Determinants of artificial intelligence use in research at higher learning institutions of Tanzania

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ABSTRACT

Artificial Intelligence (AI) is increasingly recognized as a transformative tool in higher education, yet its adoption for research purposes in Tanzanian Higher Learning Institutions (HLIs) remains limited. This study assessed the determinants of using AI in HEIs of Tanzania, specifically, the study examined the extent of AI usage in research and the factors influencing its adoption, it was guided by the Unified Theory of Acceptance and Use of Technology (UTAUT) model. A cross-sectional research design with a mixed-methods approach was used. The target population for the study comprised 1872 academic staff, however, only 253 participants were studied. The study sample was selected using systematic, purposive, and convenience sampling techniques from Sokoine University of Agriculture (SUA), Mbeya University of Science and Technology (MUST), and the University of Dodoma (UDOM). Collected data was coded on IBM SPSS version 20. Descriptive statistical analysis, such as mean, frequency, and percentages, was used, and multiple linear regression was used to analyze the determinants of using AI in Research activities. The findings revealed that AI tools, such as Grammarly, QuillBot, and ChatGPT, were primarily used for research tasks such as grammar checking, paraphrasing, and brainstorming ideas. Moreover, ChatGPT was used in brainstorming and literature reviews. Furthermore, the study reveals that performance expectancy (β=0.23), effort expectancy (β =0.20), teaching experience (β =-.039), and workload (β =-.083) significantly influenced AI adoption. The study concludes that AI tools were seldom used for research purposes. The study recommends that, in order to enhance AI usage, there is a need for universities to create awareness and increase knowledge on AI among academics, as well as to integrate AI tools into the research life cycle.

Keywords: AI Tools, Artificial Intelligence, Higher Learning Institutions, Research, Tanzania, UTAUT

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I. INTRODUCTION

Research is one of the three primary functions of all Higher Learning Institutions (HLIs) worldwide. It serves as a key determinant of a university's reputation, status, and institutional quality, including the recognition of a center of excellence (Meneses & Moreno, 2019). Therefore, universities are striving to be more productive in research to boost universities reputation. Abramo and D'Angelob (2014) defined research productivity as activities that encompass publishing research in scientific journals, academic books, and conference proceedings; gathering and analyzing original evidence; obtaining competitive research grants; carrying out editorial duties; obtaining patents and licenses; and producing monographs and papers presented at professional meetings.

Despite its significance, research productivity in many African HLIs remains low due to limited competencies, insufficient funding, inadequate policies, and lack of modern technology (Henry et al., 2020). Therefore, this affects Africans' contribution to the world's knowledge production. However, most universities employ technologies in different functions, including access to digital materials, e-learning, administrative tasks, communication and teamwork, educational data analysis, and ensuring accuracy in research and scholarly endeavors (Nagy et al., 2024).

One of the noticeable advancements in higher learning environments is Artificial Intelligence (AI) (Wang et al., 2021). The emergence of AI offers opportunities to address these challenges. AI tools assist researchers in data analysis, drafting proposals, idea generation, citation management, and collaborative research. When properly integrated, AI has the potential to enhance research significantly while maintaining ethical and scholarly standards (Lakshmi et al., 2023).

Therefore, many HLIs create different initiatives to harness the capabilities of Artificial Intelligence in learning processes and enhancing research (Slimi & Carballido, 2023). That is why there is an increased use of artificial intelligence tools in research activities (Dorta- et al., 2024).

AI technologies assist students and academicians in completing their academic tasks quickly (Slimi & Carballido, 2023). These technologies and tools help researchers in data analysis and interpretation; preparing grant proposals, idea generation and brainstorming, automatic citation and referencing, drafting research papers and editing, finding related articles, and facilitating research collaborations (Aithal & Aithal, 2023). In addition, AI supports research methodologies by leveraging automated data analysis and improving efficiency (Chintalapati & Pandey, 2021). Thus, the implementation and application of AI have been shown to significantly enhance research. Hence, adoption of AI among academic can boost their research capacity. However, human control is needed on the use of AI to ensure usage is improving teachers' and students' capabilities and productivity while maintaining ethical issues without compromising scholarly aspects (Duong et al., 2023; Lakshmi et al., 2023).

AI usage in academic activities including research production has been observed in various countries in the world. In South Africa, Egypt, Nigeria, and Ethiopia, for example, educators are using AI for automated grading, content creation, virtual teaching, language translation, collaborative learning, research assistance, and literature reviews, which facilitate faster and flexible learning processes by saving instructors' time (Coetzee, 2024). Use of AI benefits HLIs by increasing research productivity and efficiency of their work (Aithal & Aithal, 2023; Chatterjee & Bhattacharjee, 2020). Despite of the positive benefits of AI higher education institutions, its adoption is influenced by several factors. Chatterjee and Bhattacharjee (2020) study in India found that adoption of AI in higher education is influenced by various factors such as perceived risk, effort expectancy, performance expectance and attitude. In Spain, the adoption of AI in academic institutions is affected by researcher perception, facilitating conditions, skills, funding, training resources, and data availability (Dorta- et al., 2024). Nascimento and Nascimento, (2022) reported nine factors that influence the adoption of AI are performance expectancy, business model, effort expectancy, self-efficacy, trust, business compatibility, social influence, trial ability and technical support.

1.1 Statement of the Problem

Higher learning institutions worldwide are harnessing the potential of AI to enhance research; however, in HLIs of Africa, including Tanzania, there is low adoption and use of AI technologies in research (Kangiwa; & Shehu, 2024; Ponera & Stephen Madila, 2024). Consequently, research output remains low, hindering the institutions' ability to produce impactful research, compete globally, and address societal challenges effectively (Kadikilo et al., 2024).

Previous studies have focused on the usage of Artificial Intelligence in academia among HEIs in Tanzania (Ponera & Madila, 2024), usage of Artificial Intelligence in the management of research (Manyengo, 2024), while (Lashayo et al., 2023) examined the extent of adoption and integration of Artificial Intelligence content in universities' curricula. However, none of them have investigated the factors influencing the adoption of Artificial Intelligence for research purposes in Tanzania HLIs. Therefore, this study aimed to explore the factors influencing the adoption of AI in research in Tanzania HLIs to bridge this gap.

1.2 Research Objectives

The study was guided by the following objectives

i. To examine the extent of using AI in the research processes of the selected HEIs in Tanzania
ii. To assess factors influencing the adoption of AI technologies in research in the selected HLIs in Tanzania

II. LITERATURE REVIEW

2.1 Theoretical Review

2.1.1 Unified Theory of Acceptance and Use of Technology (UTAUT)

The study adopts the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine the factors influencing AI adoption in the research. The UTAUT model is a widely used framework for understanding the adoption of technology. It identifies four key constructs that influence the adoption of technology that are: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) (Venkatesh et al., 2003).

Therefore, performance expectancy refers to the degree to which an individual believes that using technology will help them achieve in their job performance (Venkatesh et al., 2003). In the present study, PE is understood as the degree to which academics believe that AI tools will improve their research output, collaboration, and overall productivity. Efforts Expectancy is the degree of ease perceived in using technology (Venkatesh et al., 2003). For this study, EE means the ease of use, efforts required, and user-friendly interface of AI, which can influence its usage in research processes.

Furthermore, social influence refers to the degree to which individuals perceive that important others (e.g., peers, seniors, and management) believe that they should use a technology (Venkatesh et al., 2003). In this study, SI is the encouragement/inspiration and support of peers, management, mentors, and other colleagues who drive AI adoption. Additionally, a facilitating condition is the availability of resources, infrastructure, and support systems that fuel technology adoption (Buraimoh et al., 2023; Venkatesh et al., 2003). In the present study, FC is viewed as the availability of a supportive environment, technical support, funds, policy, and trainings which can simplify AI adoption among academic staff.

2.2 Empirical Review

2.2.1 Extent of Artificial Intelligence use in Research Activities in Higher Learning Institutions

Studies worldwide reported that AI tools adopted in research processes, particularly in data analysis, literature reviews, reporting, providing feedback, presents and disseminating information (Okunlaya, 2022). In developed countries, AI tools such as ChatGPT, Quillboot, Grammarly and SciSpace are widely used to enhance research efficiency and accuracy. For example, ChatGPT is mostly used in various research processes, such as identify research idea, paraphrase, grammar editing, and generate insights (Chukwuere, 2024). Again (Arslan et al., 2025), reported that Grammarly and ChatGPT were used to improve language quality, hence removing the language barrier among international students.

It is noted in literature that AI technologies have the potential to revolutionize research processes in higher learning institutions by automating repetitive tasks, improving data accuracy, and enabling advanced analytics (Khalifa & Albadawy, 2024). AI tools can automate research tasks like literature reviews to generate visualizations, making it easier for researchers to identify patterns and trends. For example, SciSpace can automate literature reviews by summarizing research papers, identifying key themes, and suggesting relevant references (Devi et al., 2024; Jain et al., 2023). This significantly reduces the time researchers spend on literature reviews, allowing them to focus more on critical aspects of their work (Bolaños et al., 2024; Wagner et al., 2022). Moreover, AI tools can also facilitate collaboration among researchers by providing tools for real-time communication, data sharing, and project management. This is strengthening the collaboration among national and international researchers that can enhance the quality and impact of research. Although various studies have been conducted worldwide, there is a lack of empirical research on the extent to which AI is being used in research activities in Tanzania.

2.2.2 Determinant of Artificial Intelligence Adoption

Empirical studies found a strong relationship between performance expectancy and the adoption of new technologies (Jain et al., 2022; Rana et al., 2024). It is observed that AI tools can positively enhance performance in various fields, including research. Studies found that, AI tools can automate literature review, generate ideas, process data, improve accuracy, and reduce the time required for complex issues (Dwivedi et al., 2021). HLIs highlighted that disciplinary differences play a role in AI acceptance, with fields such as computer science and engineering having a higher AI adoption rate compared to social sciences (Khanfar et al., 2024).

In adopting AI, effort expectancy is critical since the perceived complexity of AI tools can act as a barrier or attribute to its adoption. Therefore, academics may be hesitant to adopt AI tools if they perceive that the learning curve is too high or if they lack the necessary skills (R. Jain et al., 2022). Studies found that effort expectancy strongly drives the use of technology (Chatterjee & Bhattacharjee, 2020). Effort expectancy is closely linked to performance expectancy, since users are more likely to adopt technologies that are easy to use and beneficial at the same time. Literature opined that user-friendly and training positively reduce perceived efforts required to use AI, which in turn increases the AI adoption rate (Rana et al., 2024). The lack of it could discourage researchers from adopting AI, even if they recognize its potential benefits (Sukums et al., 2023).

Additionally, social influence plays a major role in the adoption of AI tools, since researchers may be influenced by their peers and institution leaders. In an organizational environment, social influence acts as a strong predictor for AI adoption. Because users can face some issues like compliance or benefits of the technology at its initial use (Venkatesh et al., 2003). AI adoption in organizations, institutional support and leadership, coworkers, and department heads may play a crucial role in encouraging others to use technology (Jain et al., 2022; Rana et al., 2024). This means that social influence usually develops a positive attitude towards technology. Thus, strong advocacy from institutional leaders or peers, researchers may influence the adoption of AI technologies.

Likewise, studies found that facilitating conditions determine the acceptance and use of AI (Jain et al., 2022), making it easier for researchers to integrate AI into their work. Hence, facilitating conditions like access to AI tools, technical support, training, and institutional policies play an important role in the adoption of AI tools (Alshehhi et al., 2022). However, literature shows that the lack of adequate infrastructure and resources can significantly hinder technology adoption in developing countries (Ponera & Stephen Madila, 2024). In addition, technical support and training are necessary to overcome resistance to adoption and ensure that researchers are able to use AI effectively (Dwivedi et al., 2021).

2.3 Conceptual Framework

The conceptual framework is based on the UTAUT model. The conceptual framework has the dependent and independent variables, where the dependent variable is the usage of Artificial Intelligence (AI) in research activities which, is assumed to be influenced by four independent variables. The study hypothesizes that researchers who perceive that using AI would increase their performance, AI easy to use, are likely to have higher use of AI in research. Also, the study assumes that when researchers think and see others using AI will also encourage them to use AI in research. Moreover, researchers who are surrounded by a conducive environment and infrastructure would like to have usage of AI in research. In this study the conceptual framework also include the control variables such as age; sex and experience; ICT Competencies, Teaching Workload, Leadership Position, Academic Rank and Area of Specialization to account for confounding effect that can affect the relationship between the independent and dependent variables.

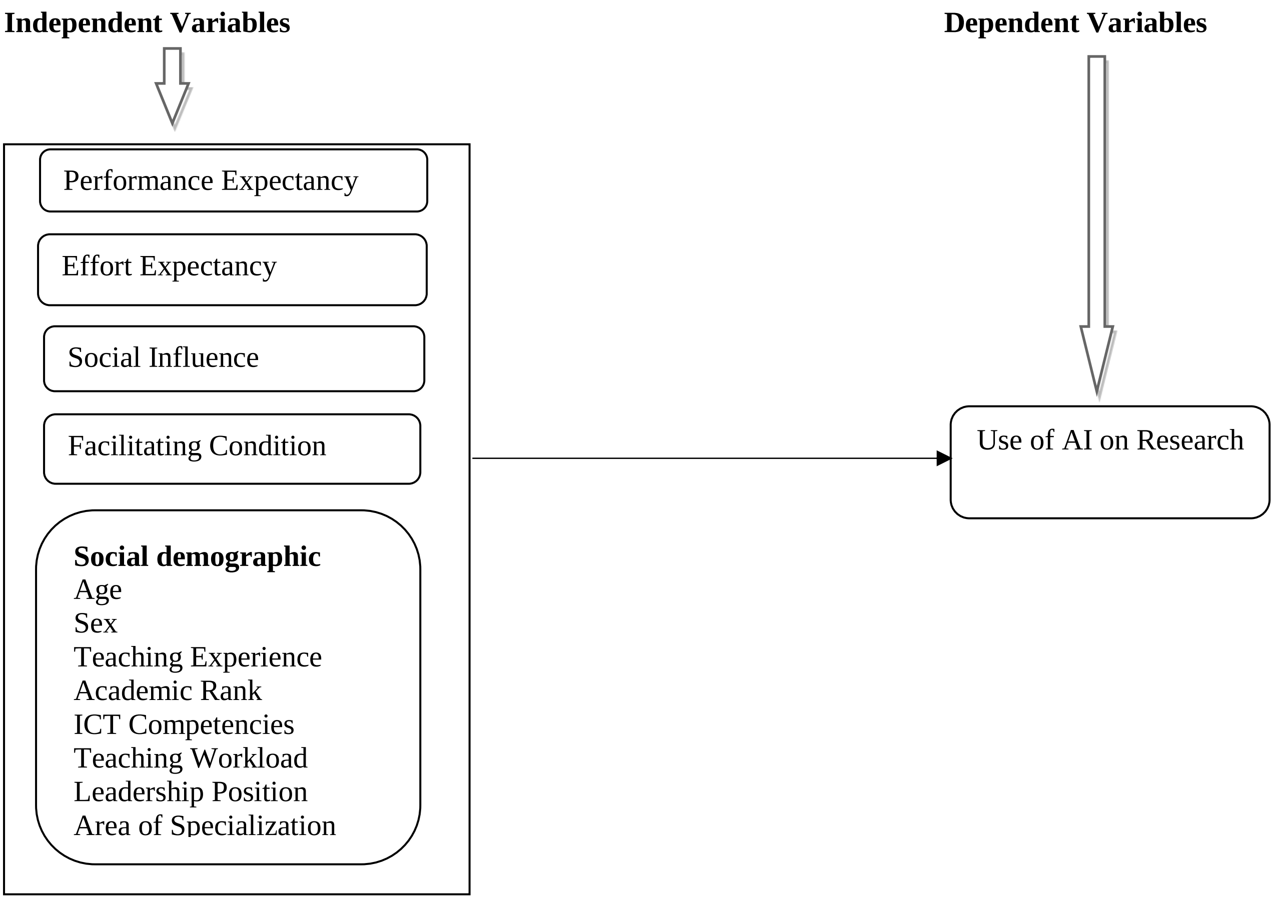

Figure 1
Conceptual Framework

III. METHODOLOGY

The study was conducted at Sokoine University of Agriculture (SUA), Mbeya University of Technology (MUST), and the University of Dodoma (UDOM). These universities were deliberately selected. The selected Higher Learning Institutions are representative of public universities in Tanzania and provide a suitable context for exploring the influence of AI on research. In addition, Sokoine was chosen because it is a well-known university for its research and impact (SUA, 2023).

The study adopted a cross-sectional sequential design and employed mixed methods, which allow data to be collected at a single point in time. The design was used because it allows researchers to explore the relationship among variables. Also, researchers use a cross-sectional design to look at different factors at once. The population for this study was 1872, which includes academic staff from the selected universities. The sample size for the study was 253, which was calculated from the total population using the Yamane formula.

Where

$n= N/(1+N(e^2))$

$n=1872/(1+1872(0.0585^2))$

$n= 253$

Purposive sampling was used to select academic staff from the selected institutions. To ensure gender representation, respondents were grouped by gender (male and female), and systematic sampling techniques were applied to select participants. Also, convenience sampling was used to get academicians who were easily available. A total of 253 respondents participated in the study, UDOM has 113, SUA with 77 and MUST with 63 respondents.

Both questionnaire (online and printed) were used in the data collection process. Because some respondents preferred an online questionnaire, emails and WhatsApp were used to share a link to the online survey using Google Forms. Furthermore, face-to-face and telephone (WhatsApp call) interviews were used to gather deeper information from respondents.

To measure factors influencing the adoption of AI, items were formulated for each item: Performance Expectancy (6 items), Efforts Expectancy (5 items), Social Influence (6 items), and Facilitating Condition (6 items). A Five-points Likert scale, ranging from strongly disagree (1) to strongly agree (5) was used to measure factors influencing AI use in research activities. Again total score of each construct was computed by summing up the responses to get the index score a method adopted from (Mwalukasa, 2022, 2023). The higher value of Performance Expectance, Efforts Expectance, Social Influence, and Facilitating Condition indicates the respondent believed that AI increases performance, requires less effort, social group affects AI adoption, and the environment is supportive.

To measure AI usage in research, respondents were requested to indicate the extent of using AI tools in research activities using a five-point Likert scale, where 1 represents the least frequent and 5 represents the most frequent. Furthermore, the AI usage index score was computed by summing the responses from all the items. Low values imply low usage, while high values imply high usage of AI in research activities.

Quantitative data collected from the questionnaire were coded and analyzed using SPSS (version 20). Descriptive statistics, such as mean were used to analyze the extent and factors influencing Al adoption and use in research. While linear regression was used to determine relationships between influencing factors and AI use in research activities.

$$Y= \beta_0+ \beta_1X_1+ \beta_2X_2+ \beta_3X_3... \beta_{11}X_{11}$$

Where:

Y= AI usage index score

β_0 = Interception

$\beta_1 \ldots \beta_{11}$= Regression coefficients

X_1 = Effort Expectancy index score

X_2 = Performance Expectancy index score

X_3 = Social Influence index score

X_4 = Facilitating Conditions index score

X_5 = ICT competence index score

X_6 = Age

X_7 = Sex

X_8 = Teaching experience

X_9 = Academic rank

X_{10} = Teaching workload

X_{11} = Leadership position

Before conducting multiple linear regression analysis, key assumption was tested to ensure the validity of the model. Multicollinearity was examined using Variance Inflation Factor (VIF) and Tolerance values, Autocorrelation was assessed through the Durbin-Watson statistics.

Reliability of analysis was conducted to assess the correlation among study variables. The reliability of the instrument was ensured by pilot study with 23 academic staff. The Sprit half Cronbach’s Alpha analyzed and it was obtained 0.78 which indicate that research tools is reliable since is good as recommended (Pallant, 2020). In additional, the internal reliability of the scales was assessed using Cronbach alpha of specific construct was 0.86 for EE; 0.93 for PE; 0.80 for SI; and 0.87 for FC which indicating the scales are reliable. Validation of the research instruments was ensured by borrowing already validated items and modified to fit the study; and Principal Component Analysis (PCA) using Varimax rotation, with factor loadings suppressed at 0.4 to assess the validity of the items for each factor. The study followed all ethical guidelines in research practices, such as seeking permission before starting data collection, maintaining the confidentiality of collected data, and requesting consent from respondents before data collection.

IV. FINDINGS & DISCUSSION

4.1 Demographic Characteristics of the Respondents

The study sought to examine selected demographic characteristics of the study participants. The findings were presented in Table 1.

Table 1
Social Demographic Information of Respondents (n=253)

Social Demographic Information		**n**	**%**
Sex of respondent	Male	164	64.8
	Female	89	35.2
Respondent Age	<25	3	1.2
	26-35	81	32.0
	36-45	114	45.1
	46-55	48	19.0
	56+	7	2.8
Working Experience	<5	78	30.8
	6-10	87	34.4
	11-15	55	21.7
	16-20	25	9.9
	Above 21	8	3.2
Academic Ranks	Tutorial assistant	54	21.3
	Assistant lecturer	107	42.3
	Lecturer	65	25.7
	Senior lecturer	21	8.3
	Associate professor	3	2.1
	Full Professor	3	1.2
Teaching Workload	<50	83	41.3
	60-150	59	29.4
	150-200	25	12.4
	200-250	14	7.0
	Above 250	20	10.0
Leadership Position	Director	4	1.6
	Head of Department	18	7.1
	Coordinator	37	14.6
	Dean/ Principle	4	1.6
	None	190	75.1
Area of Specialization	Natural Science	140	55.3
	Social Science	113	44.7

The results as presented in Table 1 showed that more than half (64.8%) were male respondents, while only 35.2% were female. The dominance of male academics can be attributed by high number of male academic staff in higher learning institution. This is similar to the report by (Tanzania Commission for Universities, 2024) which reported that the higher number of male academic staff in higher learning institution in Tanzania.

Regarding respondent age, the largest group of respondents (45.1%) and (32%) was between the ages of 36-45 and 26-25. This suggests that researcher in higher education institutions in Tanzania is mostly dominated by early to mid-career academics and researchers. This group often aspire to climb that ladder thus they are active engage in research activities. As maintained in the study by (D'Arrietta et al., 2024) who found there is more young researcher in their early carrier to mid-career research and more active in research compared to their counterpart.

Concerning working experience, a considerable portion of respondents, only 30.8% have the research experience less than 5 years. This imply that most of respondents have more than 5 years research experience. Higher experienced respondent might be in good position to utilize various Information Technology resources in improving their research activities. This results corroborate with the study by (Sadallah, 2024) who revel that most of the respondents in higher learning have higher experience in research activities.

The findings indicate that the largest group was assistant lecturers (42.3%), and lecturers (25.7%) (Table 1). The observed dominance of junior academic ranks can be caused by the fact that Tanzania government and higher education institution has hired the high number of academic staff recently. Contrary to previous studies that reported most academic staff in academic institutions are senior lecture, assistant and associate professor (Sadallah, 2024).

On teaching workload, where some smaller group reported workloads that exceeding 200 hours (Table 1). This implies that having heavy teaching loads that can be caused by a shortage of academic staff in many universities, hence this may limit staff engaging in technology use. (Sife et al., 2007) indicated that workload is a significant barrier to ICT integration in Tanzania's higher education institutions, which affects staff engagement in innovative academic practices.

Regarding leadership position, results showed that the majority of respondents (75.1%) reported that they do not hold any leadership positions, while a few served as coordinators (14.6%) and heads of departments (7.1%). This attributed by the fact that in many universities leadership positions or managerial duties are limited in numbers due to hierarchical structure. As maintained by (Rana et al., 2024) leadership roles are concentrated among a small fraction of faculty, with most academics focusing on teaching or research.

4.2 ICT Competence

Respondents' levels of ICT competence among academic staff were also assessed. The findings were presented in Table 2.

Table 2

Respondents ICT Competencies (n=253)

SN	Level of ICT Skills among academics	N	%
1	Low	8	3.1
2	Moderate	5	1.9
3	High	240	95.0
	Total	**253**	**100**

The results show that the majority (95.0%) reported high levels of ICT proficiency in basic digital skills (Table 2). This implies that most of the academic staff are well-equipped with ICT competencies that are essential for modern academic roles, teaching, communication, and research. This could be due to the training provided regularly by universities as part of staff development. In addition, majority of academic staff have greater exposure to digital tools through their education and daily life experiences. This is contrary to a study by Ferede et al., (2023), who reported that in Ethiopia, academic staff have low ICT competence.

4.3 Extent of Use of Artificial Intelligence in Research Activities

The extent of use of AI in research activities was also investigated. The finding regarding the level of use of various AI platforms were presented in Table 3.

Table 3

Extent of Using AI by Academics (n=253)

		Mean of each AI Tool			
SN	**AI Usage**	**Grammarly**	**Quilboot**	**ChatGPT**	**SciSpace**
1	Plagiarism detection of my research articles/ manuscript	2.34^{b}	2.03^{b}	1.80^{d}	1.13^{b}
2	Checking grammar on my research articles	2.68^{a}	2.60^{a}	2.35^{b}	1.15^{b}
3	Paraphrasing my research	2.64^{a}	2.59^{a}	2.37^{b}	1.16^{b}
4	Literature Review	2.08^{c}	1.56^{c}	2.03^{c}	1.50^{a}
5	Citation and referencing	1.36^{d}	1.67^{c}	1.81^{d}	1.26^{b}
6	Brain storming for research ideas	1.19^{d}	1.31^{d}	3.13^{a}	1.15^{b}
7	Data analysis	1.21^{d}	1.28^{d}	1.50^{e}	1.11^{b}
8	Content structuring to meet journals requirement	1.20^{d}	1.27^{d}	1.43^{e}	1.11^{b}
9	Editing and reviewing articles from the authors	1.22^{d}	1.30^{d}	1.43^{e}	1.11^{b}
10	Manuscript tracing to the publisher	1.20^{d}	1.28^{d}	1.43^{e}	1.11^{b}
11	Searching materials for research	1.21^{d}	1.37^{d}	2.49^{b}	1.12^{b}

The findings indicate that Grammarly was among the frequently used tools for grammar checking and paraphrasing (with 2.68 and 2.64 means, respectively), and their difference was significant ($P<0.05$) (Table 3). The higher usage of grammar could be due to the need for grammar check among the respondents. This could be due to the reason that most academic publications require fluency in English, thus respondents use the tool to minimize errors in their works. The findings corroborate with previous (Alotaibi & Alshehri, 2023; Arslan et al., 2025; Chui, 2022; Nja et al., 2023) who reveal that Grammarly were higher-used AI tool for grammar editing and enhancing language quality.

The results showed paraphrasing and grammar checking being the most common uses of QuillBot (with means of 2.60, 2.59, respectively) (Table 3). The findings suggest that QuillBot is mainly used for paraphrasing and grammar checking support. The frequent use of QuillBoot could be attributed by the respondents' need for language and sentence structure refinement. This indicates that respondents usually want to improve sentence clarity, rephrase content to avoid plagiarism, and enhance readability of their works. The results aligned with the study by (Raheem et al., 2023; Widiati et al., 2023) who, reported that QuillBot mainly used for paraphrasing to avoid plagiarism and improve sentence structure.

The finding showed a higher score for brainstorming ideas (mean, 3.13), followed by searching for research materials, paraphrasing, and grammar checking (with means of 2.49, 2.3, and 2.35, each) (Table 3). The findings indicate that ChatGPT seems as the more flexible tool and is used across multiple research functions. Its utility is observed in both the early stage and content development phases of research. Meaning that ChatGPT is the widely adopted AI tool across various stages of the research process compared to other tools. This indicates the ability of ChatGPT in supporting the creative and conceptual phases of research, where researchers may seek diverse ideas. These results are similar to (Chukwuere, 2024; Widiati et al., 2023), who found that ChatGPT is a multifunctional tool capable of assisting in language improvement, brainstorming, and refining content. A unique insight from the data is the role of ChatGPT in searching for research materials, which emphasizes the potential of ChatGPT as a knowledge and information resource (Chen & Fan, 2024; Zhu et al., 2023). This allows researcher to search for some information that relates to their research topics or ideas.

The highest mean score is 1.50 for literature reviews and citation and referencing being 1.26 (Table 3). The findings indicate that SciSpace is a rarely used tool among the sampled researchers. This low usage shows a significant gap in the awareness, accessibility, or perceived usefulness of SciSpace among the academic staff. This suggests that SciSpace is either not well known or its value is not communicated within the academic community. The findings corroborate the study by (Barrot, 2025), who reported that SciSpace is not always fully used due to a lack of understanding and knowledge on how to use it effectively. This limited usage persists despite SciSpace's capabilities in supporting tasks such as literature summarization, understanding complex research articles, and structuring content that are crucial for academic productivity (Devi et al., 2024; Jain et al., 2023).

4.4 Factors Influencing the Use of Al in Research Activities

Furthermore, the study investigated the various factors that influenced the use of AI in research activities. The findings were presented in Table 4.

Table 4

Mean of Factors Influencing AI adoption as per UTAUT model (n=253)

	Mean	Std. Deviation
Effort Expectance	3.32^{a}	.839
Performance Expectance	3.46^{a}	.795
Social Influence	3.08^{b}	.776
Facilitating Conditions	2.38^{c}	.768

The results showed that performance expectance recorded the highest mean score, 3.46 (Table 4). This implies that participants perceive AI as a valuable and useful tool and enhances their performance in research processes. This could be due to the fact that AI tools reduce time and improve accuracy in different research tasks. It assists researchers' tasks such as idea generation, paraphrasing, editing, summarizing, and literature reviews. This is similar to a study by (Zhu et al., 2023), who found that most of the respondents have the higher perception that AI improves research performance and saves their time.

Effort Expectance, as Table 4 showed relatively high mean of 3.32, implying that participants perceive that AI tools are easy to use in research contexts. The results indicate that academics in higher education find AI tools are easy to use and do not require high efforts in learning and becoming skilled. This could be attributed to the user-friendly interface and processing capabilities of AI tools. Meaning that AI has an intuitive interface hence lowering learning curve that promote the adoption of the tools. This finding confirms to previous studies that found easiness of the technology or systems significantly impact intention to adapt and utilize AI (Rana et al., 2024). In addition, if academic staff believe that AI does not require excessive effort, they can adopt and use it (Jain et al., 2022).

Social Influence (SI) score moderately mean (3.08) (Table 4). The findings show that there is a low perceived social encouragement for the use of AI in research among Tanzanian academic staff. This can be due to less peer pressure or institutional mandate, and ethical debates on AI might defeat social testimony. The findings contradict previous studies such as (Rana et al., 2024), who reported positive effects of other people (peers, colleagues, managers) in influencing AI adoption in India. Also, (Jain et al., 2022) found that AI is greatly accepted by the employees if the institution or other group members use it. However, in Tanzania, academic staff are not impacted by each other in using and adopting AI tools. This indicates that researchers may not yet feel supported by their professional networks or institutions to integrate AI into their research workflows. Additionally, this shows there are few or no AI champions in the studied sample who may influence others.

The findings in Table 4 show that the facilitating condition had the lowest mean score (2.38). The results indicate that the environments under the investigation are not supportive of AI integration in research. This could be attributed by budget constraints, an inadequate AI expert, availability and accessibility of formalized training, workshops, and technical support. The findings oppose previous studies (Jain et al., 2022; Rana et al., 2024) reported strong association between facilitating conditions and AI adoption in higher education. A study by (Jain et al., 2022) further opined that organization provides support such as trainings and infrastructure that influence AI adoption in higher education. Developed countries they have robust support systems that support AI integration.

4.5 Factors Influencing the Usage of AI in Research

Prior to analyzing the extent of factors influencing the adoption of AI in research, validation was conducted to assess the validity of each item within its respective component using Principal Component Analysis (PCA). The results were presented in Table 5.

Table 5

Communalities after extraction

Items	Initial	Extraction
Use Artificial Intelligence on research is easy for me	1.000	.676
Learning to use Artificial Intelligence in research is easy for me.	1.000	.716
I will not need high effort to use Artificial Intelligence in research	1.000	.613
It is easy for me to become skillful at using Artificial Intelligence in research	1.000	.725
My interaction with Artificial Intelligence in research will be clear and understandable	1.000	.634
Using Artificial Intelligence will be useful in carrying out research activities	1.000	.701
Artificial Intelligence will improve quality of my research	1.000	.697
Artificial Intelligence enable me to accomplish research quickly and efficient	1.000	.776
Artificial Intelligence tools will improve the quality of my research	1.000	.840
Using Artificial Intelligence increases my chances of achieving important research goals	1.000	.735
Using Artificial Intelligence tools enhances my research performance	1.000	.745
People who are important to me will recommend me to use Artificial Intelligence in research	1.000	.695
My institution supports the use of Artificial Intelligence in research	1.000	.717
My peers will expect me to use Artificial Intelligence in research	1.000	.775
People who influence my research ability will recommend me to use Artificial Intelligence	1.000	.792
My colleagues who use Artificial Intelligence have more prestige in the research fields	1.000	.737
I observe that most people around me are adopting AI tools for their research	1.000	.322
My institution provides the hardware and software required to Use of Artificial Intelligence	1.000	.367
My institution has enough money to implement and maintain some of Artificial Intelligence tools that support research activities	1.000	.562
My organizational policies and procedures support the use of AI tools in daily tasks.	1.000	.499
I can get technical support if I experience difficulties with Artificial Intelligence tools	1.000	.651
My team encourages and supports the adoption of AI tools for improving work efficiency.	1.000	.558
My institution provides trainings on the use of Artificial Intelligence in research	1.000	.615

Kaiser-Meyer-Olkin Measure of Sampling Adequacy=.887; Bartlett's Test of Sphericity=3999.0; df=253, p=0.000.

The results in Table 5 showed that the Kaiser-Meyer-Olkin (KMO) value was 0.887, which is higher than the minimum cutoff point of 0.5, as recommended by (Pallant, 2020). This implies that the measure of sampling adequacy is acceptable. Additionally, Bartlett's Test of Sphericity was significant ($p = 0.000$), indicating that the correlation matrix is significantly different from the identity matrix. This suggests that there are correlations among the study variables, making the data suitable for factor analysis.

The results in Table 5 indicate that the communalities after extraction ranged from 0.32 to 0.84, which is above the minimum recommended value of 0.3 (Pallant, 2020). Communalities less than 0.3 imply that an item does not fit well with other items in the component. These results indicate that all items fit well within their respective factors. Therefore, all items were retained for factor analysis**.**

The results in Table 6 showed that the four components of the factor loading explained 65.86% of the total variance of the factors influencing the adoption of AI. The first principal component (PCA1) accounted for 38.56% and included items related to performance expectancy. The second principal component accounted for 13.59% and included items related to social influence. The third factor accounted for 7.44% and included items related to effort expectancy. The last principal component accounted for 6.27% and included items related to facilitation conditions. The factor loading items for each component ranged from 0.51 to 0.83, which are higher than 0.5, implying that there is a correlation between each item and its respective component. This implies that all items are valid for their respective components.

Table 6

Pattern Matrix for Exploratory Factor Analysis after Oblique Rotation

Items	PCA1 (38.56%)	PCA2 (13.59%)	PCA3 (7.44%)	PCA4 (6.27%)
Artificial Intelligence tools will improve the quality of my research	.860			
Artificial Intelligence enable me to accomplish research quickly and efficient	.832			
Using Artificial Intelligence tools enhances my research performance	.813			
Using Artificial Intelligence will be useful in carrying out research activities	.799			
Artificial Intelligence will improve quality of my research	.777			
Using Artificial Intelligence increases my chances of achieving important research goals	.774			
I observe that most people around me are adopting AI tools for their research				
People who influence my research ability will recommend me to use Artificial Intelligence		.824		
My peers will expect me to use Artificial Intelligence in research		.789		
People who are important to me will recommend me to use Artificial Intelligence in research		.774		
My colleagues who use Artificial Intelligence have more prestige in the research fields		.748		
My institution supports the use of Artificial Intelligence in research		.722		
It is easy for me to become skillful at using Artificial Intelligence in research			.769	
I will not need high effort to use Artificial Intelligence in research			.755	
Use Artificial Intelligence on research is easy for me			.693	
Learning to use Artificial Intelligence in research is easy for me.			.690	
My interaction with Artificial Intelligence in research will be clear and understandable			.678	
I can get technical support if I experience difficulties with Artificial Intelligence tools				.799
My institution provides trainings on the use of Artificial Intelligence in research				.772
My institution has enough money to implement and maintain some of Artificial Intelligence tools that support research activities				.723
My team encourages and supports the adoption of AI tools for improving work efficiency.				.686
My organizational policies and procedures support the use of AI tools in daily tasks.				.668
My institution provides the hardware and software required to Use of Artificial Intelligence				.513

PCA1: Performance expectance; PCA1: Social Influence; PCA3: Effort expectance; PC4: Facilitation condition

4.6 Regression Analysis

Multiple linear regression was performed to examine how various factors influence AI adoption and use in research. The multiple regression was performed to examine the influence of demographic factors, as well as UTAUT constructs (Effort Expectancy, Performance Expectancy, Social Influence, and Facilitating Conditions), on AI usage in research. The results showed that the variance Inflation factor (VIF) ranged from 1.05 to 3.40, which is less than 10, implying that the data have no multicollinearity problems as recommended by (Hair et al.,2014). In addition, the Durbin-Watson values were 1.591, which lie within the recommended values of 1.5 to 2.5, meaning that the data do not have the autocorrelation as per (Pallant, 2020).

Performance expectance had a beta coefficient of 0.23, and it was statistically significant (p = 0.01 (Table 7). This implies that a one-unit increase in performance expectancy index score increases AI adoption for research by 0.02

scores. This implies that respondents who believed that AI tools would improve or be useful to their research had have higher adoption rate of using AI in research. This significant positive relationship suggests that when academic staff believe AI tools can enhance their performance, such as improving the quality or speeding the research processes, they will be in a good position to adopt them. This is confirmed by interview that perceived enhancement of research efficiency encourages AI adoption. As one of the interviewees said "AI helped me organize my literature review quickly, so it has saved me a lot of time". Consistent with findings (R. Jain et al., 2022; Rana et al., 2024), who observed that performance impact encourages AI usage and adoption in academic institutions.

The results showed that effort expectance significantly influenced adoption of AI in research. The variable had a positive beta of 0.20, and it was statistically significant (p = 0.02) (Table 7). This indicates that a one-unit increase in the effort expectancy index score leads to 0.145 unit increase in AI adoption for research purposes. This suggests that ease of use positively influences AI adoption, which implies that respondents who perceived AI tools easy to use were more likely to adopt them. The results showed that academic staff found AI tools are user friendly and need less effort. To support this, an interview was conducted and revealed that ease of use reduces barriers and promote AI adoption among academic staff. For instance, one respondent stated that: "most AI tools are easy to use, you do not need to be technical expert, once you try them, and it becomes straightforward". This is supported by previous studies, including (R. Jain et al., 2022; Rana et al., 2024), who found ease of use to be a key enabler in AI and modern technology adoption in higher learning institutions.

Regarding social influence, the beta coefficient was 0.02, and it was not statistically significant (p = 0.79) (Table 7). This indicates that the perceived pressure, encouragement from colleagues, supervisors, or peers, however, does not significantly affect the adoption of AI tools. This might imply that AI adoption is more individually driven rather than socially influenced. As per interview, it has been reported that adoption of AI is driven by personal initiative rather than peer or institution. During the interview, one respondent narrated that: "I started using AI on my own, no one in the department encouraged it". This result contrasts with the study by Nascimento & Nascimento (2022); Rana et al., (2024), who reported that social influence is often found to be a significant contributing factor in AI adoption, especially in structured institutional environments.

The beta value for facilitating condition was 0.08, which was also statistically not significant (p = 0.24) (Table 7). This implies that the presence of supportive infrastructure, such as access to devices, internet, training, and institutional policies, did not play a major role in influencing AI adoption among respondents. This can be due to a lack of support for enhancing the adoption of AI among academic staff. During an interview with academic staff, one reported a lack of institutional support, like training, infrastructure, and funds which limits the role of external factors in AI adoption. As confirmed by one respondent, "we have never received formal support or training to use AI in academic activities". This finding contradicts prior studies (Chen & Fan, 2024; Rana et al., 2024), which found that facilitating conditions were crucial in driving AI adoption in Higher Learning Institutions.

The beta coefficient for ICT competence was 0.01, with a non-significant p-value (p = 0.79) (Table 7). This implies that individual ICT skill level does not significantly influence AI adoption, possibly because AI tools use does not require advanced skills. To confirm these results, respondents were asked in an interview, and it was noted that basic ICT skills are enough, as AI is designed to be accessible to all skill level. Since one of the respondents said that "even those of us we are using these tools, because they are intuitive". The findings contradicts previous studies that found ICT skills has the direct role in influencing technology adoption, specifically it mediate perceived ease of use and perceived usefulness (Callum & Jeffrey, 2013).

The beta coefficient for age was 0.02, was not statistically significance (p= 0.78) (Table 7). This suggests that age does not play a significant role in AI adoption among academic staff. The results imply that both younger and older academic staff are equally likely (or unlikely).

The beta coefficient for sex was -0.04, and it was not statistically significant (p = 0.47) (Table 7). This suggests that gender does not have a meaningful influence on adoption Al in research. This implies that usage of AI was similar for both sexes. This is contrary to previous studies, which reported that gender was an important factor influencing technology acceptance, where males have a habit of being more technological adopters than women (Goswami & Dutta, 2016).

The beta coefficient for teaching experience was -0.07, and it was statistically significant (p=0.05) Table 7). This implies that the more experienced academic staff are slightly less likely to adopt AI. This could be attributed by respondents with many years of teaching experience might be less rigid in the adoption of new technology and may see little need to modify their existing methods, even if AI could enhance them. This is confirmed by the qualitative results that younger or less experienced academics are more open to adopting new technologies. During the interview, one respondent said that: "We (senior lecturers) often prefer traditional methods, we have been publishing for years without these tools". Similar to a study by (Dorta- et al., 2024), who found that early-career researchers tend to use AI tools more compared to mid-career and senior researchers.

Academic rank had a small beta coefficient of 0.00 and a p-value ($p = 0.99$) (Table 7), indicating no significant relationship between rank and AI adoption. This implies that whether a respondent is a tutorial assistant, lecturer, or professor does not affect their use of AI tools. To support this interview was conducted with academic staff, and it was reported that all academic ranks do use AI. One of the respondents stated that: "even tutorials are using these tools, so the issue is not ranking, it's whether you are interested or not".

Teaching workload had a negative beta coefficient of -0.17, which was statistically significant ($p = 0.00$) (Table 7). This implies that higher teaching responsibilities negatively impact AI adoption. Academic staff with heavier teaching loads may lack time to explore AI tools in their research. Interview results also confirmed that a heavy teaching load acts as a barrier to AI adoption due to time constraints. As one of the respondents during the interview said that "we are overloaded with classes, no room for attending training or learn new technologies". This supports studies like Mercader, (2020), which noted excessive workload as a barrier to educational technology integration in institutions.

Moreover, the presented beta coefficient for leadership position was 0.09, and it was statistically not significant ($p = 0.16$) (Table 7). This implies that holding a managerial or leadership role does not significantly influence the adoption of Al for research purposes. The findings contrast with previous studies that identified a positive and significant relationship between leadership and AI adoption (Kurup, 2022).

Table 7

Regression Results of Factors Influencing Artificial Intelligence adoption

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.843	.467		3.943	.000		
	Effort Expectancy Score	.145	.065	.203	2.231	.027	.458	2.181
	Performance Expectancy Score	.217	.162	.231	2.273	.019	.557	1.796
	Social Influence Score	.018	.070	.023	.257	.797	.459	2.177
	Facilitating Condition Score	.064	.055	.081	1.158	.248	.769	1.301
	ICT Competence Score	.018	.068	.017	.260	.795	.897	1.115
	Respondent age	.020	.071	.026	.275	.784	.410	2.438
	Respondent Sex	-.058	.081	-.046	-.714	.476	.906	1.103
	Teaching experience	-.039	.063	-.070	-.619	0.05	.294	3.402
	Academic rank	.000	.066	.001	.006	.995	.306	3.267
	Teaching workload	-.083	.030	-.174	-2.750	.006	.945	1.059
	Leadership position	.052	.037	.093	1.400	.163	.855	1.169
	Area of specialization	-.045	.077	-.038	-595	.552	.938	1.067

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

Artificial Intelligence (AI) represents a critical advancement in modern research, offering transformative potential for academic productivity, efficiency, and timeliness. Despite the benefits of AI on research production, the findings generally indicate low usage. AI tools such as ChatGPT, Grammarly, and Quillbot were frequently used for tasks such as language refinement, brainstorming, searching materials, and literature reviews. Also, ChatGPT is found to be the most versatile tool used across multiple research tasks, while SciSpace in underutilized due to low awareness of the perceived benefits of this tool.

Furthermore, the study concludes that Performance Expectancy and Effort Expectancy, were positively influenced by AI adoption in research. Indicating that researchers who perceive AI tools as beneficial/useful, and easy to use have higher usage. Moreover, researchers with heavy Teaching Workload and older academics have low usage of AI in research, indicating that they are reluctant to AI.

5.2 Recommendations

Creating awareness and provision of training on AI tools to increase knowledge and skills on AI tools among academicians, particularly for those unfamiliar with them. This can be done by universities through workshops, seminars, and demonstration sessions.

Universities in Tanzania should integrate AI tools into research workflows like research writing, plagiarism checks, language editing, AI detection, and data analysis. This can be done by the Directorate of Research and

Publications of a particular university through the establishment of toolkit services and/or approved software lists. Minimizing teaching workload to academicians who reported the teaching burden so as to free them and have some time for learning and exploring new technologies that could help them in their academic life.

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