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# Factors Shaping the Adoption of Artificial Intelligence Tools by Higher Education Students in Tanzania

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**Abstract**

Artificial Intelligence (AI) has emerged as a significant innovation with far-reaching global impacts. Nevertheless, students in higher education institutions utilise AI tools inconsistently for various reasons, affecting their practical use. This research examines the factors influencing the adoption of AI tools for academic purposes, specifically learning and research, by higher education students in Tanzania. The study involved 142 students from diverse higher learning institutions and employed a binary probit regression framework to analyse these factors. The results indicate that access to technology increases the likelihood of students adopting AI tools. Additionally, their perceived ease of use and usefulness positively influence the likelihood of adoption. Gender analysis reveals that female students are less likely to adopt AI tools than their male counterparts. Moreover, limited user-friendliness negatively impacts AI tool adoption. The findings highlight the necessity of improving user-friendly interfaces, enhancing technological access, and providing technical support to promote adoption. This research contributes to our understanding of the dynamics of AI adoption in higher education contexts, offering practical implications for policymakers, academic institutions, and developers interested in encouraging the use of AI among students.

**Keywords:** Adoption, Perceived Usefulness, Ease of Use, Resource Availability, Higher Education Students, Artificial Intelligence Tools

**JEL Classification Codes:** O33, I23, D83

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## 1. INTRODUCTION

Education is one of the many sectors transformed by digital technology, primarily characterised by AI. AI mimics human cognitive functions, such as self-correction, reasoning, and learning (Sheth et al., 2023). It creates adaptive and personalised tools that can be implemented across various sectors, including education. AI-powered systems can establish learning pathways, provide immediate feedback, and adjust instructional strategies according to students' progress and individual needs (Mote, 2024; Rane, 2024; Sajja et al., 2023). The pedagogical potential of AI to revolutionise student engagement with content and learning is significant. QuillBot, Grammarly, Turnitin, and ChatGPT assist students in streamlining academic tasks, enhancing their writing, generating ideas, and preventing academic dishonesty.

AI-powered technologies offer real-time feedback, adaptive content, and personalised learning experiences tailored to each student's learning style and requirements (Mallillin, 2024; Ou, 2024). AI-powered platforms can also provide interactive, personalised, and flexible learning experiences that help students develop independent learning skills (Pratama et al., 2023). By automating routine academic tasks such as content creation and grammar checking, AI tools enable students to focus on learning objectives and self-expression. Furthermore, adaptive learning platforms and intelligent tutoring systems utilise AI to customise educational content based on the needs of each student, thereby enhancing academic performance and increasing engagement (Suntharalingam, 2024). AI's ability to deliver personalised, dynamic learning experiences fosters student engagement with content and boosts their academic performance.

Although the implementation of AI in education has increased in developed countries, it remains limited in developing nations (Tahiru, 2020). In countries with a reliable digital infrastructure, students can integrate AI tools into their daily academic and personal routines. These technologies have become indispensable for students' productivity, facilitating their acquisition of AI-powered educational tools and enhancing their learning experiences. Nevertheless, students in developing countries face challenges when trying to utilise AI. Many students cannot fully capitalise on AI technologies due to the high costs of procuring AI-powered tools, unreliable internet access, and inadequate digital infrastructure (Aderibigbe et al., 2023).

Research indicates that the adoption of AI by students is influenced by a variety of factors, with perceived usefulness and ease of use being among the most significant (Börekci & Çelik, 2024; Wardani et al., 2024; Zia et al., 2024). Students are more inclined to adopt AI tools if they believe these will enhance their academic performance and are user-friendly, according to the Technology Acceptance Model (TAM). Furthermore, research demonstrates that the intention to use AI technologies is influenced by trust, which operates through perceived utility and user attitudes (Choung et al., 2022).

Adopting AI depends on the availability of resources, such as affordable devices, reliable Internet, and adequate technological infrastructure (Krishnan et al., 2023; Radhakrishnan & Chattopadhyay, 2020). Moreover, adopting AI tools is shaped by personal interest in AI, access to technology, user-friendliness, knowledge of AI, and satisfaction with AI applications. Students who are familiar with and find value in these tools are more likely to adopt them (Acosta-Enriquez et al., 2024; Alzahrani, 2023; Chan & Zhou, 2023; Daher & Hussein, 2024; Surugiu et al., 2024; Zhou et al., 2024).

Demographic factors also influence the adoption of AI, with students' attitudes towards AI often being shaped by their age and gender (Alzahrani, 2023; Ofosu-Ampong, 2023). In many cases, the adoption rates among younger students and males are higher (Raman et al., 2024). However, these trends can vary across different contexts and may be affected by societal, cultural, and local factors. For example, older or female students may face challenges or incentives that affect their decision to adopt AI tools. Understanding this landscape is essential for developing strategies encouraging the widespread adoption of AI among students.

In developing countries, various issues exacerbate the challenges associated with AI adoption. Limited access to reliable digital infrastructure, unreliable internet, and the high cost of AI-powered tools create significant barriers (Ciecierski-Holmes et al., 2022). Many students cannot afford the subscriptions required to access AI tools because they are expensive. Access to AI tools is limited, and the lack of affordable alternatives hinders their widespread use (Bulathwela et al., 2024). Furthermore, students may be reluctant to adopt AI tools due to concerns about managing their personal and academic data (Weber, 2020). Privacy and security concerns also pose a barrier. It is imperative to address these issues to encourage the adoption of AI technologies in academic environments.

Despite the extensive literature on adopting AI tools across various fields, there has been limited focus on higher education students in developing countries like Tanzania. Existing research has predominantly examined AI adoption in other businesses and industries, while paying scant attention to how higher education students embrace such technologies. This study seeks to fill this gap by exploring the factors influencing AI adoption among higher education students in Tanzania for academic purposes, specifically in learning and research activities.

This research contributes to strategies for overcoming the challenges of AI integration in education systems by providing an understanding of the determinants of AI adoption among students. The results of this study can serve as a valuable resource for policymakers, developers, and educational stakeholders in developing countries to enhance their support for AI adoption. These insights will help create supportive environments that facilitate students' effective use of AI tools and improve digital literacy. Ultimately, this research advances students' academic success by advocating for the incorporation of AI as an enabler of educational performance and learning.

## 2. MATERIALS AND METHODS

### 2.1. Study area

This study was conducted online using Google Forms and targeted higher education students in mainland Tanzania. The selection of participants followed a convenience sampling approach, with the survey link distributed through digital channels such as Facebook pages, WhatsApp groups, and Instagram accessible to students in several regions, including Arusha, Dar es Salaam, Morogoro, Iringa, and Mbeya. Although these regions host several higher education institutions, the study did not impose strict geographical quotas, as participation relied entirely on students' voluntary and convenient access to the online survey forms.

### 2.2. Study Design

This study employed a cross-sectional design to examine the factors influencing the adoption of AI tools for academic purposes, specifically learning and research activities, among higher education students in Tanzania. This design involves collecting data at a singular time, enabling researchers to investigate the relationships among variables associated with the adoption of AI. It was chosen because it provides a snapshot of AI adoption among students during a specific period. As this study aimed to understand the current landscape of AI adoption, the selected design was fitting. It facilitates rapid data collection and is ideal for capturing a clear picture of students' behaviours, attitudes, and the factors influencing their use of AI tools. A significant advantage of this approach is that it allows for the simultaneous examination of multiple variables and their interrelationships (Sewando et al., 2023). Furthermore, given the evolving nature of AI tools, analysing current trends is essential for understanding contemporary adoption.

### 2.3. Sampling Strategy

A convenience sampling approach was employed to reach students and examine factors influencing the adoption of AI tools for academic purposes. The survey, conducted via Google Forms, facilitated voluntary participation based on students' access to online channels and their interest in the study. The survey link was shared on social media platforms such as Facebook, WhatsApp, and Instagram to maximise outreach among students with internet access. The target population comprised undergraduate and postgraduate students enrolled in higher education institutions during the 2023/2024 academic year, resulting in a final sample size of 142 students. Those who were not actively enrolled or had incomplete responses were excluded from the analysis.

### 2.4. Data Collection Methods

The data for this survey, collected between 1 March and 30 April 2024, included information on the geographic distribution of respondents, who were students from institutions in Arusha, Morogoro, Dar es Salaam, Dodoma, Iringa, and Mbeya. The fields of study were diverse, encompassing disciplines such as project management, education, economics, statistics, community development, law, business management, procurement, gender studies, records keeping, and social work. Data was collected through an online survey administered via Google Forms, designed to gather quantitative data on factors influencing higher education students' adoption of AI tools. The survey focused on essential variables, including perceived usefulness, ease of use, trust in AI, resource availability, interest, satisfaction, demographic factors, knowledge, technology preferences, and user-friendliness of AI tools.

The survey link was distributed through popular social media platforms such as WhatsApp, Facebook, and Instagram, allowing participants to complete it conveniently. The Google Forms included an introduction to the study and informed consent to ensure that participants understood the purpose and significance of the research. This approach facilitated broad participation, thereby supporting the diversity and generalisability of the findings. To enhance the reliability and validity of the data, the survey was pilot tested with 20 students to refine the questions. The final version was semi-structured and accessible online for 60 days to maximise responses.

### 2.5. Data Processing and Analysis

The data collected were exported from Google Sheets, managed, and analysed using Stata SE software version 18. Descriptive statistics, such as frequency and percentage, were computed for the study participants. This technique provided a clear overview and identified patterns in the study data. This study employs a binary probit model. The binary outcome captures whether a student adopts AI tools (coded as 1) or not (coded as 0). This approach is suitable for binary outcomes as it applies the cumulative normal probability distribution to estimate the likelihood of each outcome based on independent variables.

Prior studies highlight the model's suitability for qualitative responses with binary values (Utonga et al., 2023). The model interprets the decision to use AI as a probabilistic outcome, reflecting the underlying propensity to adopt the tool. This method reveals how specific factors increase or decrease the likelihood of AI adoption among students. The binary probit model assumes that each student possesses an underlying, unobserved latent variable (Y*) representing their propensity to use AI. A set of independent variables influences the latent variable. The model is specified as follows:

$$Y_i^* = \beta_0 + \sum_{k=1}^{k} \beta_k X_{ki} + \varepsilon_i$$

Where:

- $\boldsymbol{Y_i^*}$ is the latent variable representing the propensity to use AI for academic purposes.
- $\boldsymbol{X_{ik}}$ are the independent variables influencing this propensity,
- $\boldsymbol{\varepsilon_i}$ is the error term assumed to follow a standard normal distribution.

We determine the binary outcome ($\boldsymbol{Y_i}$) by comparing the latent variable ($Y$*) to a threshold $\boldsymbol{T}$. If the latent variable exceeds the threshold, the student is deemed to use AI tools (i.e., $Y_i=1$), and if it is below the threshold, the student is deemed not to use AI (i.e., $Y_i=0$). This scenario can be expressed as follows:

$$Y = \begin{cases} 1 & if\ Y^* \geq \mathrm{T} \\ 0 & if\ Y^* < \mathrm{T} \end{cases}$$

The threshold is set to zero for simplicity, so if $Y_i^*$ is positive, the student was classified as using AI tools. Given the parameters, the following likelihood function represents how likely it is to observe the data.

$$L(\beta) = \prod_{i=1}^{n} \Phi(X_i\beta)]^{Y_i}\,[1 - \Phi(X_i\beta)]^{1-Y_i}$$

Where:

- $\boldsymbol{\Phi}(\cdot)$ is the cumulative distribution function (CDF) of the standard normal distribution,
- $\boldsymbol{X_i\beta}$ is the linear combination of independent variables for each student.

To make the model estimation computationally feasible, the log-likelihood function is typically used:

$$\log L(\beta) = \prod_{i=1}^{n} [Y_i \log(\Phi(X_i\beta)) + (1 - Y_i)\log(1 - \Phi((X_i\beta))]$$

This function is maximised to find the parameter estimates that best fit the observed data. Maximum Likelihood Estimation (MLE) is a method used to estimate the parameters ($\beta$ ) of the binary probit model. MLE identifies the values of $\beta$ that maximise the likelihood (or log-likelihood) function. The probability of a student intending to use AI, given the independent variables, is calculated using the following cumulative distribution function (CDF):

$$P(Y = 1 \mid X) = \Phi(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki})$$

**Where:**

- $\Phi(\cdot)$ is the CDF, transforming the linear combination of predictors into a probability between 0 and 1.

The coefficients (β) in the model indicate the direction and magnitude of the effect of each independent variable on the likelihood of adopting AI. A positive coefficient implies that the likelihood of AI adoption increases as the corresponding independent variable increases, whereas a negative coefficient shows the opposite. The statistical significance of these coefficients was assessed using z-tests and p-values. Model validation was carried out to ensure that the results were reliable. Diagnostic checks, including likelihood ratio tests and goodness-of-fit measures, were performed to assess the appropriateness of the model.

### 2.6. Description and Measurements of Variables

The data also includes information on the geographic distribution of respondents who were students from institutions in Arusha, Morogoro, Dar es Salaam, Dodoma, Iringa, and Mbeya. The fields of study encompassed disciplines such as project management, education, economics, statistics, community development, law, business management, procurement, gender studies, records keeping, and social work.

This study categorises the variables into dependent and independent variables, with each measured to capture their influence on students' adoption of AI tools. The descriptions and measurement details of each variable are outlined in Table 1 as follows:

**Table 1. Description and measurements of the variables**

| Variable | Description | Variable Type | Measurement | Expected Sign |
|---|---|---|---|---|
| AI Adoption | Whether a student uses AI tools in academic activities. | Dependent | Binary (1 = Uses AI, 0 = does not use) | N/A |
| Perceived Usefulness | Whether students believe AI tools enhance academic productivity. | Independent | Binary (1 = useful, 0 = not useful) | Positive (+) |
| Perceived Ease of Use | Whether students find AI tools easy | Independent | Binary (1 = easy to use, 0 = not easy to use) | Positive (+) |
| Trust in AI Technologies | Students' confidence in the reliability and safety of AI tools | Independent | Binary (1 = high trust, 0 = low trust) | Positive (+) |
| Resource Availability | Availability of resources (e.g., internet, devices) for AI use | Independent | Binary (1 = sufficient resources, 0 = insufficient resources) | Positive (+) |
| Interest in AI | Level of interest in AI applications | Independent | Binary (1 = interested, 0 = not interested) | Positive (+) |
| Satisfaction with AI Applications | Satisfaction with existing AI tools | Independent | Binary (1 = satisfied, 0 = not satisfied) | Positive (+) |
| Age of the Student | Age of students | Independent | Continuous (years) | (+/-) |
| Gender of Student | Gender of the student | Independent | Binary (1 = male, 0 = female) | (+/-) |
| Knowledge of AI use | Self-assessed knowledge of AI | Independent | Binary (1 = knowledgeable, 0 = not knowledgeable) | Positive (+) |
| Technology Preferences | Preferences for using technology in academic work | Independent | Binary (1 = prefers technology, 0 = does not prefer) | Positive (+) |
| User Friendliness | Perceived ease and intuitive design of AI tools | Independent | Binary (1 = user-friendly, 0 = not user-friendly) | Positive (+) |
| Technology Access | Access to the necessary technology for AI usage | Independent | Binary (1 = sufficient access, 0 = insufficient access) | Positive (+) |
| Privacy and Security Concerns | Students' concerns about data privacy and security when using AI tools | Independent | Binary (1 = concerns present, 0 = no concerns) | Negative (-) |

**Source:** Study construction, 2024

### 2.7. Ethical Considerations

Before completing the online form, participants were thoroughly informed about the study's purpose, objectives, and voluntary nature. An explicit consent statement was placed at the beginning to ensure that they understood their right to decline or withdraw at any time without consequence. Responses were anonymised to prevent identifying information from being linked to participants, and no personal information was collected. All data were securely stored, accessible only to authorised research team members, and protected by encryption to prevent unauthorised access, which is in line with privacy safeguards. Additionally, participants were informed about how their data would be used, emphasising its sole purpose of contributing to the findings.

## 3. RESULTS AND DISCUSSION

### 3.1. Demographic characteristics of the respondents

The data collected for this study included demographic and academic information from 142 students at higher education institutions in Tanzania. Table 2 presents the demographic characteristics of the study participants and their adoption rate of AI tools.

**Table 2. Demographic Analysis Results**

| Variable | Category | Frequency | Percentage |
|---|---|---|---|
| Age | 20 – 24 | 70 | 49 |
| | 25 – 29 | 39 | 27 |
| | 30 – 34 | 19 | 13 |
| | 35 – 39 | 10 | 7 |
| | 40 – 44 | 4 | 3 |
| Gender | Male | 65 | 46 |
| | Female | 77 | 54 |
| Study Program | Certificate/Diploma | 19 | 13 |
| | Bachelor’s Degree | 109 | 77 |
| | Postgraduate | 14 | 10 |
| Rate of AI Adoption | Adopted | 124 | 87 |
| | Not Adopted | 18 | 13 |

Source: Survey data compilation, 2024

Demographic and adoption-related statistics reveal a high rate of AI adoption among students, with 87% of respondents reporting the use of AI tools for academic and research activities. The results demonstrate a strong preference for ChatGPT and AI tools such as Gemini, Bard, QuillBot, Ask AI, Brain Chat, and Bing Chat. Students commonly access these tools via computers and smartphones. This finding is consistent with studies by Balabdaoui et al. (2024), who also reported high student AI adoption rates. The widespread use of AI tools in current research indicates that, similar to other global trends, students increasingly recognise the value of these technologies for academic success. However, the 13% non-adoption rate aligns with findings from other scholars like Ofosu-Ampong et al. (2023), who observed that some students resist AI adoption due to concerns about privacy, lack of awareness, and disruptions to the teacher-student relationship.

The age distribution of the respondents revealed that the majority were relatively young, with 49% in the 20-24 age group and 27% in the 25-29 range. These results demonstrate that the sample primarily consists of students who are likely in their undergraduate years. Younger students are typically more familiar with and open to new technologies, which may contribute to a higher adoption of AI tools in academic contexts. This outcome aligns with Chan and Lee (2023), who found that students are more inclined to adopt generative AI tools like ChatGPT than older generations. As age increases, the proportion of respondents decreases, with only 3% in the 40-44 age group. This age trend is consistent with general patterns in student populations, where there are fewer older students, possibly reflecting a lower interest in AI tool adoption.

The gender distribution in this study reveals a nearly equal split, with 46% male and 54% female respondents, ensuring that the findings are generalisable across both genders. This balance enhances the robustness of the results, consistent with Dickinson et al. (2012), who emphasise the importance of gender balance for representativeness and statistical power in research. Regarding study programmes, most respondents (77%) were enrolled in bachelor's degree programmes, reflecting the typical demographic of higher education institutions. Smaller proportions of respondents were engaged in certificate/diploma (13%) and postgraduate (10%) programmes. The relatively low representation of postgraduate students indicates that they constitute a smaller group within the academic population.

### 3.2. Binary Probit Regression Results

The probit regression analysis identified several significant predictors of students' adoption of AI. The regression model yields the results presented in Table 3:

**Table 3. Binary Probit Model Estimation Results**

| Variable | Marginal Effect | Coefficient | Std. error | Z-statistic |
|---|---|---|---|---|
| Constant | - | -.5159993 | .9373731 | -0.55 |
| Privacy and security concerns | -.0247852 | -.1752326 | .0523593 | -0.47 |
| Technology Access | .1983572 | 1.233406*** | .0664231 | 2.99 |
| Perceived Ease of Use | .1007354 | .8198038** | .0453227 | 2.22 |
| Perceived Usefulness | .0984798 | .909389** | .047174 | 2.09 |
| Trust in AI Technologies | -.0779907 | -.4961555 | .096274 | -0.81 |
| Resource Availability | .1207211 | .9076521*** | .044924 | 2.69 |
| Personal Interest in AI | .0870019 | .7145415* | .0443404 | 1.96 |
| Satisfaction with AI Tools | -.0584418 | -.38587 | .0660999 | -0.88 |
| Age | .0055302 | .0395302 | .0047939 | 1.15 |
| Gender | -.1313172 | -.9739225 *** | .0452006 | -2.91 |
| Knowledge of AI | .0338377 | .2467309 | .0508092 | 0.67 |
| Technology Preference | -.0281896 | -.1954046 | .0517208 | -0.55 |
| User-Friendliness | -.232592 | -1.662591*** | .0750378 | -3.10 |
| Log-likelihood | -36.400767 | | Akaike I.C. | 100.8015 |
| Restricted Log-L | −45.123456 | | Schwarz I.C. | 142.1831 |
| McFadden pseudo-R2 | 0.3257 | | | |
| $X^2$(*df=13*) | 39.09 | | | |
| Significance level | 0.0002 | | | |
| Hosmer-Lemeshow $X^2$ | 86.90 | | | |
| Predicted percentage correction | .7042 | | | |

Note: (***), (**), and (*) denote significance at 1%, 5%, and 10% levels, respectively.

**Source:** Output from Probit Model Estimation (2024)

Table 3 presents the results estimated from the binary probit model. The model reveals significant findings at the 1% level, highlighting its effectiveness in capturing variations in students' intentions to adopt AI for academic purposes. The estimated coefficients and standard errors illustrate how various factors influence the likelihood of students adopting AI tools. A statistically significant coefficient indicates that the probability of students using AI tools increases or decreases in response to changes in the relevant explanatory variables.

The likelihood ratio test statistic indicates that several factors are statistically significant at the 1%, 5%, and 10% levels, highlighting important aspects of AI adoption among students. McFadden's Pseudo-$R^2$ is calculated at 0.3257, demonstrating that the independent variables in the model explain a substantial variation in adoption decisions. This statistic reflects moderate explanatory power concerning the influences on students' AI adoption. Additionally, a Chi-square statistic of 39.09 with a significance level of 0.0002 indicates the model's overall fit, suggesting strong model performance. The Hosmer-Lemeshow test yielded a Chi-square value of 86.90, further supporting the model's adequacy. Notably, the correct prediction rate obtained from the probit model was 70.42%, signifying that the model accurately predicted AI adoption among students for over 70% of the observations.

#### *3.2.1. Access to Technology*

The results in Table 3 indicate that access to technology positively and significantly influences students' adoption of AI tools. With a marginal effect of 0.1984 and a coefficient of 1.2334, which is significant at the 1% level, the findings suggest that students with better access to technology are considerably more likely to adopt AI tools. Specifically, students with the necessary technological resources, such as computers, smartphones, and other devices supporting AI, are 19.84% more likely to utilise AI for learning and research activities.

These results demonstrate that access to technology is a crucial driver of AI adoption among students in higher education. These findings highlight the role of technological accessibility in encouraging the uptake of AI tools among students in higher learning institutions. These findings correspond with research by Alzahrani (2023), which identifies that access to technology significantly influences students' intentions to use AI in educational contexts. Alzahrani's study emphasises that the availability of technological resources enables students to engage with AI and enhances their perception of AI as a valuable resource for learning.

#### ***3.2.2. Perceived* ease of use**

This study's results emphasise the role of perceived ease of use in influencing students' adoption of AI tools in higher education settings. With a marginal effect of 0.1007 and a coefficient of 0.8198, significant at the 5% level, the findings indicate that students who perceive AI tools as easy to use are 10.07% more likely to adopt them in their academic activities.

These findings correspond with Zia et al. (2024), who similarly highlight that students who find AI tools easier to use are more likely to incorporate them into their academic pursuits. Furthermore, their study indicates the broader implications of ease of use on students' performance and self-efficacy. When students feel assured in their ability to navigate AI tools, they are more inclined to utilise them and explore their potential to enhance their learning outcomes. This interaction between usability and academic success reinforces the idea that usability is not merely a peripheral factor but a central determinant of AI adoption.

These results resonate with TAM, which theorises that perceived ease of use is a precursor to perceived usefulness. TAM suggests that if users find technology easy to use, they are more likely to view it as beneficial, leading to increased adoption. This study's findings demonstrate this relationship: a higher perceived ease of use correlates with a greater likelihood of AI adoption among students.

### ***3.2.3. Perceived* Usefulness**

The study's results demonstrate the significant impact of perceived usefulness on students' adoption of AI tools for academic purposes. With a marginal effect of 0.0985 and a coefficient of 0.9094, which is significant at the 5% level, the findings indicate that students who view AI tools as beneficial for their academic work are 9.85% more likely to adopt them.

These findings align with the research by Wardani et al. (2024), who similarly found that students who view AI tools as beneficial are more inclined to adopt them. However, they also noted that while perceived usefulness drives adoption, students often express concerns about the limitations and drawbacks of AI tools. This duality implies that, while the perception of AI's benefits is a strong motivator, addressing and mitigating students' apprehensions regarding these tools is essential to foster acceptance and usage.

From a theoretical perspective, the results can be interpreted within the TAM, which posits that perceived usefulness is a crucial factor influencing user intentions to adopt a technology. According to TAM, individuals are more inclined to embrace technology if they believe it will enhance their performance in a given task, in this case, academic work. These findings reinforce the model's relevance and indicate that educational institutions should highlight the benefits AI tools can provide students, such as improving efficiency, enhancing research capabilities, and facilitating personalised learning experiences.

### ***3.2.4. Resource* availability**

The study findings show a strong and significant positive relationship between resource availability and the adoption of AI tools. With a marginal effect of 0.1207 and a coefficient of 0.9077, which is statistically significant at the 1% level, the results indicate that students with access to adequate resources, such as training, technical support, and the Internet, are 12.07% more likely to adopt AI tools. This highlights the importance of resource availability as a catalyst for promoting the adoption of AI tools among higher education students.

These findings align with Krishnan et al. (2023), who found that resource availability influenced students' adoption of AI-powered educational resources. They argued that when educational institutions provide adequate resources, including training sessions, support systems, and access to technology, students feel more empowered to integrate AI tools into their learning processes. Such resources enhance students' confidence in using AI tools and diminishes potential barriers to adoption. This scenario transitions to AI-facilitated learning, making it more accessible and appealing. Similarly, access to financial resources is crucial for adopting digital technologies, as Dimoso and Utonga (2024) observed, emphasising the significance of financial resources in driving the adoption and utilisation of digital tools in the contemporary digital landscape.

### ***3.2.5. Gender***

The probit model results revealed a significant negative relationship between students' gender and their adoption of AI tools. Specifically, the marginal effect of -0.1313 and a coefficient of -0.9739, statistically significant at the 1% level, imply that female students are 13.13% less likely to adopt AI tools than their male counterparts. This finding highlights a gender disparity in adopting AI tools, suggesting that female students encounter substantial barriers or may have less intention to use AI in academic settings than male students.

These results align with the findings of Ofosu-Ampong (2023), who identified that gender differences negatively affect students' perceptions and use of AI-based tools in higher education. Ofosu-Ampong further emphasised that female participation in Science, Technology, Engineering, and Mathematics continues to lag behind that of males, potentially contributing to lower AI adoption rates among female students. This gap in AI tool adoption may reflect societal trends in which women are underrepresented in fields traditionally associated with technology and digital innovations.

### *3.2.6.* User-friendliness

The findings regarding the user-friendliness of AI tools revealed a significant negative relationship with students' adoption of these technologies for academic purposes. With a marginal effect of -0.2326 and a coefficient of -1.6626, statistically significant at the 1% level, the results indicate that when AI tools lack user-friendliness, students are 23.26% less likely to adopt them. This percentage demonstrates the role of fostering positive engagement with AI applications in educational contexts.

These results resonate with Acosta-Enriquez et al. (2024), who found that ChatGPT user-friendliness positively influences students' adoption. Their study emphasises that when students perceive an AI tool as easy to navigate and straightforward, their willingness to adopt it increases. This finding aligns with the TAM framework, which posits that perceived ease of use is an important determinant of technology adoption. If students find AI tools cumbersome or complicated, they will likely resist integrating these technologies into their academic workflows.
Moreover, previous research supports the significance of user-friendly design in technology adoption, indicating that complex or unclear applications can alienate users, particularly in educational settings (Al-Sa'di & McPhee, 2021). Students are more likely to engage with technologies they can easily comprehend and utilise without substantial barriers.

## 4. CONCLUSION AND RECOMMENDATIONS

### 4.1. Conclusion

This study examined the factors influencing higher education students' adoption of AI tools for academic purposes, namely learning and research activities in Tanzania. The findings show that access to technology, user-friendliness, gender, resource availability, usefulness, and ease of use significantly influence higher education students' decisions to integrate AI tools into their academic activities. Access to technology and resource availability emerged as strong factors, whereas user-friendliness was identified as a critical barrier to adoption. Furthermore, gender differences highlighted a notable gap in AI adoption, suggesting that female students may require encouragement to engage with these tools. The results demonstrate the necessity of creating an enabling environment that fosters the effective use of AI to enhance student engagement and academic performance in higher education contexts.

### 4.2. Recommendations

Based on the findings, the following recommendations are proposed:

Academic institutions should convey the practical benefits of AI tools in enhancing academic performance to stimulate student interest and professional engagement. Workshops, seminars, and success stories can serve as effective platforms for showcasing the value of these technologies in real academic contexts.

Academic institutions should ensure that students have access to training programmes, workshops, and ongoing support related to AI tools. This support can help students build confidence in using AI ethically, thereby increasing its adoption.

Academic institutions should prioritise enhancing access to essential technological resources and ensuring that all students, particularly those from disadvantaged backgrounds, can utilise AI tools for practical and ethical purposes. This could involve supplying computer devices through laboratories, increasing internet access points, and offering technical support.

Developers should collaborate with users to design AI-powered platforms featuring simpler interfaces, clear instructions, and minimal technical jargon. They can accomplish this by properly incorporating user testing feedback during development to identify key concerns and refine the navigation.

Policymakers ought to establish an enabling environment that fosters access to affordable and reliable internet services and infrastructures and facilitates the effective, efficient, and ethically productive use of AI tools.

**Conflicts of Interest**

The authors declare that they have no conflicts of interest related to the publication of this study.

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