



Determinants of AI-Driven Tools Adoption by Senior High School Mathematics Teachers: A Partial Least Squares Structural Equation Modelling Approach

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Abstract

The integration of artificial intelligence-driven tools in education has become increasingly popular and widespread in recent years. This study, therefore, investigated how the constructs of the Unified Theory of Acceptance and Use of Technology predict senior high school mathematics teachers' intention to adopt and use AI tools in their lessons. The study employed a quantitative cross-sectional survey design and a structured questionnaire to collect data from 141 mathematics teachers at selected public senior high schools in the Kumasi metropolitan area. The questionnaire showed acceptable reliability ($\alpha > 0.70$). Data was analysed using PLS-SEM in SmartPLS4. Results show that teachers' behavioural intention to adopt AI tools is significantly influenced by Performance Expectancy ($\beta = 0.405$, $t = 4.841$, $p < .001$), Social Influence ($\beta = 0.192$, $t = 2.344$, $p = .019$), and Facilitating Conditions ($\beta = 0.240$, $t = 2.807$, $p = .005$). However, Effort Expectancy ($\beta = 0.136$, $t = 1.751$, $p = .080$) was not a significant predictor. This study provides valuable insights into the factors that influence how senior high school mathematics teachers perceive and intend to integrate AI tools into their teaching practices. The study also provides practical suggestions for school authorities and administrators on how to ensure the smooth integration of AI tools to enhance mathematics teaching.

Keywords: Artificial Intelligence, Behavioural intention, Mathematics education, Teacher adoption, UTAUT

Introduction

Mathematics is generally viewed as a key subject in students' education, as it serves to develop their critical thinking and problem-solving skills (Awuah & Ogbonnaya, 2020). These skills are considered essential for the advancement of science and technology, which drive nations' economic development and significance. This is why mathematics is a core component of most education curricula worldwide (Oppong-Gyebi et al., 2023). However, evidence suggests that many students perceive mathematics as complex, struggle to learn and understand mathematics, and generally do not perform well in the subject (Aguilar, 2021; Akpalu et al., 2025; Bornaa et al., 2023).

To enhance students' learning of mathematics, various technological tools have been employed in the teaching and learning process over the years. In recent decades, various computer technologies have been utilised for teaching and learning mathematics, and some of these technologies have been found to

benefit students' understanding of certain mathematical concepts and their performance on the subject (Liaga et al., 2025; Ogbonnaya & Mushipe, 2020).

The rapid advancements in Information and Communication Technologies (ICTs), particularly in machine learning and artificial intelligence, over the past decade, have brought about significant transformations in the educational landscape. Today, Artificial Intelligence (AI) has gained widespread adoption in education across many parts of the world, particularly in developed countries such as the USA, China, and the UAE, among others, where significant investments in educational technology are being made (Elad, 2025; Townsend, 2025).

The adoption of AI in the educational arena has significantly impacted various aspects of the educational process, including teaching, learning, and general management. For example, Intelligent Tutoring Systems (ITS); AI driven learning systems

that provide personalised and adaptive instruction for students (Lin et al., 2023), can be utilised to provide students with individualised instruction that is similar to one-on-one human tutoring, thereby making the delivery of educational content tailored to the specific needs of the individual student (Imamguluyev et al., 2024). AI systems can assist teachers with various administrative tasks, including lesson planning, assessment, grading, and managing student records (Lappay et al., 2025).

Although AI seems to be widely adopted in education in some parts of the world. In the developing countries in the global south, its adoption is still limited (Khan et al., 2024; Modiba et al., 2025; Mokoena & Seeletse, 2025). Many factors, including usefulness, ease of use, institutional support, social context, etc, influence the adoption of new technology in education (Lappay et al., 2025; Ogbonnaya, 2019; Venkatesh et al., 2003). In Ghana, there is limited knowledge about teachers' adoption of AI in education. Understanding the disposition and utilisation of AI by teachers, especially mathematics teachers, is important, as students' meaningful mathematics learning is imperative for the country's technological and economic development. This study, therefore, examined the determinants of AI tools adoption by senior high school mathematics teachers.

Theoretical Background

To achieve this study objective, the researchers used the Theory of Acceptance and Use of Technology (UTAUT) as the theoretical basis for the study design, data collection and analysis, and interpretation of the findings (see Figure 1). The theory, as proposed by Venkatesh et al. (2003), suggests that an individual's intention to adopt and use a technology depends on psychological and social factors. They explain that these factors include the individuals perception of how the technology can be effective in helping them achieve their work goals (Performance Expectancy), how easy or difficult is it to operate the technology or the effort required to manage the technology (Effort Expectancy), their perception of availability of both human and infrastructural resources that will ensure smooth operation of the technology (Facilitating Conditions) and how important people in their work place thinks about the new technology (Social Influence). They further suggest that these factors are moderated by age, experience, voluntariness of use, and gender. In this study, the researchers excluded the moderating factors for several reasons. Firstly, the use of AI tools in the classroom in Ghana is at an early stage; hence, experience and voluntariness of use are not expected to have a significant impact on teachers' adoption intention. Moreover, this study does not aim to examine how other moderator variables affect adoption; hence, only the four primary constructs and their effects on behavioural intention are studied.

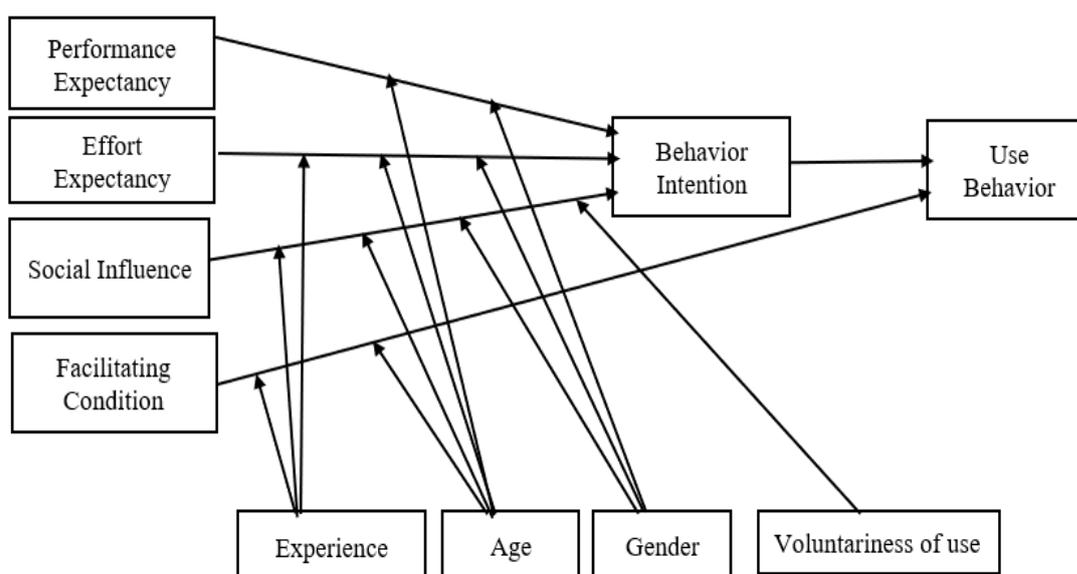


Figure 1: Unified Theory of Acceptance and Use of Technology

Hypothesis development

Performance expectancy

Before an individual decides to adopt a particular technology, Venkatesh et al. (2003) argue that the individual must be convinced that the technology will be effective in helping them accomplish a specific task effectively. This perceived effectiveness is referred to as performance expectancy. This concept of effectiveness of a technology is explained similarly by the Technology Acceptance Model (TAM) as perceived usefulness (Davis, 1989). This perceived usefulness explains why users believe that using a technology will improve their job performance. This concept stresses the usefulness of a technology to the user. Across various sectors, performance expectancy has emerged as a strong determinant of technology adoption and users' intention to use a particular technology (Batucan et al., 2022; Chao, 2019; Diao et al., 2024; Jadil et al., 2021). The findings from these studies largely align with those of Agarwal and Prasad (1998) who argued that performance expectancy was the most influential factor in the UTAUT framework. Drawing on results from these previous studies, it can be argued that senior high school mathematics teachers will be more willing to adopt AI technologies in their teaching if they perceive that these technologies will help them work more efficiently.

Effort expectancy

Effort expectancy (EE) is a key variable that explains users' perception of how easy or difficult it will be to use a technology (Venkatesh et al., 2003). In all the Technology Acceptance Models (TAM/TAM2/TAM3), this idea has been referred to as perceived ease of use (PEOU) (Davis, 1989). EE has emerged as a key predictor of intention to use a technology in several educational technology studies. For instance, Hu et al. (2020) identified EE as a key determinant in acceptance of emerging technologies in the classroom. Moreover, in other studies like Das and Datta (2024) and Acquah et al. (2024), EE was found to be a key determinant of adoption. According to Wu et al. (2023), when a system has a friendly user interface, it reduces the effort required to use the system and increases the likelihood of its use. Consequently, if the teachers perceive AI tools as easy to use, they are likely to adopt them.

Social Influence

In the Theory of Planned Behaviour, Fishbein and Ajzen (1975) introduced the concept of Subjective

norms to explain how people accept technologies based on how important figures perceive them. They argue that in a corporate environment, people adopt technologies when they believe their colleagues or superiors will support them. Similar ideas are espoused in the UTAUT as proposed by Venkatesh et al. (2003). They put forward an argument that people tend to accept new technologies when they perceive their peers, working colleagues, and significant others agree to their use. Cortez et al. (2024) and Strzelecki (2024) further explain that social influence concerns interpersonal relationships in shaping individuals' decisions to adopt new technologies. Even though these arguments may allow for optionality, Venkatesh (2022) thinks that social influence may not always be about an individual's choice to make a decision based on others' perceptions, but may be driven by compulsion, as some decisions to adopt a technology may be obligatory rather than voluntary. This assertion may help explain the inconsistent findings regarding the impact of social influence on the adoption of technology. In this study, the researchers postulate that mathematics teachers will be inclined to adopt AI tools in their teaching when they perceive that their colleagues, supervisors, and school administrators will support their use.

Facilitating Conditions

Facilitating conditions refer to the extent to which an individual believes that resources are available to support the use of technology (Venkatesh, 2022; Venkatesh et al., 2003). Several studies have consistently demonstrated that facilitating conditions are a key determinant of technology adoption (Alkaabi et al., 2025; Garcia-Varela et al., 2025; Onalapo & Oyewole, 2018). Arthur et al. (2025) further demonstrated that facilitating conditions play an important role in the adoption of ChatGPT by higher education students. The researchers believe that if teachers perceive the availability of suitable infrastructure, internet, computers, and support staff, they will be inclined to adopt the AI tools in their lesson delivery.

Based on the previous findings, the researchers propose the following study model and study hypotheses.

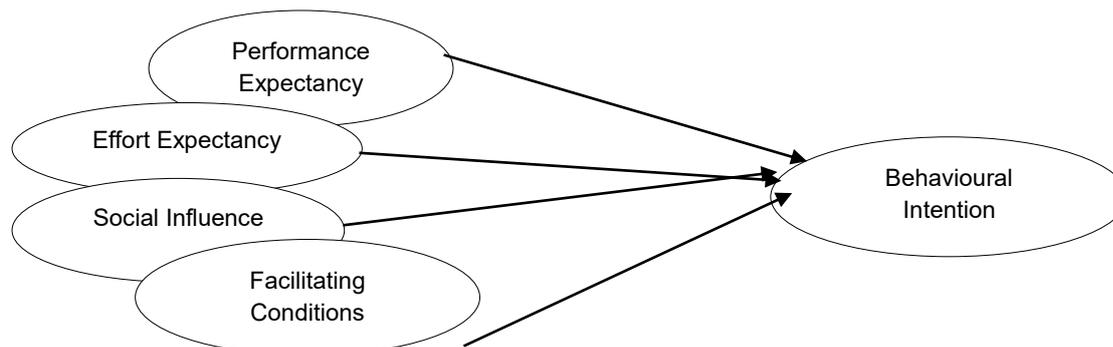


Figure 2: Study model by Authors

The following hypotheses were proposed for testing, as presented in the conceptual framework in Figure 2

- H1: Performance expectancy positively influences teachers’ adoption behaviour
- H2: Effort expectancy positively influences teachers’ adoption behaviour
- H3: Facilitating conditions positively influence teachers’ adoption behaviour
- H4: Social influence positively influences teachers’ adoption behaviour

Methodology

The study employed a cross-sectional survey design (Creswell & Creswell, 2023). Data were collected from 141 mathematics teachers using a closed-ended questionnaire adapted from Venkatesh et al. (2003), comprising 20 items (had four for each of the five constructs of UTAUT). All items on the instruments were rated using a five-point Likert scale: 1=

Strongly Disagree, 2= Disagree, 3= Neutral, 4= Agree, and 5= Strongly Agree. The items were adapted from Venkatesh et al. (2003) to align with the study objective of examining teachers' AI adoption intention. The questionnaire was distributed online using Google Forms to facilitate data collection and for a wider reach (Nyaaba et al., 2024).

The internal consistency reliability of the data collection instrument was measured using Cronbach’s alpha. The pilot study was conducted with 37 respondents. All the constructs showed a satisfactory reliability with alpha (α) values above 0.70, as shown in

Table 1. The results indicate that the questionnaire was reliable and appropriate for data collection (Cheung et al., 2024).

Table 1: Reliability results for pilot study

Construct	Cronbach’s alpha
Performance expectancy	0.850
Effort expectancy	0.709
Social influence	0.812
Facilitating conditions	0.871
Behavioural intention	0.711

Source: Authors

The minimum number of respondents needed for a model of four predictors was determined to be 129 using a priori power analysis, as proposed by Kang (2021). *G*Power software* was used with the following parameters: effect size (0.15), power (95%), and significance level (0.05). Data were analysed using partial least squares structural

equation modelling (PLS-SEM) on SmartPLS4 (Ringle et al., 2024).

Findings

The result presentation followed the two-stage procedure proposed by Hair et al. (2017) and Ringle et al. (2020). The two steps involved the outer model

assessment and the inner model (structural path) assessment.

Measurement Model Assessment

To ensure the model's robustness, the researchers evaluated the reliability and validity of the constructs PE, EE, SI, FC, and BI. The assessment employed Cronbach's alpha, composite reliability, average variance extracted, and discriminant validity using the Heterotrait-Monotrait (HTMT) ratio (Cheung et al., 2024).

Convergent Validity and Reliability

Construct validity, which indicates how well the instrument measures theoretical concepts, was assessed. According to Hair et al. (2018), an item's factor loading can be used as a criterion for assessing its validity. In this study, a minimum threshold value

of 0.5 for factor loading was considered appropriate (Barua & Urme, 2025). As presented in Table 2, all items have loadings greater than the threshold. EE4 and FC1, representing effort expectancy and facilitating conditions, respectively, showed loadings below the minimum; hence, they were removed from the analysis.

Internal consistency reliability was measured using Cronbach's alpha and composite reliability at a minimum value of 0.7 (Das & Datta, 2024). The constructs showed strong internal consistency, as the values were above the minimum (see Table 2). The alpha values of EE and FC, which are slightly below the usual limit, are acceptable given the exploratory nature of the study (Nunnally, 1978). Moreover, alpha values ranging between 0.6 and 0.7 are deemed acceptable if the items were adapted (Izah et al., 2023).

Table 2: Validity and Reliability

Constructs	Items	Factor Loadings	CA	CR	AVE
Behavioural intention	BI1	0.815	0.759	0.845	0.584
	BI2	0.845			
	BI3	0.539			
	BI4	0.816			
Effort Expectancy	EE1	0.865	0.669	0.811	0.597
	EE2	0.852			
	EE3	0.564			
Facilitating conditions	FC2	0.628	0.667	0.769	0.534
	FC3	0.628			
	FC4	0.902			
Performance expectancy	PE1	0.875	0.852	0.900	0.693
	PE2	0.891			
	PE3	0.759			
	PE4	0.799			
Social influence	SI1	0.642	0.804	0.868	0.625
	SI2	0.801			
	SI3	0.868			
	SI4	0.832			

To determine whether related items correlated strongly, the convergent validity of the items was assessed using the AVE (see Table 2). All values exceeded the 0.5 threshold proposed by (Fornell & Larcker, 1981). This suggests that all the correlates strongly measure an underlying construct.

Discriminant validity

Discriminant validity was measured using the Fornell-Larcker criterion. The criteria state that the

square root of the AVE of every construct must be greater than that of other constructs. To further evaluate discriminant validity, we used the Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2015). They proposed that HTMT values must be below 0.85 to establish discriminant validity. The values presented in

Table 3 and Table 4 show that all the constructs are distinct from one another.



Table 3: Results of the Fornell-Lacker criterion for discriminant validity

Latent variable	BI	EE	FC	PE	SI
Behavioural intention	0.764				
Effort expectancy	0.471	0.773			
Facilitating condition	0.556	0.343	0.731		
Performance expectancy	0.634	0.412	0.436	0.833	
Social influence	0.513	0.447	0.485	0.355	0.791

Source: Authors

Table 4: Discriminant validity of the variables (HTMT ratio)

Latent variable	BI	EE	FC	PE	SI
Behavioural intention					
Effort expectancy	0.593				
Facilitating condition	0.651	0.689			
Performance expectancy	0.778	0.523	0.512		
Social influence	0.587	0.655	0.669	0.416	

Source: Authors

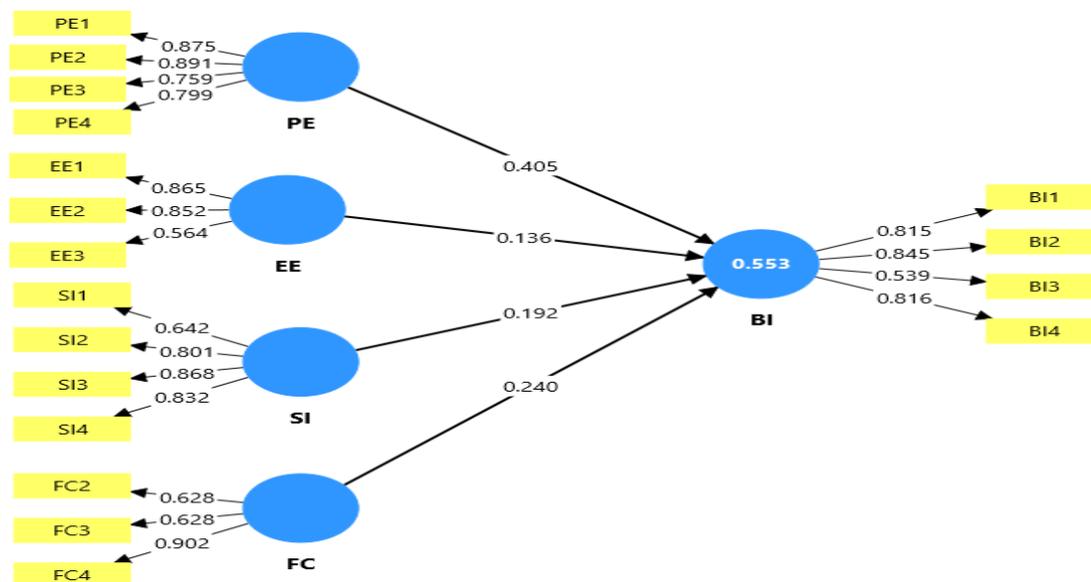


Figure 3: PLS-SEM outer model

Structural model evaluation

This stage examines the values that establish the model’s predictive relevance. Key criteria, including the coefficient of determination (R^2), path coefficients, and t-statistics, were analysed.

Collinearity Test (VIF)

To ensure that the contributions of the exogenous variables to the endogenous variable do not

overlap, checks for possible collinearity was conducted (Barua & Urme, 2025).

Table 5 presents the variance inflation factor (VIF), which measures the degree of collinearity among the predictor variables. Hair et al. (2018) suggested that VIF values below 5 are generally acceptable, indicating no collinearity. The results indicate no collinearity, suggesting that each construct makes a unique contribution to explaining the dependent variable.

Table 5: Collinearity statistics (VIF)

Construct	BI
Behavioural intention	
Effort expectancy	1.382



Facilitating conditions	1.467
Performance expectancy	1.376
Social influence	1.492

Source: Authors

Path Analysis

To assess the hypothesised paths, a bootstrapping procedure was conducted using 5000 subsamples. The results presented in

Table 6 and visualised in Figure 4 show that Performance Expectancy ($\beta=0.405$, $t\text{-value}=4.841$,

$p < 0.001$), Facilitating Conditions ($\beta = 0.240$, $t\text{-value} = 2.807$, $p = .005$), and Social Influence ($\beta = 0.192$, $t\text{-value} = 2.344$, $p = .019$) had a positive and significant effect on teachers' Behavioural Intention to adopt AI tools in their lesson delivery. However, Effort Expectancy ($\beta = 0.136$, $t = 1.751$, $p = .080$) showed a positive but nonsignificant effect.

Table 6: Direct effects of UTAUT constructs on BI

Hypothesis	Path	β	M	SD	t-values	p-value	Results
H1	PE -> BI	0.405	0.397	0.084	4.841	0.000	Supported
H2	EE -> BI	0.136	0.145	0.078	1.751	0.080	Not supported
H3	FC -> BI	0.240	0.251	0.085	2.807	0.005	Supported
H4	SI -> BI	0.192	0.193	0.082	2.344	0.019	Supported

Source: Authors

Coefficient of Determination (R^2)

R^2 measures the extent to which exogenous variables explain the variation in the endogenous variable. As illustrated in Figure 4, the R^2 value for the BI was 0.553. This indicates that 55.3% of the variation in teachers' intention to adopt AI tools in their teaching is explained by exogenous variables. Researchers suggest that R^2 values of 0.25, 0.50, and 0.75 are weak, moderate, and strong, respectively (Barua &

Urme, 2025; Hair et al., 2021). Therefore, the R^2 value in this study was considered moderate.

Effect Size (f^2)

To assess how each predictor variable uniquely contributes to the variance in the dependent variable, the effect size was determined. Cohen (1988) outlined effect size values and their interpretation as presented in

Table 7. The results show that PE showed a medium effect, while the rest exhibited small effects.

Table 7: Effect sizes of exogenous variables

Construct	f^2	Cohen's interpretation
Performance expectancy	0.267	Medium effect
Effort expectancy	0.030	Small effect
Social influence	0.055	Small effect
Facilitating conditions	0.087	Small effect

Source: Authors

Predictive Relevance (Q^2)

The main objective of this study was to model how the UTAUT constructs predict mathematics teachers' adoption behaviour of AI tools in their lessons. To achieve this, the predictive relevance of

the model must exceed zero ($Q^2 > 0$) (Hair et al., 2021). The model's predictive relevance is above zero, demonstrating the predictive significance of the exogenous variables (see Figure 4)

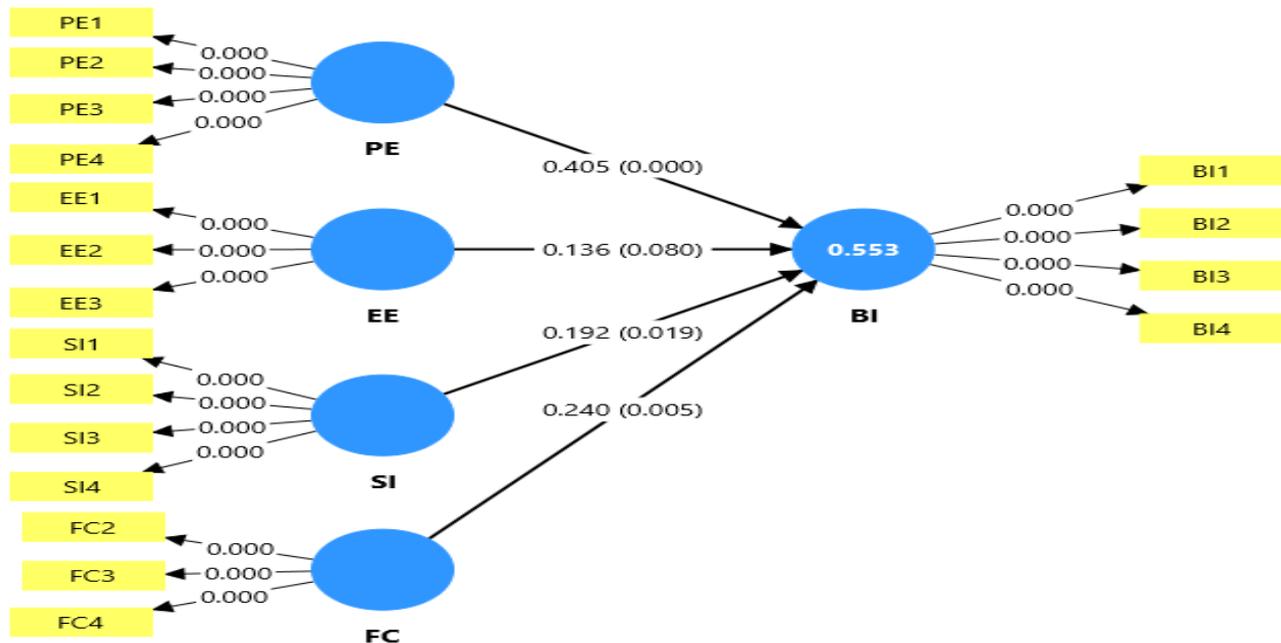


Figure 4: Bootstrapping results of the PLS-SEM

Discussion

The aim of this study was to determine how the constructs of UTAUT predict the intention of mathematics teachers in selected public senior high schools in the Kumasi metropolitan area to adopt AI-driven instructional tools. This section presents the findings in relation to the research hypotheses.

H1 postulated that performance expectancy (a dimension of AI-powered tools) would significantly influence mathematics teachers' decision to adopt AI tools in their teaching. Findings from the study validated this hypothesis as performance expectancy emerged as the strongest predictor of adoption behaviours ($\beta = 0.405$, $t = 4.841$, $p < .001$). This aligns with the key proposition of Venkatesh et al. (2003) which rates PE as the highest predictor of technology adoption. This result suggests that mathematics teachers perceive AI tools as a means to augment their efforts by providing personalised feedback to students with learning needs, grading, and assisting in preparing lesson plans, among other uses. AI learning platforms (such as ALEKS, MathGPT, Khan Mingo) can reduce teacher workload by helping them prepare lessons, and analyse students' performance to identify at-risk students (Tan et al., 2025). If teachers believe that these AI-powered tools can help reduce their workload, they will be more inclined to adopt them. Our findings align with those of Hu et al. (2020) who found that performance expectancy strongly influenced teachers in higher education institutions to adopt emerging technologies for instructional purposes. More importantly, the finding establishes a strong relationship between performance expectancy and adoption. This study contributes to previous

research that supports the notion that the effectiveness of AI tools is the primary consideration for adoption. Policy-wise, the findings can inform policymakers of the value teachers place on how technologies can augment their work rather than just adding to the plethora of existing technologies.

Regarding hypothesis 2, the findings demonstrated that ease or difficulty of using AI tools did not significantly influence their adoption ($\beta = 0.136$, $t = 1.751$, $p = .080$). This suggests that the teachers did not place much emphasis on the operational difficulties of these tools. This may have arisen for two reasons. Firstly, there is a possibility that the teachers believe they have attained basic technological skills (Ghalia & Karra, 2023), which will enable them to operate AI tools with less difficulty or even with minimal training. On the other hand, the teachers may have underestimated the difficulties associated with these tools because they have not had a sustained engagement with them. Even though this finding contradicts that of Acquah et al. (2024), who found that effort expectancy was a major predictor of the adoption of *T-Bot* AI tool for lesson planning among preservice teachers, it aligns with those previous studies, such as Alruthaya et al. (2025), Ayaz and Yanartaş (2020), and Surya Bahadur et al. (2024), who found that effort expectancy was not a determinant of technology adoption.

The finding supported hypothesis 3, reinforcing the role of facilitating conditions in determining the adoption of AI tools among the teachers. This finding gives a clear indication that the teachers will adopt and use AI tools if they perceive the availability of resources and institutional support. Continuous

professional training, the availability of support staff, computers, and high-speed internet, not only ensure the adoption of these tools but also their sustainable usage in the classroom. Findings from previous studies that examined determinants of technology adoption (e.g., Acquah et al., 2024; Das & Datta, 2024; Venkatesh, 2022) are corroborated by this finding.

Social influence emerged as a major predictor of AI adoption among the mathematics teachers in this study, indicating that the teachers value the opinions of colleagues and other influential personalities. It may also be a result of what Venkatesh (2022) noted as a compulsion rather than volition. That notwithstanding, these results clearly align with those of recent studies, as they also found the same results (Azizi et al., 2020; Bhukya & Paul, 2023; Bowers et al., 2024; Cortez et al., 2024). In institutions such as senior high schools, where teachers primarily interact and share knowledge on subjects, this finding is crucial, as it can help sustain AI use among teachers. Nevertheless, this will be more effective if school authorities deliberately implement reforms to ensure that teachers work in a professional learning community, where they meet periodically to share ideas.

Conclusion

This study aimed to determine how the four basic constructs of UTAUT predict senior high school mathematics teachers' behavioral intention to adopt AI tools in their lessons. Findings reveal that teachers are more inclined to adopt these tools if they perceive that they can help them become more effective teachers. Moreover, social influence and facilitating conditions were also significant predictors. Ease of use was not supported, suggesting that the teachers were not particularly concerned about the ease or difficulty of operating these AI tools.

This study contributes to the literature by identifying how psychological and social factors, as espoused in UTAUT, predict mathematics teachers' intention to adopt AI tools. This is important as this study models the adoption perception of a unique group of individuals in the education ecosystem. Additionally, it presents empirical findings on what is necessary to ensure the practical and sustainable use of AI tools in the mathematics classroom.

Recommendations

Based on the findings, the following recommendations have been proposed.

1. Policymakers and school authorities must prioritise providing infrastructure to schools in order to aid the proper integration of AI

2. Teacher training programs and continuous professional training must be focused on demonstrating the effectiveness of AI tools rather than putting more emphasis on just adoption.

Limitations and suggestions for future studies

This study employed a cross-sectional approach to collect data from respondents. Future studies may adopt a longitudinal approach to track adoption patterns across contexts and subject areas. Future studies may also extend this study to areas with scarce resources, as this study was conducted in an urban area where teachers may have access to sophisticated resources.

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