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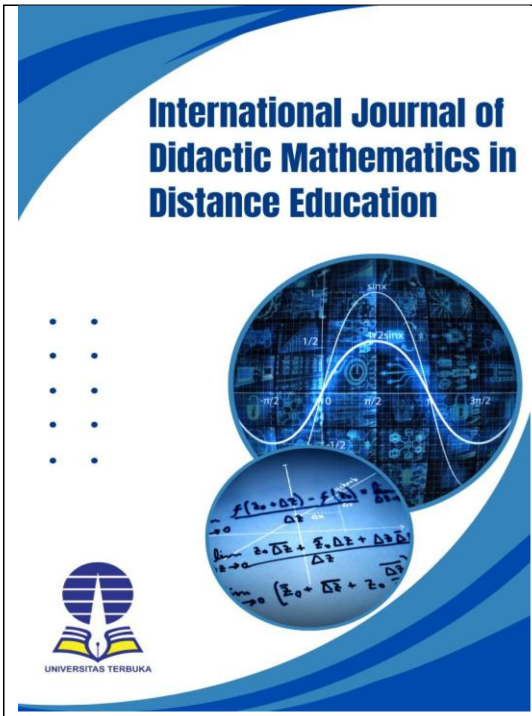


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# Influence of artificial intelligence tool perceptions on mathematics undergraduates' academic engagement: role of attitudes and usage intentions

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**Abstract**
In African higher education, particularly among STEM students, the rapid integration of Artificial Intelligence (AI) into teaching and learning has created both opportunities for innovation and concerns about ethical use, however, there remains scarce studies about how students perceive and use these technologies in ways that influence their academic engagement and learning outcomes in Mathematics. This study, which focuses on attitudes and usage intentions, seeks to investigate the Influence of AI Tool Perceptions on the academic engagement of mathematics undergraduates from the lens of Technology Acceptance Model (TAM). The Structural Equation Modelling (SEM) approach was used to examine the perceptions of Mathematics undergraduates regarding AI usage and academic engagement. Data collected from 1,518 Mathematics undergraduates from Southwest Nigerian universities through a survey hosted online was analysed using PLS-SEM. The findings indicate that perceptions (perceived ease of use and perceived usefulness) influence attitudes towards and intentions to use AI tools while intention ($\beta = -0.179$, $t = 2.426$, $p < 0.05$), attitude towards ($\beta = 0.216$, $t = 2.541$, $p < 0.05$), and actual use of AI ($\beta = 0.797$, $t = 11.904$, $p < 0.05$) influences academic engagement, intention. According to this study, improving the mathematics students' perceptions towards the use of AI tools could result in more engaging learning experiences. It highlights the necessity of developing positive attitudes and perceptions to foster academic engagement among undergraduate students in Mathematics programs, as well as the importance of developing supportive learning systems, and institutional regulations that support ethical and effective ways of incorporating AI.

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## 1. Introduction

The application of Artificial Intelligence (AI) tools in nearly all core functions of higher education institutions is transforming the way various activities are conducted. These tools make learning more interactive and personalized, helping students feel more connected to their coursework. Unlike traditional digital tools, AI applications such as adaptive tutoring systems, automated assessment platforms, and predictive analytics provide personalized support and interactive learning opportunities (Ateeq et al., 2024; Kaswan et al., 2024). As a result, many are experiencing improved academic performance and greater satisfaction with their educational journey (Adewale et al., 2024; Rodway & Schepman, 2023). The AI technologies have the potential to enhance students' learning experiences by fostering autonomy, efficiency, and flexibility. In mathematics education, where students often face cognitive overload and disengagement, the adaptive capabilities of AI can support critical thinking, problem-solving, and conceptual understanding (Isnawan et al., 2024; Molina & Yabut, 2025). However, while the potential of AI in higher education is widely acknowledged, its actual impact on students' engagement and learning outcomes remains non critically investigated.

One of the main factors affecting how students view AI tools is their perception of the technology. Existing studies highlight that students' perceptions of ease of use and usefulness strongly influence their attitudes toward adopting educational technologies (Davis, 1989; Elkaseh et al., 2016). These perceptions are shaped not only by their personal experiences with the technology but also by the environment in which they are learning. For example, students who find AI tools intuitive and helpful for their academic needs tend to use these tools regularly in their studies (Falebita & Kok, 2024; Tan et al., 2023). Conversely, negative attitudes, shaped by difficulties of use or limited relevance to academic needs, reduce adoption and limit effectiveness (Kashive et al., 2020; Nuryakin et al., 2023). These mixed findings indicate that attitudes and perceptions are not universal but could vary with context, discipline, and technological design. This emphasizes the essentiality of designing AI tools that are user-friendly and beneficial for students' academic success, ensuring that they feel confident and motivated to engage with them.

In addition, while the Technology Acceptance Model (TAM) has been widely applied to explain AI technology adoption in education (Ayanwale & Molefi, 2024; Osman, 2025), most studies have focused on general digital learning environments rather than discipline-specific contexts. Mathematics undergraduates, who often require intensive engagement with abstract concepts and problem-solving tasks, represent a distinct group whose interaction with AI tools may differ significantly from students in other fields (Falebita & Olofin, 2020; Xerri et al., 2018). However, there is scarcity of empirical studies have systematically investigated how mathematics undergraduates' perceptions, attitudes, and usage intentions influence their academic engagement with AI tools.

Furthermore, studies conducted over the last few decades in education have demonstrated that student academic engagement, which explains the extent to which students become actively involved in academic activities, is a crucial factor in educational success (Kahu & Nelson, 2018; Lynam et al., 2024; Xerri et al., 2018). The level of engagement has been indicated to correlate positively with enhanced learning outcomes, retention rates, as well as an increased understanding of the course content (Green et al., 2018; James et al., 2025; Wang & Xue, 2024). However, academic engagement is not only motivated by course content or the educator's teaching ability but can also be influenced by the resources and equipment available to a student. Although prior research connects engagement with instructional quality and course content, there is limited evidence on how AI tools, mediated by students' attitudes and intentions, shape mathematics learners' academic engagement. This gap restricts both theoretical understanding and practical strategies for leveraging AI to enhance mathematics education. As AI tools become more popular in education, it's crucial to understand how students' perceptions of these technologies shape their attitudes, intentions, and engagement in academics.

Additionally, attitude towards AI tools could also be the primary factors contributing towards students' academic engagement. The attitude towards AI tools refers to how someone feels about using AI technologies, shaped by their experiences and beliefs about how helpful and user-friendly these tools are in enhancing their learning or work effectiveness. Students who perceive AI tools as useful and easy to use in enhancing their studies tend to have a positive attitude towards their use (Kashive et al., 2020; Tan et al., 2023). On the other hand, when they find these tools difficult to use and unhelpful to their learning, they are likely to use them less, resulting in lower adoption and usage levels (Elkaseh et al., 2016; Falebita & Kok, 2024a; Nuryakin et al., 2023). Hence, perceived ease of use and usefulness are key factors in defining students' attitudes towards AI tools and their intention to incorporate them into their learning processes. However, there is scarcity of studies that consider the connection between attitude towards AI and students' academic engagement especially in mathematics education.

Another issue that arises within the context of AI integration in education is the intention to utilise its tools. Intention to use refers to the likelihood that a student will actively engage and utilise AI tools. Such intent is typically conditioned by students' attitudes towards the tool and their perception of its practical usefulness and ease of use (Ayanwale & Molefi, 2024; Osman, 2025). When students feel that they have access to AI tools that are easy to use, assist the learning process, and support academic achievement, they may be more inclined to use those tools, leading to actual usage for academic engagement. However, there is gap in research that investigates the relationship between intention to use AI tools and academic engagement in Mathematics education.

Therefore, this study aims to examine the interplay between mathematics undergraduates' perceptions, attitudes, intentions, and actual use of AI tools in shaping academic engagement. By addressing this gap, the research contributes to a more nuanced understanding of how AI adoption processes unfold in discipline-specific contexts. Ultimately, the findings are expected to inform institutional policies, guide educators in designing effective AI-supported learning environments and support the responsible integration of AI in mathematics education. To achieve this, the study is guided by the following research questions:

1) How do students' attitudes towards AI tools influence their intention and actual use of AI, and their academic engagement?
2) What role does usage intentions play in the actual use of AI tools and academic engagement of mathematics undergraduates?

## 2. Literature Review

### Theoretical Framework

This study is anchored on the Technology Acceptance Model (TAM), which explains the factors shaping user acceptance and utilization of technology. TAM was first created by (Davis, 1989), and presumes that the perceived ease of use (PEU) and the perceived usefulness (PU) are critical in influencing a person's intention in the usage of a technology especially new ones. In the context of artificial intelligence (AI) in education, the framework is especially relevant as students and educators are increasingly required to engage with AI-driven platforms. For instance, when mathematics students perceive AI-powered tutoring systems as intuitive and supportive in clarifying abstract concepts, they are more likely to accept and integrate these tools into their learning practices (Ayanwale & Ndlovu, 2024; Davis, 1989). Within this study, PEU reflects how confidently students believe AI tools can be used without complexity, while PU denotes the extent to which students perceive AI technologies as beneficial for enhancing learning. For example, AI-driven feedback mechanisms and problem-solving tools can support deeper mathematical understanding, foster higher engagement, and improve academic performance (BaiDoo-Anu & Owusu Ansah, 2023; Toros et al., 2024). Collectively, PEU and PU shape students' attitudes and intentions, making TAM an appropriate lens for examining AI adoption and academic engagement in Nigerian higher education.

### AI Perceived Ease of Use (PEU)

Perceived ease of use remains a dominant predictor of AI acceptance, as highlighted in recent literature on educational technology adoption. Studies reveal that students tend to embrace AI tools when they are straightforward, accessible, and do not demand extensive technical skills (Chan & Lee, 2023; Lestari & Indrasari, 2019). Within mathematics education, the ability of AI platforms to simplify complex problem-solving and provide step-by-step explanations reduces cognitive overload and enhances usability. However, findings are mixed, while some research shows that PEU significantly influences PU and adoption of AI tools (Falebita & Kok, 2024; Geddam et al., 2024; Lestari & Indrasari, 2019), other studies report that ease of use alone does not guarantee consistent utilization (Falebita & Kok, 2024). This suggests that user characteristics, prior exposure to technology, and the academic context could play vital roles in shaping PEU. Importantly, Nigerian students often face infrastructural challenges such as unstable internet access and limited exposure to AI (Abdulmajeed et al., 2020), which may undermine PEU despite the tools being well-designed. Studies have shown that the intention to use AI tools is significantly predicted by PEU, PU, and self-efficacy (Osman, 2025; Osman et al., 2024). The TAM has been widely utilized, indicating that PU and PEU positively affect the intention to use AI, both directly and indirectly through attitude (Osman et al., 2024). Research has shown that the PEU of AI tools affects attitudes on their use (Chibisa et al., 2022; Falebita & Kok, 2024a; Geddam et al., 2024; Toros et al., 2024). All in all, these studies emphasize that PEU itself does not depend solely on the technological aspect but can also be determined by user characteristics, system design, and usage context. However, the gap remains that most of these studies concentrated on general education with little studies focusing on mathematics education in Nigeria context.

Understanding these dynamics from this perspective can facilitate the development of not only functional AI tools but also user-friendly systems, leading to increased adoption rates and user satisfaction among mathematics students.

**AI Perceived Usefulness (PU)**

Perceived usefulness (PU) is the level to which a student deems that the use of a specific AI tool will boost their academic engagement and performance or help achieve specific goals effectively. PU is a key construct of the TAM, which has been found in the literature to influence individuals' intentions, attitudes, and actual usage of AI tools. Research shows that when students believe AI enhances comprehension, provides personalized support, or improves grades, their likelihood of adoption increases (Mutambara & Chibisa, 2022; Osman, 2025). In mathematics education, PU becomes particularly important since AI can provide stepwise problem explanations, adaptive exercises, and immediate feedback, thereby addressing common learning difficulties. Geddam et al. (2024) demonstrated that PU positively shapes attitudes and actual use, suggesting its strong predictive role in fostering academic engagement. Collectively, these studies underscore that PU is not merely a cognitive assessment but a dynamic factor that shapes users' attitudes and behaviours towards AI tools. Understanding the multifaceted role of PU can inform the design and implementation of AI tools that align with users' expectations and enhance their adoption and effective utilization. However, PU is not static, it is influenced by student expectations, peer norms, and institutional policies. In Nigeria, where traditional methods dominate mathematics teaching, students' perception of AI usefulness may be shaped by its ability to complement limited classroom interaction and resource scarcity. Thus, PU extends beyond individual cognitive evaluation, representing a dynamic factor shaped by both pedagogical demands and contextual realities, underscoring its pivotal role in driving adoption.

**Attitude towards AI Use**

Attitude towards AI tools is how an individual feels, whether positively or negatively, about using AI tools, and this mindset plays a big role in whether they are willing to try and stick with these tools. Recent literature has discussed the acceptance of AI in different fields. The intention to use AI depends significantly on the PU and PEU, being mediated by attitude towards use (Geddam et al., 2024). Several studies have revealed that attitude is critical to the adoption of AI tools, especially in higher education institutions. A positive attitude often results from perceiving AI as practical, supportive, and non-threatening, while negative attitudes may arise from anxiety, ethical concerns, or mistrust. Within higher education, studies have consistently found attitude to be a critical determinant of AI adoption (Ayanwale et al., 2024; Falebita & Kok, 2024a; Toros et al., 2024). In mathematics classrooms, attitudes toward AI may be influenced by whether students see AI as replacing traditional learning or complementing it by simplifying abstract problem-solving. Falebita and Kok (2025) noted that fostering positive attitudes requires addressing students' concerns while demonstrating significant academic benefits. In Nigeria, this means ensuring that AI is framed as a supportive learning companion rather than a substitute for teacher instruction. Cultivating such positive perceptions through training and exposure is vital for improving adoption rates and ensuring effective integration of AI into mathematics education.

**Intention to and Actual Usage of AI tools**

The issue of intention to use and actual use of AI tools in education has been recently discussed in several studies. Intention to use AI tools refers to a user's planned or expected behaviour of adopting and engaging with AI technologies based on their perceptions and attitudes towards the tool. Actual use of AI tools, on the other hand, involves the real, observable application and interaction with AI technologies in practice, reflecting the translation of intention into behaviour. The results of the literature review in terms of the significance of predictors of the behavioural intention to use AI tools pointed to attitude and self-efficacy being significant in terms of predicting the behavioural intention to use AI tools in tertiary institutions (Lavidas et al., 2024; Mutambara & Chibisa, 2022; Osman, 2025). Additionally, Attitudes and subjective norms had a significant impact on the intention to use AI tools, which in turn influenced actual tool usage (Kim et al., 2025). Several studies have shown that behavioural intention has a significant influence on the adoption of AI tools (Ayanwale & Ndlovu, 2024; Mutambara & Chibisa, 2022; Osman, 2025). However, studies also highlight that intention does not always translate into consistent practice, especially in contexts with infrastructural or institutional barriers. For example, while students may intend to use AI tutoring platforms, inconsistent electricity and poor internet access in Nigeria may prevent actual engagement. These findings suggest that adoption is not solely a matter of individual decision-making but also a product of structural and social conditions. Thus, promoting both intention and actual usage requires providing enabling environments, institutional support, and clear policies that encourage integration of AI into mathematics learning.

**AI Use and Academic Engagement**

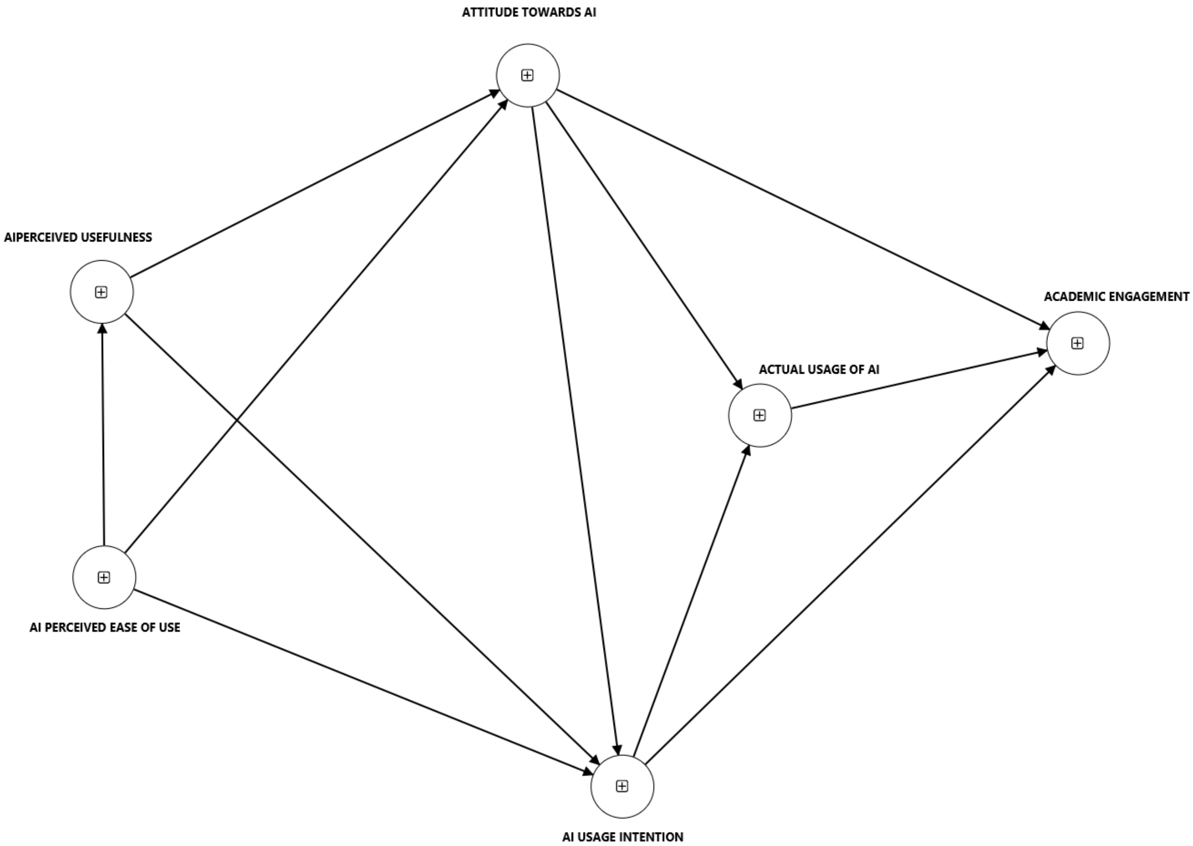
Research has shown that AI tools can offer features such as personalised learning, instant feedback, and adaptive learning, which ultimately translate to students been engaged with various academic activities and later improve their academic achievement. Although AI offers several advantages, such as increased engagement and collaboration among students, It also raises questions regarding potential and academic integrity. Studies have demonstrated a substantial, favourable relationship between using AI tools, especially generative AI, and learners' academic engagement; however, they also indicate a risk of dependency (Aieron et al., 2024). An intervention study confirmed that AI-based chatbots can improve behavioural, cognitive, and emotional engagement among Chinese EFL learners (Wang & Xue, 2024). Furthermore, AI-enhanced learning tools have been shown to foster more targeted and receptive learning, which could lead to greater engagement and academic achievement across different levels of education (Ellikkal & Rajamohan, 2024). Moreover, research conducted by Anierobi et al. (2025) found that the use of AI tools had a positive impact on self-efficacy, academic engagement, and student satisfaction with their learning. Similarly, a study presented by Ward et al. (2024) showed that AI technologies have advanced study skills, time management, and feedback roles, resulting in increased Grade Point Averages (GPAs). The results suggest that AI gadgets can facilitate individualised learning, customise test conditions, and provide real-time analysis of classes, thereby increasing engagement in academic activities. However, it is essential to note that excessive reliance on AI tools can be problematic, including the erosion of critical thinking and potential ethical concerns (Cotton et al., 2024). Within the Nigerian context, AI can play a transformative role in addressing disengagement among mathematics students, who often struggle with abstract concepts and limited instructional resources. However, educators must balance AI integration with strategies that foster independent reasoning and problem-solving. Hence, while AI offers promising avenues for enhancing academic engagement, careful, context-sensitive adoption is necessary to maximize benefits while mitigating risks.

Based on the reviewed literature, it becomes evident that students' perceptions of AI tools, their attitudes, and subsequent intentions and usage play a critical role in shaping academic engagement; therefore, this study advances the following hypotheses to empirically test these relationships within the context of mathematics undergraduates.

In this study, we therefore proposed the following hypotheses;

H1: AI PEU influences PU.
H2: AI PEU influences attitude towards AI use.
H3: AI PEU influences intention to use AI tools.
H4: AI PU influences attitude towards AI use.
H5: AI PU influences intention to use AI tools.
H6: Attitude towards AI use influences academic engagement.
H7: Attitude towards AI use influences actual use of AI tools.
H8: Attitude towards AI use influences intention to use AI tools.
H9: The actual use of AI tools influences academic engagement.
H10: Intention to use AI tools influences academic engagement.
H11: Intention to use AI tools influences actual use of AI tools

Figure 1.
*Proposed AI Use and Academic Engagement Model*




## 3. Method

### 3.1. Research Design

For the study, a cross-sectional survey approach was employed, as it enables the collection of data at a single point in time to explore relationships among variables within a given population (Creswell & Creswell, 2018). Since a survey design efficiently collects insightful information and data that may guide decision-making while reducing possible sources of bias and error, it is crucial for gathering accurate and trustworthy data (Creswell, 2014). The survey is used to provide a quantitative picture of the students' attitudes, intentions, PEU, and PU of AI tools. The study utilized a questionnaire hosted online through Google Forms to collect opinion-based data from undergraduate mathematics students. All categories and variables in the data were analysed using descriptive statistics, and the partial least squares-structural equation modeling (PLS-SEM) was then used to test the proposed hypotheses.

### 3.2. Sample, Sampling Technique and Data Collection

The study's sample comprises 1518 undergraduate students enrolled in Mathematics Education (642) or Mathematics Science (876). In this study, the convenience sampling technique was employed in the survey, with an emphasis on representativeness, voluntary participation, and ease of access. This strategy is necessary as it enables the researchers to collect data from a population that is easily accessible while guaranteeing that participants are able and ready to participate, improving the validity of the results (Etikan et al., 2015). With this technique, the survey was shared via various online platforms (WhatsApp, Google Classroom, and Telegram), targeting mathematics undergraduates from public universities in three states (Ekiti, Ondo, and Ogun) of Southwest Nigeria. The respondents' demographic details are shown in Table 1. The results show that male respondents (58.9%) had a higher representation compared to females (41.1%), suggesting that a gender imbalance may reflect broader trends in the fields of mathematical science and mathematics education. In terms of specialization, many respondents (57.7%) are focused on Mathematics Science, while 42.3% are in Mathematics Education. This suggests a stronger interest in the scientific aspects of Mathematics than in Mathematics Education. The age distribution shows a predominance of younger respondents, with nearly 40% aged between 18 and 20 years. This demographic trend is likely to yield perspectives that are more open to technological adoption, as younger generations typically exhibit greater comfort with digital tools (Nawaz, 2020). The representation across academic levels also indicates a balanced distribution, with 33.2% in their final year (400L), suggesting that insights gained from this group could provide a nuanced understanding of AI tool usage as students prepare to transition from university to the professional world.

Table 1
*Demographic Characteristics of Respondents*

| Characteristics | Level | N | % |
|---|---|---|---|
| Gender | Male | 894 | 58.9 |
| | Female | 624 | 41.1 |
| Specialization | Mathematics Science | 876 | 57.7 |
| | Mathematics Education | 642 | 42.3 |
| Age | Less than 18years | 120 | 7.9 |
| | 18 – 20years | 606 | 39.9 |
| | 21 – 23years | 528 | 34.8 |
| | 24 – 26years | 120 | 7.9 |
| | Above 26years | 144 | 9.5 |
| Level | 100L | 192 | 12.6 |
| | 200L | 396 | 26.1 |
| | 300L | 426 | 28.1 |
| | 400L | 504 | 33.2 |
| | Total | 1518 | 100 |

.

### 3.3. Instrument for Data Collection

This study examines the responses to various independent variables that influence the adoption and use of AI tools, as well as academic engagement, among undergraduate mathematics students. The TAM questionnaire serves as the primary instrument. The TAM model is a widely used technology adoption model in research because it has proven practical over the years in capturing users' perceptions of new technologies. The survey tool was designed to achieve the specific objectives of the study. It included six major constructs: Attitude Towards AI (ATT), Perceived Usefulness (PU), Perceived Ease of Use (PEU), AI Usage Intention (AIUI), AI Usage (AIU), and Academic Engagement. The PU and PEU constructs were adapted from (Mutambara & Chibisa, 2022) whose reliability indices were 0.852 and 0.855, respectively. Items of ATT were adapted from (Falebita & Kok, 2024a), whose reliability coefficient is 0.838. Similarly, the items of AIU and AIUI were adapted from (Ayanwale et al., 2024) whose instrument reliability yielded 0.86 and 0.95, respectively. Also, the items of the academic engagement constructs were adapted from (Freda et al., 2023).The items of the questionnaire were also appropriately adjusted to be relevant and meaningful to the intended population, which is mathematics undergraduates in Southwest Nigeria. This meant that some new elements were introduced, while others were dropped to align the constructs with the study's objectives. The final instrument consisted of 24 items, each construct with four items. These measures were assigned a 5-point Likert scale on agreement to obtain a well-balanced interpretation of the respondents' perceptions, attitudes, intentions, behaviour, and academic engagement.

### 3.4. Data Analysis Approach

PLS-SEM was considered for data analysis in the study. This approach was preferable due to the technique's flexibility and robustness, particularly in handling complex models that involve latent variables, as well as its capacity to work effectively with non-normal statistics and smaller sample sizes. Amidst these benefits, PLS-SEM, with its flexibility in addressing various constructs, was selected as the most suitable method for exploring the connections and correlations between the constructs essential to analysing academic engagement within the AI usage domain. The data were analysed with the aid of SmartPLS 4 SEM software (Ringle et al., 2024), a popular structural equation modelling software. This analysis was conducted in two steps, as suggested by (Hair et al., 2017). In the first step, in order to confirm the validity and reliability of the constructs, the measurement model was tested. The given step included Confirmatory Composite Analysis (CCA) that served to test the validity of the operationalized constructs. Several metrics were used to verify the psychometric quality of the model, i.e. Cronbachs Alpha (CA) was used to determine the internal consistency of the scales; factor loadings were used to check the items were sufficiently representing constructs; Average Variance Extracted (AVE) was used to determine the degree of variance explained by each construct and another metric, Composite Reliability (CR) was used to determine the reliability of a composite variable. Lastly, the Fornell-Larcker Criterion was used to evaluate the discriminant validity. The in-depth assessment provided additional confidence that the constructs in the questionnaire were valid and that the model aligned with the measurement requirements (Hair et al., 2019). In the second step, the analysis was moved to the structural model, where the connections among the relations of latent variables were tested. This was done by reviewing the relationships between the constructs to identify their strength and importance. The findings provided empirical evidence in support of the proposed relations and offered insights into the effects of various factors, such as perceived usefulness, attitude towards, and intention to use AI tools in the academic environment. The data analysis approach, which integrates both measurement and structural modelling, enabled the validation of the constructs prior to testing the theoretical relationships, making the study's outcome quite strong and significant (Hair et al., 2021).

## 4. Results and Discussion

### 4.1 Results

#### 4.1.1. Measurement Model Assessment

The findings of the measurement model analysis support the overall strength of the instrument by establishing that the constructs used in this investigation are valid and reliable. As revealed in Table 2, the outer loadings of the majority of items in the survey were relatively high, typically exceeding the suggested minimum of 0.7, indicating that they can be well-representative of the underlying constructs (Hair et al., 2014). There was, however, an item whose loadings were less than 0.7 but took an area between 0.6 and 0.7. Although this item did not meet the ideal cutoff, it was still included in the model, and this was purposefully explained. The Academic Engagement (AE) construct had a loading between 0.617 and 0.849, with the lowest value being 0.617 in the case of AE4. This is lower than the classical 0.7 but acceptable, considering that this most important item was used in estimating the academic engagement. The deletion of this item may have reduced the representation of the construct, but it still aligned with an essential domain in academic engagement. Also, one of the factors considered in structural equation modelling is the Variance Inflation Factor (VIF), which measures the degree of multicollinearity among variables. In the research, the VIF ranged from 1.174 to 3.649, which falls below the threshold value of 5 (Hair et al., 2017). This suggests that the model's multicollinearity is not a major problem. According to the guiding principles, items that substantially add to the overall explanation of the construct and have loadings between 0.6 and 0.7 are often kept (Sander & Teh, 2014; Sarstedt et al., 2017). In this instance, the item was important to retain to achieve the comprehensiveness of the construct. Besides, the general reliability of the model was high, which was evidenced by CA and CR values, which were far beyond the recommended value of 0.7. The CA for the constructs AIPEU, AIPU, ATAIU, AUAI, AE, and IUAI are 0.831, 0.868, 0.868, 0.909, 0.704, and 0.863, respectively, while their CR are 0.833, 0.874, 0.871, 0.917, 0.863, and 0.864, respectively. This provided further justification for retaining the items with lower loadings, as their inclusion did not adversely affect the consistency of the measurement model. Furthermore, each construct's AVE values were higher than 0.5; 0.664, 0.716, 0.717, 0.785, 0.558 and 0.709 for AIPEU, AIPU, ATAIU, AUAI, AE, and IUAI, respectively. This again suggested that the constructs had sufficient variance captured, despite one item not meeting the loading threshold of 0.7.

Table 2
*Assessment of Reliability and Convergent Validity*

| Construct | Item | Outer loadings | VIF | CA | CR | AVE |
|---|---|---|---|---|---|---|
| AI Perceive Ease of Use | AIPEU1 | 0.795 | 1.971 | 0.831 | 0.833 | 0.664 |
| | AIPEU2 | 0.819 | 1.939 | | | |
| | AIPEU3 | 0.790 | 1.774 | | | |
| | AIPEU4 | 0.855 | 2.282 | | | |
| AI Perceive Usefulness | AIPU1 | 0.830 | 2.017 | 0.868 | 0.874 | 0.716 |
| | AIPU2 | 0.889 | 2.569 | | | |
| | AIPU3 | 0.849 | 2.027 | | | |
| | AIPU4 | 0.816 | 1.918 | | | |
| Attitude towards AI Usage | ATAIU1 | 0.818 | 1.833 | 0.868 | 0.871 | 0.717 |
| | ATAIU2 | 0.818 | 2.106 | | | |
| | ATAIU3 | 0.888 | 2.822 | | | |
| | ATAIU4 | 0.861 | 2.178 | | | |
| Actual Usage of AI | AUAI1 | 0.882 | 2.753 | 0.909 | 0.917 | 0.785 |
| | AUAI2 | 0.853 | 2.669 | | | |
| | AUAI3 | 0.915 | 3.649 | | | |
| | AUAI4 | 0.892 | 2.864 | | | |
| Academic Engagement | AE1 | 0.849 | 1.174 | 0.704 | 0.863 | 0.558 |
| | AE2 | 0.777 | 1.770 | | | |
| | AE3 | 0.727 | 1.725 | | | |
| | AE4 | 0.617 | 1.215 | | | |
| Intention to Use AI | IUAI1 | 0.795 | 1.834 | 0.863 | 0.864 | 0.709 |
| | IUAI2 | 0.838 | 2.154 | | | |
| | IUAI3 | 0.857 | 2.232 | | | |
| | IUAI4 | 0.877 | 2.506 | | | |

Additionally, the Fornell-Larcker Criterion is employed to assess the discriminant validity. This is to determine whether the constructs in the model are distinct, as it is an essential consideration in assessing whether the constructs in the frameworks are measuring something entirely different. The off-diagonal numbers in Table 3 represent the correlation between the different constructs, whereas the square root of the AVE of each construct is shown along the diagonal. The requirement is that the correlation coefficient between a given construct and other constructs must be less than the square root of the AVE of that construct (Fornell & Larcker, 1981). The values for the constructs AE, AIPEU, AIPU, ATAIU, AUAI, and IUAI, which are 0.747, 0.815, 0.846, 0.847, 0.886 and 0.842, respectively, were found to be higher than their correlations with other constructs.

Table 3
*Fornell-Larcker Criterion - Discriminant Validity Analysis*

| Construct | ACAD ENGAGE | AIPEU | AIPU | ATAIU | AUAI | IUAI |
|---|---|---|---|---|---|---|
| ACAD ENGAGE | 0.747 | | | | | |
| AIPEU | 0.444 | 0.815 | | | | |
| AIPU | 0.480 | 0.730 | 0.846 | | | |
| ATAIU | 0.620 | 0.669 | 0.774 | 0.847 | | |
| AUAI | 0.711 | 0.593 | 0.676 | 0.688 | 0.886 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| IUAI | 0.592 | 0.765 | 0.793 | 0.802 | 0.751 | 0.842 |

#### 4.1.2. Structural Model Assessment

In assessing the structural model, the path size, significance of the path, t-value, mean, standard deviation, VIF, effect size (f-square), and predictive relevance (R-squared) were considered. The constructs were examined for any collinearity problems using the VIF; a value greater than 5.0 suggested a potential multicollinearity concern (Hair et al., 2021). As indicated in Table 4, the VIF of the paths ranges from 1.000 to 3.555, indicating that there is no collinearity issue among the paths. Also, the mean value of the paths ranges from -0.179 to 0.732 while the standard deviation ranges from 0.030 to 0.085. All the tested hypotheses were supported. Using a well-adapted threshold, $f2 \geq 0.02$, $f2 \geq 0.15$, and $f2 \geq 0.35$ were considered as small, medium, and large, respectively (Cohen, 1988). The path AIPEU → AIPU ($\beta = 0.730$, $t = 24.520$, $p < 0.05$) was found to be significant with large effect size ($f^2 = 1.141$), AIPEU → ATAIU ($\beta = 0.222$, $t = 2.853$, $p = 0.05$) is also significant with small effect size ($f^2 = 0.061$), while AIPEU → IUAI ($\beta = 0.312$, $t = 6.135$, $p < 0.05$) is significant with moderate effect size ($f^2 = 0.179$). In addition, AIPU → ATAIU ($\beta = 0.611$, $t = 8.964$, $p < 0.05$) is significant with a large effect size ($f^2 = 0.462$), while the paths AIPU → IUAI ($\beta = 0.264$, $t = 6.721$, $p < 0.05$), ATAIU → ACAD ENGAGE ($\beta = 0.216$, $t = 2.541$, $p < 0.05$), and ATAIU → AUAI ($\beta = 0.240$, $t = 3.616$, $p < 0.05$) were all significant with small effect sizes. Also, the path ATAIU → IUAI ($\beta = 0.390$, $t = 7.751$, $p < 0.05$) is significant with moderate effect size ($f^2 = 0.240$) while AUAI → ACAD ENGAGE ($\beta = 0.797$, $t = 11.904$, $p < 0.05$) is significant with large effect size ($f^2 = 0.809$). Additionally, the path IUAI → ACAD ENGAGE ($\beta = -0.179$, $t = 2.426$, $p < 0.05$) is significant with a small effect size, while IUAI → AUAI ($\beta = 0.558$, $t = 9.212$, $p < 0.05$) is significant with a large effect size ($f^2 = 0.267$). In other words, the significance across the paths suggests that AI PEU influences PU, attitude towards AI use, and intention to use AI tools. Additionally, AI PU influences attitudes towards AI use and intentions to use AI tools. In addition, Attitude towards AI use influences academic engagement, actual use of AI tools, and intention to use AI tools. Additionally, the intention to use AI tools influences both academic engagement and actual use of these tools. Lastly, the actual use of AI tools influences academic engagement.

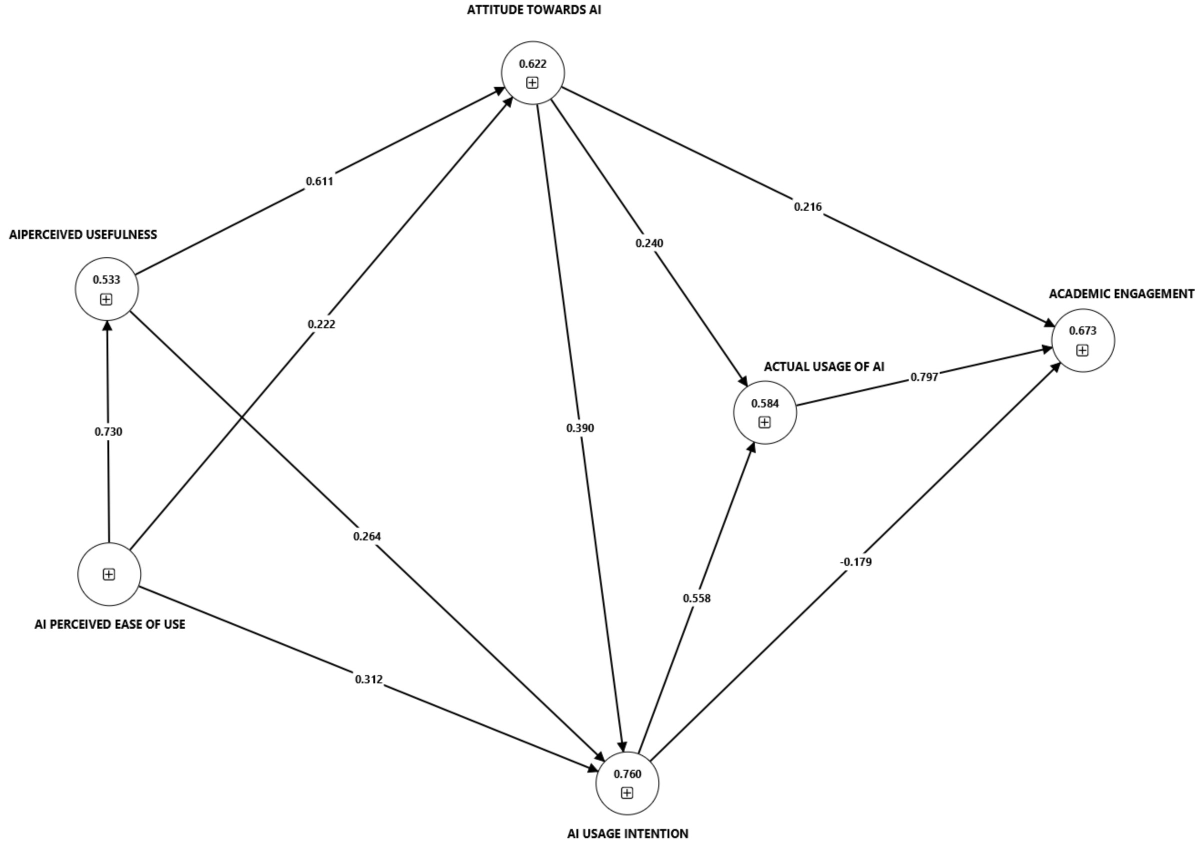
In evaluating the model's explanatory power, the coefficient of determination ($R^2$) is used. A coefficient of determination with an $R^2 \geq 0.19$, 0.33, or 0.67 is considered weak, moderate or strong in the level of predictive accuracy (Ayanwale & Molefi, 2024; Hair et al., 2021). It turns out that the independent factors help predict the dependent variable to a reasonable extent. An explanatory power ($R^2$) measure, with values ranging from 0 to 1, is used to assess the model's performance. Moderate explanatory power, indicated by values less than 0.50, is considered moderate, while high power is indicated by values over 0.50 (Adelana et al., 2024). According to the findings *(see Table 4 and Figure 2)*, ACAD ENGAGE, AIPU, ATAIU, AUAI, and IUAI, with indices of 0.673, 0.533, 0.622, 0.584, and 0.760, all demonstrated a high level of explanatory power. The model's predictive relevance ($Q^2$) was tested; according to (Chin, 1998), a predictive relevance score of zero or higher is deemed adequate. The endogenous variables' ACAD ENGAGE, AIPU, ATAIU, AUAI, and IUAI had $Q^2$ values of 0.190, 0.528, 0.440, 0.348 and 0.584, respectively. All of these factors are important and connected to predicting students' academic engagement as their values are greater than zero.

Table 4
*Summary of Structural Model Assessment*

| Path | β | mean | SD | t-value | VIF | P values | f-square | Result |
|---|---|---|---|---|---|---|---|---|
| AIPEU → AIPU | 0.730 | 0.732 | 0.030 | 24.520 | 1.000 | 0.000 | 1.141 | S** |
| AIPEU → ATAIU | 0.222 | 0.226 | 0.078 | 2.853 | 2.141 | 0.004 | 0.061 | S |
| AIPEU → IUAI | 0.312 | 0.311 | 0.051 | 6.135 | 2.272 | 0.000 | 0.179 | S* |
| AIPU → ATAIU | 0.611 | 0.608 | 0.068 | 8.964 | 2.141 | 0.000 | 0.462 | S** |
| AIPU → IUAI | 0.264 | 0.264 | 0.039 | 6.721 | 3.129 | 0.000 | 0.093 | S |
| ATAIU → ACAD ENGAGE | 0.216 | 0.215 | 0.085 | 2.541 | 2.944 | 0.011 | 0.048 | S |
| ATAIU → AUAI | 0.240 | 0.239 | 0.066 | 3.616 | 2.806 | 0.000 | 0.049 | S |
| ATAIU → IUAI | 0.390 | 0.388 | 0.050 | 7.751 | 2.644 | 0.000 | 0.240 | S* |
| AUAI → ACAD ENGAGE | 0.797 | 0.799 | 0.067 | 11.904 | 2.404 | 0.000 | 0.809 | S** |
| IUAI → ACAD ENGAGE | -0.179 | -0.179 | 0.074 | 2.426 | 3.555 | 0.015 | 0.028 | S |
| IUAI → AUAI | 0.558 | 0.558 | 0.061 | 9.212 | 2.806 | 0.000 | 0.267 | S** |
| Variable | | R-square | Q-square Predict | | | | | |
| ACAD ENGAGE | | 0.673 | 0.190 | | | | | |
| AIPU | | 0.533 | 0.528 | | | | | |
| ATAIU | | 0.622 | 0.440 | | | | | |
| AUAI | | 0.584 | 0.348 | | | | | |
| IUAI | | 0.760 | 0.584 | | | | | |

S=significant with small effect; S*=significant with moderate effect; S**=significant with large effect.

Figure 2
*AI Use and Academic Engagement Structural Model*



### 4.2 Discussion

This study examines the influence of Mathematics undergraduates' perceptions about the usage of AI on their academic engagement while looking at their attitude towards the tools and intention to use the tools. To evaluate the influence of AI tool perceptions, attitude, intention, and actual usage on the academic engagement of mathematics undergraduates, the structural equation modelling (SEM) approach was employed. The study's findings indicated that all the proposed hypotheses (H1 through H11) were supported. AI perceived ease of use (PEU) explains 53.3% of the observed variation in AI perceived usefulness (PU), PEU and PU explain 62.2% of the variation in attitude towards AI tool use, while PEU, PU and attitude towards AI explain 76.0% of the variance in AI usage intention. Similarly, attitude towards and intention to use AI explain 58.3% of the variance in actual use of AI. On the other hand, attitude, AI usage intention, and actual use all explain 67.3% of the variance in academic engagement.

The findings of the study show that AI PEU influences PU. This suggests that students' perceptions of AI tools as easy to operate significantly influence their views on the usefulness of these tools. This aligns with the guiding principles of the TAM, which suggests that when people find technology familiar and straightforward to use, they are more likely to see it as positive and helpful (Davis, 1989). This finding aligns with previous studies (Falebita & Kok, 2024a; Lestari & Indrasari, 2019), which have established PEU as a major influencer of PU. In higher education, this finding highlights the importance of developing user-friendly AI tools. When students are confident, they can use such tools without requiring extensive time or financial investment in training and technical support, and their likelihood of perceiving these tools as beneficial to their studies increases. This underscores the need for educational institutions to prioritise user-friendly AI tools in instructional platforms, so that they are objectively regarded as useful. Additionally, the PEU of AI significantly influences attitudes towards AI use. This suggests that the usability of AI tools has a significant impact on students' attitudes toward using these tools. Particularly, when perceived as being easy to use, students are considered to have a favourable attitude towards AI tools (Chibisa et al., 2022). This finding concurs with previous studies such as (Geddam et al., 2024; Toros et al., 2024), who revealed that PEU determines an individual's attitude towards AI. This implies that there is potential for students to develop a positive attitude toward AI tools and adopt them from the very beginning of their interaction with them. Therefore, the educators and developers should focus on the intuitive design to create positive attitudes towards AI and, ultimately, increase the overall utilisation of AI in the educational context. In addition, the perceived ease of use of AI was found to influence the intention to use AI tools. This suggests that PEU is a key factor in defining students' intention to use AI tools. Feeling that AI tools are easy to use makes students more willing to use them regularly. This result supports the earlier results from various studies, which reveal that the intention to use AI tools is significantly predicted by perceived ease of use (Osman, 2025; Osman et al., 2024). Seamless and efficiently designed AI tools that will attract student attention and encourage them to visit their service frequently are more likely to become popular. Thus, developers are encouraged to ensure that AI tools not only demonstrate utility but also be easy to use, thereby facilitating sustainable and regular use.

The study's findings reveal that the perceived usefulness of AI influences attitudes towards AI use. This demonstrates that students tend to have a positive attitude towards the use of AI tools when they regard them as helpful, especially for enhancing their academic success. This recon with the result from (Geddam et al., 2024) study, which has earlier shown that PU determines attitude towards the use of AI. This also suggests that AI tools, which can be considered to boost academic achievements by helping students comprehend difficult concepts or save time, are more likely to promote a positive attitude among students. Therefore, the purpose of AI tools in enhancing academic achievements must be clearly explained to students so that a positive attitude towards their use can be fostered. In addition, AI perceived usefulness was found to influence intention to use AI tools. The finding emphasizes that the students will express their willingness to use AI tools once they see it beneficial to their learning experience. This finding supports earlier findings from (Mutambara & Chibisa, 2022; Osman, 2025) who revealed that perceived usefulness creates a strong encouragement since it influences the decisions and intentions of students to make use of a technology. This also aligns with the TAM, which suggests that the perceived benefit of using a technology has an impact on behavioural intentions (Davis, 1989). The more students have confidence that AI tools can directly aid their academic achievement, the more they will be encouraged to use these tools in their education. Educators should promote the utilitarian aspects of AI tools, such as improved learning efficiency or personalised learning experiences, to encourage students to incorporate them into their studies.

The results also show that attitudes towards AI use influence academic engagement. This implies that the attitude towards AI tools directly influences the extent of academic engagement that students may perform. This also suggests that a positive attitude towards AI may lead students to be more willing to engage in various academic activities when using AI tools. This observation aligns with the findings of (Aieron A et al., 2024; Anierobi et al., 2025; Ward et al., 2024) which shows that the positive attitude towards the adoption of AI tools promotes academic engagement among students. This further suggests that students with a positive mindset and a belief in AI tools will be more likely to engage in regular academic activities. Thus, the development of a positive attitude towards AI can be regarded as one strategy to increase student engagement in the learning process. Additionally, attitude towards AI use was also found to influence actual use of AI tools. This finding demonstrates that the attitude toward AI tools has an impact not only on the set intentions of students, but also on the degree to which they use such tools themselves. This finding supported the findings of (Ayanwale et al., 2024; Falebita & Kok, 2024a; Toros et al., 2024), who reveal that attitude plays a significant role in the adoption of AI tools. This underscores that the connection between attitude and usage is not merely hypothetical; students with a positive attitude toward AI tools are more likely to use them in their educational process. For students to use AI consistently in their learning, schools need to provide the right tools and create an environment that encourages them to embrace and make the most of these technologies. In addition, the attitude towards AI use was also found to influence the intention to use AI tools significantly. This shows that students with a positive attitude toward AI tools will eventually have a stronger desire to make use of the tools in the future. This observation emphasises the cyclic attitude-intention relationship: a positive attitude leads to a more serious intention to apply AI tools, which, in turn, increases the chances of actual use (Mutambara & Chibisa, 2022; Osman, 2025). To foster a long-term intention to utilise AI tools, educators can create an environment that encourages students to develop positive attitudes towards platforms, tools, and technologies, thereby facilitating their gradual adoption in academic contexts over time. Therefore, it is essential to establish an acceptance and appreciation for the use of AI tools so that they can be utilised engagingly.

The study's results indicate that the actual use of AI tools has a significant influence on academic engagement. This finding establishes a direct correlation between the actual use of AI tools and the academic engagement of mathematics students. When students get engaged in their learning through the application of AI tools, they will be more engaged in their studies. This conclusion supports the argument that engagement is an active process, and it depends on the tools that students have to explore their education (Aieron A et al., 2024; Wang & Xue, 2024). This further suggests that the AI tools actively applied in the learning environment enable students to become deeply engaged with the material, providing them with timely feedback and allowing them to interact with the content in meaningful ways. In this way, the more students apply AI tools, the more they become academically engaged, and consequently, their learning outcomes improve.

The study reveals that the intention to utilise AI tools influences academic engagement. This suggests that the willingness of students to use AI tools may cause an indirect impact on their academic engagement. When students intend to use AI tools, they will be more engaged with the tool once it becomes accessible to them, which enables them to be more engaged with academic tasks (Wang & Xue, 2024). This means that the development of an intention to apply AI tools may increase the degree of involvement in the learning process. The most important part is to motivate students to perceive the opportunity of AI tools in enhancing their learning experience, ensuring that they will implement this intention and utilise the technology in a meaningful way. Additionally, intention to use AI tools was also found to influence actual use of AI tools. This establishes the fact that the higher the chances of students having the implementation intention of AI tools, the more likely they are to use them. The observation aligns with the statement made by TAM that intention is one of the mediators of technology adoption (Davis, 1989). Students are more willing to pursue and work with AI tools, as long as they are motivated by the intentions behind their use (Ayanwale & Ndlovu, 2024; Mutambara & Chibisa, 2022; Osman, 2025). Institutions of learning should make opportunities available for utilising AI tools by initiating AI literacy. Positive intent will also maximize consistency and the quality of using AI tools provided by the teacher, which will eventually result in better engagement and academic performance. In addition, the development of a healthy perception of AI can make students question the usage and consequences of the technology. When interacting with AI tools, the students need to be prompted to analyze and understand their learning experiences and findings, as well as form a perspective with regard to innovation and ethical aspects of using the technology. The greater level of mental interaction does not just improve their academic performance but also makes them ready to handle the challenges that an AI-driven world will bring.

**Limitations**

This research has limitations, despite its interesting results. Only students enrolled in mathematics education and mathematics sciences programs at public institutions in southwest Nigeria were considered for participation in the study. Therefore, to fully comprehend the influence of undergraduates' perception regarding AI tools on their academic engagement, it is essential to take into account the involvement of students from different disciplines within the university system, as well as from other geographical places. Additionally, TAM has been widely used to explore factors impacting the adoption of AI; there is a need to explore other theories in this direction. Furthermore, using just a quantitative approach limits the quality of data obtained from students on the variables considered concerning AI tools usage and academic engagement. For triangulation reasons and to account for other variables that could influence the adoption of AI tools and academic engagement, a mixed-method approach should be taken into consideration.

## 5. Conclusion

In conclusion, this study underscores the important role AI tools play in enhancing students' academic engagement. The results indicate that students' perceptions of AI tools' ease of use, their usefulness, attitudes and intentions towards using them all significantly influence the extent to which AI is incorporated into their learning. To make AI tools more effective, schools need to focus on making them user-friendly, promoting positive attitudes towards AI, and encouraging students to engage with these tools actively and ethically. The study also contributes to the understanding of how AI is adopted in education, strengthening established theories like the TAM, and highlighting the importance of students' intentions to use AI. Ultimately, this research provides useful insights for educators and institutions looking to harness AI tools to improve learning outcomes. Looking ahead, more research is needed to further explore the factors influencing AI adoption and how it can be optimized to better support students' academic journeys.

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**Author Contribution**

Author 1: Conceptualization, Writing - Original Draft, Data analysis, Editing and Visualization;
Author 2: Writing - Review & Editing,
Author 3: Validation and Supervision.

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**Conflict of Interest**

The authors declare no conflict of interest.

**Additional Information**

Additional information is available for this paper.

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