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Assessment of Factors Influencing the AI Use Intention among Postgraduate Students in Higher Learning Institutions Using the UTAUT Model

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ABSTRACT

This study investigates the factors influencing students' intention to use Artificial Intelligence (AI) technologies in higher learning institutions, with particular emphasis on the mechanisms through which social influence affects AI use intention via performance expectancy and effort expectancy, as conceptualised in the Unified Theory of Acceptance and Use of Technology (UTAUT). A cross-sectional mixed-methods design was employed. Quantitative data were collected from 328 postgraduate students at the Open University of Tanzania (OUT) using a structured questionnaire grounded in UTAUT constructs, while qualitative insights were obtained from 25 key informant interviews. Structural equation modelling using SmartPLS 4 was applied to test direct and mediating relationships among facilitating conditions: effort expectancy, social influence, performance expectancy, and AI use intention. The results indicate that facilitating conditions, effort expectancy, performance expectancy, and social influence all have significant positive effects on students' intention to use AI technologies. Social influence emerged as the strongest direct predictor of AI use intention. Importantly, performance expectancy and effort expectancy were found to partially mediate the relationship between social influence and AI use intention, demonstrating that social endorsement shapes AI adoption both directly and indirectly by strengthening perceptions of usefulness and ease of use. The findings extend the UTAUT framework by empirically validating mediated pathways in the context of AI adoption within Open and Distance Learning (ODL) environments in a developing country. Practically, the study highlights the need for higher learning institutions to strengthen infrastructural support, provide targeted AI training, and foster positive academic norms to promote ethical, effective, and sustainable AI use among students.

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1.0 Introduction

AI has become an increasingly important technology in higher learning institutions due to its potential to enhance learning efficiency, support academic research, and improve decision-making processes in education (Cheng, 2023; Zawacki-Richter *et al.,* 2019). Across the higher education sector, AI technologies are being integrated into teaching, assessment, student support services, and learning management systems, thereby expanding their scope and influence within digitally mediated learning environments (Crompton & Burke, 2023; Ouyang & Jiao, 2021).

However, despite the growing availability and potential benefits of AI tools, students' intention to use these technologies remains uneven and, often, limited (Al Mashagbeh *et al.,* 2025; Chan & Hu, 2023; Siyab & Saira, 2024; Wong & Chapman, 2023). This inconsistency suggests that multiple technological, social, and institutional factors shape students' willingness to adopt AI, yet these factors are not fully understood, particularly within developing country contexts (Maina & Kuria, 2024; Zhang & Lu, 2021). As a result, there is a pressing need to systematically assess the factors that influence AI use intention among students in higher learning institutions, using a robust theoretical framework such as the UTAUT (Venkatesh *et al.,* 2003).

Existing research on AI use intention in higher learning institutions demonstrates that students' willingness to adopt AI technologies is shaped by a combination of technological, social, and institutional factors (Kohnke *et al.,* 2023; Shahjahan *et al.,* 2022). Studies conducted in developed educational contexts consistently show that students are more inclined to use AI tools when they perceive them as beneficial for improving academic performance, enhancing learning efficiency, and supporting research-related activities (Aggarwal *et al.,* 2024; Zawacki-Richter *et al.,* 2019). These findings align closely with the performance expectancy construct of the UTAUT model, which has repeatedly emerged as a strong predictor of technology use intention in educational settings (Venkatesh *et al.,* 2003; Wong & Chapman, 2023).

Beyond perceived usefulness, prior studies have emphasised the role of effort expectations in shaping students' AI use intentions. Empirical evidence suggests that students are more likely to adopt AI technologies when they are easy to learn, intuitive to use, and compatible with existing academic workflows (Madhu *et al.,* 2024; Zhang & Lu, 2021).

Conversely, complex interfaces, limited technical skills, and a lack of formal training increase perceived effort and reduce students' intention to engage with AI tools (Alfredo *et al.,* 2024; Chan & Hu, 2023). This relationship between effort expectancy and use intention has been widely documented in technology acceptance studies, particularly in digitally mediated learning environments (Ifenthaler & Yau, 2020; Venkatesh *et al.,* 2003).

The literature further highlights social influence as a key determinant of students' AI use intention. Research indicates that encouragement from peers, lecturers, and institutional leadership significantly affects students' perceptions of the appropriateness and legitimacy of AI use in academic work (Moorhouse *et al.,* 2023; Santiago *et al.,* 2023).

In contexts where AI use is socially endorsed and institutionally supported, students tend to develop stronger intentions to adopt such technologies (Kohnke *et al.,* 2023). Moreover, emerging studies suggest that social influence not only affects use intention directly but also shapes students' beliefs about the usefulness and ease of AI technologies, thereby influencing both performance expectancy and effort expectancy (Shahjahan *et al.,* 2022; Venkatesh *et al.,* 2003).

In addition, facilitating conditions have been identified as a critical factor influencing students' intention to use AI technologies. Access to reliable internet connectivity, availability of digital devices, technical support services, and clear institutional policies are consistently associated with higher levels of technology adoption (Mathew & Mgina, 2024; Ponera & Madila, 2024). Studies conducted in resource-constrained environments reveal that inadequate facilitating conditions significantly limit students' ability to effectively engage with AI tools, even when they perceive them as useful or simple to use (Kanyemba *et al.,* 2023; Maina & Kuria, 2024).

Despite these insights, several important gaps remain in the existing literature. Much of the empirical evidence on AI use intention is derived from developed-country contexts, with limited focus on higher learning institutions in developing countries, particularly within ODL environments (Crompton & Burke, 2023; Zawacki-Richter *et al.,* 2019). Furthermore, many studies examine only the direct effects of UTAUT constructs on use intention, paying little attention to the mediating roles of performance expectancy and effort expectancy in the relationship between social influence and AI use intention (Wong & Chapman, 2023).

Additionally, postgraduate students who are highly engaged in research-intensive and technology-mediated academic activities remain under-represented in AI adoption research (Abgaryan *et al.,* 2023; Oliveira *et al.,* 2024). Consequently, there is a clear need for theory-driven, context-specific studies that systematically examine both direct and mediated relationships among UTAUT constructs to better understand the factors influencing AI use intention among students in higher learning institutions.

Accordingly, this study examines whether performance expectancy functions as a mediating mechanism through which social influence translates into students' intention to use AI technologies. By explicitly modelling this indirect relationship, the study explains how socially constructed academic norms and peer or instructor endorsements shape students' beliefs about the performance-enhancing value of AI. In doing so, the study extends the UTAUT framework to the context of AI use intentions in higher learning institutions, particularly within ODL environments in developing countries.

The main goal of this study is to find out what factors affect students' plans to use AI technologies in higher education institutions. The UTAUT is used as a theoretical framework (Venkatesh *et al.,* 2003). To achieve this overarching goal, the study focuses on examining the key UTAUT constructs that are theorised to shape technology use intention in educational contexts.

Specifically, the study seeks to examine the effect of facilitating conditions on students' intention to use AI technologies, assess the influence of effort expectancy on AI use intention, and determine the effect of social influence on students' intention to use AI. In addition, the study evaluates the influence of performance expectancy on AI use intention and examines how social influence affects both performance expectancy and effort expectancy in the context of AI adoption (Shahjahan *et al.,* 2022; Wong & Chapman, 2023).

Furthermore, this study aims to examine whether performance expectancy and effort expectancy mediate the relationship between social influence and students' intention to use AI technologies in higher learning institutions. Collectively, these specific objectives provide a comprehensive and systematic approach to understanding the direct and indirect factors influencing AI use intention among students in higher learning institutions (Jesús & Raluca, 2023; Venkatesh *et al.,* 2003).

In line with the stated objectives and grounded in the UTAUT model, this study proposes a set of hypotheses that specify the expected relationships among the study variables. It is hypothesised that facilitating conditions, effort expectancy, social influence, and performance expectancy each have a significant and positive impact on students' intention to use AI technologies (Kohnke *et al.,* 2023; Venkatesh *et al.,* 2003). In addition, the study predicts that social influence positively affects both performance expectancy and effort expectancy, reflecting the role of social context in shaping students' beliefs about the usefulness and ease of AI technologies (Shahjahan *et al.,* 2022).

Finally, the study hypothesises that performance expectations and effort expectations mediate the relationship between social influence and AI use intentions, thereby explaining the mechanisms through which social factors translate into behavioural intentions (Wong & Chapman, 2023).

The importance of these hypotheses lies in their ability to extend the application of the UTAUT framework to the emerging context of AI use intention in higher education. By examining both direct and mediated relationships, the study provides deeper theoretical insight into how technological perceptions and social dynamics jointly influence AI use intention.

Moreover, the findings are expected to offer practical guidance for higher learning institutions and policymakers in designing supportive environments, training initiatives, and policy frameworks that encourage ethical, effective, and inclusive use of AI technologies (Aggarwal *et al.,* 2024; Zawacki-Richter *et al.,* 2019).

Based on the stated objectives and hypotheses, this study adopts the UTAUT as its guiding framework. Accordingly, the literature review is organised around the key UTAUT constructs: facilitating conditions, effort expectancy, social influence, and performance expectancy, along with their direct and mediating relationships to AI use intentions among students in higher learning institutions.

2.0 Literature Review

2.1 Facilitating Conditions and AI Use Intention

Facilitating conditions refer to the extent to which individuals believe that organisational and technical infrastructure exists to support the use of a particular technology (Venkatesh *et al.,* 2003). Within the context of AI adoption in higher learning institutions, facilitating conditions encompass access to reliable internet connectivity, availability of appropriate digital devices, institutional learning management systems, technical support services, training opportunities, and clear policy guidelines governing AI use (Crompton & Burke, 2023; Zawacki-Richter *et al.,* 2019). These conditions are particularly critical in digitally mediated learning environments, where students' academic engagement depends heavily on technological infrastructure and institutional support mechanisms (Ifenthaler & Yau, 2020).

Existing empirical research consistently demonstrates that facilitating conditions have an important impact on determining students' intention to use emerging technologies, including AI (Chan & Hu, 2023; Wong & Chapman, 2023). Studies indicate that when students perceive adequate infrastructural support and institutional readiness, they are more likely to develop positive intentions toward AI adoption. For example, access to stable internet services and institutional platforms that integrate AI tools enhances students' confidence in using such technologies for learning, research, and assessment purposes (Aggarwal *et al.,* 2024).

Conversely, limited infrastructure, high data costs, and inadequate technical support have been shown to discourage students from engaging with AI technologies, even when such tools are perceived as useful (Mathew & Mgina, 2024).

In developing countries, facilitating conditions are often identified as a major barrier to technology adoption (Kanyemba *et al.,* 2023). Research conducted in Sub-Saharan Africa reveals that insufficient digital infrastructure, uneven access to devices, and weak institutional policy frameworks significantly constrain students' ability to effectively utilise AI technologies in higher education (Alfredo *et al.,* 2024; Ponera & Madila, 2024).

In ODL environments, where students rely almost entirely on online platforms for academic activities, the absence of strong facilitating conditions further exacerbates challenges related to accessibility, consistency, and equitable AI use (Maina & Kuria, 2024).

From a theoretical perspective, UTAUT posits that facilitating conditions are a direct determinant of behavioural intention and actual system use (Venkatesh *et al.,* 2003). Although early applications of UTAUT placed greater emphasis on facilitating conditions as predictors of usage behaviour, more recent studies extend their influence to intentions, particularly in contexts where technology adoption is voluntary and institutionally mediated, such as higher education (Wong & Chapman, 2023; Xue *et al.,* 2024; Yuliani *et al.,* 2024). Accordingly, students are more likely to intend to use AI technologies when they perceive that their institutions provide adequate support, guidance, and infrastructure.

Despite the recognised importance of facilitating conditions, empirical evidence of their influence on AI use intentions among students in higher learning institutions remains limited, particularly in developing countries and ODL contexts. Addressing this gap and guided by the UTAUT framework, this study examines the effect of facilitating conditions on students' intention to use AI technologies and, based on the reviewed empirical and theoretical evidence, hypothesises that facilitating conditions have a significant positive effect on students' AI use intention.

2.2 Effort Expectancy and AI Use Intention

Effort expectancy refers to the degree of ease associated with the use of a particular technology (Venkatesh *et al.,* 2003). In the context of AI adoption in higher learning institutions, effort expectancy reflects students' perceptions of how easy AI tools are to learn, understand, and integrate into their academic activities (Ouyang & Jiao, 2021). This includes the clarity of AI interfaces, the simplicity of generating outputs, the level of technical skill required, and the extent to which AI tools can be used without extensive training or prior experience (Madhu *et al.,* 2024).

Existing literature indicates that effort expectancy is a critical determinant of students' intention to adopt new technologies, especially in educational environments where learners engage with multiple digital platforms simultaneously (Chan & Hu, 2023; Venkatesh *et al.,* 2003). Studies indicate that students are more likely to develop positive intentions toward AI use when they perceive AI tools as intuitive, user-friendly, and requiring minimal cognitive or technical effort (George, 2020; McGrath *et al.,* 2023). Applications, such as generative AI platforms, automated writing assistants, and AI-powered research tools, are often perceived favourably because they reduce the time and effort required to complete academic tasks.

Empirical evidence further suggests that high perceived effort can discourage AI adoption, even when the technology is considered useful (Zhang & Lu, 2021). In higher education contexts, students who experience difficulties in navigating AI tools, understanding system outputs, or resolving technical issues tend to report lower intention to use such technologies (Abgaryan *et al.,* 2023). This challenge is particularly pronounced in ODL environments, where limited real-time support and varying levels of digital literacy can increase the perceived complexity of AI tools (Manyengo, 2024).

Research from developing countries highlights that effort expectancy is strongly shaped by contextual factors such as digital skills, exposure to technology, and availability of training opportunities (Kanyemba *et al.,* 2023; Mathew & Mgina, 2024). In many higher learning institutions, students lack formal orientation on AI tools, which increases perceived effort and reduces intention to use.

Conversely, when institutions provide guidance, tutorials, or structured learning opportunities related to AI, students' perceptions of ease of use improve, leading to stronger adoption intentions (Aggarwal *et al.,* 2024). Within the UTAUT, effort expectancy is posited as a direct predictor of behavioural intention, particularly during the early stages of technology adoption (Venkatesh *et al.,* 2003). Applied to AI in higher education, this framework suggests that students' intention to use AI technologies increases when they perceive such tools as easy to use and compatible with their academic routines. Despite this theoretical relevance, empirical studies examining the role of effort expectancy in shaping AI use intention remain limited, especially in ODL contexts and developing countries (Zawacki-Richter *et al.,* 2019).

In light of the identified gaps and based on the reviewed empirical and theoretical evidence, this study examines the influence of effort expectancy on students' intention to use AI technologies in higher learning institutions and, by situating effort expectancy within the UTAUT framework, hypothesises that effort expectancy has a significant positive effect on students' AI use intention, thereby enhancing understanding of how perceived ease of use shapes AI adoption intentions among students.

Social influence refers to the degree to which an individual perceives that important others believe they should use a particular technology (Venkatesh *et al.,* 2003). In higher learning institutions, social influence emerges from peers, lecturers, supervisors, institutional culture, and broader academic norms that shape students' perceptions and acceptance of emerging technologies such as AI (Santiago *et al.,* 2023).

Existing research indicates that social influence plays an important role in determining technology adoption intentions in educational settings (Korchak *et al.,* 2025). Studies indicate that when peers actively use AI tools for academic writing, research assistance, or learning support, students are more likely to perceive AI use as acceptable and beneficial (Okonkwo & Ade-Ibijola, 2021). Similarly, positive attitudes and guidance from lecturers and supervisors can legitimise AI use and reduce uncertainty (Kohnke *et al*., 2023).

In the context of AI, social influence is particularly salient due to ongoing debates surrounding academic integrity, ethical use, and originality (Matto, 2024; Moorhouse *et al.,* 2023). Many higher learning institutions lack clear institutional guidelines, leading to uncertainty about the encouragement or discouragement of AI use. As a result, students often rely on informal cues from peers and lecturers to determine appropriate AI usage behaviours (Williamson & Eynon, 2020).

Empirical studies from developing countries further highlight the contextual importance of social influence (Kanyemba *et al.,* 2023). Exposure to international practices, online academic communities, and collaborative learning platforms can normalise AI use and increase students' intentions to adopt AI tools even in the absence of formal institutional endorsements (Zawacki-Richter *et al.,* 2019).

Within UTAUT, social influence is conceptualised as a direct predictor of behavioural intentions, particularly in environments characterised by uncertainty or early-stage adoption. Applied to AI use in higher learning institutions, this framework suggests that students are more likely to intend to use AI technologies when influential academic and social actors express positive attitudes toward AI adoption. However, despite its theoretical relevance, empirical evidence of the role of social influence in shaping AI use intentions remains limited, especially in ODL contexts.

This study therefore examines the influence of social influence on students' intention to use AI technologies in higher learning institutions and, drawing from preceding empirical findings and the UTAUT framework, hypothesises that social influence has a significant positive effect on students' AI adoption intention, thereby contributing to a complex understanding of how peer effects, academic norms, and institutional expectations shape AI use within higher education.

2.3 Expectations for Performance and the Intention to Use AI

Performance expectancy refers to the extent to which an individual believes that using a particular technology will enhance their academic or task performance (Venkatesh *et al.,* 2003). Within higher learning institutions, performance expectancy reflects students' perceptions of whether AI tools can improve learning efficiency, academic productivity, research quality, and overall academic outcomes (Crompton & Burke, 2023).

In the context of AI adoption, students are more likely to develop a strong intention to use AI technologies when they perceive clear academic benefits. Empirical studies consistently demonstrate that AI tools enhance students' ability to complete assignments efficiently, improve the quality of academic writing, and support complex cognitive tasks (George, 2020; Madhu *et al.,* 2024). These perceived gains significantly strengthen students' intention to adopt AI technologies.

Performance expectancy is particularly salient among postgraduate students, whose academic responsibilities involve intensive research and independent learning (Gouveia *et al.,* 2023; Oliveira *et al.,* 2024). However, concerns related to academic integrity and limited institutional guidance (Moorhouse *et al.,* 2023) may moderate the perceived performance benefits in developing countries.

However, the influence of performance expectancy on AI use intention is not uniform across contexts. In developing countries' higher education settings, including ODL environments, perceived performance benefits may be moderated by concerns related to academic integrity, ethical use, and limited institutional guidance. Some students express uncertainty regarding whether AI-assisted work is academically acceptable, which can weaken the positive effect of performance expectancy on use intention, despite recognising AI's functional benefits.

Within the UTAUT framework, performance expectancy is theorised to have a direct and positive effect on behavioural intentions, particularly when users perceive technology as instrumental in achieving valued outcomes.

Applied to AI adoption in higher learning institutions, this theory implies that students who believe AI technologies enhance learning effectiveness, research quality, and academic success are more likely to intend to use them. Nevertheless, empirical evidence examining this relationship in African higher education contexts remains limited.

Accordingly, in light of the empirical evidence and theoretical arguments presented and by situating performance expectancy within the UTAUT model and the specific context of AI adoption, this study investigates the influence of performance expectancy on students' intention to use AI technologies in higher learning institutions and hypothesises that performance expectancy has a significant positive effect on students' AI use intention, thereby enhancing understanding of how perceived academic benefits shape students' adoption behaviour.

2.4 Social Influence and Performance Expectancy

Social influence refers to the extent to which individuals perceive that important others, such as peers, instructors, supervisors, and institutions, believe they should use a particular technology (Venkatesh *et al.,* 2003). In higher learning institutions, social influence plays a critical role in shaping students' beliefs, norms, and expectations regarding the use of emerging technologies, including AI (McGrath *et al.,* 2023; Williamson & Eynon, 2020). Beyond directly affecting use intention, social influence can also shape students' perceptions of a technology's usefulness, thereby influencing performance expectancy.

Performance expectancy reflects students' beliefs about whether using AI technologies will enhance their academic performance. These beliefs are often socially constructed and reinforced through interactions with peers, lecturers, and academic communities (Wong & Chapman, 2023). When influential actors endorse AI tools, integrate them into teaching practices, or demonstrate their academic value, students are more likely to perceive AI as beneficial for learning, research, and academic productivity (Crompton & Burke, 2023). Consequently, social influence can strengthen performance expectations by legitimising AI use and highlighting its perceived academic advantages (Santiago *et al.,* 2023).

Empirical studies indicate that peer recommendations, lecturer guidance, and institutional discourse significantly affect how students evaluate the usefulness of AI technologies (Kohnke *et al.,* 2023; Okonkwo & Ade-Ibijola, 2021). For example, when lecturers encourage the use of AI for academic support or when peers share positive experiences of improved efficiency and learning outcomes, students tend to develop stronger beliefs that AI enhances academic performance (Madhu *et al.,* 2024). Conversely, when academic staff express scepticism or institutions lack clear guidance on AI use, students may doubt the academic value of AI tools even when they recognise their technical capabilities (Moorhouse *et al.,* 2023).

In technology-emerging and ODL contexts, the role of social influence becomes particularly salient (Kanyemba *et al.,* 2023). In such environments, students often rely heavily on peer networks and informal academic communities for guidance on technology use due to limited institutional support and training (Manyengo, 2024). As a result, social cues play a substantial role in shaping students' understanding of whether AI technologies are academically beneficial, acceptable, and worth adopting. This dynamic suggests that social influence does not merely encourage or discourage AI use directly but also shapes the perceived performance benefits associated with AI technologies.

Within the UTAUT framework, social influence is theorised to affect performance expectations by framing how technologies are evaluated in relation to academic goals (Venkatesh *et al.,* 2003). Applied to AI adoption, this dynamic implies that students who perceive strong social endorsement of AI use are more likely to believe that AI technologies enhance academic performance. However, empirical research explicitly examining the relationship between social influence and performance expectancy in the context of AI adoption in higher education remains limited, particularly within African institutions (Zawacki-Richter *et al.,* 2019).

Accordingly, grounded in the reviewed literature and the theoretical propositions of the UTAUT model, this study examines the influence of social influence on performance expectancy in relation to AI use among students in higher learning institutions and hypothesises that social influence has a significant positive effect on performance expectancy, thereby addressing an important theoretical and empirical gap regarding students' beliefs about the academic usefulness of AI technologies.

2.5 Social Influence and Effort Expectancy

Social influence refers to the extent to which individuals believe that significant others, such as peers and instructors, think they should use a particular technology (Venkatesh *et al.,* 2003). In higher learning institutions, social influence arises from interactions with peers, lecturers, academic supervisors, and institutional norms, all of which shape students' attitudes and expectations toward emerging technologies such as AI (Williamson & Eynon, 2020). While social influence is commonly examined as a direct predictor of technology use intention, it also plays an important part in determining effort expectancy, that is, students' perceptions of the ease associated with using AI technologies.

Effort expectancy reflects the extent to which students believe that using AI tools requires minimal effort and is easy to learn and apply in academic activities (Ouyang & Jiao, 2021). Social interactions and shared experiences often influence these perceptions (Chan & Hu, 2023). When peers or instructors demonstrate AI tools, provide informal guidance, or share positive experiences regarding ease of use, students are more likely to perceive AI technologies as user-friendly and manageable (Okonkwo & Ade-Ibijola, 2021). Conversely, negative social cues such as reports of technical difficulties or lack of guidance can heighten perceptions of effort and discourage engagement with AI tools (Mathew & Mgina, 2024).

Empirical studies suggest that peer learning and social modelling significantly influence students' perceptions of technological complexity (George, 2020; McGrath *et al.,* 2023). Observing classmates effectively using AI tools for academic writing, research assistance, or learning support can reduce anxiety and uncertainty, thereby lowering perceived effort. Similarly, lecturer encouragement and integration of AI tools into coursework can normalise AI use and signal that such technologies are accessible and learnable (Aggarwal *et al.,* 2024).

In ODL contexts, where students often have limited access to formal technical support, social influence becomes even more important (Manyengo, 2024). Students rely heavily on peer networks, online discussion forums, and informal communication channels to learn how to use digital tools. In such environments, positive social influence can reduce perceived effort by facilitating knowledge sharing and collective problem solving, whereas weak or negative social influence can reinforce perceptions that AI technologies are difficult to use or unsuitable for academic purposes (Kanyemba *et al.,* 2023).

Within the UTAUT framework, social influence is theorised to affect effort expectancy by shaping users' beliefs about how easy or difficult technology is to adopt (Venkatesh *et al.,* 2003). Applied to AI adoption in higher learning institutions, this theory suggests that students who perceive strong social endorsement and support for AI use are more likely to view AI technologies as easy to use. However, empirical research explicitly examining the relationship between social influence and effort expectancy in the context of AI adoption remains limited, particularly in developing countries and ODL settings (Zawacki-Richter *et al.,* 2019).

Therefore, grounded in empirical evidence and supported by the UTAUT framework, this study examines the influence of social influence on effort expectancy in relation to AI use among students in higher learning institutions and hypothesises that social influence has a significant positive effect on effort expectancy, thereby addressing a key gap in the existing literature.

2.6 Mediating Role of Performance Expectancy

Performance expectancy refers to the extent to which individuals believe that using a particular technology will help them attain gains in task performance (Venkatesh *et al.,* 2003). In the context of higher learning institutions, performance expectancy reflects students' beliefs that AI technologies can enhance academic productivity, improve learning outcomes, support research activities, and increase efficiency in completing academic tasks (Crompton & Burke, 2023). Within the UTAUT framework, performance expectancy is widely recognised as one of the strongest predictors of technology use intentions.

Social influence plays a critical role in shaping students' beliefs about the usefulness and value of AI technologies (Williamson & Eynon, 2020). When peers, lecturers, or institutional authorities endorse AI tools or demonstrate their academic benefits, students are more likely to perceive these technologies as performance-enhancing (Santiago *et al.,* 2023). Observing classmates use AI tools to improve academic writing or streamline research processes can strengthen students' beliefs that AI contributes positively to academic success (Madhu *et al.,* 2024).

The mediating role of performance expectancy suggests that social influence does not merely exert a direct effect on students' intention to use AI but also operates indirectly by shaping beliefs about AI's usefulness (Venkatesh *et al.,* 2003). In this pathway, social cues first influence students' perceptions of AI's performance benefits, which in turn motivate their intention to adopt and use these technologies.

Empirical research increasingly recognises the importance of mediation effects within the UTAUT framework (Yang & Walsh, 2024; Yuli Hapsari & Lisdayanti, 2024). However, in the specific context of AI adoption in higher learning institutions, particularly within developing countries and ODL, empirical evidence on this mediating relationship remains limited (Zawacki-Richter *et al.,* 2019).

Accordingly, this study examines the mediating role of performance expectancy in the relationship between social influence and students' intention to use AI technologies, proposing that social influence indirectly affects AI use intention by shaping students' beliefs about the performance-enhancing benefits of AI. By empirically testing this mediation mechanism, the study extends the UTAUT framework to the emerging context of AI adoption in higher learning institutions, particularly within ODL environments in developing countries.

2.7 Mediating Role of Effort Expectancy

Effort expectancy refers to the degree of ease associated with the use of a technology, reflecting users' perceptions of how simple, understandable, and manageable a system is to operate (Venkatesh *et al.,* 2003). In higher learning institutions, effort expectancy captures students' beliefs about how easily AI technologies can be learned and integrated into academic activities such as studying, research, assessment, and academic writing (Ouyang & Jiao, 2021).

Social influence plays a central role in shaping students' perceptions of effort associated with new technologies (Chan & Hu, 2023). Students encounter shared experiences, demonstrations, and informal guidance related to AI tools through interactions with peers, lecturers, and institutional actors (Okonkwo & Ade-Ibijola, 2021). When AI technologies are portrayed as intuitive and simple to use, students are more likely to perceive lower levels of effort required for adoption (Aggarwal *et al.,* 2024).

The mediating role of effort expectancy implies that social influence may indirectly affect AI use intention by shaping students' perceptions of ease of use (Venkatesh *et al.,* 2003). This mechanism is particularly salient in ODL contexts, where students rely heavily on self-directed learning and peer support (Manyengo, 2024).

This mediating relationship becomes even more significant in ODL contexts. Students in ODL institutions frequently operate with limited real-time technical support and must rely on self-directed learning and peer networks to navigate digital tools (Joshi *et al.,* 2024; Maphalala & Nkosi, 2025). Positive social influence in such settings can significantly reduce perceived effort by facilitating knowledge sharing and building confidence in using AI technologies. In contrast, weak social support structures may increase perceptions of difficulty and hinder adoption intentions.

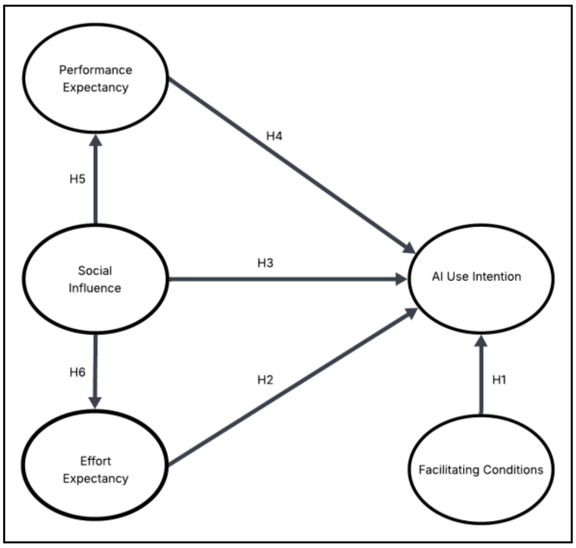
Although previous studies have examined the direct effects of social influence and effort expectancy on technology use intention, empirical evidence on the mediating role of effort expectancy, particularly in relation to AI adoption in higher learning institutions, remains scarce.

This gap is especially pronounced in developing countries and ODL contexts, where infrastructural constraints and varying levels of digital literacy shape students' experiences with emerging technologies.

Despite its theoretical relevance, empirical evidence on the mediating role of effort expectancy in AI adoption is still limited, especially in developing country contexts; therefore, this study aims to examine effort expectancy as a mediating variable in the relationship between social influence and students' intention to use AI technologies, hypothesising that effort expectancy mediates this relationship and thereby extends the UTAUT framework while addressing a significant gap in AI adoption research.

As illustrated in Figure 1, the conceptual framework is grounded in the UTAUT. Social influence is modelled as both a direct predictor of AI use intention and an indirect predictor of performance and effort expectancy. This structure allows the study to capture not only the direct social effects on AI adoption but also the psychological mechanisms through which social norms and academic endorsement influence students' beliefs about the usefulness and ease of AI technologies.

Figure 1
The Conceptual Framework of the UTAUT Theory



Source: (Venkatesh *et al.,* 2003)

3.0 Materials and Methods

This study is guided by the UTAUT-based conceptual framework and the hypotheses developed from the literature review. This section describes the methodological procedures employed to empirically test the proposed relationships. Specifically, it outlines the study population, sampling techniques, measurement of constructs, and data analysis methods used to examine both the direct and mediating effects influencing students' intention to use AI technologies.

3.1 Population and Sample

The population for this study comprised all postgraduate students enrolled in higher learning institutions in Tanzania during the 2024/2025 academic year. However, for the purposes of empirical investigation and manageability, the study focused on postgraduate students at the Open University of Tanzania (OUT), which operates exclusively under the ODL mode. OUT was considered an appropriate and relevant study site due to its heavy reliance on digital platforms for teaching, learning, assessment, and academic support, as well as its increasing exposure to AI-enabled tools within academic activities (Anghelo Josué et a*l.,* 2023).

According to institutional records, the total population (N) of postgraduate students enrolled at OUT during the study period was 4,072 students across various faculties and academic programmes. This population was deemed suitable for examining factors influencing AI use intention, as postgraduate students engage intensively in research, academic writing, and independent learning activities where AI technologies are increasingly applied.

The sample size for the quantitative component of the study was determined using the formula proposed by Kothari (2004), which is appropriate for finite populations. Using a 95% confidence level (Z-Score= 1.96), a margin of error (e = 0.05), the proportion of graduates who use AI was 63.4% (p) (Freeman, 2025). Upon substitution into the formula:

$$n \frac{NZ^2 pq}{Ne^2 + Z^2 pq - e^2} \text{ .... (1)}$$

Whereas:

n:	Sample size of graduates to be used in this study
N:	Total of postgraduates academic year 2024/2025 (4072)
e:	Margin errors (set to 0.05)
Z:	Standard deviation (set to 1.96 for the 95% confidence interval used in this study)
p:	The proportion of graduates who use AI was 63.4% (Freeman, 2025).
q=1-p:	The proportion of graduates who do not use AI was 36.6% (Freeman, 2025).

Thus, the required sample size is established as 328. This sample size was considered sufficient to ensure statistical power and reliable estimation of relationships among the study variables.

The study employed a probability-based simple random sampling technique adapted to the ODL context to select respondents for the survey. A sampling frame was obtained from the postgraduate students' registry, which provided a comprehensive list of all eligible students enrolled in the study programmes. Each eligible student was assigned a unique identification number to facilitate the random selection process, after which a computer-generated randomisation procedure was used to select the required 328 postgraduate students.

This approach ensured that every postgraduate student had an equal and independent probability of being included in the study, regardless of programme, geographic location, or level of participation in ODL activities, thereby minimising selection bias and enhancing the representativeness of the sample.

Given the geographically dispersed nature of postgraduate students within the ODL system, data collection was conducted online. The questionnaire link was distributed exclusively to the randomly selected participants through institutional email systems, official academic communication channels, and postgraduate student online platforms. Reminder messages were sent only to the originally selected participants to improve response rates without replacing non-respondents, thus preserving the probabilistic integrity of the sample.

Accordingly, although the mode of data collection was online, the sampling process remained strictly probability-based because participant selection was completed prior to questionnaire distribution using the official student registry, consistent with recommended methodological practices for probability sampling in online and distance learning research.

In addition to the quantitative sample, a purposive sample of 25 Key Informant Interviews (KII) was conducted to gather qualitative information and provide key insights for the qualitative outputs. Key informants included academic staff, ICT personnel, programme coordinators, and administrators involved in digital learning and technology-related decision-making at OUT.

The qualitative sample complemented the survey data by providing contextual insights into institutional readiness, infrastructural support, and policy considerations related to AI adoption, derived from face-to-face interviews that enabled in-depth exploration of participants' experiences and perspectives.

3.2 Measures

This study employed a structured questionnaire to measure the latent variables specified in the conceptual framework, namely facilitating conditions, effort expectancy, social influence, performance expectancy, and AI use intention. All measurement items were adapted from established and validated instruments grounded in the UTAUT to ensure conceptual consistency, reliability, and validity. Responses were captured using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

3.3 Facilitating Conditions

Facilitating conditions refer to the degree to which students believe that organisational and technical infrastructure exists to support the use of AI technologies. In this study, facilitating conditions were measured using items adapted from Venkatesh *et al.* (2003), and later applications in educational technology contexts (Kohnke *et al.,* 2023; Or, 2023; Or & Chapman, 2022). The items assessed students' access to reliable internet connectivity, availability of institutional support, access to AI-related resources, and adequacy of technical assistance.

Conceptually, facilitating conditions were operationalised as a unidimensional construct represented by a single latent factor measured using four reflective items rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Previous studies using similar items reported Cronbach's alpha values ranging from 0.78 to 0.88, indicating good internal consistency (Cerri *et al.,* 2023).

During the adaptation process, original UTAUT items referring to "system use" were reworded to reflect AI technologies used for academic activities. All four adapted items were retained after pilot testing and measurement validation, as they demonstrated acceptable reliability and conceptual clarity.

3.3.1 Effort Expectancy

Effort expectancy was defined as the extent to which students perceive AI technologies to be easy to learn and use for academic purposes. Measurement items were adapted from the original UTAUT scale developed by Venkatesh *et al.,* (2003) and subsequently validated in higher education contexts (Aliaño *et al.,* 2019; Holmes & Miao, 2023). The items captured perceptions of ease of learning, clarity of interaction, and overall usability of AI tools.

Effort expectancy was modelled as a single-factor construct measured using four reflective items assessing perceived ease of learning AI tools, interaction clarity, user friendliness, and overall ease of use. Prior empirical studies have reported Cronbach's alpha coefficients for effort expectancy ranging between 0.80 and 0.91 (Cerri *et al.,* 2023). The adaptation involved contextual modification of wording to align with AI-supported academic tasks, followed by expert review and pilot testing to ensure content validity. All adapted items met the reliability and factor-loading criteria and were therefore retained in the final instrument.

3.3.2 Social Influence

Social influence refers to the extent to which students perceive that important others, such as peers, lecturers, supervisors, and the institution, encourage or expect them to use AI technologies. Items measuring social influence were adapted from Venkatesh *et al.*(2003),and extended by later studies in educational and digital learning environments (Matto, 2024; Or, 2023). These items examined peer endorsement, lecturer encouragement, and perceived institutional expectations regarding the use of AI.

The construct was specified as a unidimensional latent factor initially measured using five adapted items. Previous research reports Cronbach's alpha values for social influence typically ranging from 0.75 to 0.89 (Cerri *et al.,* 2023). Following pilot testing and preliminary measurement analysis, one item exhibiting low factor loading and conceptual redundancy was removed. Consequently, four items were retained in the final scale, all demonstrating satisfactory psychometric performance.

3.3.3 Performance Expectancy

Performance expectancy was operationalised as students' beliefs that using AI technologies enhances their academic performance, productivity, and learning outcomes. Measurement items were drawn from Venkatesh *et al.*(2003), and adapted to reflect AI-supported academic activities, including research, writing, assessment, and learning efficiency (Crompton & Burke, 2023; Jesús & Raluca, 2023). Earlier studies using similar scales reported Cronbach's alpha values ranging from 0.83 to 0.92, demonstrating strong reliability (Cerri *et al.,* 2023).

Performance expectancy was measured as a single-factor construct comprising four reflective items capturing perceived improvements in academic productivity, task performance, learning effectiveness, and research efficiency. The adaptation process involved contextual rephrasing of original UTAUT items to reflect AI-assisted learning environments. All four items satisfied reliability and validity thresholds and were retained without modification.

3.3.4 AI Use Intention

AI use intention refers to students' willingness and intention to use AI technologies in their academic activities. Items measuring behavioural intention were adapted from the UTAUT behavioural intention scale (Venkatesh *et al.,* 2003), and contextualised for AI use in higher learning institutions (Manyengo, 2024; Obed *et al.,* 2025). These items assessed students' likelihood of continued AI use, intention to adopt

AI tools in future academic work, and overall readiness to engage with AI technologies. Prior studies reported Cronbach's alpha coefficients for use intention ranging from 0.82 to 0.93 (Musawa *et al.*, 2024).

The construct was operationalised as a unidimensional latent factor measured using three reflective items rated on a five-point Likert scale. The adaptation process included refining the wording to explicitly reference AI technologies in academic contexts, expert validation, and pilot testing. All three items demonstrated acceptable internal consistency and factor loadings and were therefore retained in the final measurement model.

3.4 Methodological Clarification

The instrument comprised five unidimensional constructs derived from the UTAUT framework, with an initial pool of 20 adapted items. Following contextual adaptation, expert review, pilot testing, and psychometric evaluation, 19 items were retained in the final questionnaire. Item retention decisions were guided by reliability analysis and factor loading criteria to ensure construct validity and internal consistency within the AI adoption context in higher education.

Instrument validity was ensured through expert review, theoretical mapping of items to UTAUT constructs, and a pilot study conducted at the University of Dodoma at the College of Informatics and Virtual Education (CIVE). Since the measurement instrument was developed by the researcher, expert review was undertaken to evaluate content adequacy, theoretical alignment, and clarity of item wording, ensuring that each item accurately represented the intended UTAUT constructs and was appropriate for the target population. Content, face, and construct validity were further strengthened through stakeholder feedback and factor analysis, which confirmed appropriate alignment between measurement items and their underlying theoretical constructs.

Reliability was assessed using Cronbach's alpha, with 0.70 adopted as the acceptable threshold for internal consistency. All constructs demonstrated strong reliability, including performance expectancy (α = 0.931), internet self-efficacy (α = 0.930), and facilitating conditions (α = 0.857).

Accordingly, these high reliability coefficients, when considered alongside the results of the pilot study, provide robust empirical evidence that the measurement instrument was both stable and internally consistent, thereby supporting its suitability for assessing AI use intention constructs among postgraduate students in higher learning institutions.

Data collected through the structured questionnaire were coded, cleaned, and analysed using SmartPLS 4 software. Before analysis, the dataset was screened for completeness, missing values, and outliers to ensure data quality and suitability for inferential analysis. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were first computed to summarise respondents' demographic characteristics and provide an overall overview of students' perceptions of AI adoption.

The study used CFA to examine the structure of the scale constructs, considering scale items with factor loadings ≥0.4, as suggested by Stevens (2002) in Field, (2018). Also, the original scale by Gregor and O'Brien, (2016) and other studies that validated it, such as Kim *et al.*,(2016), used 0.4 as the cut-off point for retaining scale items.

To examine the underlying structure of the measurement items and confirm their suitability for further analysis, exploratory factor analysis was conducted. Sampling adequacy was assessed using the Kaiser Meyer Olkin (KMO) measure and Bartlett's test of sphericity to ensure that the data met the assumptions required for factor analysis.

Reliability analysis was then performed using Cronbach's alpha to assess the internal consistency of the measurement scales.

Inferential statistical techniques were employed to test the study's hypotheses. Correlation analysis was used to examine the relationships among the key UTAUT constructs. Multiple regression analysis was conducted to assess the direct effects of facilitating conditions, effort expectancy, social influence, and performance expectancy on students' intention to use AI technologies. Mediation analysis was further performed to examine the indirect effects of social influence on AI use intention through performance expectancy and effort expectancy, in line with the proposed conceptual framework.

All statistical tests were conducted at a 5 per cent level of significance. The results of the analyses were interpreted in relation to the study objectives, hypotheses, and the Unified Theory of Acceptance and Use of Technology, providing empirical evidence on the factors influencing AI use intention among students in higher learning institutions.

4.0 Results

In line with the study objectives and hypotheses outlined earlier, this section presents the results of the data analysis conducted to test the proposed UTAUT-based model. The analysis begins with the demographic characteristics of the respondents, followed by an assessment of the measurement model to establish the reliability and validity of the latent constructs used in the study, and then proceeds to the structural equation model and mediation analysis. All analyses were conducted using SmartPLS 4.

4.1 Demographic Characteristics of the Respondents

The findings of this study provide strong theoretical support for the UTAUT framework by confirming both the direct and indirect roles of social influence in shaping students' intention to use AI technologies.

Specifically, the results demonstrate that performance expectancy plays a complementary, partial mediating role in the relationship between social influence and AI use intention. This indicates that social influence not only directly motivates AI adoption but also indirectly operates by strengthening students' beliefs about the academic performance benefits of AI, thereby extending the explanatory power of UTAUT in the context of AI adoption within ODL institutions.

Table 1
Demographic Information

Variable	Attribute	Freq.	(%)
Sex	Female	96	30.77
	Male	216	69.23
Education Level	Master's Degree	233	74.68
	Doctorate	51	16.35
	Postgraduate Diploma	28	8.97
The Faculty Respondent	Arts and Social Science	90	28.85
	Law	12	3.85
	Business Management	41	13.14
	Education	53	16.99
	Science, Technology, and Environmental Studies	116	37.18

Source: Collected data sets (2025)

Table 1 presents the descriptive statistics for the characteristics of the respondents in the study area. The findings in Table 1 indicate that 328 respondents responded to the survey. In addition, the findings of Table 1 revealed that among those respondents who were responding to the study, the majority were male (69.23%), while the females accounted for 30.77%.

Furthermore, the results in Table 1 showed that among the postgraduate students who participated in the survey, the majority were master's students (74.68%), followed by PhD scholars or PhD students (16.35%), while postgraduate diploma students constituted a smaller group (8.97%) of the total respondents. Lastly, the findings revealed that the majority of respondents were from the Faculty of Science, Technology, and Environmental Studies (28.85%), followed by students from the Faculty of Arts and Social Science (28.85%), and other faculties were Education (16.99%), Business Management (13.14%), and Law (3.85%). Furthermore, this trend was also reflected during the KII with staff of the OUT, who confidently stated, "The majority of Tanzanians prefer studying up to the master's degree level; they do not seem to perceive significant benefits in pursuing higher academic qualifications beyond that." (KII-02, personal communication, 28/02/2025).

4.2 Exploratory Factor Analysis

Table 2
Factor Analysis

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.888
Bartlett's Test of Sphericity	Approx. Chi-Square	4359.019
	Df	190.000
	Sig.	0.000

	Component				
	1	2	3	4	5
AUI2	0.860				
AUI1	0.859				
AUI4	0.858				
AUI3	0.847				
FC2		0.903			
FC3		0.888			
FC4		0.884			
FC1		0.872			
EE3			0.837		
EE4			0.834		
EE2			0.823		
EE1			0.809		
PE4				0.857	
PE1				0.813	
PE3				0.810	
PE2				0.792	
SI2					0.826
SI4					0.805
SI1					0.800
SI3					0.728

Source: Collected data sets (2025)
Note: SI: Social Influence, AUI: AI use Intention, PE: Performance Expectancy, EE: Effort Expectancy, FC: Facilitating Conditions. See Appendix 1

Before extracting the factors, various tests must be employed to evaluate the appropriateness of the respondent data for factor analysis. The tests encompass the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. The KMO index is recommended when the ratio of instances to variables is below 1:5. The KMO index ranges from 0 to 1, with a value of 0.50 considered appropriate for factor analysis. For factor analysis to be appropriate, the Bartlett's test of sphericity must yield a significant result ($p < .05$). The results in Table 2 indicate that the Kaiser-Meyer-Olkin measure is 0.888, exceeding the threshold of 0.5, and Bartlett's Test of Sphericity is significant at a level below 0.05. These findings imply that the data employed is adequate and acceptable for factor analysis.

Table 2 shows the exploratory factor analysis (EFA), which revealed a clear five-factor structure underlying the data, suggesting that the measured items cluster into five distinct latent constructs. The analysis demonstrated adequate factor loadings, with the lowest loading being 0.728, which exceeds the commonly accepted threshold of 0.50, indicating a meaningful contribution of all items to their respective factors. Additionally, the highest loading value was 0.903, suggesting that each variable shares a reasonable amount of variance with the extracted factors. This reflects a positive overall representation of the items within the factor model. The factors likely capture key dimensions relevant to the construct being measured. The model's clarity and strength support its use for further analysis. These results affirm the appropriateness of using EFA for identifying underlying structures in the data.

4.3 Factors Cross-Loading

Table 3

Cross Loading

	AUI	EE	FC	PE	SI
AUI2	**0.860**	0.078	0.177	0.112	0.186
AUI1	**0.859**	0.120	0.203	0.107	0.183
AUI4	**0.858**	0.158	0.169	0.154	0.190
AUI3	**0.847**	0.144	0.194	0.177	0.149
FC2	0.109	**0.903**	0.030	0.016	-0.031
FC3	0.109	**0.888**	0.019	-0.028	-0.033
FC4	0.058	**0.884**	0.104	-0.029	-0.060
FC1	0.139	**0.872**	-0.018	-0.054	-0.055
EE3	0.169	0.014	**0.837**	0.033	0.131
EE4	0.162	0.091	**0.834**	0.063	0.177
EE2	0.149	0.060	**0.823**	0.098	0.165
EE1	0.193	-0.022	**0.809**	0.043	0.239
PE4	0.105	0.021	0.052	**0.857**	0.153
PE1	0.084	-0.101	0.049	**0.813**	0.173
PE3	0.103	-0.012	0.065	**0.810**	0.127
PE2	0.164	-0.004	0.050	**0.792**	0.141
SI2	0.210	-0.001	0.199	0.132	**0.826**
SI4	0.195	-0.102	0.211	0.094	**0.805**
SI1	0.143	-0.070	0.175	0.203	**0.800**
SI3	0.149	-0.039	0.183	0.328	**0.728**

Source: Collected data sets (2025)

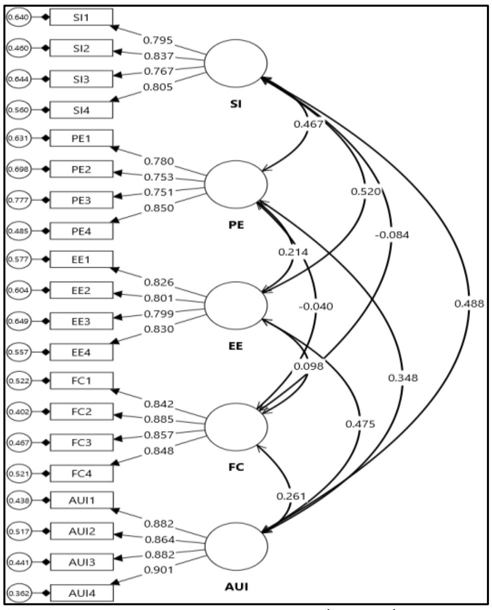
In Table 3, cross-loadings were examined to assess discriminant validity among the constructs further. The results presented in Table 3 indicate that each indicator loads highest on its respective build and does not exhibit substantial loadings on other constructs. Specifically, all items demonstrate strong loadings on their intended latent variables, while cross-loadings on noncorresponding constructs are considerably lower. This pattern confirms that the indicators are appropriately associated with their designated constructs and supports the establishment of discriminant validity based on the cross-loading criterion.

4.4 Confirmatory Factor Analysis (CFA)

The study employed CFA to evaluate the structure and factor loadings of the scale constructs. Moreover, the scale items with factor loadings ≥ 0.50 were considered acceptable, as recommended by Field (2018). In addition to that original scale by Yahya *et al.* (2025), Ustun *et al.* (2024), and Ustun *et al.* (2023), all of which indicate that the factor loadings are ≥0.50, they employed 0.50 as the cut-off point for retaining the scale items. In the present study, all items of the scale showed adequate factor loading ranging from 0.751 to 0.901; hence, all 16 items were retained (see Figure 1 & Table 4).

Figure 2

The CFA



Source: Collected data sets (2025)

Table 4

Measurements, Factor Loadings, CR, and AVE

Items	λ	α	CR (rho_a)	CR (rho_c)	AVE
AUI		0.93	0.94	0.95	0.83
AUI1	0.91				
AUI2	0.90				
AUI3	0.91				
AUI4	0.92				
EE		0.89	0.89	0.92	0.75
EE1	0.88				
EE2	0.86				
EE3	0.85				
EE4	0.87				
FC		0.92	0.92	0.94	0.80
FC1	0.89				
FC2	0.91				
FC3	0.90				
FC4	0.88				
PE		0.86	0.86	0.91	0.71
PE1	0.84				

Items	λ	α	CR (rho_a)	CR (rho_c)	AVE
PE2	0.83				
PE3	0.82				
PE4	0.88				
SI		0.88	0.89	0.92	0.73
SI1	0.85				
SI2	0.88				
SI3	0.84				
SI4	0.85				

Source: Collected data sets (2025)

Note: λ: factor loading,α: Cronbach's alpha, Composite reliability (rho_a), Composite reliability (rho_c), Average variance extracted (AVE)

Table 4 shows that the measurement model was assessed using factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). The results indicate that all indicator factor loadings exceed the recommended threshold of 0.70, demonstrating that the observed items are strong and reliable measures of their respective latent constructs.

In addition, the Composite Reliability values for all constructs exceed 0.70, confirming satisfactory internal consistency. Furthermore, the AVE values meet the minimum recommended criterion, indicating that each construct explains more than 50% of the variance in its indicators. Collectively, these results provide strong evidence of adequate reliability and convergent validity for the measurement model.

Table 5

Model Fit Indices of the Measurement Model

Model Fit Indices	Threshold	Statistic	Interpretation
Chi-Square (X2)/Degree of freedom (df)	≤ 3.00	1.193	Good Fit
Comparative Fit Index (CFI)	≥ 0.90	0.993	Good Fit
Normed Fit Index (NFI)	≥ 0.90	0.957	Good Fit
Goodness of Fit Index (GFI)	≥ 0.90	0.945	Good Fit
Tucker–Lewis Index (TLI)	≥ 0.90	0.991	Good Fit
Root Mean Square Error of Approximation (RMSEA)	≤ 0.08	0.024	Good Fit
Standardised RMR (SRMR)	≤ 0.08	0.033	Good Fit

Source: Collected data sets (2025)

According to Hu and Bentler (1999), the Root Mean Square Error of Approximation (RMSEA) and the Standardised Root Mean Square Residual (SRMR) should ideally fall between 0 and 1, with values below 0.08 generally considered acceptable for a good model fit. Schumacker and Lomax (2010) further suggest that values below 0.05 reflect an excellent fit. Similarly, the Tucker–Lewis Index (TLI) and Comparative Fit Index (CFI) values approaching 0.90, preferably 0.95, indicate a strong model fit, with values closer to 1 representing the best fit, as noted by Bentler and Bonett (1980) and McDonald and Marsh (1990). Additionally, a chi-square to degrees of freedom ratio (CMIN/DF) of 5 or lower is deemed acceptable according to the guidelines of Wheaton *et al.* (1977). Therefore, to assess the model's adequacy, the researcher used key fit indices, including RMSEA, SRMR, TLI, CFI, GFI, and CMIN/DF. The fit statistics summarised in Table 5 indicate that the confirmatory factor analysis (CFA) model meets acceptable fit standards.

Table 6

Convergent and Discriminant validity Fornell-Larker criterion (1981)

Items	CR (rho_a)	CR (rho_c)	AVE	AUI	EE	FC	PE	SI
AUI	0.94	0.95	0.83	0.91				
EE	0.89	0.92	0.75	0.43	**0.86**			
FC	0.92	0.94	0.80	0.24	0.08	**0.90**		
PE	0.86	0.91	0.71	0.32	0.19	-0.04	**0.84**	
SI	0.88	0.92	0.73	0.44	0.46	-0.08	0.42	**0.85**

Source: Collected data sets (2025)

The Fornell-Larcker criterion was used to assess discriminant validity among the five latent variables. According to this criterion, discriminant validity is established when the square root of the Average Variance Extracted (AVE) for each construct exceeds its correlations with all other constructs. As shown in Table 6, the diagonal values of the square roots of AVE for all five constructs are higher than the corresponding inter-construct correlations. This indicates that each construct explains more variance in its own indicators than it shares with other constructs.

Although the Fornell-Larcker method is a traditional and widely accepted approach for assessing discriminant validity, it has been noted in recent SEM literature that this criterion may not always detect discriminant validity issues when constructs are conceptually related. Therefore, while the Fornell-Larcker results provide initial evidence of adequate discriminant validity, an additional, more stringent assessment was conducted using the Hetero Trait-Mono Trait ratio (HTMT) approach to confirm these findings.

Table 7
Discriminant Validity Hetero Trait Mono Trait ratio

	AUI	EE	FC	PE	SI
AUI					
EE	0.475				
FC	0.257	0.098			
PE	0.352	0.216	0.064		
SI	0.488	0.518	0.092	0.483	

Source: Collected data sets (2025)

The HTMT was employed as a more rigorous test of discriminant validity. HTMT is considered a superior and more sensitive method, particularly in variance-based SEM, with recommended threshold values of 0.85 (strict criterion) or 0.90 (liberal criterion). As presented in Table 7, all HTMT values among the five constructs are well below the recommended threshold, indicating that the constructs are empirically distinct.

The results of the HTMT analysis are consistent with the Fornell–Larcker findings, as no values approached the critical threshold, and no discrepancies were observed between the two methods. The convergence of results across both approaches strengthens confidence in the discriminant validity of the measurement model and confirms that the five constructs represent statistically distinct concepts.

4.5 Structural Model

Table 8
Relationships Testing (Test of Hypotheses H1 to H6 Total Effects)

	β	T	P values	Confidence Interval		Hypothesis
				Lower Limit	Upper Limit	
EE -> AUI	0.255	5.251	0.000	0.160	0.349	H2: Supported
FC -> AUI	0.248	5.660	0.000	0.165	0.339	H1: Supported
PE -> AUI	0.162	3.216	0.001	0.063	0.261	H4: Supported
SI -> AUI	0.462	10.895	0.000	0.377	0.543	H3: Supported
SI -> EE	0.459	10.120	0.000	0.367	0.544	H6: Supported
SI -> PE	0.423	9.627	0.000	0.337	0.508	H5: Supported

Source: Collected data sets (2025)

Table 8 presents the structural model results, indicating that Effort Expectancy (EE), Facilitating Conditions (FC), Performance Expectancy (PE), and Social Influence (SI) all have a positive and statistically significant influence on AI Use Intention (AUI). Specifically, EE has a significant positive effect on AUI ($\beta = 0.255$, $t = 5.251$, $p < 0.001$), suggesting that the easier students perceive AI technologies to be, the stronger their intention to use them. The findings indicate that prior experience with digital learning platforms influences students' ability to adopt AI technologies. As one respondent noted, "Students familiar with online learning systems found AI tools easy to learn and apply in academic tasks" (KII-05, personal communication, 03/03/2025). The interview responses, therefore, reinforce the statistical evidence that perceived ease of use enhances students' willingness to adopt AI technologies.

Similarly, FC shows a positive and significant relationship with AUI (β = 0.248, t = 5.660, p < 0.001), confirming that institutional and technical support structures significantly influence AI adoption intentions. The findings also revealed infrastructural and institutional challenges affecting AI adoption. As one participant observed, "Unstable internet connectivity, limited technical support, and absence of formal AI guidelines constrained effective use of AI technologies among students." (KII-07, personal communication, 07/03/2025).

While the quantitative results show that facilitating conditions positively drive intention, the interviews highlight the practical challenges that may either strengthen or hinder this influence. Thus, both strands of evidence converge in demonstrating the critical role of infrastructural and institutional support in shaping AI use intention.

The effect of PE on AUI is also positive and statistically significant (β = 0.162, t = 3.216, p = 0.001), indicating that students are more likely to adopt AI technologies when they perceive performance benefits. The findings further indicate that students recognised the practical benefits of AI technologies in supporting their academic activities. As one participant explained, "AI tools were primarily valued for enhancing research efficiency, academic writing, and overall productivity" (KII-06, personal communication, 04/03/2025). The interview data, therefore, substantiate the statistical evidence by illustrating the specific academic advantages that motivate students to use AI tools.

In addition, SI exhibits the strongest positive influence on AUI (β = 0.462, t = 10.895, p < 0.001), indicating that social influence is the most powerful predictor among the independent variables. The findings also highlight the role of social dynamics in shaping AI adoption among students. As one participant observed, "Peer encouragement and lecturers' attitudes strongly shaped students' willingness to adopt AI tools for academic purposes." (KII-01, personal communication, 27/02/2025). The qualitative evidence not only aligns with the quantitative results but also explains why social influence emerged as the dominant predictor of students' AI adoption decisions, which are significantly shaped by their academic social environment.

Furthermore, the analysis reveals that SI has a significant positive influence on EE and FE, suggesting an indirect role of SI within the model. Specifically, SI positively affects EE (β = 0.459, t = 10.120, p < 0.001), implying that higher levels of SI lead to increased levels of EE. Likewise, SI has a significant positive effect on FE (β = 0.423, t = 9.627, p < 0.001), indicating that SI contributes to strengthening FE. These findings suggest that SI not only directly influences Y but also indirectly affects Y through its impact on EE and FE, highlighting its central role in the structural model.

Altogether, the qualitative findings largely corroborate the quantitative results, with no major contradictions observed. Instead, the interviews provide explanatory depth, illustrating how perceived ease of use, infrastructural support, performance benefits, and social encouragement operate in practice to influence AI use intention. The convergence of both data strands strengthens the validity of the study's conclusions.

Table 9

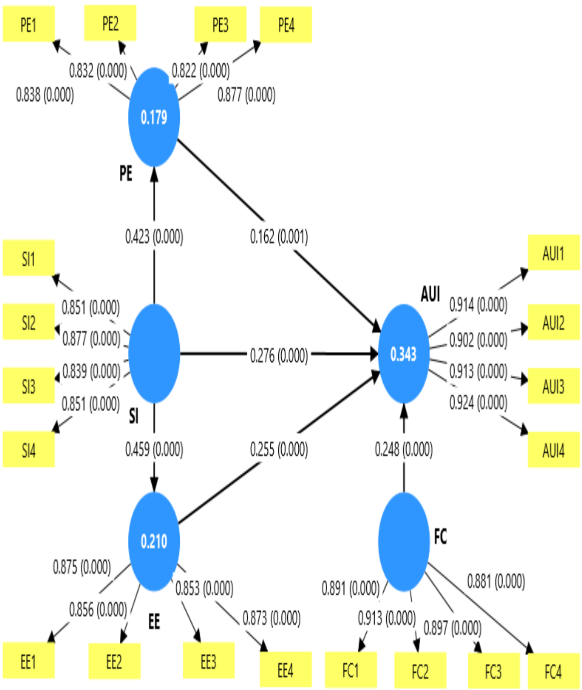
Mediation Analysis Results (Test of Hypothesis H7-H8)

Total Effects (SI -> AUI)			Direct effects (SI -> AUI)			Hypothesis	Indirect effect of SI on AUI			Percentile bootstrap 95% confidence interval	
B	T	P	B	T	P		B	T	P	Lower	Upper
0.462	10.895	0.000	0.276	5.478	0.000	H7: SI -> PE -> AUI	0.069	2.996	0.003	0.026	0.117
						H8: SI -> EE -> AUI	0.117	4.568	0.000	0.069	0.169

Source: Collected data sets (2025)

Note: SI: Social Influence, AUI: AI use Intention, PE: Performance Expectancy, EE: Effort Expectancy, FC: Facilitating Conditions

Figure 2
Structural Equation Modelling (SEM)



Source: Collected data sets (2025)

4.6 Mediation Analysis

The mediation analysis was conducted to examine the mediating roles of performance expectancy (PE) and effort expectancy (EE) in the relationship between social influence (SI) and AI use intention (AUI), while facilitating conditions were treated as a control variable.

The findings presented in Table 9 and Figure 2 indicate that social influence has a significant indirect effect on AI use intention through performance expectancy (H7: β = 0.069, t = 2.996, p = 0.003). The total effect of social influence on AI use intention was significant (β = 0.462, t = 10.895, p < 0.001), and after introducing performance expectancy as a mediator, the direct effect remained significant (β = 0.276, t = 5.478, p < 0.001), indicating complementary partial mediation. The qualitative findings further suggest that social discourse within academic environments can influence students' perceptions of AI technologies. As one participant noted, "Positive peer and institutional discourse around AI strengthened students' beliefs about the academic value of AI technologies." (KII-04, personal communication, 03/03/2025).

Moreover, the interview evidence aligns with the quantitative result, suggesting that social influence enhances students' intention to use AI not only directly but also indirectly by strengthening their perceptions of AI's academic performance benefits. In other words, the qualitative data help explain how social endorsements translate into increased performance-related expectations, thereby reinforcing AI use intentions.

Similarly, Table 9 shows a significant indirect effect of social influence on AI use intention through effort expectancy (H8: β = 0.117, t = 4.568, p < 0.001). The direct effect of social influence remained significant (β = 0.276, t = 5.478, p < 0.001), indicating complementary partial mediation via effort expectancy. The findings also indicate that collaborative learning environments can influence students' perceptions of AI usability. As one participant explained, "Social support and shared peer experiences reduced perceived difficulty in using AI tools, thereby encouraging continued use." (KII-03, personal communication, 28/02/2025). The interviews, therefore, illustrate the psychological process underlying the statistical mediation effect: social encouragement and shared experiences reduce perceived complexity, which in turn strengthens students' behavioural intentions.

In general, the qualitative findings corroborate and elaborate upon the quantitative mediation results. While the statistical analysis confirms that both performance expectancy and effort expectancy partially mediate the influence of social factors on AI use intention, the interviews clarify the mechanisms through which this occurs, namely, by shaping students' beliefs about AI's usefulness and reducing perceived difficulty. The convergence of both data strands enhances the validity of the mediation conclusions and offers a more thorough comprehension of the mechanisms of social influence in the AI adoption process.

4.7 Assessment of the Structural Model

Table 10

Saturated Model Results

Construct	R^2	Adj.R^2	F^2	Q^2	VIF	SRMR
AUI	.34	.34		.26		.04
EE	.21	.21	.08	.21	1.29	
PE	.18	.18	.03	.17	1.03	
FC			.09		1.22	
SI			.08		1.51	

Source: Collected data sets (2025).

In Table 10 the structural model was evaluated using the coefficient of determination (R^2), adjusted R^2, effect size (f^2), predictive relevance (Q^2), variance inflation factor (VIF), and the standardised root mean square residual (SRMR). The R^2 values for the endogenous constructs range from 0.15 to 0.35, indicating weak to moderate explanatory power according to commonly accepted guidelines.

This suggests that the exogenous variables explain between 15% and 35% of the variance in the dependent constructs, which is considered acceptable in behavioural and social science research. The adjusted R^2 values are slightly lower but consistent with the R^2 values, confirming the robustness of the model while accounting for model complexity. The effect size (f^2) values indicate the relative contribution of each exogenous construct to the endogenous variables, with small, medium, and large effects observed based on established thresholds.

The predictive relevance of the model was assessed using the Stone-Geisser Q^2 statistic, and all Q^2 values are greater than zero, demonstrating that the model has satisfactory predictive relevance. Furthermore, the VIF values for all constructs are below the recommended threshold, indicating the absence of multicollinearity issues among the predictor variables.

Finally, the SRMR value is below the recommended cut-off of 0.08, suggesting a satisfactory overall model fit. Collectively, these results confirm that the structural model demonstrates adequate explanatory power, predictive relevance, and overall goodness of fit.

5.0 Discussion

The discussion is organised into three main sections: theoretical implications, practical and managerial implications, and limitations, along with directions for future research. The discussion ends with an overall conclusion that synthesises the key contributions of the study.

5.1 Theoretical Implications

The findings of this study provide strong theoretical support for the applicability and robustness of the UTAUT model in explaining students' intention to use AI technologies in higher learning institutions. The study found that facilitating conditions, effort expectancy, social influence, and performance expectancy all significantly positively affect AI use intention. One of the most significant theoretical contributions of this study is the identification of social influence as the strongest predictor of AI use intention. The study also confirms the central role of performance expectancy and effort expectancy as key determinants of AI use intention. Importantly, the study extends the UTAUT framework by empirically demonstrating the mediating roles of performance expectancy and effort expectancy in the relationship between social influence and AI use intention. The results show that social influence affects students' intention to use AI both directly and indirectly by shaping their beliefs about AI's academic usefulness and ease of use.

These findings are consistent with the original UTAUT propositions (Venkatesh *et al.,* 2003). They also align with the recent AI-in-education scholarship, which emphasises that AI adoption in higher education is a multidimensional socio-technical process influenced not only by technological perceptions but also by institutional and social contexts (Alshahrani *et al.,* 2024; Mohsin *et al.,* 2024; Zawacki-Richter *et al.,* 2019). While earlier technology acceptance studies often privilege performance expectancy as the dominant determinant (Davis, 1993;

Venkatesh *et al.,* 2003), the finding that social influence is the strongest predictor aligns with more recent studies conducted in collectivist and emerging educational contexts. It shows that peer norms, lecturer endorsement, and institutional culture exert heightened influence on students' technology-related decisions (Dwivedi *et al.,* 2021; Namabira *et al.,* 2022). In environments characterised by uncertainty regarding ethical, acceptable, and legitimate AI use, such as higher educational institutions, students rely heavily on cues from peers, lecturers, and institutional discourse to guide their adoption decisions.

These findings, therefore, have important theoretical implications. They confirm that belief-based cognitive evaluations remain critical even in advanced AI-driven learning environments, consistent with extensive prior research on educational technology adoption (Al-Emran *et al.*, 2018; Davis, 1993). However, unlike earlier studies that treat these constructs as isolated predictors, the present study situates them within a broader social influence mechanism, offering a more integrated explanatory model. The identification of complementary partial mediation suggests that social endorsement enhances adoption intentions not only through normative pressure but also through belief formation processes. This finding resonates with social cognitive theory, which emphasises that social environments shape individual beliefs and expectations that in turn guide behaviour (Bandura, 2001). By empirically testing these mediation mechanisms, the study contributes to theory by moving beyond direct-effect models of technology adoption that dominate much of the UTAUT literature. It provides a more nuanced explanation of how social dynamics translate into behavioural intention through cognitive evaluation pathways, a dimension often underexplored in AI adoption studies (Dwivedi *et al.,* 2021; Huang *et al.,* 2025; Wu *et al.,* 2024). Furthermore, by situating the analysis within an ODL institution in a developing country context, the study extends the external validity of the UTAUT model and responds directly to calls for more Global South-based empirical evidence (Xue *et al.,* 2024; Zawacki-Richter *et al.,* 2019).

5.2 Practical and Managerial Implications

The findings of this study have several important practical and managerial implications for higher learning institution policymakers and educators seeking to promote effective and responsible adoption of AI technologies.

First, the significant effects of the facilitating conditions underscore the need for institutions to strengthen their technological and organisational infrastructure. Reliable internet connectivity, access to digital devices, availability of AI-enabled platforms, and responsive technical support services are critical for encouraging students to engage with AI technologies. This finding aligns with prior studies showing that infrastructural readiness remains a foundational prerequisite for meaningful digital transformation in African higher education (Babalola & Genga, 2024; Hategekimana, 2022). Institutional investment in these areas is particularly important in ODL environments, where students depend heavily on digital systems for academic participation.

Second, the influence of effort expectations suggests that institutions should prioritise reducing the perceived complexity of AI technologies. This can be achieved by incorporating AI literacy and skills training in postgraduate programmes, offering targeted workshops and tutorials, and providing clear, user-friendly guidance on AI tools. Existing studies consistently show that a lack of digital confidence and skills is a major barrier to AI adoption among students and educators (Bian *et al.,* 2024; Flores & Chiappe, 2025). When students feel confident in their ability to use AI technologies, their intention to adopt such tools increases significantly.

Thirdly, the strong role of social influence highlights the importance of leveraging academic and peer networks to normalise AI usage. Lecturers, supervisors, and academic leaders should model appropriate and ethical use of AI technologies in teaching, research, and assessment. This supports emerging evidence that educator attitudes and practices play a critical gatekeeping role in shaping students' acceptance of AI tools (Kasneci *et al.,* 2023). Clear institutional communication regarding acceptable AI use can reduce uncertainty and reinforce positive social norms. Peer-supported learning initiatives, such as online discussion forums and collaborative AI learning communities, can further enhance positive social influence, particularly in ODL settings.

From a policy perspective, the findings suggest that national and institutional AI strategies should not focus solely on technological deployment but also address social, ethical, and cultural dimensions of adoption. Developing clear guidelines, ethical frameworks, and capacity-building initiatives can help create an enabling environment that supports responsible and inclusive AI use in higher education, in line with global policy recommendations (Areba *et al*., 2025; Holmes & Miao, 2023; OECD, 2024).

5.3 Limitations and Future Research Directions

This study has several limitations that warrant acknowledgement. First, the study was conducted at a single ODL institution, which may limit the generalisability of the findings to other higher education institutions with different instructional modes or institutional contexts. This limitation is common in institution-based technology adoption studies (Magali, 2020). Future studies could extend the research to multiple universities to enhance external validity.

Second, the study employed a cross-sectional research design, capturing students' perceptions and intentions at a single point. As AI technologies, institutional policies, and societal debates continue to evolve rapidly, it is recommended that longitudinal studies examine changes in AI use intentions and adoption behaviours over time (Dwivedi *et al*., 2021).

Third, the study relied primarily on self-reported data, which may be subject to social desirability bias or common method variance. Although reliability and validity tests were conducted, future research could strengthen methodological rigour by incorporating objective usage data, system logs, or experimental designs (Hershkovitz & Alexandron, 2025). Mixed-methods approaches could also better understand how students negotiate ethical and pedagogical tensions surrounding AI use.

Future research directions may explore additional theoretical frameworks, such as the Technology Acceptance Model (TAM), the Technology Organization Environment (TOE), or sociomaterial perspectives, either independently or in combination with UTAUT, to capture broader organisational, regulatory, and cultural influences. Comparative studies involving undergraduates, academic staff, or cross-national contexts would further enrich understanding of AI adoption dynamics and support theory building in AI-enabled higher education.

6.0 Conclusion

This study examined the factors influencing students' intention to use AI technologies in higher learning institutions using the Unified Theory of Acceptance and Use of Technology. The findings demonstrate that AI use intention is shaped by facilitating conditions, effort expectancy, performance expectancy, and social influence, operating through both direct and indirect pathways.

By empirically confirming the mediating roles of performance expectancy and effort expectancy, the study provides deeper theoretical insight into how social influence translates into behavioural intention through students' beliefs about the usefulness and ease of AI technologies. These findings extend the application of the UTAUT framework to the emerging context of AI adoption in ODL institutions within a developing country setting.

Generally, the study contributes to theory, practice, and policy by highlighting the importance of supportive infrastructure, user-friendly technologies, perceived academic benefits, and positive social norms in promoting effective, ethical, and sustainable adoption of AI in higher education.

7.0 Recommendations

To support a more inclusive, effective, and ethical integration of AI into higher education, targeted and collaborative action is required across various institutional and national stakeholders.

First, the OUT management is urged to develop a clear institutional framework that supports the structured integration of AI into both academic programmes and administrative functions. This framework should be accompanied by capacity-building initiatives for faculty and clear ethical guidelines to ensure that AI enhances rather than disrupts the academic experience.

In parallel, non-technical faculties, such as those within education, law, and business management, should initiate cross-disciplinary training workshops that demystify AI tools and demonstrate their relevance across different academic contexts. By fostering a culture of experimentation and inquiry, these faculties can bridge the divide between technological and non-technological disciplines.

The directorate of ICT services at the OUT should prioritise infrastructural improvements, including reliable internet access and the integration of AI-enhanced learning platforms. These foundational investments are critical to enabling equitable and consistent access to AI resources across the student population.

At the national level, the Ministry of Education, Science, and Technology (MoEST) in Tanzania is encouraged to mandate the inclusion of AI literacy modules in all accredited postgraduate programmes. Such a move would promote a baseline competency in AI across disciplines, thereby preparing graduates to engage with emerging technologies in ethically responsible and professionally relevant ways.

For academic staff, there is a need to proactively incorporate discussions of AI ethics and usage policies into course syllabi. Lecturers should be trained to recognise AI-generated work and guide students in using these tools constructively and responsibly, fostering a culture of academic integrity along with innovation.

Meanwhile, student leadership bodies, such as the Open University of Tanzania (OUTSO), can play a pivotal role in normalising the use of AI through peer learning networks. These networks can serve as safe and collaborative spaces where students share experiences, troubleshoot challenges, and collectively build digital confidence.

Lastly, research and development units within OUT should establish systems for continuous monitoring and evaluation of AI use. This would involve tracking both student learning outcomes and institutional effectiveness in deploying AI tools, ensuring that policies and practices remain adaptive, evidence-based, and responsive to the needs of learners.

This human-centred approach to AI usage not only recognises the transformative potential of technology but also prioritises the lived realities of students and educators. By aligning policy, infrastructure, training, and support with the diverse needs of its academic community, the OUT and, by extension, Tanzanian higher education can harness AI as a force for inclusive and meaningful educational innovation.

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10.0 Declaration of Conflicting Interests

The authors declare no conflict of interest.

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