case of model fitness, the absolute fit was tested using Chi-square (x2), incremental fit through the Confirmator Fit Index (CFI), and the parsimonious fit was assessed by Chi-square/df.

6 Results and Discussion

The structural model consisting of five constructs and 23 measurement items was modelled in Smart PLS 4 as seen in Figure 2. It was then tested for reliability and validity before proceeding to further steps of analysis. It can be seen that all the factor loadings are greater than 0.5 indicating that the model has attained a unidimensionality condition.

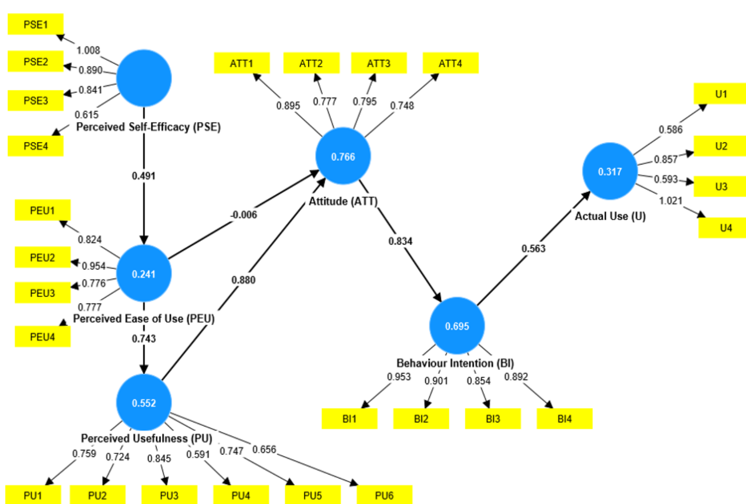

Figure 2: Structural Model of the study

The construct reliability and validity parameters of the model are seen in Table 1. It can be seen that all values of Cronbach Alpha are above 0.5 and the Composite reliability (rho_c) are above 0.7, indicating that the model is valid and reliable to produce results for path analysis.

Table 1: Construct reliability and Validity Parameters

path	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
BI	0.719	0.733	0.826
PEU	0.734	0.745	0.826
PSE	0.56	0.58	0.745
PU	0.768	0.77	0.843
U	0.77	0.778	0.844
ATT	0.67	0.78	0.789

The results of the Discriminant Validity assessment are performed using the Heterotrait-monotrait Ratio of Correlations (HTMT) and it showed that all values are less than 0.9 indicating that the model is reliable because each construct has the strongest relationships with its indicators in the PLS path model [24].

The analysis of how powerful the model is in testing the hypotheses was performed using Q2 and the results are seen in Table 2. 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 2: Q2 predictive relevance

Construct	Q^2predict	RMSE	MAE
Actual Use (U)	0.162	0.986	0.669
Attitude (ATT)	0.616	0.686	0.526
Behaviour Intention (BI)	0.45	0.877	0.66
Perceived Ease of Use (PEU)	0.36	0.973	0.662

The results of the path analysis are seen in Table 3 where all hypotheses and their associated p-values are indicated.

Table 3: Path analysis results

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Attitude (ATT) -> Behaviour Intention (BI)	0.763	0.744	0.091	8.405	0
Behaviour Intention (BI) -> Actual Use (U)	0.522	0.53	0.121	4.31	0
Perceived Ease of Use (PEU) -> Attitude (ATT)	0.126	0.121	0.15	0.84	0.401
Perceived Self-Efficacy (PSE) -> Perceived Ease of Use (PEU)	0.008	0.033	0.175	0.045	0.965
Perceived Usefulness (PU) -> Attitude (ATT)	0.687	0.681	0.129	5.318	0
Perceived Ease of Use (PEU) -> Perceived Usefulness (PU	0.745	0.432	0.112	6.344	0

S.E-Standard Error, ***P<0.05

a) The direct influence of Perceived Ease of Use on Perceived Usefulness (H1b)

This study proposed that perceptions of the perceived usefulness of AI would be directly influenced by their perceptions of its ease of use. Certain research regarding the use of mobile phone technology has corroborated this [35, 36].

Table 3 presents the study's findings, which demonstrate that H1a was statistically significant. This indicates that the hypothesis is validated. Therefore, this study implies that employees' perceptions of the usefulness of mobile phones increased with their perception of their ease of use. This is in line with the findings of Mushi, R [11, 17].

b) The direct influence of Perceived Usefulness on the Attitude toward using AI (H1d)

It was also shown that there was a statistically significant association between perceived usefulness and attitude towards using AI in Tanzanian HEIs. This hypothesis was supported, implying that the more they perceive that AI is useful to their activities, the more significantly the attitude of the users toward using AI.

c) Direct Influence of Perceived Ease of Use on Attitude (H1c)

According to this study, it was hypothesised that the perceived ease of use will positively influence attitudes towards using AIs in Tanzanian HLIs. This hypothesis was rejected as seen in Table 3 (p=0.401). This implies that the easier use of AI applications does not guarantee that there will be an influence on the attitude towards using AI in Tanzanian HLIs. The stakeholders and policymakers should therefore focus on other aspects as being easy to use does not guarantee an increase in attitude of the people towards using AI.

d) Direct Influence of Behavior Intention Actual Usage (H1e)

This study assumed that the usage of AI in Tanzanian HLIs would possibly be influenced by the intentions to use technology in the first place. This is based on the previous research on technology use where, in most cases, it was found that whenever people intend to use a technology in a particular circumstance, they will finally use it [5, 11, 17, 26].

The results in Table 3 demonstrate that this research has supported the proposed hypothesis. This implies that the actual use of AI in Tanzanian HLIs is well influenced by the intention to use technology. In this case, proper awareness of the best use of AI needs to be imparted to all HLI stakeholders so that they can understand the positive roles of technology to increase their intentions to finally use it for the benefit of the educational industry.

e) Direct Influence of Perceived Self-Efficacy on Perceived Ease of Use (H1a)

It was previously hypothesised that the more people perceive that they have confidence in the use of AI in performing their duties, their perception of ease of use will also be elevated. As seen in Table 4, this hypothesis was strongly rejected (p=0.965). This finding implies that the AI can already be perceived to be easy to use even if there is no sense of confidence on whether the technology can be used to perform teaching and learning activities in Tanzanian HLIs.

Direct Influence of Attitude to Behaviour Intention (H1f)

It was previously hypothesised that the more people have a positive and strong attitude towards using AI would positively influence their intention to use a technology. As seen in Table 3, this hypothesis was supported (p=0). This research therefore supports the thought that attitude tends to influence the intention to use AI even in teaching and learning environments. The stakeholders and policymakers should learn that there are best practices which are demonstrated to the instructors, students and other staff at the Tanzanian HLIs on how to best use AI in performing various duties to make it easier and as a normal routine. By doing that, such people will intend to use AI which is a fundamental requirement of eventually using it.

7 Critical Discussions

One of the main challenges facing the adoption and acceptance of technologies in various contexts is self-efficacy. It is essential that people have enough confidence that they understand the technology at hand and that they know that such a technology will do whatever it is claimed to be able to do. This research focuses on AI as it is still at the entrance stage to the Tanzanian HLIs making it necessary to uncover such perspectives. The insights from this research provide critical issues which can potentially raise the use of AI and justify various investments made by governments and other stakeholders. Such contributions provide the necessary basis for the formulation of policies and legislatures and some theoretical underpinnings to the body of knowledge.

8 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 self-efficacy before testing the model through a survey comprising 179 respondents belonging to the Tanzanian HLIs. The research results have shown that all the proposed hypotheses except two of them. Among others, this research provided various insights about the use of AI in Tanzanian HLIs and how the factors relate to each other. Further research may focus on the assessment of more current technologies particularly Blockchain on their influence as they are used to achieve various roles in various contextual settings.

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