

Determinants of artificial intelligence tools use in research among postgraduate students: Evidence from selected public universities in Tanzania

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<https://doi.org/10.51867/ajernet.7.3.60>

ABSTRACT

This study examines the determinants of the use of Artificial Intelligence tools in research among postgraduate students at Tanzanian universities, with two objectives: the extent of AI use in research and the factors influencing its use. This study was grounded in the extended Unified Theory of Acceptance and Use of Technology (UTAUT-3). The study adopted a convergent parallel mixed-methods design. The population comprised 2830 postgraduate students; a sample of 350 participants was selected using purposive, stratified, and simple random sampling techniques from the University of Dar es Salaam (UDSM) and Sokoine University of Agriculture (SUA). Quantitative data were collected using a structured questionnaire and analysed using descriptive statistics and multiple linear regressions. The findings showed that ChatGPT and SciSpace were the most frequently used AI tools for idea generation and literature searching, while Grammarly and QuillBot were mainly used for writing improvement and paraphrasing. The regression model was statistically significant ($F(10, 310) = 15.311, p < .001$) and explained 33.1% of the variance in AI tool use ($R^2 = .331$; Adjusted $R^2 = .309$). Performance expectancy ($\beta = .345, p < .001$), price value ($\beta = .218, p = .004$), year of study ($\beta = .113, p = .025$), and effort expectancy ($\beta = -.201, p = .007$) significantly influenced AI tool use. However, age, sex, social influence, facilitating conditions, habit, and personal innovativeness did not significantly predict AI tool use ($p > .05$). The study concludes that AI tool use among postgraduate students is still in early development, as they have not yet fully integrated them into all aspects of their research workflow. The study recommends that universities, through the Directorates of Research and Postgraduate (DRP), establish training and workshops on the effective use of AI tools for postgraduate students to maximise their benefits in research processes.

Keywords: AI Tools, Artificial intelligence, Research, Tanzania, UTAUT, University

1. INTRODUCTION

Research writing is a critical component of postgraduate degree requirements in many universities around the globe (Kahangwa, 2024). Universities require this for a variety of reasons, including preparing students for professional careers and further academic study. In order to be awarded their qualification, a postgraduate student must complete a research write-up and submit it to the institution (Kahangwa, 2024). Research writing, as the core of scholarship and information sharing across disciplines, demands robust skills in information searching, analysis, critical evaluation and academic writing (Khanh, 2025; Solanki et al., 2026).

As such, the rapid emergence of Artificial Intelligence (AI) in higher education has been universally acclaimed as a disruptive force that can reshape education and enhance research quality (Nugrahawati, 2023). As tools capable of emulating human intelligence, AI systems learn to think and behave as humans would (Madanchian & Taherdoost, 2025). They have the capacity to learn reason, perceive, and predict in ways similar to human intelligence. AI acts as a complement to human creativity, assisting students with hypotheses generation, problem-solving and tasks automation such as literature searches, data collection and analysis (Madanchian & Taherdoost, 2025). Researchers in developing countries are finding creative new uses for AI in various stages of the research process, from brainstorming new ideas to writing assistance, editing and proofing and even for sophisticated data analysis (Khalifa & Albadawy, 2024).

A considerable number of academic institutions located in developed countries like the U.S and UK have established innovative frameworks for integrating AI into teaching, learning, and research, although the researchers report an increased use of AI tools within universities that did not have existing structures (Akbar, 2025; Deng & Liu, 2025). A study in India by Shimray and Subaveerapandiyan(2025), for example, shows that their postgraduates utilise AI in the field of proof reading, generating research ideas, literature reviews and academic work in general. In Africa

however, and in particularly Tanzania, AI tool use remains low and is less recognised in higher education research contexts (Mfaume, 2026; Utonga et al., 2025; Owan et al., 2025).

In Africa, the quality of research among post-graduates has faced some scrutiny due to difficulties in dissertation and thesis writing as well as difficulties in finding and reporting information and coming up with an original contribution to research. The result is an extended period of study for students, publication challenges and ultimately poor output. (Kahangwa, 2024; Mkhai, 2023; Chime et al., 2025). In this research article AI tools have been cited as a promising intervention to overcome those limitations related to research quality issues affecting post-graduate students in Tanzania. It is from this perspective that the researcher proposed conducting research to fill this gap by identifying the factors influencing postgraduate students' use of AI tools in research, since adoption and use are influenced by different factors.

1.1 Statement of the Problem

Universities across the world are increasingly incorporating Artificial Intelligence tools in research activities to improve research writing processes (Reynoso et al., 2024). Despite this potential, the actual use of AI tools in research activities among postgraduate students in developing countries, including Tanzania, is low (Mfaume, 2026; Utonga, 2025; Owan et al., 2025). As a result, postgraduates face challenges in producing high-quality research, leading to delays in dissertation and thesis completion, which eventually affect research productivity and innovation in universities (Said & Sheikh, 2024; Hokororo, 2021; Kadikilo et al., 2024).

Previous studies have inspected several aspects of Artificial intelligence in universities. For instance, in Nigeria, studies by Owan et al. (2025) investigated the acceptance and use of AI for self-directed research learning, and by (Asongo et al., 2024) investigated awareness and utilization of AI tools to enhance research. Another study in Uganda by Mabirizi et al. (2025) reviewed the impact of generative AI on postgraduate research, examining opportunities, challenges and ethical implications. In the Tanzania study by Mfaume (2026) explored the place of AI ethical literacy among lecturers and postgraduate students, another study by Manyengo (2024) reviewed the management of research using AI and Lashayo et al. (2023) examined the extent of adoption and integration of AI content in university curricula. Despite all these contributions, none have assessed the determinants of AI use in research among postgraduate students in Tanzania, using the extended UTAUT theory (UTAUT-3) with the additional variables of habit, hedonic motivation, price value, and personal innovativeness. Thus, the study aimed to investigate determinants of AI tools use in research among postgraduate students in Tanzania.

1.2 Research Objectives

- i. To examine the extent of AI tools, use in research among postgraduate students in selected public universities in Tanzania.
- ii. To examine factors influencing postgraduate students' use of AI tools in research in selected public universities in Tanzania

1.3 Research Question

- i. What is the extent of AI tools use in research among postgraduate students in selected public universities in Tanzania
- ii. What are the factors influencing postgraduate students use of AI tools in research selected universities in Tanzania

II. LITERATURE REVIEW

2.1 Theoretical Review

2.1.1 Theories and Models of Technology Acceptance and Use Behaviour

There are several of theories and models presented to explain technology use behaviour. Theories such as the Theory of Reasoned Action (TRA), introduced by Fishbein & Ajzen (1977), are general in nature and describe user behaviour from a social-psychological perspective. This theory arises from the Theory of Planned Behaviour (TPB) from (Ajzen, 1991). Then follow other theories from this base, such as the Technology Acceptance Model (TAM) by Davis (1986) the first known and widely accepted research model to explain technology adoption behaviour, especially in the information technology context, and now used in research on information systems. The TAM theory explains that when an individual generates an intention to use a new system or technology, they encounter two belief variables, such as perceived usefulness and perceived ease of use of such a system, which are identified as the most well-known factors in a person's intention to use such technology. The Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), was introduced with four main constructs, such as performance expectancy, effort expectancy, social influence and facilitating conditions as the direct factors of adoption and usage behaviour intention. The UTAUT theory goes further and introduces moderating constructs, such as gender, age, experience, and voluntariness of use, that moderate the four main constructs related to the intention to adopt and use technology. Moreover, these theories continue to be explored and improved by new researchers with different user populations. The UTAUT theory has been extended

up to UTAUT3 by Farooq et al. (2017), adding hedonic motivation, price value, habit and personal innovativeness as additional determinants of technology adoption. UTAUT-3 variables can be defined as follows; performance expectancy is the belief that using a system will improve job performance, effort expectancy perceived easiness in using AI platforms, social influence is the extent to which an individual perceives that important other that he or she should use the AI, facilitating condition is the confidence that an individual believe there is technical and institutional support in using AI, habit is an automatic tendency formed by the previous experience caused by frequency use of AI in learning, price value cost and price that affect use of AI Venkatesh et al. (2012) and personal innovativeness an individual level of readiness to voluntarily try new technology (Nurkhin et al. (2026). The extended UTAUT-3 is considered relevant for investigating the determinants of postgraduate students' use of Artificial intelligence tools because it integrates technological, personal, and social factors needed to understand how postgraduate students adopt and use AI tools to enhance research processes. However, not all constructs are applicable; hedonic motivation is excluded as it does not align with the academic context of AI use especially in research.

2.2 Empirical Review

2.2.1 Extent of Artificial Intelligence Tools Use in Research Activities among Postgraduate Students.

Empirical studies across the world highlight that recently, there has been an increased use of Artificial Intelligence tools in research processes among postgraduate students. They use AI tools to assist them at several stages of the research process, such as academic writing, idea generation, literature searching, proofreading, data analysis, and more (Khalifa & Albadawy, 2024). A study conducted by Shimray and Subaveerapandiyan (2025) in India reported the common uses of AI tools among postgraduate students in research activities such as proofreading, generating research ideas, literature review and assistance in academic writing. AI tools that are frequently used in developed countries include ChatGPT, Quillbot, Grammarly, and SciSpace, which are used to assist in research processes, such that ChatGPT and SciSpace are mostly used in several research stages, like literature review, generating research ideas, paraphrasing, and correcting grammar (Biondi-zoccai et al. 2025; Chukwuere, 2025). A study conducted by Deep et al. (2025) and Jamshed et al. (2024) found that ChatGPT and Grammarly were primarily used to enhance language quality, thereby reducing language barriers among students. In Africa, studies show that the extent of AI tool use among postgraduate students is generally moderate but progressively increasing. For example, a study conducted in Nigeria shows that postgraduate students are aware of various AI tools and use them to enhance research tasks; however, there is variation in the level of utilisation among postgraduate students (Owan et al., 2025). These AI tools were commonly used for summarising articles, generating research ideas, and enhancing writing quality; however, for complex tasks such as methodological design and advanced data analysis, AI tools were less frequently used (Lazuwardiyyah & Setiawan, 2024). Despite all this literature, there is limited empirical evidence on the extent to which postgraduate students use AI tools in research activities in Africa, particularly in Tanzanian universities.

2.2.2 Factors influencing Postgraduate Students' Use of Artificial Intelligence Tools in Research Activities.

Studies have been conducted globally to examine factors influencing the adoption and use of Artificial intelligence tools in academic research. The most frequently identified determinant is perceived usefulness, for which researchers report a strong relationship with improvements in research performance (Qiu & Zhu, 2026). The other determinant is perceived ease of use that significantly influenced the adoption and use of AI in research activities, means that users and researchers are more willing to integrate and use technologies which are easy to learn and operate, same apply to the AI tools students will use these tools in their research processes when they are easy to learn and operate (Mai, 2025; Vieriu & Petrea, 2025; Wang, 2025). Additionally, in a higher education environment, there is a strong influence from peers and supervisors; they play a part in motivating others to use AI technologies in research activities simply because these tools have become beneficial to them, which makes social influence another important determinant in influencing the use of AI tools and adoption in research processes (Liang, 2025; Mai, 2025; Wang, 2025; Mbilinyi et al., 2025). Moreover, studies identify that facilitating conditions, such as the availability of digital infrastructure, internet connectivity, institutional support (e.g., policies and regulations), training opportunities, and technical support, are crucial in determining AI tool usage among researchers (Liang, 2025; Mai, 2025; Wang, 2025; Mbilinyi et al., 2025). Studies have also found factors such as trust, behavioural beliefs, control beliefs, and normative behaviour as determinants of AI tool use among researchers (Anani et al., 2025). However, other important determinants need to be verified, namely the habit, personal innovativeness of information technology and price value, that have been overlooked. Moreover, the available studies focus on general technology adoption in higher education rather than specifically investigating the determinants influencing postgraduate students' use of AI tools in research activities, especially in African higher education institutions.

III. METHODOLOGY

3.1 Research design

The study adopted the Convergent parallel research design. The researcher simultaneously collected and analysed both quantitative and qualitative data to describe the association between the study variables, which is suitable for developing a multipurpose matching explanation of the situation (Bhana, 2024).

3.2 Target Population

The population of this study comprised 2830 individuals, including postgraduate students from Sokoine University of Agriculture (530) and the University of Dar es Salaam (2300), from the academic years 2024/2025 and 2025/2026. The population data were obtained from the postgraduate students' admission office. The Universities were selected due to their research and publication impact (SUA, 2023).

3.3 Sampling techniques and Sample size

The study employed a two-stage multistage sampling design. The first stage was selecting universities in Tanzania, in which purposive and stratified sampling were used to obtain SUA and UDSM, and the second stage was selecting postgraduate students, for which simple random sampling was used to obtain 350 postgraduate students from the two universities. Every postgraduate student had an equal chance of being selected. Simple random sampling was used to minimize bias and increase sample representation, making the findings more generalizable (Khalid, 2024).

The sample was calculated using the Yamane formula and obtained a sample of 350. Where as; $n = N / (1 + N(e^2))$

$$n = 2830 / (1 + 2830(0.05^2))$$

$n = 350.46$ approximated to 350.

To calculate the sample size for each university, the researcher used the formula for a stratified proportional sample size.

$nh = (Nh/N) \times n$, Where, nh = Population of Stratum, Nh = Total population of a specific stratum, N = Total population, n = total sample size.

SUA, $nh = (530/2830) \times 350 = 66$. UDSM, $nh = (2300/2830) \times 350 = 284$. Thus, the sample sizes for SUA and UDSM were 66 and 284, respectively.

3.4 Data collection

The researcher developed the closed-ended questionnaire as a data collection tool from the survey method. The questionnaire had three (3) parts: social demographic information, the extent of AI tools uses among postgraduate students, and factors influencing postgraduate students' use of AI tools in research. To measure AI usage in research, respondents were asked to show the extent to which they use AI tools in research; a five-point Likert scale was employed that ranges from 1, which represents least frequent, to 5, which represents most frequent, and all item responses were computed using the summation method to obtain the index score. The high value indicates greater use of AI tools in research, while the low value indicates lower use. Moreover, to measure factors of AI tool use in research activities, items were formulated for each factor. There are 7 factors, each with 5 items. The items were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Thus, after computing the factors, a higher value indicates that respondents believe a given factor increases the use of AI tools. The demographic information was measured as follows;

Age of postgraduate students was measured as respondents' age in years.

Sex was measured as one being a male or female, using codes such as (1=Male, 2=Female)

Level of education was measured as literacy level (1 = post-diploma, 2 = Master's degree, 3 = Doctor's degree (PhD)).

Years of study were measured in terms of academic stage (1=first year, 2=second year, 3=third year and 4=fourth year)

3.5 Data analysis

The quantitative data collected from the respondents were coded and analysed using SPSS version 20. The extent of AI tool usage and the factors influencing AI tool use in research were measured using descriptive statistics, whereas linear regression was used to determine relationships between the factors and the dependent variable, AI tool use in research. Using the formula;

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_{10} X_{10}$$

Where Y = AI use index score,

β_0 = Costant or Intercept, β_1 - β_{10} = Regression Coefficient, X_1 = Effort expectancy index score, X_2 = Performance expectancy index score, X_3 = Social influence index score, X_4 = Facilitating condition index score,

X5=Habit, X6= Price value, X7= Personal innovativeness in IT, X8= Sex, X9= Age, X10= Education level, X11= Year of Study.

Also, major assumptions were tested before conducting the multiple linear regression to maintain the validity of the model; Variance Inflation Factor (VIF) and Tolerance values were used to examine multicollinearity; Durbin-Watson statistics assessed autocorrelation; and ANOVA was used to test for statistical significance difference. Qualitative data were collected from (ten) 10 PhD students and analyzed using thematic analysis, as it is a well-established and rigorous method for interpreting qualitative data (Vieriu & Petrea, 2025).

3.6 Reliability and validity

The instrument's reliability was also assessed using the Spearman-Brown split-half Cronbach's alpha, with 20 questionnaires administered online to postgraduate students at Sokoine University of Agriculture (SUA). The reliability coefficient for AI tools was 0.83, and for determinants of AI tool use was 0.82, both of which were above 0.7, indicating that the scale was reliable (Hair et al., 2010). However, the scale coefficient of ChatGPT use rises after omitting two items, leaving 8 items. To ensure the validity of each item, Principal Component Analysis (PCA) using Varimax rotation was used, with factor loadings ranging from 0.581 to 0.916, indicating a strong fit as it exceeded the accepted threshold of 0.5.

3.7 Ethical Consideration

Before data collection, the researcher sought permission to collect data. Additionally, during data collection, the researcher ensured that respondents provided consent while maintaining the confidentiality of the collected data.

IV. FINDINGS & DISCUSSION

4.1 Social Demographic Information of the Respondents

Table 1 show the demographic information for all 350 respondents who participated in this study. In relation to distribution of sex, there are 216 (61.7%) and 134 (38.3%) who were males and females respectively. The findings indicate that male respondents outnumbered the number of female respondents in our sample.

According to age distribution, the bulk of respondents were aged 26-35 (n=180, 51.4%), this was then followed by the 36-45 years with 129(36.9%). Respondents below 25 years accounted for 29 (8.3%), while those aged 46–50 years represented 12 (3.4%). The information indicates that those who join in postgraduate studies in the current research were primarily young adults and mid aged professional workers.

Regarding education level, the majority of respondents were master's students (n=326, 93.1%), while PhD students accounted for 14 (4.0%) and post-diploma students 10 (2.9%). Concerning the year of study, most respondents were in their second year (n=191, 54.6%), followed by first-year students (n=134, 38.3%). Third- and fourth-year students represented 23 (6.6%) and 2 (0.6%), respectively. The dominance of master's students, particularly at second year implies that a number of them engaged with dissertation studies at this year, hence deemed relevant to respond to the questions with regard to usage of AI tool in research.

The results align with those of Alsayd et al. (2025), who reported that, notably, over half of respondents were master's students in the thesis preparation stage and were strongly engaged in academic research processes.

Table 1

Social Demographic Information

Social Demographic information		N	P
Sex of respondent	Male	216	61.7
	Female	134	38.3
Respondent Age	<25	29	8.3
	26-35	180	51.4
	36-45	129	36.9
	46-50	12	3.4
Level of education	Post-diploma	10	2.9
	Master degree	326	93.1
	Doctor degree (PhD)	14	4.0
Years of study	1 year	134	38.3
	2 years	191	54.6
	3 years	23	6.6
	4 years	2	0.6

4.1.1 Extent of Using of AI Tools in Research Activities by Postgraduate Students

The findings on correcting grammar and writing errors show that SciSpace recorded the highest mean score ($M=3.22$), followed by Grammarly ($M=3.16$) and ChatGPT ($M=3.13$). However, the absence of significant differences among the AI tools (indicated by the same superscript letter "a") suggests that postgraduate students reported similar levels of use of these tools for improving grammar and writing quality. This result suggests that grammar checking is the primary task that AI tools can perform. This is because most postgraduate students require their research to be written in good English, and grammar correction relies on standard language processing features. The findings of the study align with (Mbilyinyi et al. (2025); Nja et al. (2023); Chime et al. (2025) who reported that Grammarly and QuillBot were highly used in text editing and enhancement of language quality.

Findings on summarising a large academic text and paraphrasing show that Grammarly ($M=3.41$, 3.30) and QuillBot ($M=3.24$, 3.24) are significantly higher than SciSpace ($M=3.13$, 3.01) and ChatGPT (3.12). This implies that postgraduate students choose Grammarly and QuillBot to summarise their research tasks and paraphrase research content. They prefer these tools because they are designed specifically for text summarisation and rewriting or paraphrasing, which provide clearer, more relevant outputs than ChatGPT and SciSpace, whose functions are more general. The findings are similar to those of (Mbilyinyi et al. (2025); Raheem et al. (2023); Widiati et al. (2023b) who revealed that Grammarly and QuillBot are used specifically in summarising and paraphrasing so as to avoid plagiarism.

Regarding Research idea generation, data analysis and citation and referencing, ChatGPT ($M=3.26$, 3.08, and 3.30, respectively, Table 2) shows a higher mean than the other tools, such that Grammarly ($M=3.03$, 3.04, and 2.91, respectively), SciSpace ($M=3.10$, 2.96, and 3.19 respectively) and QuillBot ($M=2.87$, 2.60 and 2.72 respectively) shows lower mean. This result indicates that postgraduate students prefer ChatGPT for idea generation and brainstorming, data analysis and citation and referencing. This is contributed to the fact that ChatGPT was designed to perform interactive and generative tasks, enabling users to navigate various concepts, provide detailed explanations of the content, and ask real-time questions, while also providing assistance with data analysis, citation, and referencing. The findings of this study are in agreement with Chen et al.(2025), Chukwuere (2025) and Zhu et al.(2023) whose studies show that ChatGPT is a multifunction AI tool that is capable of generating research ideas, performing data analysis and assisting in citation and referencing.

Findings from the literature review, literature search, research gap identification, and understanding methodologies show that ChatGPT ranked highest with means of $M=3.36$, $M=3.53$, $M=3.33$, and $M=3.41$, respectively, followed by SciSpace with means of $M=3.11$, $M=3.09$, $M=3.19$, and $M=3.28$, respectively. While Grammarly and QuillBot show a low mean. The results imply that postgraduate students rely more on ChatGPT for literature review, literature search, identifying research gaps, and understanding methodologies. This is because ChatGPT can explain complex concepts simply and provide step-by-step explanations that help postgraduate students integrate them into their research tasks. This is similar to the findings from Mabungela et al. (2025) who reported that ChatGPT assist with data analysis and writing papers for release. Moreover, the moderate use of SciSpace indicates that students are not well aware of its potentiality in assisting with the literature search, in identifying research gap and understanding of methodologies (Mbilyinyi et al., 2025; Barrot, 2025).

Table 2

Extent of using AI tools by postgraduate students (n=350)

AI Usage	ChatGPT	SciSpace	Grammarly	Quillboot
Correct grammar and writing errors in my research		3.13 ^a	3.22 ^a	3.16 ^a
Summarizing a large academic text		3.13 ^b	3.41 ^a	3.24 ^a
Paraphrasing research contents	3.12 ^b	3.01 ^b	3.30 ^a	3.24 ^{ab}
Generating research ideas	3.26 ^a	3.10 ^{ab}	3.03 ^c	2.87 ^c
Data analysis	3.08 ^a	2.96 ^{ab}	3.04 ^{ab}	2.60 ^d
Citation and referencing	3.30 ^a	3.19 ^a	2.91 ^b	2.72 ^b
Literature review	3.36 ^a	3.11 ^b	2.93 ^{bc}	2.73 ^{cd}
Literature search	3.53 ^a	3.09 ^b	3.00 ^{bc}	2.84 ^{cd}
Identify the research gap	3.33 ^a	3.19 ^{ab}	3.03 ^{bc}	2.93 ^c
Understanding methodologies	3.41 ^a	3.28 ^{ab}	3.07 ^{bc}	2.85 ^c

4.1.2 Factors Influencing the Use of AI Tools in Research by Postgraduate Students

From the findings, Effort expectancy (EE) and performance expectancy (PE) show no significant difference; both have the highest means ($M= 3.66$ and $M= 3.64$). This implies that postgraduate students use AI tools because they are easy to use, require less effort, and help enhance their research performance. The results align with Liang (2025), who found that EE and PE have higher means in influencing the use of AI tools, with EE having the higher mean. Moreover, Qiu & Zhu (2026) found that EE has the largest mean effect on usage, whereas PE shows no effect. A study

by Zhu et al. (2023) found that PE is the most influential factor, followed by EE, indicating that most postgraduate students use AI tools that require little effort and offer significant benefits. Findings further show that personal innovativeness (PI) has a higher mean, ($M=3.336$), indicating that postgraduate students are enthusiastic about trying new technologies, especially AI tools. This is because postgraduates who are willing to try new digital research platforms are more likely to use them. The results resonate with previous studies by Amin et al. (2026) and Goto & Ramnarain (2026) who reported that personal innovativeness is one of the factors influencing students' use of AI tools.

For Habit (H) and Price value (PV), both with the mean ($M = 3.20$) show significant differences from the top factors. This implies that these two factors have a lower mean than EE, PE, and PI. The repeated use of AI tools and the confidence in their use moderate AI tool use among postgraduate students. This is because of different perceptions regarding the adoption of new technologies, such as AI, and the credibility of education. However, the findings contradict Strzelecki (2024) who reported that repeated use of AI tools is the best determinant, followed by PE, in determining students' behaviour in using AI tools. On the other hand, the results on price value show that affordability and the cost in terms of effort and time are moderate determinants of postgraduates' use of AI tools in research. These results are attributed to the fact that AI tools are still new technologies in research, and that few to moderate postgraduates understand their potential in research compared to the costs they incur in terms of money, time, and effort. In contrast, those unaware of the benefits see these tools as expensive. Findings resonate with Sergeeva et al. (2025), who also reveal that price value positively influences intention to use AI technologies among students.

Social Influence (SI) show the mean is neutral ($M=3.00$) and significantly below the mentioned determinants. This suggests that peers, supervisors, and lecturers have limited influence on postgraduate students' use of AI tools in research. Conflicting views on the pros and cons of AI tools in education still influence this. However, the findings contradict those of a previous study Wang (2025), which reported that peers' recommendations and instructors' endorsements influence Chinese students' use of AI. Facilitating Condition (FC) shows the lowest mean score ($M=2.76$) and is significantly different from all other factors. This implies that unfavorable conditions supporting the use of AI tools among postgraduate students, such as a lack of policies and regulations, and that these results also contribute to the fear of unethical use of AI tools. Results agree with Mbilinyi et al. (2025), who reported that the environment does not support AI adoption due to a lack of training, workshops, budget constraints, and other related factors, thereby limiting their influence on AI usage.

Table 3

Factors influencing the use AI tools in research by Postgraduate Students

Variable	Mean
Effort Expectancy (EE)	3.66 ^a
Performance Expectancy (PE)	3.64 ^a
Social Influence (SI)	3.00 ^d
Facilitating Condition (FC)	2.76 ^c
Habit (H)	3.20 ^c
Price Value (PV)	3.20 ^c
Personal innovativeness on IT (PI)	3.36 ^b

To examine how the selected factors influence postgraduate students' use of AI in research, the researcher conducted a multiple regression analysis. Before regression, validity of items and different assumptions were tested.

4.1.3 Assessment of the Validity of Each Item in the Factors

From Table 4, communalities range from 0.543 to 0.884, indicating a generally strong fit, as they exceed the accepted threshold of 0.50 (Pallant, 2020). This indicates that no items need removal due to low communality. Additionally, Kaiser-Meyer-Olkin (KMO) value 0.876 explains a very good sampling adequacy, which means data were suitable for factor analysis, and Bartlett's Test of Sphericity $\chi^2 = 7040.226$, $df=595$, $p<.0001$ is statistically significant, indicating that the correlation matrix is not an identity matrix, and the correlation among variables is sufficient to justify factor analysis.

Table 4*Communalities after extraction*

Item	Initial	Extraction
AI tools are easy for me to use during research activities.	1.000	.717
Learning how to use AI tools for research is straightforward.	1.000	.844
Interacting with AI tools in my research tasks is clear and understandable.	1.000	.616
I find it simple to navigate the different AI features required for my research work.	1.000	.577
Using AI tools makes it easy for me to increase my research skills	1.000	.666
Using AI tools improves the quality of my research work.	1.000	.709
AI tools increase the research skills that assist me in completing my research on time.	1.000	.543
AI tools help me achieve better research outcomes.	1.000	.710
AI tools make my research work more efficient.	1.000	.547
Using AI tools widens the opportunity to attain important research goals	1.000	.722
People who are important to me suggest I should use AI tools for research.	1.000	.617
My lecturers and supervisors encourage the use of AI tools in research	1.000	.656
My colleagues influence my decision to use AI tools in research	1.000	.667
AI tool usage in research is a common practice in my academic environment.	1.000	.643
My university supports the use of AI tools in research activities	1.000	.711
I have access to the necessary resources, such as the internet and devices, to use AI tools in my research	1.000	.713
My university provides adequate support for the use of AI tools in research	1.000	.712
I have the technical skills required to use AI tools effectively.	1.000	.555
My university provides training on the use of Artificial Intelligence in research activities	1.000	.662
My institution provides clear guidelines on the acceptable use of AI tools in research.	1.000	.679
Using AI tools in my research has become part of my routine.	1.000	.718
I frequently rely on AI tools without needing to think about it.	1.000	.795
I feel incomplete conducting research without using AI tools.	1.000	.735
I automatically turn to AI tools whenever I start a research task.	1.000	.832
Frequently using AI tools increases my ability to do my research better.	1.000	.681
The cost of using and accessing an AI tool is not high compared to the benefits.	1.000	.616
AI tools save time in doing research that justifies the cost.	1.000	.713
Am ready to incur costs for AI tools that improve my research performance.	1.000	.651
Affordable and open-access AI tools motivate me to use them in my research activities.	1.000	.683
The cost of subscription acts as a limitation for me to use advanced AI tools for research.	1.000	.724
Am always ready to try new AI technologies for research purposes	1.000	.817
I do not fear trying new technology that can improve my research performance.	1.000	.644
Am among the first people to try new digital technology for research	1.000	.716
Learning to try new technology is a passion of mine.	1.000	.631
The complexity of AI tools does not stop me from learning how to use them and apply them.	1.000	.666

Kaiser-Meyer-Olkin Measure of Sampling Adequacy=.876, Bartlett's Test of Sphericity=7040.226, $df=595$ $p<.0001$

4.1.4 The Pattern Matrix for Exploratory Factor Analysis after Oblique Rotation

The Principal Component Analysis results from the Pattern Matrix revealed that four extracted components jointly explain a considerable amount of the total variance in the factors influencing postgraduate students' use of AI tools in research. Generally, the factor loadings for the retained items range from 0.518 to 0.916; they exceed the minimum threshold of 0.50 Pallant (2020), indicating robust correlations between the items and their components and confirming that the items are an effective measure of the underlying constructs.

Table 5*The Pattern Matrix for Exploratory Factor Analysis after Oblique Rotation*

Item	Component			
	PCA1 (31.63%)	PCA2 (11.425)	PCA3 (6.24%)	PCA (5.26%)
AI tools are easy for me to use during research activities.	.654			
Learning how to use AI tools for research is straightforward.	.649			
Interacting with AI tools in my research tasks is clear and understandable.	.749			
I find it simple to navigate the different AI features required for my research work.	.541			
Using AI tools makes it easy for me to increase my research skills	.704			
Using AI tools improves the quality of my research work.	.808			

AI tools increase the research skills that assist me in completing my research on time.	.759			
AI tools help me achieve better research outcomes.	.862			
AI tools make my research work more efficient.	.706			
Using AI tools widens the opportunity to attain important research goals	.731			
People who are important to me suggest I should use AI tools for research.				
My lecturers and supervisors encourage the use of AI tools in research			.660	
My colleagues influence my decision to use AI tools in research				
AI tool usage in research is a common practice in my academic environment.		.520		
My university supports the use of AI tools in research activities			.665	
I have access to the necessary resources, such as the internet and devices, to use AI tools in my research				.737
My university provides adequate support for the use of AI tools in research			.584	
I have the technical skills required to use AI tools effectively.				.610
My university provides training on the use of Artificial Intelligence in research activities			.880	
My institution provides clear guidelines on the acceptable use of AI tools in research.			.855	
Using AI tools in my research has become part of my routine.				
I frequently rely on AI tools without needing to think about it.				
I feel incomplete conducting research without using AI tools.	.518			
I automatically turn to AI tools whenever I start a research task.				
Frequently using AI tools increases my ability to do my research better.	.546			
The cost of using and access AI tool is not large compare to the benefits.		.736		
AI tools save time in doing research that justify the cost.		.623		
Am ready to incur cost for AI tools that improve my research performance		.792		
Affordable and open access AI tools motivate me to use them in my research activities		.684		
The cost of subscription act as limitation for me to use advanced AI tools for research.		.637		
Am always ready to try new AI technologies for research purposes		.526		
I do not fear to try new technology that can improve my research performance		.653		
Am among the first people to try new digital technology for research		.895		
Learning to try new technology is a passion to me		.771		
The complexity of AI tools does not stop me from learning how to use them and apply them.		.916		

Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization. Rotation converged in 7 iterations.

Model Summary: From Table 6, the Durbin-Watson value is 1.716, indicating no serious autocorrelation, as the value falls from 1 to 3 (Pallant, 2020). Additionally, R Square value is 0.331, which is 33.1%, indicating that 33.1% of the variation in the dependent variable is explained by the independent variables. The 66.9% is for the other factors which are not included in the study.

Table 6

Model Summary

Model summary ^b	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
	.575 ^a	.331	.309	.80866	1.716

^a Predictor: determinants (EE, PE, SC, FC, H, PV and PI)

^b Dependent variable: Use of AI

4.2 Analysis of Variance (ANOVA)

From Table 7, the ANOVA value is 0.000, which is below 0.05. This indicates that the model fits the data well and that all independent variables jointly contribute significantly to explaining changes in the dependent variables. Thus, the model is suitable for explaining the study.

Table 7

ANOVA

ANOVA ^a Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	100.120	10	10.012	15.311	.000 ^b
	Residual	202.718	310	.654		
	Total	302.838	320			

a Dependent variable: Use of AI

b Predictor: determinants (EE, PE, SC, FC, H, PV and PI).

P < .001*

4.3 Regression Analysis

Collinearity diagnostics indicate no multicollinearity in the data: tolerance values range from 0.388 to 0.886, all above 0.1, and variance inflation factors (VIFs) range from 1.128 to 2.578, all below the threshold of 5. This shows that the predictors are sufficiently independent and that regression-based estimation is reliable. Results from Table 8 show that age has a beta coefficient of 0.91 and $p=0.07$, indicating no statistically significant effect on AI tool use. This indicates that students' age is not a predictor of AI use in research. This is because postgraduates of different ages, being higher or lower age, they can use or not using the technology, thus does not predict the use of AI tools in research. The results are similar to those of Mbilinyi et al. (2025), who reported that age has no significant influence on the use of AI tools in research.

Likewise, sex from Table 8 had a beta coefficient of 0.04, but it was not statistically significant for AI tool use ($p=0.31$). These results suggest that sex differences do not significantly affect the use of AI tools in research. This is attributed to the gradual increase in AI technology in higher education, which makes everyone curious to adopt it, especially at the postgraduate level, due to its benefits, resulting in no gender differences in the use of AI tools in research. The results are similar to those of Mbilinyi et al. (2025), who reported that differences in sex have no significant influence on the use of AI tools in research. The beta coefficient for the year of studies value is 0.11, which is positive and statistically significant, influencing AI use ($p=0.02$; Table 8). This demonstrates that postgraduate students in advanced years are more likely to use AI tools in research. This is because postgraduate students from the second year and above are more engaged in dissertation and thesis writing, which requires a greater use of digital technologies, especially AI, to accomplish their writing. This is confirmed by an interview when one interviewee stated that “I started using AI tools in my research seriously when I was preparing the reports for my findings”

Effort expectancy from Table 8 had a beta coefficient of -0.20, $p=0.007$, indicating a statistically significant negative influence on AI tool use in research. This suggests that when postgraduate students face challenges related to ease of use, they may reduce their use of AI tools in research. The negative relationship is attributed to the fact that postgraduates lack sufficient training to use those tools effectively to realise their benefits; as a result, they perceive AI tools as difficult to use. To support this finding, an interview was conducted, and one respondent stated that “there are some advanced AI tools that seem confusing, we need support to understand them”. These findings contradict previous studies by Jain et al. (2022), Mbilinyi et al. (2025), and Rana et al. (2024) which reported that ease of use positively influences behavioural intention to use AI tools in higher learning institutions for research purposes.

The beta coefficient value of performance expectancy was 0.34, which is a strong positive and statistically significant ($p<0.001$) Table 8), and it explains that an increase of one unit in performance expectancy increases the use of AI tools in research by 0.40 units. This happens because postgraduate students believe that using AI tools will improve their research performance in terms of quality, efficiency, and time to completion. To ensure that AI use among postgraduates is influenced by their benefits, an interview was conducted, and one of the interviewees stated that “Most of us are using AI tools because they improve the quality of our work from grammar correction, paraphrasing, summarising, and literature search, and also it helps to save time”. The findings resonate with previous studies by (Jain et al., 2022) Jain et al. (2022), Mbilinyi et al. (2025), and Rana et al. (2024), who reported that performance expectancy influences the use and adoption of AI in research.

Regarding social influence, the beta coefficient was 0.11, indicating a positive effect but not a statistically significant effect of AI tool use in research ($p=0.076$; Table 8). This suggests that motivation from peers, supervisors, and lecturers appears to have a positive effect on AI, but the influence was not sufficient to reach statistical significance. This is because most postgraduates are independent learners; using AI tools depends on personal perceptions and motivations, but not from peers. During an interview, one respondent reported that “The perception I had about AI is what made me use them and not the influence from supervisors, lecturers, or my fellow students”. This report confirms that social influence is insignificant in influencing AI use. The findings are contrary to those of Li & Wang (2026), who found that social influence was the strongest predictor of usage intention.

The beta coefficient value of the facilitating condition was -0.05, which is the negative effect on AI use, but also not statistically significant ($p=0.258$) Table 8). This suggests that the availability of supportive infrastructure, institutional support, technical support and internet connectivity did not independently influence the use of AI tools.

This is contributed to by poor support from the university authorities, including training, internet connectivity, and digital infrastructure. The question about institutional support was asked during an interview, and the respondent's answer supports these results, stating that “Ever since I was admitted to the university, I have never received or heard about any training or workshop for effective utilisation of AI tools to cultivate its benefits in research processes”. The findings contradict those of Qi et al. (2025) and Yuan et al. (2023), who found that facilitating conditions represent the availability of organisational and technical resources that influence the usage behaviour of AI tools.

Likewise, the beta coefficient for habit was 0.10 and $p=0.144$ in Table 8, indicating a positive but not statistically significant influence of AI tool use. This demonstrates that perhaps students using AI regularly may become confident in using them, but habit in itself cannot significantly influence the usage of AI tools. Also, this is contributed to by limited training on the effective ways to use AI tools to increase research performance. A response from one interviewee stated that, “I use AI frequently in my academic tasks, but limited training hinders me from maximising the benefits of AI tools in research”. This response supports the finding that frequent use of AI tools may not affect their effective use in research. The studies are similar to those of Tang et al. (2024), which found that habit has a smaller effect on behavioural intention. While Sergeeva et al. (2025) disagreed with the results, finding that habit is the most influential predictor of students' adoption and use of AI tools.

Price value showed a beta coefficient value of 0.21 and $p=0.004$ (Table 8). This is a positive and statistically significant influence on the use of AI tools in research. This implies that postgraduate students are likely to use AI tools when the benefits exceed the cost. This is because postgraduate students are only using those technologies they can afford, despite the benefits they offer. Additionally, cost plays a major role in influencing postgraduates to use AI tools in research. During an interview, the respondent stated, “I pay for Grammarly software every year, and it really helps me with my writing tasks to produce high-quality work in terms of language.” This confirms the result that postgraduates will use AI tools with greater benefits than the cost. Results resonate with the previous study by Sergeeva et al. (2025), who reported that price value positively influences behavioural intention to use AI technologies among students.

Lastly, Personal innovativeness from Table 8 has a beta value of 0.08 and $p=0.21$, which is positive but statistically insignificant on the use of AI tools in research. This implies that, despite postgraduate students' willingness to try new technologies, this does not significantly influence AI use. This is because the absence of guidance on using AI among postgraduate students may lead to ineffective use and lower performance, even though they are enthusiastic about new technologies such as AI. The finding is supported by one respondent in an interview who stated that “we are excited to try new technology, most especially in AI, but there is limited guidance from Institutions and supervisors on how these tools can effectively be used in research”. The results resonate with a previous study by Nurkhin et al. (2026), which reported that personal innovativeness has an insignificant effect on AI use in research.

Table 8
Coefficient

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	.026	.386		.067	.946		
Age	.130	.073	.091	1.775	.077	.830	1.205
Sex	.099	.098	.049	1.002	.317	.886	1.128
Year of studies	.182	.081	.113	2.254	.025	.854	1.171
Effort Expectancy	-.264	.097	-.201	-2.716	.007	.396	2.528
Performance Expectancy	.408	.086	.345	4.748	.000	.408	2.452
Social Influence	.132	.074	.111	1.782	.076	.551	1.814
Facilitating Condition	-.078	.069	-.058	-1.133	.258	.823	1.215
Habit	.107	.073	.102	1.463	.144	.445	2.247
Price Value	.244	.084	.218	2.920	.004	.388	2.578
Personal innovativeness	.098	.079	.088	1.250	.212	.433	2.310

$P<.005^*$

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

The researcher concluded that postgraduate students show gradual development in the use of AI tools, as the results show moderate use of AI tools; They strategically select AI tools based on task-specific functionality, such that ChatGPT are used for idea generation and literature-related tasks, and Grammarly is used for writing improvement and paraphrasing, which are the most used tools. However, they have not yet fully integrated them into all aspects of their research workflow. Additionally, Performance expectancy, year of study, and price value are the most influential factors,

positively influencing postgraduate students to utilise AI tools in their research activities, while effort expectancy, negatively influencing AI use, indicates a challenge associated with ease of use. Social influence, facilitating conditions, habit, and personal innovativeness show no significant influence. This implies that there is still a challenge with the acceptance of AI use in the education sector, especially in higher education institutions. There is little support, including insufficient or absent workshops, guidelines, policies, budgets, and technical support. This suggests that the technology is advancing rapidly, but we are behind it, meaning that postgraduate students are aware of Artificial Intelligence tools and their benefits but do not know how to use them effectively to improve the quality of their research. Thus, there is a strong need to provide training on the proper and effective use of these tools in research activities.

5.2 Recommendations

The Directorate of Research and Postgraduate Studies in universities can establish AI training programs for postgraduate students, organized as seminars, hands-on training, and workshops on effectively and ethically using AI tools in research processes. Also, universities should improve reliable internet access, institutional subscriptions to AI tools, access to premium AI tools, and the development of digital libraries. Additionally, lecturers and supervisors should encourage a sensible use of AI tools rather than over-relying on them. Lastly, postgraduate students should continue to develop their skills in using AI tools strategically to improve their research performance.

Declaration of Interest

The authors declare that they do not have any known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding Declaration

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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