# Artificial Intelligence Adoption and Usage for Academic Writing: A Technology Acceptance Model Perspective in Tanzanian Higher Learning Institutions

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***Abstract***
*This study aims to examine the determinants influencing the adoption and continued usage of AI tools for research writing among academicians, focusing on the Tanzania Institute of Accountancy and Mzumbe University (Mbeya Campus). Grounded in the Technology Acceptance Model (TAM), the research investigates the effects of Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavioral Intention (BI), and Actual Usage (AU) on both adoption and continued usage intentions. A quantitative, cross-sectional design was employed using structured questionnaires distributed to 93 purposively selected academic staff. Exploratory Factor Analysis (EFA) confirmed the reliability and validity of constructs, and multiple regression analysis was used to test the hypothesized relationships. The findings reveal that AU, PEU, and BI are significant predictors of AI tool adoption and continued use, while PU does not have a statistically significant impact. The model explained 62.0% of the variance in adoption and 82.2% in continued usage intention, indicating strong explanatory power. The study concludes that behavioural engagement and tool usability are more critical than perceived usefulness in predicting the sustained use of AI tools in academic writing. It recommends that institutions enhance AI training, promote ethical usage, integrate AI into academic systems, and address user experience concerns to foster widespread and responsible AI adoption in Tanzanian higher education.*

***Keywords:*** *Artificial Intelligence (AI), Academic Writing, Technology Acceptance Model (TAM), Higher Learning Institutions, AI Adoption and Usage, Continued Usage Intention, Tanzania*

## INTRODUCTION
The integration of Artificial Intelligence (AI) tools into academic writing has emerged as a transformative trend in higher education, particularly in

research-intensive contexts. These tools have demonstrated substantial potential in enhancing writing performance, increasing efficiency, and streamlining the scholarly writing process (Agarwal, 2022; Upadhyay et al., 2022; William, 2024; Zhao et al., 2023). In recent years, their application has expanded rapidly among researchers in higher learning institutions, offering critical advantages such as improved productivity, grammar support, idea generation, and facilitation of self-regulated learning, especially for non-native English speakers (Grassini, 2023; Perkins & Roe, 2024). This growing reliance on AI is evident in the way academicians now incorporate tools like ChatGPT, Grammarly, and Turnitin to support various stages of the research writing process (Romero et al., 2024; Salas-Pilco & Yang, 2022; Selim, 2024). Nevertheless, the integration of AI into scholarly work raises important ethical concerns, particularly around authorship, originality, and academic integrity (Ahn & Al, 2024; Masukume, 2024; Zhao et al., 2023). As generative AI becomes more advanced, the academic community faces pressing questions regarding the authenticity and intellectual rigor of AI-assisted outputs (Amirjalili et al., 2024). While various studies have explored the adoption and use of AI tools among scholars globally (Abd-Elsalam & Abdel-Momen, 2023; Romero et al., 2024; Wang, 2024), there is a notable dearth of empirical research focusing on Tanzania. The unique socio-cultural landscape, varying digital literacy levels, and institutional dynamics in Tanzanian higher learning institutions demand localized investigations. Understanding the motivations behind academicians' sustained use of AI tools in such settings is critical for informing both practice and policy (Salas-Pilco & Yang, 2022; UNESCO, 2023). Context-specific studies can also contribute to a more nuanced global understanding of how cultural and institutional factors shape the adoption and integration of educational technologies (Nazaretsky et al., 2025; Wu et al., 2024). Despite the maturity of research on individual-level technology acceptance, especially to AI, most investigations have yet to address the continued usage of such tools within Tanzanian academia. The Technology Acceptance Model (TAM), originally developed by Davis (1989) and later expanded by Venkatesh & Bala (2008) provides a robust framework for analyzing user adoption of information technologies. This model has been widely applied in education and information systems research, with consistent empirical support (Cao et al., 2023b; Na et al., 2022). TAM posits that two primary constructs, Perceived Usefulness (PU) and Perceived Ease of Use (PEU), influence Behavioral Intention (BI), which in turn predicts Actual Usage (AU). These relationships offer valuable insights for understanding both initial adoption and sustained engagement with digital tools. However, limited studies have applied TAM within the specific context of Tanzanian higher learning institutions to examine continued usage intention of AI tools in research writing. Addressing this gap is essential, particularly given the potential of AI to revolutionize academic research processes. Exploring the drivers of both actual usage and continued intention will not only expand the theoretical application of TAM but also provide practical insights for fostering effective AI integration in local academic environments (Shoah & Putela, 2024; Upadhyay et al., 2022). The study focuses on the Tanzania Institute of Accountancy (Mbeya Campus) and Mzumbe University (Mbeya Campus College), both located in the Southern Highlands. These institutions serve as strategic settings for understanding emerging trends in AI adoption in the country. Based on the existing literature, Southern Highland has been underrepresented in empirical studies on digital transformation and AI adoption in higher education. By selecting institutions from this region, the study contributes new insights from an area where empirical evidence is still limited, thus enriching the national understanding of AI integration in academia. Thus, this study aimed to investigate the major predictors of actual usage of AI tools in research writing and examine whether the major determinants of actual usage can predict continued usage intention of AI tools in research writing.

## LITERATURE REVIEW

### Theoretical Perspectives

The adoption and continued use of technology have been widely studied using well-established theoretical models, with the Technology Acceptance Model (TAM) being among the most influential. Originally developed by (Davis, 1989), and further refined by (Venkatesh & Bala, 2008), TAM has been extensively applied across diverse contexts to understand how individuals accept and utilize new technologies, including those related to e-learning and artificial intelligence (AI) based systems (Na et al., 2022; Venkatesh et al., 2003). The model provides a robust theoretical foundation for analyzing user behavior and has been shown to account for a significant portion of the variance in users' intentions and actual usage of information technologies.

TAM theorizes that two primary constructs, Perceived Usefulness (PU) and Perceived Ease of Use, serve as the key drivers of Behavioral Intention (BI) to use a technology. These behavioral intentions subsequently influence Actual Usage (AU). PU is defined as the extent to which a user believes that using a specific technology will enhance their performance or productivity. In the context of academic research writing, PU reflects academicians' belief that AI tools improve research efficiency and writing quality. Perceived Ease of Use, on the other hand, refers to the degree to which a user perceives a technology as easy to learn and apply. The easier a tool is to use, the more likely users are to adopt it and incorporate it into their daily academic practices (Davis, 1989; Venkatesh et al., 2003). These relationships have been empirically validated in numerous studies involving technology use in higher education, making TAM a suitable framework for examining AI adoption among academicians in Tanzanian higher learning institutions. In addition to the core TAM variables, factors such as gender, age, voluntariness, and experience have also been recognized in extended models as potential moderators that may directly or indirectly shape technology usage behavior (Venkatesh & Bala, 2008). This is particularly relevant in the Tanzanian context, where digital literacy levels, infrastructural availability, and institutional support vary considerably. This study adopts TAM to explore both the adoption and continued usage intention of AI tools for research writing. The proposed conceptual model hypothesizes that Actual Usage is determined by perceived usage, Perceived Ease of Use, and Behavioral Intention, and in turn, Actual Usage influences the intention to continue using AI tools. Understanding these dynamics is crucial for ensuring the effective integration of AI in academic settings, especially in environments with heterogeneous digital readiness like Tanzanian universities (Na et al., 2022). By applying this model, the study aims to generate insights that not only extend the theoretical application of TAM but also offer practical recommendations for promoting AI adoption in Tanzanian higher learning institutions.

*Perceived Usefulness of AI*

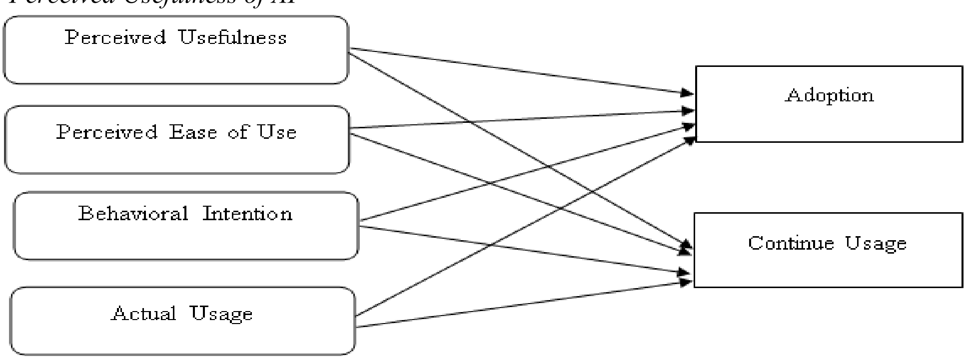


**Figure 1: Conceptual Framework**
Source: Modified from Technology Acceptance Model (TAM) (Davis, 1989)

## Perceived Usefulness

Perceived usefulness was defined as the individual's perception of the extent to which the use of a given technology improves performance (Venkatesh & Bala, 2008). Perceived usefulness is a key concept in the Technology Acceptance Model (TAM), which explains how users come to accept and use new technologies. Perceived usefulness has been consistently identified as a key factor influencing the adoption and usage of AI across various fields (Abdallah et al., 2023; Agarwal, 2022; Cheng et al., 2023; Na et al., 2023; Nouraldeen, 2022; Qahtani & Alsmairat, 2023; Sadriwala & Sadriwala, 2022). The reviewed literature provides strong evidence for the significant and positive influence of perceived usefulness on the usage and adoption of AI across various contexts, including marketing, human resources, healthcare, and smart home technologies.

## Perceived Ease of Use

Perceived ease of use was defined as the degree to which a person believes that using a particular system is free of determination (Na et al., 2022; Venkatesh & Bala, 2008). It was suggested that self-efficacy had a predictive role in decision-making about technology use. Perceived ease of use is a key determinant of user acceptance and adoption of AI technologies, as highlighted in several studies (Cao et al., 2023a; Geddam et al., 2024; Lai, 2017; Laurim et al., 2021; Wulyani et al., 2024). The reviewed literature consistently highlights the significant and positive influence of perceived ease of use on the acceptance and usage of AI technologies. Ensuring the user-friendliness and ease of use of AI systems is a crucial factor in promoting their adoption and utilization across various domains.

## Behavioral Intention

Behavioral intention refers to an individual's readiness to perform a particular behavior, which, in this context, pertains to the continued use of artificial intelligence (AI) tools for research writing (Venkatesh & Bala, 2008). Several studies emphasize that the integration of AI into academic writing has improved researchers' productivity, writing quality, and efficiency, leading to greater behavioral intention to continue its use (Romero et al., 2024; Shopovski, 2024). The behavioral intention to adopt AI tools for research writing is further shaped by ethical considerations, academic integrity concerns, and perceived effectiveness in enhancing the writing process. Despite these challenges, empirical findings suggest that academicians with a positive perception of AI's utility are more inclined to adopt and continuously use AI in research writing, particularly in higher learning institutions (Abd-Elsalam & Abdel-Momen, 2023; Salas-Pilco & Yang, 2022).

## METHODOLOGY

This study employed a quantitative approach and adopted a survey research methodology to investigate the factors influencing the adoption and continued use of Artificial Intelligence (AI) tools for research writing among academics. A multistage sampling procedure was used to select study areas, focusing on the Mbeya Region, with the second stage involving the selection of two higher learning institutions. The study sampled Mzumbe University (Mbeya Campus) and the Tanzania Institute of Accountancy (Mbeya Campus). Both Mzumbe University and TIA are public higher education institutions with comparable governance and operational procedures, making them suitable for addressing the research problem. A total of 93 academic staff members 47 from Mzumbe University and 46 from TIA were purposively sampled to ensure the inclusion of the intended study subjects. Data collection employed structured, self-administered questionnaires distributed physically to academic staff at the selected institutions. Respondent selection was based on teaching experience and engagement in academic research writing. The survey tools were developed using validated constructs from the Technology Acceptance Model (TAM), including Actual Usage (AU), Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavioral Intention (BI), Adoption (A), and Continued Usage Intention (CUI). All items were measured on a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). For data analysis, a two-step approach was used. First, Exploratory Factor Analysis (EFA) tested the construct validity and reliability of the research variables, using principal component analysis with varimax rotation. The Kaiser-Meyer-Olkin (KMO) test and Bartlett’s test of sphericity assessed sampling adequacy and data factorability. Cronbach’s alpha coefficients measured internal consistency reliability for each construct. In the second step, multiple regression analysis examined the relationships between independent variables (AU, PU, PEU, BI) and dependent variables (Adoption and Continued Usage Intention of AI tools). All analyses were performed using SPSS version 26. The regression results provided insights into the strength and significance of each predictor, and overall model fit was assessed through $R^2$, F-statistic, and the Durbin-Watson statistic. Collinearity diagnostics were also conducted to rule out multicollinearity concerns. This methodological design ensured a rigorous empirical examination of the key factors influencing AI adoption and sustained use in research writing, specifically within Tanzanian higher learning institutions.

## RESULTS AND DISCUSSION

### Demographic information of respondents

The demographic picture of respondents offers critical insights into the characteristics influencing AI adoption among academicians. The results indicate that the majority of the respondents were males (76.4%) and in the 26–35 age group (51.2%). These findings align with patterns identified in global research indicating that younger male academics tend to exhibit higher engagement with emerging technologies such as AI. Concurring to these Soulami *et al*. (2024) outlined the need for inclusive AI studies that examine how age, gender, and education level affect adoption behaviors, as existing literature often overlooks demographic disparities in AI acceptance. With respect to educational qualifications, most respondents held a master's degree (78.0%), followed by PhDs (16.5%), which is consistent with findings that AI adoption in academia is higher among those with advanced academic qualifications who are more likely to understand and integrate complex digital tools (Poenaru *et al*., 2024). Furthermore, assistant lecturers (74.0%), probably due to their familiarity with technology, have reported the predominance of usage of AI technologies. Gander & Shaw (2024), who found that mid-level academic staff are increasingly engaging with AI for teaching and research tasks, support this study. Additionally, the findings reveal that 36.2% of respondents have 5–10 years of experience, indicating that academics with moderate experience are more inclined to adopt AI tools, likely balancing familiarity with traditional academic processes and openness to innovation. Another study by Soodan *et al*. (2024) found that technology fit and colleague influence significantly affect AI adoption decisions among university faculties, echoing this trend. These findings underscore the importance of considering demographic factors when designing AI adoption strategies in academic settings.

**Table 1:**
*Demographic Characteristics*

| Variable | Frequency (n) | Percentage (%) |
|---|---|---|
| ***Sex*** | | |
| Male | 97 | 76.4 |
| Female | 30 | 23.6 |
| ***Age*** | | |
| 18-25 | 7 | 5.5 |
| 26-35 | 65 | 51.2 |
| 36-45 | 44 | 34.6 |
| Above 45 | 11 | 8.7 |
| ***Education*** | | |
| Bachelor | 7 | 5.5 |
| Master | 99 | 78.0 |
| PhD | 21 | 16.5 |
| ***Academic Rank*** | | |
| Tutorial Assistant | 8 | 6.3 |
| Assistant Lecturer | 94 | 74.0 |
| Lecturer | 19 | 15.0 |
| Senior Lecturer | 3 | 2.4 |
| Professor | 3 | 2.4 |
| ***Experience*** | | |
| Less than 5 years | 31 | 24.4 |
| 5-10 | 46 | 36.2 |
| 11-20 | 38 | 29.9 |
| More than 20 years | 12 | 9.4 |

**Source:** Field Data (2025)

## Awareness and Usage of AI Tools among academicians

The findings from the data set demonstrate a significant level of awareness and utilization of AI tools among researchers engaged in academic writing. With 95.3% of participants reporting familiarity with AI-based tools, this suggests a widespread acknowledgement of their utility in scholarly environments. This is consistent with broader academic discussions that highlight the increasing prevalence of AI technologies in education and research. For instance, studies by Koos & Wachsmann (2023) noted that the accessibility and growing sophistication of tools like ChatGPT have significantly shaped research practices in higher education, particularly post-pandemic, where digital reliance has increased. In terms of frequency, data reveals that 39.4% of respondents use AI tools weekly, and 16.5% do so daily. This reflects an emerging norm where AI assistance is no longer sporadic but integrated into regular research routines. This pattern resonates with the evidence presented by Geddam *et al*. (2024) and Wulyani et al. (2024) on their studies, which emphasized the increasing integration of AI-driven chatbots and writing assistants in academic settings, noting their potential to streamline time-consuming tasks and improve productivity. Nevertheless, for the purpose of use, grammar and style correction emerged as the leading reason (45.7%), followed by reference management (42.5%) and plagiarism detection (39.4%). These findings are in line with (Abd-Elsalam & Abdel-Momen, 2023; Maphoto et al., 2024; Zhao *et al*., 2023) analysis of AI tool usage in academic writing, which shows that scholars predominantly use AI as an assistive rather than a generative tool. Users rely on AI to enhance the quality and integrity of their writing, while remaining cautious about ethical concerns related to full content generation. The diversity of tools used further underscores this assistive orientation. ChatGPT, the most utilized tool at 51.2%, was closely followed by Grammarly (48%) and Turnitin (46.5%). Other tools such as QuillBot, Scispace, and ChatPDF were also employed, suggesting a preference for modular AI support tailored to specific academic tasks. A number of scholars (Grassini, 2023; Ioku *et al.*, 2024; Kong et al., 2024) outlined diversified views with respect to the adoption and affordances of each tool, ranging from paraphrasing and summarization to citation generation and literature discovery, to optimize their workflow. The findings reflect a high level of academic engagement with AI tools, not merely as novel innovations but as practical instruments integrated into scholarly writing routines. The consistency of these findings with recent literature reinforces the view that AI tools have become indispensable in modern research environments, where efficiency, accuracy, and ethical writing practices are paramount.

**Table 2.**
*Awareness and Usage of AI Tools among Academicians*

| Variable | Frequency (n) | Percentage (%) |
|---|---|---|
| ***Are you aware of AI tools used for research writing?*** | | |
| Yes | 121 | 95.3 |
| No | 6 | 4.7 |
| ***How often do you use AI tools for Research?*** | | |
| Daily | 21 | 16.5 |
| Weekly | 50 | 39.4 |
| Monthly | 19 | 15.0 |
| Rarely | 30 | 23.6 |
| Never | 7 | 5.5 |
| ***What is the primary purpose for using AI tools in research writing?*** | | |
| Grammar and style correction | 58 | 45.7 |
| Content generation | 32 | 25.2 |
| Reference management | 54 | 42.5 |
| Plagiarism detection | 50 | 39.4 |
| Literature searching | 48 | 37.8 |
| ***AI tools used for research writing*** | | |
| Grammarly | 61 | 48 |
| ChatGPT | 65 | 51.2 |
| Turnitin | 59 | 46.5 |
| Quill Bot | 34 | 26.8 |
| Scispace | 41 | 32.3 |
| Scite.ai | 5 | 3.9 |
| Elicit | 1 | 0.8 |
| Gemini | 4 | 3.1 |
| ChatPDF | 17 | 13.4 |

**Source:** Field Data (2025)

## Exploratory Factor and reliability analysis of an AI tool for research writing

The findings of the Exploratory Factor Analysis (EFA) and reliability analysis confirm the validity and internal consistency of the measurement model assessing AI adoption constructs among academicians. All factor loadings exceeded 0.65, indicating strong item-construct relationships, consistent with studies such as Ahmad et al. (2023) and Topal *et al. (*2025), who reported similarly high loadings in AI literacy and attitude scales. The Kaiser-Meyer-Olkin (KMO) values ranged from 0.756 to 0.838, and Bartlett's Test of Sphericity was significant at $p < 0.001$, confirming sampling adequacy and data suitability for factor analysis, as seen in studies by Abd-Elsalam & Abdel-Momen (2023), Koos & Wachsmann (2023 Nazaretsky *et al. (*2025).

The explained variance for each factor ranged from 44.742% to 62.569%, aligning with the accepted standard in psychometric studies and recent research, such as Wu *et al. (*2024), who reported a 58.4% variance in AI attitude scales. Cronbach's alpha values from 0.741 to 0.848 reflect good internal consistency, similar to the findings by Nguyen et al. (2024) on AI technology adoption in professional settings. These results reinforce the instrument's robustness for capturing Actual Usage (AU), Adoption (A), Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavioral Intention (BI), and Continuous Usage Intention (CUI) in the academic AI adoption context.

**Table 3:**
*Exploratory Factor and Reliability Analysis of AI Tools for Research Writing*

| | **Component** | **Component** | **Component** | **Component** | **Component** | **Component** |
|---|---|---|---|---|---|---|
| **Factor** | 1(AU) | 2 (A) | 3(PU) | 4(PEU) | 5(BI) | 6(CUI) |
| **Items Factor Loadings** | AU10.801 | A10.689 | PU10.714 | PEU10.667 | BI10.728 | CUI10.714 |
| | AU20.821 | A20.670 | PU20.764 | PEU20.702 | BI20.795 | CUI20.698 |
| | AU30.701 | A30.666 | PU30.759 | PEU30.650 | BI30.767 | CUI30.691 |
| | AU40.793 | A40.734 | PU40.728 | PEU40.706 | BI40.681 | CUI40.654 |
| | AU50.833 | A50.726 | PU50.760 | PEU50.698 | BI50.740 | CUI50.760 |
| | | A60.712 | | PEU60.682 | | |
| **Bartlett's test** | 251.512($p<0.001$) | 205.917($p<0.001$) | 171.659($p<0.001$) | 145.964($p<0.001$) | 169.847($p<0.001$) | 120.958($p<0.001$) |
| **Kaiser-Meyer-Olkin (KMO)** | 0.838 | 0.756 | 0.815 | 0.838 | 0.817 | 0.781 |
| **Eigenvalue** | 3.128 | 2.941 | 2.778 | 2.685 | 2.763 | 2.468 |
| **Total variance explained (%)** | 62.569 | 49.018 | 55.564 | 44.742 | 55.262 | 49.363 |
| **Cumulative variance explained** (%) | 62.569 | 49.018 | 55.564 | 44.742 | 55.262 | 49.363 |
| **Cronbach alpha** | 0.848 | 0.791 | 0.800 | 0.751 | 0.797 | 0.741 |

**Source:** Field Data (2025)
**Note**: *AU=Actual Usage, A=Adoption, PU=Perceived Usefulness, PEU=Perceived Ease of Use, BI=Behavioral Intention, CUI=Continual usage Intention*

**Regression Results of Factors Influencing the Adoption of AI Tools**

The regression analysis underscores several key predictors of AI tool adoption, including Actual Usage (AU), Perceived Ease of Use (PEU), and Behavioral Intention (BI), while showing that Perceived Usefulness (PU) is not statistically significant. The strong positive correlation between AU and AI adoption (coefficient = 0.388, $p < 0.001$) aligns with existing literature that emphasizes the importance of prior hands-on experience in driving sustained use of AI technologies. Researchers are more likely to adopt AI tools when they are already using them in their daily academic workflows, indicating a reinforcement loop between familiarity and continued usage (Arora et al., 2023). This is further supported by evidence from Sasikumar & Sunil (2023), who noted that experiential familiarity enhances user confidence, which in turn promotes the integration of AI into academic routines. The finding that Perceived Ease of Use (PEU) negatively correlates with AI adoption (coefficient = -0.274, $p = 0.002$) is both surprising and significant. Traditionally, models such as the Technology Acceptance Model (TAM) suggest that greater ease of use facilitates technology adoption. However, recent literature suggests a more complex dynamic in the context of AI. Advanced users might associate ease of use with a lack of sophistication or perceive simplified tools as offering less control over outcomes. The studies by Ahn & Al (2024; Zhao et al. (2023) discuss how users may become skeptical of overly simplistic AI tools, questioning their robustness and the quality of output. Behavioral Intention (BI) also emerged as a significant positive predictor of AI adoption (coefficient = 0.218, $p = 0.014$). This supports extensive literature indicating that individuals who intend to use AI tools in the future are more likely to adopt them when opportunities arise. Intention acts as a cognitive precursor to behavior, aligning with findings in educational research that show a strong link between attitude, intention, and actual behavior in digital tool uptake. Nazaretsky et al. (2025) and Wu et al. (2025) also highlighted that positive anticipation of AI utility significantly predicts actual tool usage, particularly among digitally literate researchers. Contrary to expectations, Perceived Usefulness (PU) did not show a significant effect at $p = 0.975$, suggesting that the perceived value of the tool alone does not translate into actual adoption. This may reflect a disconnect between perceived and practical utility or suggest that usefulness is mediated through other variables like trust, context of use, or prior experience. Several recent studies challenge the long-standing assumption that perceived usefulness is a central determinant of adoption, especially in AI contexts where performance metrics and trust in algorithms also play critical roles (Ahmad *et al*., 2023; Gander & Shaw, 2024; Hajkowicz *et al*., 2023; McElheran *et al*., 2023). The model's explanatory power ($R^2 = 0.620$) and robust F-statistic (49.804, $p < 0.01$)

confirm that the chosen variables collectively provide a strong explanation for AI adoption behaviours. The Durbin-Watson statistic of 1.872 indicates minimal autocorrelation in residuals, and tolerance values all above 0.1 dismiss concerns of multicollinearity, supporting the model's statistical integrity. These findings collectively reinforce the relevance of behavioural and experiential variables over purely perceptual factors in predicting AI adoption in academia.

**Regression Results of Factors Influencing Continued Usage Intention of AI for Research Writing**

The regression results demonstrate that Actual Usage (AU), Perceived Ease of Use (PEU), and Behavioral Intention (BI) significantly influence the continued use of AI tools, whereas Perceived Usefulness (PU) does not. Actual Usage (coefficient = 0.159, $P < 0.001$) shows that prior engagement with AI tools reinforces future use. This finding is supported by (Naseri & Abdullah, 2024), who observed that habitual interactions with AI tools foster user familiarity, comfort, and trust, which are essential for sustained usage in academic settings. The strong positive association between Perceived Ease of Use and continued usage (coefficient = 0.392, $p < 0.001$) aligns with existing models of technology acceptance. Users who find AI tools intuitive and user-friendly are more likely to incorporate them into long-term workflows. This resonated in (Soulami *et al.*, 2024), who noted that ease of interaction significantly influences user retention, especially for tools integrated into educational platforms. Behavioral Intention (BI) also plays a pivotal role, with a high positive coefficient (0.385, $P < 0.001$), indicating that individuals who intend to continue using AI tools are significantly more likely to do so. This finding is consistent with research by Na *et al.* (2023; Qahtani & Alsmairat, 2023), who emphasized the predictive strength of future usage intention as a behavioral driver in digital tool engagement. High intention often stems from perceived personal or professional benefit, especially in fast-evolving academic environments. In contrast, Perceived Usefulness (PU) does not significantly influence continued use (coefficient of 0.067 at $P = 0.221$). This is an important insight, suggesting that once users begin interacting with AI tools, the decision to continue is driven more by the ease of integration and behavioral intention than by abstract beliefs about usefulness. Recent literature echoes this shift, highlighting that long-term engagement is less influenced by perceived utility and more by experiential and contextual factors such as trust, user experience, and peer influence (Nouraldeen, 2022; Sadriwala & Sadriwala, 2022). The model's robustness is further confirmed by a high $R^2$ value (0.822) and adjusted $R^2$ (0.816), indicating a strong explanatory power of the predictors. The F-statistic (140.675, $p < 0.01$) reinforces the overall model significance, while the

Durbin-Watson statistic of 2.193 confirms that residuals are independent. Additionally, collinearity diagnostics show no multicollinearity issues, making the findings statistically reliable. Continued use of AI tools is significantly driven by behavioral patterns and ease of use rather than perceived usefulness. These insights support a more user-centric approach to AI tool design and deployment in academia, emphasizing experiential engagement and intuitive interfaces.

**Table 4:**
*Regression Results Regarding Factors Influencing the Adoption of AI Tools*

| Variable | Coefficient | t-Value | Sig | Collinearity statistics tolerance |
|---|---|---|---|---|
| AU | 0.388 | 4.523 | <0.001 | 0.422 |
| PU | 0.003 | 0.031 | 0.975 | 0.451 |
| PEU | 0.274 | -3.148 | 0.002 | 0.410 |
| BI | 0.218 | 2.489 | 0.014 | 0.406 |

**=0.620** Adj.=0.608 F=49.804(p<0.01) Durbin-Watson=1.872
**Source:** Field Data (2025)
***Note:*** *AU=Actual Usage, A=Adoption, PU=Perceived Usefulness, PEU=Perceived Ease of Use, BI=Behavioral Intention, CUI=Continual usage Intention*

## CONCLUSION AND RECOMMENDATIONS

### Conclusion

This study investigated the determinants influencing the adoption and continued usage of Artificial Intelligence (AI) tools for research writing among academicians in Tanzanian higher learning institutions. Drawing upon the Technology Acceptance Model (TAM), the study empirically examined the roles of Perceived Usefulness (PU), Perceived Ease of Use (PEU), Behavioral Intention (BI), and Actual Usage (AU) in predicting both the adoption and continued use of AI tools. The findings confirm that AU, PEU, and BI are significant predictors of AI tool adoption and sustained use, while PU did not exhibit a statistically significant influence in either model. Actual Usage emerged as a strong determinant of both initial adoption and continued use, underscoring the importance of hands-on experience in shaping user behaviour. Similarly, Behavioral Intention showed a consistent and positive relationship with adoption outcomes, indicating that academicians with future-oriented motivations are more likely to embrace AI technologies. Interestingly, PEU was found to be positively associated with continued usage but negatively associated with adoption, suggesting that perceptions of ease may have nuanced effects depending on users' engagement stages. The model demonstrated a high explanatory power, particularly for continued usage (Adjusted $R^2 = 0.816$), confirming the robustness of TAM in this context. These results highlight the need for institutions to not only promote awareness of AI tools but also focus on fostering meaningful user engagement and training, which are more predictive of sustained tool usage than perceived utility alone. Furthermore, the study fills a critical gap in the Tanzanian context, offering localized insights into how digital literacy, motivation, and user experience shape AI integration in academic research writing.

**Recommendations and Policy Implications**

Higher learning institutions should implement structured workshops and hands-on training sessions to increase faculty competence and confidence in using AI tools. This would help convert intention into actual and sustained usage. Moreover, developers and vendors of AI writing tools should prioritise user-friendly interfaces and minimal learning curves to encourage broader adoption and long-term engagement among academicians. Also, institutions should consider integrating AI tools into research workflows, learning management systems, and writing support services. Official endorsement and support will normalize usage and reduce skepticism. Furthermore, academic institutions must establish clear ethical frameworks that define the appropriate use of AI tools, especially around authorship, plagiarism, and data integrity. This will safeguard academic standards while leveraging AI's benefits.

Additionally, there is a pressing need for national-level policy frameworks that guide ethical AI use in academia, in particular, to address issues of academic integrity, authorship, and data usage, and be enforced across institutions to maintain educational standards and credibility. In addition, National education policies should encourage the integration of AI technologies into university systems such as research platforms, learning management systems (LMS), and writing support services. Official institutional support legitimizes AI use and fosters a more innovation-friendly academic culture. Policymakers in higher education should mandate the development and delivery of AI literacy programs for academic staff. By institutionalizing structured training, universities can bridge the gap between intention and consistent use, ensuring faculty are equipped to harness AI tools effectively in teaching and research.

**Areas for further Study**

Future studies should adopt longitudinal designs to examine how the perception of usefulness, ease of use, and behavioral intention change over time as academicians gain more experience with AI tools. Conducting comparative studies across countries, regions, or institutional types could reveal contextual factors such as policy framers, funding structures, and institution types.

## Limitations of the Study

Despite the valuable insights generated, this study has the following limitations that should be acknowledged. The sample was restricted to academicians within Tanzania's higher learning institutions. While this provides useful insights, it limits the generalizability of the findings to other institutions. Additionally, the study focused primarily on AI tools used for research writing, excluding other academic functions such as teaching, assessment, and supervision. Assessing AI adoption across these additional academic dimensions would provide a more comprehensive understanding of AI integration in higher learning.

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