

Research Article

Investigating the factors influencing university students' adoption of technology for mathematics learning: A hybrid of TAM and TPB frameworks

Asante Gideon ^{1,*} , Yarhands Dissou Arthur ¹ , Ebenezer Appiagyeyi ¹ , and Ebenezer Kwesi Lotey ¹ ¹ Department of Mathematics Education, Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development, Ghana

* Correspondence: asantegideonprosper@gmail.com

<https://doi.org/10.59652/jetm.v3i3.612>

Abstract: This study investigates university mathematics student facilitators' technology adoption for mathematics learning, focusing on factors that predict actual technology use (ATU), as well as identifying the types, frequency, and purpose of participants' technology use while learning. Using a sample of 362 pre-service facilitators from Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development (AAMUSTED) – Kumasi campus, and a quantitative approach, the researcher employed a hybrid of the Technology Acceptance Model (TAM) and Theory of Planned Behaviour (TPB) to analyse how perceived behavioural control usefulness, attitudes, subjective norms, and ease of use influence ATU. The results revealed heavy reliance on basic tools such as calculators and YouTube but minimal adoption of advanced software like GeoGebra. Mostly, these tools were used to complete assignments. The regression analyses indicated that technology usefulness and easiness significantly predict students' attitudes regarding the use of digital tools for mathematics learning where usefulness was the stronger predictor of attitude. Additionally, attitude, peers or lecturers' influence, and students' technology confidence collectively predict ATU. The study identifies low self-beliefs (perceived behavioural control) as critical barriers to students' inability to use advanced digital tools when learning. Recommendations from this investigation include structured professional development, enhanced institutional support, and curriculum-integrated technology tasks that focus on advanced technology integration.

Keywords: University students; TAM-TPB hybrid; mathematics learning; regression analysis; technology adoption

Received: May 4, 2025

Accepted: July 18, 2025

Published: July 25, 2025



Copyright: © 2022 by the authors.
Submitted for open access publication
under the terms and conditions of the
Creative Commons Attribution (CC BY)
license
(<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The application of technology in the education has gained significant attention in the past twenty years, especially in developed nations (Facer & Selwyn, 2021). Early in 2020, a worldwide breakout of the deadly coronavirus (Covid-19) pandemic served as a catalyst, speeding up the use of technology in the classroom and emphasizing its vital role in maintaining learning continuity in these exceptional circumstances. The pandemic compelled educational establishments across the globe to close their physical classrooms, depriving more than 1.5 billion students of access to conventional learning settings (Bozkurt, 2016). The epidemic made clear how vital it is to fund instructional technologies and close the digital gap (Nhamo et al., 2024). Traditional teaching and learning approaches have changed in recent years as a result of the integration of technology into education (Alam, 2022; Burbules et al., 2020). More interactive, tailored, and effective learning experiences are now possible because of the quick development of digital tools and platforms, which has opened up new possibilities for both students and teachers (Bonfield et al., 2020; Haleem et al., 2022). The use of digital tools and platforms has led to notable advancement in mathematics instruction and student performance (Kliziene et al., 2021).

These technologies, which range from specific mathematical software such as GeoGebra, Microsoft Mathematics, Mathematica, Desmos, MATLAB, and Photomath to online learning management systems, have the potential to improve student's mathematical

comprehension, engagement, and performance (Dahal et al., 2022; Uwurukundo et al., 2022). Some authors (Dahal et al., 2022) noted that while graphing calculators like Desmos can plot different graphs together which is very helpful for students learning coordinate geometry concepts and can handle simultaneous equations as well as other variable-based problems in algebra mathematics, Microsoft mathematics is a game-changing technology that greatly improves the educational experience for students who are having difficulty with mathematics (Mendezabal & Tindowen, 2018; Rabi et al., 2021). Microsoft Mathematics assists students in overcoming challenges and developing a strong grasp of mathematical ideas by promptly identifying problems and offering thorough, iterative answers. It is an interesting and useful tool for students of all skill levels because of its customizable and interactive features. Mathematics digital tools which are developed for manipulative purposes like Geoboard, and Mathigon advance conceptual understanding of mathematics, which is concerned with ideas or responding to inquiries about how and why a certain body of knowledge or concept works (Álvarez et al., 2024; Chan & Leong, 2024). Ge, Ifenthaler, and Spector (2015) argued that visual representation tools are crucial for drawing student's attention, identifying misconceptions, and facilitating a comprehensive conceptual understanding of mathematics. Recently in Ghana, students and teachers now have greater access to technology due to the widespread distribution of digital gadgets like laptops, and tablets (Bandoh et al., 2024). Students' and facilitators' views in relation to technology use are likely regulated by the teaching-learning experiences.

Some authors (Banafaa et al., 2023; Lotey et al., 2023) claim that improvements in ICT have produced many advantages, such as new channels for communication, learning, and even how individuals function in society. In support of this claim, Bandoh, Akweitley, Lotey, Gordon, and Appiagyei (2024) assert that ICT use engages and excites students, making it one of the educational learning engines. The opportunities for global education have increased with the introduction of advanced educational software and Internet platforms. Universities benefit greatly from technology since it enables them to offer quality and effective instruction to students who will soon become technology experts. Academic development depends on effective study techniques because every student learns differently (Bevan et al., 2020). University students integrate technology into their education in several ways including searching for information, doing assignments, collaborating, and communicating since they are exposed to it regularly. Students' perceptions of these technological tools are important because their opinions regarding these tools affect how they use technology in their academic endeavours. As a result, researchers are now more interested in the study of these perceptions (Salta et al., 2022). Although a positive assessment of ICT components is a crucial first step in incorporating technology into the learning process, it does not guarantee that it will be adopted for lifelong learning among students (Gkrimpizi et al., 2023).

Despite the potential benefits of technology in enhancing mathematics education, adoption remains low in Ghanaian universities, especially among students. This problem raises questions among students concerning the potential acceptance and use of these technologies. Student's adoption of technology is influenced by their perspectives (Amri & Almaiah, 2021; Phutela & Dwivedi, 2020). Students who see technology to be useful are more inclined to its application in their concept acquisition (Liu & Ma, 2023). Contrary, students who view learning as passive knowledge acquisition, could rely on technology to retrieve information, such as automatic problem solvers or video lessons (Jeong & Hmelo-Silver, 2010; Pather et al., 2020). Additionally, how students incorporate digital tools into their study habits and academic pursuits is influenced by their motivation, experience, and level of technological confidence (Rashid & Muhammad Asghar, 2016). Therefore, understanding the factors influencing student's adoption of technology for learning mathematics is essential so that university institutions may plan and provide their services to the learners in a manner that aligns with that. While the factors affecting the adoption of technology among university students have been studied in previous research (Sayaf et al., 2022; Yakubu & Dasuki, 2019), it remains underexplored the factors that affect the adoption of technology among university students in mathematics from the perspective of Ghanaian student's using the hybrid of Technology Acceptance Model (TAM) and Theory of Planned Behaviour (TPB) frameworks.

Additionally, studies show that various factors related to student's perception of ICT affect the extent to which these tools might be effectively utilized. However, explaining the adoption of technology by combining the TAM and TPB in Ghanaian universities is less focused in the broader literature. In an exempt to fill these gaps, this study explores the types, purpose, and frequency by which university students use technology for learning mathematics and predicts the factors responsible for students' actual technology use (ATU) based on the

hybrid of TAM and TPB. The purpose of this investigation was achieved based on the following questions:

1. What types of technology do university mathematics students use for learning mathematics, and what are the purposes and frequency of their use?
2. How do technology easiness and usefulness predict university students' attitudes toward adopting technology for mathematics learning?
3. What effect do attitudes, perceived behavioural control, and subjective norms, have on students' use of technology for mathematics learning?

With these stated questions, the study's significance stems from its ability to infuse the two theoretical frameworks and real-world technological implementations in higher education, particularly concerning university-level mathematics learning. By identifying the types of technologies students use, the motivations for their use, the frequency of their engagement with these tools, and the parameters governing their usage, this study offers significant insights into the state of technology integration in mathematics education.

2. Literature Review

Information technology acceptability research has yielded a number of competing models, each with its own set of acceptance criteria. These models have evolved all over time as a result of persistent attempts to validate and broaden the models at the time of their introduction. The TPB (Ajzen, 1985; Fishbein & Ajzen, 1975), and the TAM (Davis, 1989) are among a few notable models in information system research. The TPB theory is premised on both social and psychological perspectives. The social focuses on how important people influence an individual decision to use a product. On the other hand, the psychological aspect likewise involves the user's attitude and perceived behavioural control. The social and psychological perspectives together significantly impact the individual's intention and this subsequently influences the actual of the product. The TPB was developed by Ajzen (1985) as an extraction of the theory of reasoned action (Fishbein and Ajzen, 1975). Although TRA emphasizes how ATT and SN influence behavioural intentions, TPB includes PBC, a third crucial element.

TPB is now a more complete model for comprehending and forecasting human behaviour, especially in situations when people might not have total control over their actions. In the TPB, Ajzen (1985) proposed that the term attitude describes a person's assessment, whether favourable or unfavourable, of engaging in a particular behaviour. In recent times, Ajzen (2020) describes how attitudes about a behaviour are formed using an expectancy-value model. In particular, attitudes toward the conduct are thought to be influenced by easily accessible ideas about the anticipated outcomes of the behaviour, which are referred to as behavioural beliefs. Thus, attitudes are developed using a mixture of emotive and cognitive factors (Ajzen, 2020). Beliefs and perceptions regarding behaviour and its results are part of the cognitive component. (Ajzen, 2020). For instance, a person is more likely to have a favourable attitude regarding an emerging technology if they think it would increase their productivity or make their work more efficient, and vice versa. The emotional reaction that a person identifies with the behaviour is the affective component (Ajzen, 1985; 2020). For instance, people are more likely to have a positive attitude regarding adopting or not if they find the notion of using an invention intriguing or entertaining.

SN another factor or construct in TPB as described by Ajzen (1985) involves the perceived social pressure to engage in or refrain from engaging in a behaviour. The expectations of important people (such as family, friends, and supervisors) and the drive to live up to those expectations have an impact on this component (La Barbera & Ajzen, 2020). Fishbein and Ajzen (2011) reported that SN had two forms of normality (injunctive and descriptive) belief. While the injunctive normality belief focuses on how the users believe the people agree or disagree with performing a particular behaviour, descriptive normality belief identifies if significant individuals who influence the user's decision are performing the behaviour themselves.

Ajzen (2020) noted that perceived or actual behavioural control is similar to or the same as Bandura (1977) self-efficacy construct. Internal factors like the user's skills and knowledge and external factors like resources and supportive systems can serve as PBC which influences intention and actual behaviour. For instance, if a student has access to the required technology and is proficient in its use, they may be able to follow through on their strong intention to use the digital tool for learning mathematics. Their intention alone, however, might not be enough to produce actual behaviour if the same student runs into technological difficulties,

is not given the right instruction, or finds it difficult to comprehend how to use digital tools. In this situation, they may be prevented from carrying out the intended action by their apparent lack of control. Figure 1 depicts the pictorial representation of TPB.

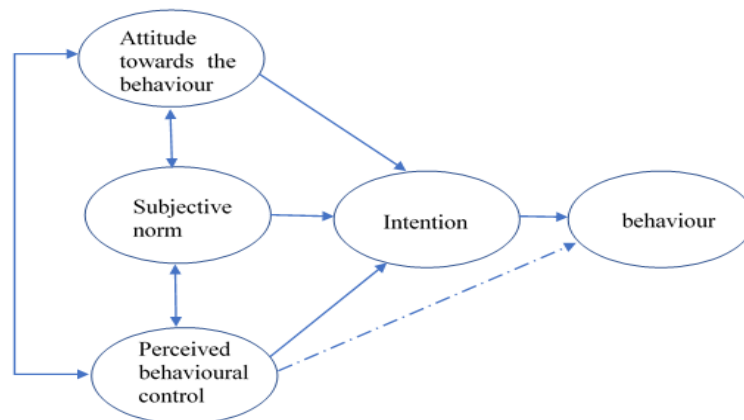


Figure 1. The TPB model.
Source: Ajzen, 1985.

The theory of reasoned action served as the theoretical foundation for the TAM. Proposed by Davis (1989), TAM is one of the most widely used frameworks for understanding technology adoption in education (Alshurideh et al., 2024; Lotey et al., 2023), transportation (Gündoğan & Keçeci, 2024), agriculture (Chen et al., 2024; Forouzani et al., 2024), business (Sciarelli et al., 2022), healthcare (Mensah, 2022), and sport (Mascret et al., 2022). It discusses key beliefs an individual considers before accepting or rejecting a technology. Perceived usefulness is described by Davis (1989) as “the degree to which a person believes that using a particular system would enhance his or her job performance.” This is inferred from the word’s definition of useful: “capable of being used advantageously.” (p. 320).

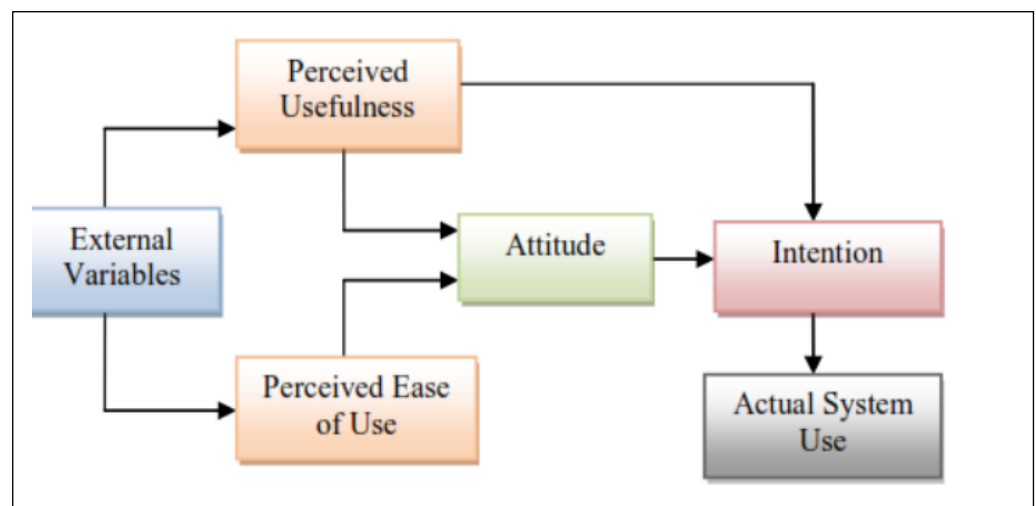


Figure 2. The original TAM.
Source: Davis, 1989.

Perceived ease of use, according to Davis (1989), refers to “the degree to which a person believes that using a particular system would be free of effort.” This aligns with the “ease” definition: “freedom from difficulty or great effort.” An application that is perceived to be easier to use than another is more likely to be accepted by users. From the initial TAM, the attitude was proposed to be predicted by usefulness and easiness associated with applying technology. However, the final TAM revealed that attitude provided inconsistency findings in the model and thereby was later removed from the model. Figure 2 represents the original TAM as proposed by TAM in 1985.

TAM postulates that with strongly perceived usefulness and positive attitude, users are

likely to have a high behavioural intention to use innovation and eventually utilise it. Attitude in TAM defines the emotional state an individual attaches to using a technology and this is impacted by perceived ease of use and usefulness. The omission of attitude in the original led to the model hinging on construct or factors. The final version of TAM is shown in figure 3.

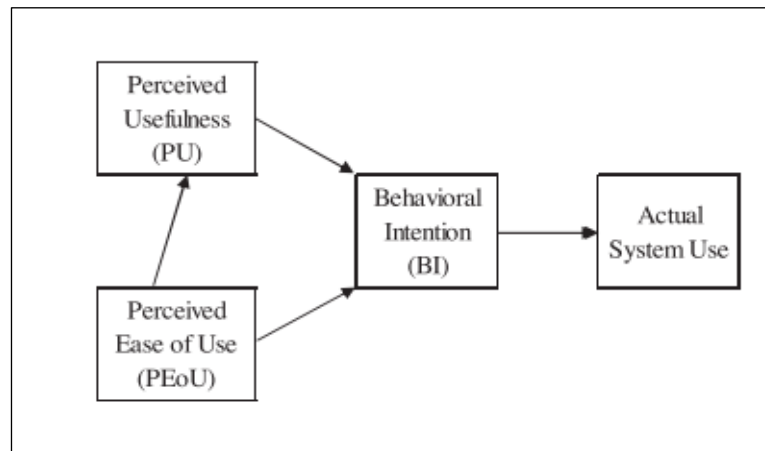


Figure 3. The final version of TAM.

Source: Davis, 1989.

The actual execution of a planned action is referred to as user behaviour. It is the visible expression of a person's intention, impacted by technological factors like usefulness and easiness, social limitations such as peers or superior influence, and personal drives like skills and attitude. One of the key factors affecting user behaviour is the degree of skill or PBC. If a person believes he or she has sufficient control over his or her actions, he or she is more likely to act on their intention. However, when an individual perceives significant external constraints, his or her intentions may not translate into behaviour. This shows the gap between intention and action which could termed as "intention-behaviour gap". The ATU was examined instead of intention due to the study's objectives and figure 4 depicts the conceptual model guiding this investigation. The challenges or shortcomings in both TAM and TPB gave room for integrating the two models in this study. TAM has drawn criticism for diverting researchers' focus from other crucial issues that affect user's technology behaviour.

Despite being likely the most prominent theory in IT adoption, Sommer (2011) together with Pavlou and Fygenson (2006) noted that the majority of TAM research emphasize the significance of PU without making a concerted attempt to explore what exactly makes a system effective. Scherer, Siddiq, and Tondeur (2019) also reported that the TAM construct's PU is also unobjective because various people have varying opinions about how valuable technology is. Due to the ever-evolving context of IT organizations, Jokonya (2017) argued that TAM's flaws stem from its diminished relevance. TAM is limited by the sociological aspect of TPB which explains human behaviour. Comparing TPB to the TAM model, its sociological component makes it the most relevant and acceptable for exploring the social factors related to users' intentions regarding technology utilisation (Jokonya, 2016). On the other hand, Taherdoost (2018) posited that if a computer system is inaccessible, then the user's attitude regarding information technology will not be very significant in the TPB. Since TPB's initial conceptions do not accurately reflect all contexts, one of its weaknesses is its inability to explain the results of testing various IS situations (Jokonya, 2016). Additionally, TPB has poor explanatory power (explain 25 to 30 percent of the variance in behaviour) as compared to TAM. Furthermore, the TPB is typically applied to a single behaviour that is precisely characterized in terms of time, context, object, and action (Ajzen, 2020).

Due to the constraints or limitations of TPB, Sniehotta, Presseau, and Araújo-Soares (2014) proposed that TPB must be retired and this was further supported by Ogden (2014). For instance, Sniehotta et al., (2014) observed that, in longitudinal studies, TPB accounts for less variance with findings being more objective than subjective also few experimental tests of the TPB have been carried out, and those that have been done have not confirmed the postulation of the theory. The TPB's static explanatory character makes it difficult to comprehend how behaviour is demonstrated to influence cognition and future behaviour (McEachan et al., 2011).

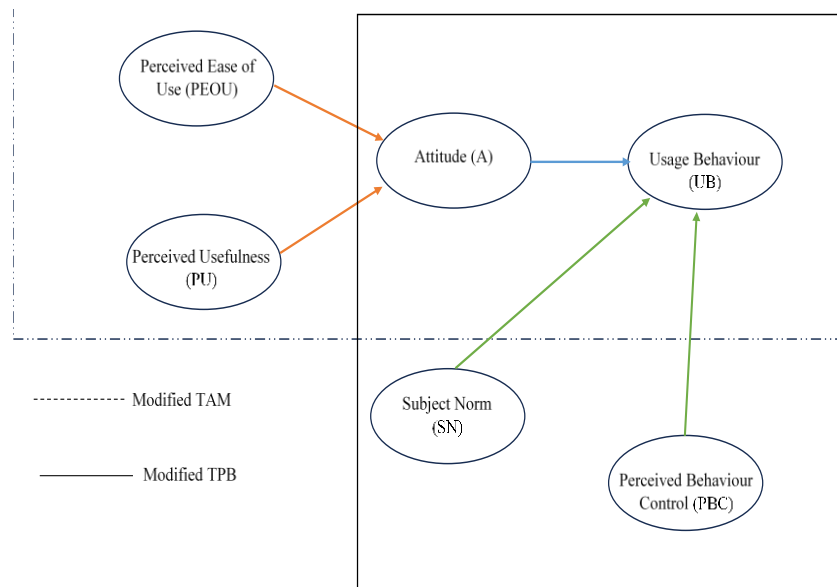


Figure 4. Conceptual framework.
Source: Own authors' development.

This study based on the reviewed literature, combined the TAM-TPB model to respond to the limitations of using TAM or TPB in isolation for examining student's adoption of technology for mathematics learning. For instance, TAM is effective in explaining technology adoption, but it lacks social and contextual factors that influence behaviour. TPB includes social and control factors but does not have high explanatory power. Combining the two models in this study could provide a more holistic understanding of university mathematics student's adoption of technology for mathematics learning. The dashed lines represent an adapted TAM while the straight line also indicates the modified TPB.

3. Materials and Methods

The study employs a quantitative approach with descriptive design and predictive correlational design. As reported by some works (Devi et al., 2022), "a descriptive design is a research study where the researcher seeks to describe a relationship among variables, without attempting to infer causal relationship while predictive design is one approach of research study to examining causal relationships between the variables". (p. 64-65). Both designs were used to enhance the study's methodological rigor and provide a more robust analysis of the data. Together, these two designs complement each other, offering both a description of the types, purpose, and frequency of students' technology use for learning and also, the prediction of factors that influence students' ATU based on the C-TAM-TPB framework.

The study's population was 680 undergraduate students from the mathematics education department at Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development (AAMUSTED) enrolled in 2022/2023 (N=320) and 2023/2024 (N=360) academic years. A stratified random sampling technique is used to ensure that the sample is representative of the target population. Using proportional allocation in stratified sampling and based on Yamane (1967) simple determination formula with 95% confidence level and precision of .5, the researcher selected 172 students from the 2022/2023 academic year and 190 students from the 2023/2024 academic year, resulting in a total sample size of 362 students. After selecting the sample from each stratum, a simple random sampling technique was used to select participants from each stratum. This ensures that every member of the stratum has an equal chance of being included in the sample.

The primary data collection instrument was a structured questionnaire designed based on the constructs of the C-TAM-TPB framework. The questionnaire consists of Likert scale items to measure the following constructs: (1) PU measures students' beliefs about the benefits of using technology for mathematics learning with 5 items, (2) PEOU measures students' perceptions of the simplicity and user-friendliness of technology with 5 items, (3) ATT measures students' overall evaluation and feelings about using technology for mathematics learning with 5 items, (4) SN measures the perceived social pressure to use technology with 5 items, (5) PBC measures students' confidence in their ability to use

technology and their perception of external constraints with 5 items, and finally, (6) UB measures students' ATU for mathematics learning with 3 items. Closed-ended questions were used to elicit the frequency, type, and purpose of the students' technology use for mathematics learning. All items were measured on a 5 Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). A portion of the questionnaire was designed to elicit students' demographic characteristics information including age, sex, and year of study. Previous studies (Ajzen, 2020; Davis, 1989; Fishbein & Ajzen, 2011; Guraya et al., 2024; Lotey et al., 2023; Venkatesh et al., 2003) were used to modify the five items for Perceived ease of use (PEOU), Perceived usefulness (PU), Attitude towards using (ATT), Subjectives norm (SN), and Perceived behavioural control (PBC), respectively.

The data designed with Google Forms was collected through online distribution platforms specifically Telegram and WhatsApp. The collection lasts for a week and all students have an equal chance of participating in this study. Before Google Forms were developed for the final data collection, a pilot study was conducted using the same procedure with final-year students (2021/2022 academic year). This was done in an effort to make the survey tools' language better. The Cronbach's coefficient (Croasmun & Ostrom, 2011; Vaske et al., 2016) assists in deciding the reliability of the items, and coefficients above 0.70 mean that the instruments have consistency as defined in Taber's (2018) studies. The data was analysed using SPSS v. 27.

4. Results

Preliminary analysis was conducted to check the reliability of the survey instrument and the assumptions (raw scores) underlying multiple regression.

Table 1 presents the reliability coefficients (Cronbach's alpha) together with the mean and standard deviation of the C-TAM-TPB constructs used in the study. The pilot study recorded an alpha between 0.69 and 0.82. UB ($\alpha=0.81$) had the highest value and SN (0.69) had the lowest. For the final study, Table 1 further shows that all scales demonstrated high internal consistency, with Cronbach's alpha values ranging from 0.810 (PEOU) to 0.912 (PBC). PBC in the final study had $\alpha = 0.912$ and PEOU ($\alpha = 0.810$) had the least. With an overall reliability of 0.906 for all 24 elements, the instrument as a whole demonstrated high consistency. These results confirm that the measurement scales are highly reliable for assessing the respective constructs. In terms of mean scores, PE (3.656) and PEOU (3.666) received the highest ratings (table 1), reflecting generally positive perceptions of technology performance and easiness. In contrast, UB (3.188) and PBC (3.186) had the lowest means, indicating slightly weaker PBC and UB. The variability is based on standard deviation values with SN (0.768) and UB (0.839) showing the strongest dispersion, indicating diverse opinions on UB and SN from the participants of the study. ATT and PBC are expressed as favourable precursors of ATU.

Table 1. Cronbach's alpha (pilot and final study), mean and standard deviation.

C-TAM-TPB items	N	PSCA	FSCA	Mean	Std. dev.
PE	5	0.75	0.837	3.656	.699
PEOU	5	0.72	0.810	3.666	.636
ATT	5	0.78	0.817	3.475	.695
SN	5	0.69	0.840	3.357	.768
PBC	5	0.74	0.912	3.186	.745
UB	3	0.81	0.896	3.188	.839
Overall	28		0.906	-	-

Note: PSCA = pilot study Cronbach's alpha, and FSCA = final study Cronbach's alpha.

Table 2 shows the correlation, variance inflation factor (VIF), and tolerance which were used to determine the multicollinearity for the study. The tolerance values above 0.10 (ranging from 0.414 to 0.603) and VIF values below the conservative threshold of 10 (ranging from 1.657 to 2.417), indicating no multicollinearity. Furthermore, the correlations for the predictor values were less than 0.90 which indicates no multicollinearity. The study shows a correlation coefficient between 0.59 to 0.77 and were all significant. The strongest connection was identified between PBC and UB (0.755) as well as ATT and UB (0.728) showing that ATT and PBC had a favourable impact on ATU. Meanwhile, the easiness students get when using technology was correlated to PE (0.645), ATT (0.766), and SN (0.755), indicating the effect of ease of use in shaping usefulness, attitudes, and social influence.

Table 2. Pearson correlation, tolerance, and VIF.

Construct	PE	PEOU	ATT	SN	PBC	UB	Tolerance	VIF
PE	1						.414	2.417
PEOU	.645*	1					.414	2.417
ATT	.711*	.766*	1				.466	2.148
SN	.664*	.755*	.617*	1			.603	1.657
PBC	.594*	.713*	.708*	.604*	1		.570	1.756
UB	.611*	.618*	.728*	.666*	.755*	1	-	-

*Sig (1-tailed) $p < 0.05$

The relationship between the variables is significant at $p < 0.05$. Skewness and kurtosis statistics were applied to examine the normality of the variables. The skewness values fell between -0.481 and 0.099, all within the acceptable range of ± 2 , suggesting a reasonably symmetrical distribution. Similarly, kurtosis values ranged from -0.275 to 0.342, well below the ± 2 threshold, indicating no significant deviation from normality (Gravetter & Wallnau, 2014). The standard errors for skewness (0.128) and kurtosis (0.256) further confirmed that the data did not exhibit substantial non-normality and this catered for common method biases (CMB).

Again, Outliers were determined for both independent and dependent variables. On the dependent variables (ATT in the second research question and UB in the third research question) the outliers were assessed utilising standardized residual (SR) which must be less than 3.3 or more than -3.3 as proposed by Tabachnick and Fidell (2007). ATT had an SR of -4.197 (minimum) and 3.280 (maximum) while UB also had an SR of -4.195 (minimum) and 2.715 (maximum). In table 3, the SR (ATT and UB) shows that there are no outliers on the dependent variables. Contrarily, the independent variables were also examined to see if there is any possible outlier based on Mahalanobis distance (MD).

Table 3. Normality test, and standard residuals.

Construct	Skewness		Kurtosis		Standard Residuals (RS)	
	Statics	Std. Error	Statics	Std. Error	Minimum	Maximum
PE	-.481	.128	.051	.256		
PEOU	-.276	.128	-.082	.256		
ATT	.099	.128	-.188	.256	-4.197	3.280
SN	-.406	.128	.342	.256		
PBC	-.014	.128	.179	.256		
UB	-.347	.128	-.275	.256	-4.195	2.715

The PEOU and PU had an MD value of 13.15 and this was compared to the critical value of 13.82. This indicates that there is a potential outlier since the MD is less than the critical value. However, Cook's distance was applied to verify if this outlier has a significant influence on the regression equation. Since Cook's distance (.096) is less than 1, it attempts to conclude that outliers have an insignificant impact on the regression equation and hence, the researcher can continue with further analysis. Furthermore, ATT, SN, and PBC had an MD value of 17.590 compared to the critical value (16.27) shows that there in outliers. Overall, the results confirm that the assumptions of normality, linearity, and multicollinearity were met, supporting the validity of subsequent regression.

4.1. RQ1: What types of technology do university mathematics students use for learning mathematics, and what are the purposes and frequency of their use?

The most common technologies (figure 5) were scientific calculators (SC) ($n = 362$, 100%) and online tutorials like YouTube ($n = 248$, 78.5%), followed by educational apps like Photomath, and Khan Academy ($n = 105$, 29.0%), while mathematics software like GeoGebra, and Excel was least used ($n = 9$, 2.5%).

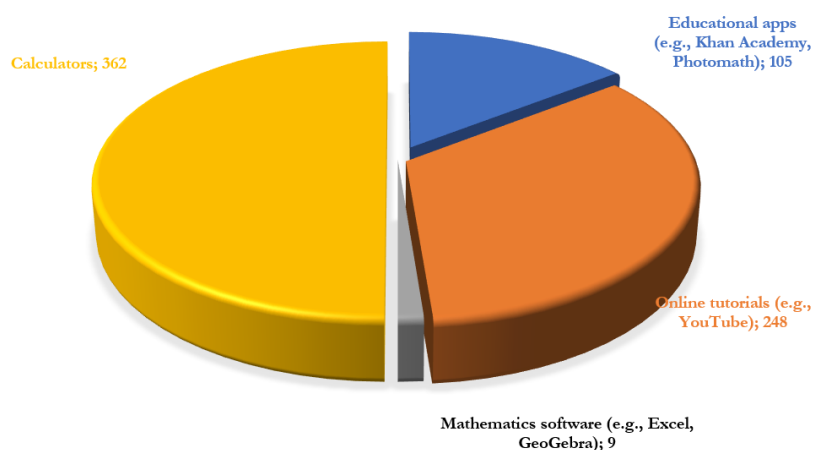


Figure 5. Types of students' technology use for mathematics learning.

The rate of students' technology use during mathematics learning is reported in figure 6. All participants ($n = 356$, 98.3%) reported daily use of technology, with only 1.7% ($n = 6$) using it 3 to 4 days a week (figure 6). This result shows that students' mathematics learning at the tertiary institution is indispensable from technology application or integration.

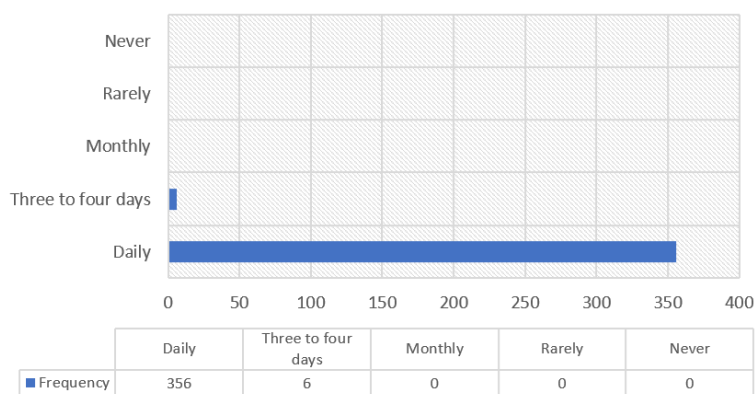


Figure 6. Frequency of students' technology use for mathematics learning.

This result suggests that students' primary use of technology was mostly for completing assignments ($n = 362$, 100%). Additionally, participants hardly use technology to collaborate with peers regarding mathematics learning. From figure 7, this was recorded as only 105 out of the 362 participants applied technology to communicate with their peers on mathematics.

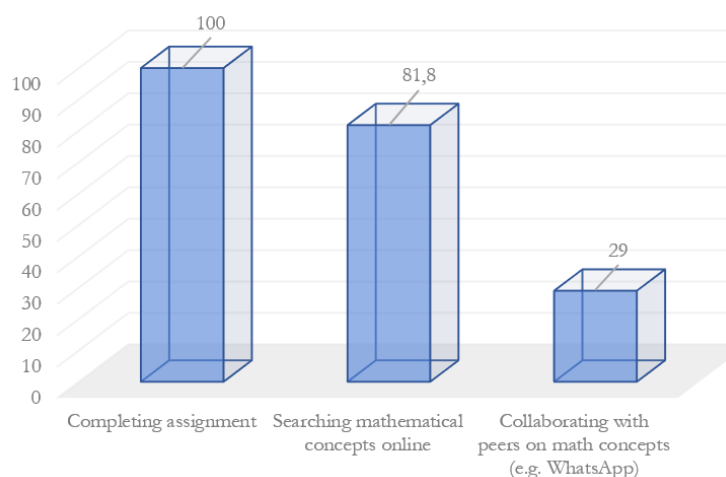


Figure 7. Purpose of students' technology use.

4.2. RQ2: How do technology easiness and usefulness predict university students' attitudes toward adopting technology for mathematics learning?

The summary of the model which shows the effect of PU and PEOU on ATT is represented in table 4. The findings indicate a positive and favourable relationship which was also significant statistically, with an $R = 0.728$, showing that PU and PEOU when combined explain a substantial variance in ATT. The $R^2 = 0.530$ discloses that approximately 53.0% of the variability in ATT is accounted for by PU and PEOU and the adjusted $R^2 = 0.528$ confirms the robustness of the model.

Table 1. First model summary.

<i>R</i>	<i>R</i> ²	Adjusted <i>R</i> ²	F Change	F-value	df1	df2	Durbin-Watson
.728 ^b	.530	.528	202.512	.000*	2	359	1.929

Note: Predictors (Constant) = PE, and PEOU; Dependent variable = ATT.

The F-change statistic was significant (202.512, $p < 0.001$). The Durbin-Watson of value 1.93 falls within the acceptable (1.5 - 2.5) criteria, which aligns with the independence of residual assumption. These findings emphasize the benefit of PEOU and PE in influencing ATT, with the model accounting for more than half of the variance in ATT. The statistical validity and strong predictive ability of the regression model spotlight the importance of PE and PEOU in ascertaining students' technology-related attitudes.

Table 5 representing the regression analysis shows that PU and PEOU significantly predict ATT. PU emerges as the stronger predictor ($\beta = 0.525$, $p < 0.001$), with each unit increase in PE associated with a 0.522 unit increase in ATT. PEOU also shows a significant but slightly weak effect ($\beta = 0.243$, $p < 0.001$), with one unit increase in PEOU corresponding to a 0.265 unit increase in ATT.

Table 5. First analysis of regression summary.

Construct	B	Std. Error	Beta	t	Sig	Part (sr)
Constant	.595	.150		3.952		
PE	.522	.056	.525	9.339	.000	.338
PEOU	.265	.061	.243	4.317	.000	.156

Note: Dependent variable = ATT.

The regression equation for predicting students' technology ATT via PE, and PEOU is:

$$ATT = .595 + .522_{PU} + .265_{PEOU}$$

The part correlations show that PU accounts for 33.8% of unique variance in ATT, while PEOU explains 15.6%, indicating that PU has a greater relative importance than PEOU.

4.3. What influence do attitudes, subjective norms, and perceived behaviour control have on students' use of technology for mathematics learning?

The regression model examining the influence of ATT, SN, and PBC on UB demonstrates strong predictive power and statistical validity (table 6). With a multiple correlation coefficient (R) of 0.793, the model indicates a substantial relationship between the predictors and the dependent variable. The R^2 value of 0.628 reveals that approximately 62.8% of the variance in UB is explained by the combined effect of ATT, SN, and PBC, while the adjusted R^2 of 0.625 confirms the model's robustness. The Durbin-Watson value (1.920) represented (table 6) falls within the criteria acceptable for supporting the independence of residual assumption.

Table 6. Model summary.

<i>R</i>	<i>R</i> ²	Adjusted <i>R</i> ²	F Change	F-value	df1	df2	Durbin-Watson
.793 ^c	.628	.625	201.805	.000*	3	358	1.920

Note: Predictors (Constant) = ATT, SN, PBC; Dependent variable = UB.

All three predictors show significant and favourable relationships with UB statistically. ATT emerges as the strongest predictor ($\beta = 0.401$, $t = 8.484$), indicating that a one-unit increase in ATT corresponds to a 0.484 unit increase in UB, with other factors being constant. SN had a significant impact ($\beta = 0.318$, $t = 7.679$) on UB. Thus, a unit increase in SN is connected to a 0.339 unit rise in UB. Additionally, PBC was significant ($\beta = 0.202$, $t = 4.739$), but demonstrates the least effect among ATT and SN, with a 0.267 unit change in PBC

increase in UB. The regression equation for predicting students' technology UB via ATT, SN, and PBC is given as follows:

$$UB = -.434 + .484_{ATT} + .339_{SN} + .267_{PBC}$$

Table 7. Second analysis of regression summary.

Construct	B	Std. Error	Beta	t	Sig	Part (sr)
Constant	-.434	.165		-2.635		
ATT	.484	.057	.401	8.484	.000	.273
SN	.339	.044	.318	7.679	.000	.247
PBC	.267	.056	.202	4.739	.000	.153

Note: Dependent variable = UB; P < 0.05.

The part correlations (sr) further clarify each predictor's unique contribution: ATT explains 27.3% of UB's variance, SN accounts for 24.7%, and PBC contributes 15.3%. These results collectively suggest that while all three factors are important determinants of UB, users' ATT, and SN play particularly influential roles, followed by PBC over technology use (table 7).

5. Discussion

5.1. The Types, Purpose, and Frequency at which University Mathematics Students Use Technology for Learning Mathematics

The findings from 362 participants of this investigations shows that SC is the most dominant technology students use for learning mathematics. Although advanced technology like GeoGebra, Excel, and Octave have been introduced to participants through professional development programs (Lotey et al., 2025), they over-reliant on SC for mathematics learning which could have an implication on their final adoption of the tools after their teacher training. The study's finding on SC dominance can be linked to some works (Agyei et al., 2023; Umugiraneza et al., 2018) results where in-service teachers were frequently observed using SC for teaching mathematics without adopting advanced tools like Microsoft Excel, GeoGebra, and Geometer's sketchpad, among others. Concerning some studies (Teoh et al., 2023), most pre-service facilitators chose suitable digital tools or resources for task completion which aligns with this study. Participants' inability to use advanced technology for mathematics learning could be a result of poor professional training in ICT. In Tiba and Condry's (2021) study, pre-service teachers reported that few teacher educators assigned them technology-based projects, and the on-campus training was insufficient to prepare them to use advanced technology in the classroom. Therefore, they only relied on SC as a teaching tool during teaching practicum.

Apart from the SC, online tools like YouTube were also adopted for mathematics learning. This result supports that of Mulenga and Marbán's (2020) investigation which shows that YouTube is the highest tool students adopt for mathematics learning. The study's result is also consistent with Akakandelwa and Walubita (2017) findings which noted that most participants from the investigation use social media for academic tasks, and to stay connected with course mates. Furthermore, the study revealed a strikingly low adoption of mathematics application software such as GeoGebra and Excel among the 362 participants, with only nine students approximately 2.5% reporting their use for learning mathematics. The study's findings could explain why few SHS facilitators with a low mean value of 1.86 use GeoGebra in mathematics instruction as reported by E. Agyei, D. Agyei, and Benning (2023). Several factors may contribute to this trend, including a lack of awareness about the software's benefits or a preference for traditional learning techniques. Additionally, the lectures may not actively incorporate these tools, leaving students without guidance on their practical applications in mathematics.

Although the study's findings show that students in one way or the other always adopt technology for learning mathematics, it appears that such usage pattern was focused on completing assignments or tasks. This finding aligns with Mulenga and Marbán (2020) where most participants with an aggregate score of 44.1 indicating a low application of social media for students' collaboration on mathematics concepts. According to Mulenga and Marbán (2020, p. 140), the "aggregate score represents the sum of the agreement for pre-service teachers who either 'sometimes' or 'regularly' use social media to support their mathematics learning".

5.2. The Influence of Technology Easiness and Usefulness on University Students' Attitude for Adopting Technology for Mathematics Learning

The study revealed that mathematics student facilitators' attitude toward adopting mathematical technology for learning was both impacted by the easiness associated with the technology and the benefit derived from its application. Thus, the attitude of students' technology use is significantly and positively influenced by technology's easiness and usefulness. This supports the investigation of Gyamfi (2016) with 380 pre-service facilitators in Ghana where PEOU and PU affect ATT. Notwithstanding, the benefits students get from technology application during mathematics learning had a higher implication on their attitude than the effort they apply when using such tools for learning. This means that the technology's usefulness is of high significance to students and regulates their attitude positively than the technology's easiness for mathematics learning. This finding was consistent with the study of Gurer (2021) in Turkey which concluded that the effect of usefulness was stronger than easiness. Accordingly, Wong (2015) study which examines the factors influencing technology acceptance among pre-service primary mathematics teachers in Hong Kong with a mixed-method approach from 234 undergraduate students through questionnaires and interviews with 14 participants revealed that PU was an influential determinant of attitude than PEOU. The findings of Ranellucci, Rosenberg, and Poitras (2020) also corroborate this investigation.

A positivist study by Teo and Milutinovic (2015) agrees with this study's result. They investigate the effect of PEOU and PE on ATT among 313 students in Serbia. However, PE emerges as the more valuable predictor of attitude meaning that when individuals find technology useful for their teaching, they develop a stronger positive attitude toward its adoption than PEOU. In educational settings, Teo (2010), examines pre-service teachers' attitudes toward computer use by applying and extending the TAM with 239 students in Singapore. Using path analysis, Teo's (2010) findings reveal that PU is the strongest predictor of attitude, while PEOU also significantly influences attitude but has a stronger effect on PU. The study highlights the importance of supportive environments, training, and infrastructure in shaping positive ATT toward technology adoption in education. This study reasserts Teo's (2010) findings but deviates from Samantray and Acharya's (2019) result where PEOU does not affect ATT.

5.3. The Impact of Attitudes, Subjective Norms and Perceived Behavioural Control on Students' Technology Use for Mathematics Learning

Mathematics student facilitators' ATT towards technology adoption for mathematics learning significantly influences their actual use. This implies that participants with positive ATT will integrate technology anytime they are learning mathematics. According to Bhattacharjee and Sanford (2009), participants' attitudes in terms of related expertise and personal relevance significantly influence ATU which is consistent with this study's result. In contradiction, the investigation of Itani, Agnihotri, and Dingus (2017) aimed to examine the role of social media use in business-to-business (B2B) sales and its impact on competitive intelligence collection and adaptive selling, with a focus on learning orientation as an enabler noted that ATT toward social media had no positive impact on usage though the regression analysis indicated that salespeople with a strong learning orientation are more likely to use social media effectively, leading to improved competitive intelligence gathering and adaptive selling strategies. Consistent with Gyamfi's (2016) result, ATT was identified as the strongest predictor of students' ATU for learning. In support of this study, However, this study result contradicts the investigation of Habibi, Riady, Samed Al-Adwan, and Awni Albelbisi (2022) among pre-service science student teachers where ATT was found not to predict ATU.

The influence of peers or lectures in AAMUSTED had a significant influence on participants' technology use for mathematics learning. The investigation of Kafyulilo, Fisser, and Voogt (2016) with 12 teachers and the data gathered from an interview supports this study. These scholars argued that a significant and positive boost of leadership in school is crucial for individual continuous use of technology. This is to say that, when mathematics student facilitators in AAMUSTED are encouraged by their lecturers or peers to use technology, they will eventually apply it during mathematics learning. The study corroborates certain results (Habibi, Razak, et al., 2022) indicating that SN significantly affects ATU. According to this research, SN was recorded as the highest predictor of student's technology use among ATT and PBC. In Baek, Jung, and Kim (2008) study with 64 participants in section one and 202 participants in the second section among Korean teachers developed to investigate the factors influencing teachers' decisions to use technology in classrooms. The

findings revealed that experienced teachers often use technology due to external pressures, while less experienced teachers adopt it voluntarily. A close look at the results of Baek et al. (2008) aligns with this current investigation where students' use of technology for mathematics learning was impacted by the role of social factors like peers and lecturers in the university community.

PBC which represents students' confidence in their ability to use technology effectively for mathematics learning together with the availability of resources and opportunities to implement technology had a significant impact on students' technology use. This findings concurs with other related works (Habibi, Razak, et al., 2022). The study's result is inconsistent with Tezci (2011) findings which reported that participants may have challenges in technology integration in the learning process as it was observed that students have little understanding of how to integrate technology leading to students' ineffective use of technology. According to Bozkurt (2016), students' ATU in learning environments is greatly influenced by their level of confidence in their capacity to incorporate it. In disagreement with this study, Aypay, Çelik, Aypay, and Sever (2012) reported from 754 pre-service facilitators in Turkey via a path analysis that self-efficacy in technology (similar to PBC) does not translate to student technology use. Lemon and Garvis (2015) recorded that confidence and competence correlate significantly with participants' use of digital tools which confirms this study's findings. This implies that self-efficacy in technology influences the users' ATU which echoes this study's results. Atman Uslu's (2022) study supports this finding.

6. Conclusions

This research explores the types, purpose, and frequency of students' technology use when learning mathematics and further investigates the factors that influence its usage from a hybrid of TAM and TPB. The results show that SC was the highest technological tool used for mathematics learning with minimal application of GeoGebra. The investigation therefore noted that these tools were used mostly every day by students when learning. However, the technology used by students was mainly for completing assignments or tasks. Though participants usually use digital tools, it was revealed that students' application of innovative and collaborative tools remains underused. The hybrid of TAM and TPB used for this study provided a robust framework for understanding adoption drivers. The technology used by students was mainly for completing assignments or tasks. The regression analysis discovered that PU had a stronger influence on ATT than PEOU, reinforcing that students prioritize practical benefits over simplicity. Moreover, ATT, SN, and PBC all significantly predicted ATU, with ATT being the strongest predictor. While students are digitally inclined, their preference for familiar tools like SC over advanced applications software such as GeoGebra highlights an untapped potential. Notwithstanding, the low application of advanced mathematics software shows a gap between available technologies and students' practical adoption. This may stem from limited training, lack of institutional support, or confidence barriers (PBC).

Address these gainsay requires effective practical professional development programs, and curriculum integration of advanced technology to foster a more technology-adaptive learning environment to support students' 21st-century learning needs. AAMUSTED and other universities should design professional development programs that provide hands-on training with advanced mathematical software like MATLAB, GeoGebra, and Microsoft Mathematics to enable students to move beyond SC use. Moreover, students should be encouraged to use collaborative tools actively via online mathematics forums, peer-led digital learning initiatives, and group projects that require the application of specialized collaborative software. Furthermore, tertiary institutions should develop faculty development programs focusing on the integration of advanced technology integration to train lecturers to model effective technological tool use in their teaching, as their influence is favourable and significantly affects student ATT and adoption patterns. Additionally, the curriculum used by lecturers at AAMUSTED should be redeveloped to systematically use technology-based tasks and assessments that would require the use of advanced tools and also make the application of such tools an expected norm rather than an optional addition. Again, universities should fortify their support systems by ensuring that all technological resources are easily accessible, and also establish technical assistance teams, for both students and lecturers to use advanced innovative learning and teaching technologies respectively. This section is not compulsory if the discussion is present but can be added to the manuscript if the discussion is too long or complex.

Future studies can explore several promising directions to deepen our understanding of technology acceptance for mathematics learning among university students. Longitudinal studies which focus on tracking pre-service facilitators from training through their early career would show how technology usage evolves in authentic classroom settings and whether university training adequately prepares them for real-world implementation. Comparative studies across different institutions may be conducted to identify how factors like curriculum design, institutional policies influence, and resource availability affect adoption patterns. A Qualitative study should be undertaken to examine the psychological and logistical barriers preventing students from utilizing advanced mathematical software. Studies on intervention studies could be conducted to test the effectiveness of enhanced professional development programs on long-term technology integration.

Author Contributions: Gideon – conceptualization and formal writing, Arthur and Appiagyei – supervision, and Lotey – review and editing.

Funding: This research received no external funding.

Informed Consent Statement: Informed consent was obtained from all students involved in the research.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Agyei, E., Agyei, D. D., & Benning, I. (2023). Teaching Mathematics with Digital Technologies: A Situational Analysis of High School Teachers' Experiences in Ghana. *African Journal of Research in Mathematics, Science and Technology Education*, 28(1), 57–70. <https://doi.org/10.1080/18117295.2023.2265241>
- Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. In J. Kuhl, J. Beckmann (eds) *Action Control. SSSP Springer Series in Social Psychology*. Springer. https://doi.org/10.1007/978-3-642-69746-3_2
- Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies*, 2, 314–324. <https://doi.org/10.1002/hbe2.195>
- Akakandelwa, A., & Walubita, G. (2017). Students' Social Media Use and its Perceived Impact on their Social Life: A Case Study of the University of Zambia. *The International Journal of Multi-Disciplinary Research*, 1–14.
- Alam, A. (2022). Employing Adaptive Learning and Intelligent Tutoring Robots for Virtual Classrooms and Smart Campuses: Reforming Education in the Age of Artificial Intelligence. In R. N. Shaw, S. Das, V. Piuri, M. Bianchini (eds) *Advanced Computing and Intelligent Technologies. Lecture Notes in Electrical Engineering*, vol 914. Springer. https://doi.org/10.1007/978-981-19-2980-9_32
- Alshurideh, M., Jdaitawi, A., Sukkari, L., Al-Gasaymeh, A., Alzoubi, H. M., Damra, Y., Yasin, S., Al Kurdi, B., & Alshurideh, H. (2024). Factors affecting ChatGPT use in education employing TAM: A Jordanian universities' perspective. *International Journal of Data and Network Science*, 8(2024), 1599–1606. DOI: 10.5267/j.ijdns.2024.3.007
- Álvarez, P. A. B., Chacón-Castro, M., Busain, R. S., & Jadán-Guerrero, J. (2024). A didactic proposal for teaching factorization cases of expressions of the form $ax^2+by+cx+ay+exy+f$ through Mathigon. *Eurasia Journal of Mathematics, Science and Technology Education*, 20(10), Article em2514. <https://doi.org/10.29333/ejmste/15198>
- Amri, M. A. and Almaiah, M. A. (2021) Sustainability Model for Predicting Smart Education Technology Adoption Based on Student Perspectives. *International Journal of Advances in Soft Computing and Its Applications*, 13, 60–77. <http://www.i-csrs.org/Volumes/ijasca/2021.2.5.pdf>
- Atman Uslu, N. (2022). Exploring Pre-service Teachers' Perception Regarding Factors in Technology Integration with Q Methodology. *Bartın University Journal of Faculty of Education*, 11(3), 543–558. <https://doi.org/10.14686/buefad.1001562>
- Aypay, A., Çelik, H. C., Aypay, A., & Sever, M. (2012). Technology acceptance in education: A study of pre-service teachers in Turkey. *TOJET: The Turkish Online Journal of Educational Technology*, 11(4), 264–272.
- Back, Y., Jung, J., & Kim, B. (2008). What makes teachers use technology in the classroom? Exploring the factors affecting facilitation of technology with a Korean sample. *Computers and Education*, 50(1), 224–234. <https://doi.org/10.1016/j.compedu.2006.05.002>
- Banafaa, M., Shayea, I., Din, J., Hadri Azmi, M., Alashbi, A., Ibrahim Daradkeh, Y., & Alhammadi, A. (2023). 6G Mobile Communication Technology: Requirements, Targets, Applications, Challenges, Advantages, and Opportunities. *Alexandria Engineering Journal*, 64, 245–274. <https://doi.org/10.1016/j.aej.2022.08.017>
- Bandoh, S. O., Akweittay, E., Lotey, E. K., Gordon, J. F., & Appiagyei, E. (2024). Using UTAUT model to assess the factors influencing the use of ICT in Ghanaian pre-tertiary mathematics education. *Journal of Digital Educational Technology*, 4(1), Article ep2407. <https://doi.org/10.30935/jdet/14297>
- Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, 84(2), 191–215. <https://doi.org/10.1037/0033-295X.84.2.191>
- Bevan, B., Ryoo, J. J., Vanderwerff, A., Wilkinson, K., & Petrich, M. (2020). “I See Students Differently”: Following the Lead of Maker Educators in Defining What Counts as Learning. *Frontiers in Education*, 5. <https://doi.org/10.3389/feduc.2020.00121>
- Bhattacharjee, A., & Sanford, C. (2009). The intention–behaviour gap in technology usage: the moderating role of attitude strength. *Behaviour & Information Technology*, 28(4), 389–401. <https://doi.org/10.1080/01449290802121230>
- Bonfield, C. A., Salter, M., Longmuir, A., Benson, M., & Adachi, C. (2020). Transformation or evolution?: Education 4.0, teaching and learning in the digital age. *Higher Education Pedagogies*, 5(1), 223–246. <https://doi.org/10.1080/23752696.2020.1816847>
- Bozkurt, G. (2016). Mathematics teachers and ICT: Factors affecting pre-service use in school placements. *International Journal of Research in Education and Science*, 2(2), 453–468.

- Burbules, N. C., Fan, G., & Repp, P. (2020). Five trends of education and technology in a sustainable future. *Geography and Sustainability*, 1(2), 93–97. <https://doi.org/10.1016/j.geosus.2020.05.001>
- Chan, C. Y., & Leong, K. E. (2024). Use of Virtual Manipulatives in Addition of Fractions Among Year Four Pupils. *Journal of Mathematics Science and Technology Education*, 1(1), 19–29. <https://doi.org/10.12973/jmste.1.1.19>
- Chen, X., Zhang, X.-e., & Chen, J. (2024). TAM-Based Study of Farmers' Live Streaming E-Commerce Adoption Intentions. *Agriculture*, 14(4), 518. <https://doi.org/10.3390/agriculture14040518>
- Croasmun, J. T., & Ostrom, L. (2011). Using Likert-Type Scales in the Social Sciences. *Journal of Adult Education*, 40(1), 19–22.
- Dahal, N., Manandhar, N. K., Luitel, L., Luitel, B. C., Pant, B. P., & Shrestha, I. M. (2022). ICT tools for remote teaching and learning mathematics: A proposal for autonomy and engagements. *Advances in Mobile Learning Educational Research*, 2(1), 289–296. <https://doi.org/10.25082/AMLER.2022.01.013>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–339. <https://doi.org/10.2307/249008>
- Devi, B., Devi, R., Pradhan, S., Giri, D., Lepcha, N., & Basnet, S. (2022). Application of Correlational Research Design in Nursing and Application of Correlational Research Design in Nursing. *Journal of Xi'an Shiyou University, Natural Sciences Edition*, 65(11), 60–69. <https://xianshiyoudaxuexuebao.com/dashboard/uploads/5.YRZ68.pdf>
- Facer, K., & Selwyn, N. (2021). Digital technology and the futures of education-towards “non-stupid” optimism. Paper commissioned for the UNESCO Futures of Education report. *Futures of Education*, UNESCO. <https://unesdoc.unesco.org/ark:/48223/pf0000377071>
- Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Reading, MA: Addison-Wesley.
- Fishbein, M., & Ajzen, I. (2011). Predicting and changing behavior: The reasoned action approach. In *Predicting and Changing Behavior: The Reasoned Action Approach*. Psychology Press. <https://doi.org/10.4324/9780203838020>
- Forouzani, M., Bondori, A., & Mombini, A. S. (2024). Why are farmers reluctant to accept biological inputs? a structural equation model of technology adoption. *Frontiers in Sustainable Food Systems*, 8. <https://doi.org/10.3389/fsufs.2024.1360887>
- Ge, X., Ifenthaler, D., & Spector, J. (2015). Moving Forward with STEAM Education Research. In X. Ge, D. Ifenthaler, J. Spector (eds) *Emerging Technologies for STEAM Education. Educational Communications and Technology: Issues and Innovations* (pp 383–395). Springer. https://doi.org/10.1007/978-3-319-02573-5_20
- Gkrimpizi, T., Peristeras, V., & Magnisalis, I. (2023). Classification of Barriers to Digital Transformation in Higher Education Institutions: Systematic Literature Review. *Education Sciences*, 13(7), Article 746. <https://doi.org/10.3390/educsci13070746>
- Gravetter, F., & Wallnau, L. (2014). *Essentials of statistics for the behavioral sciences*. Wadsworth.
- Gündoğan, O., & Keçeci, T. (2024). A TAM-Based Study on the Adoption of Digital Transformation in the Maritime Transportation Logistics Sector. *Journal of ETA Maritime Science*, 12(1), 92–105. <https://doi.org/10.4274/jems.2024.26680>
- Guraya, S. S., Clarke, E., Sadeq, A., Smith, M., Hand, S., Doyle, F., ...Harkin, D. W. (2024). Validating a theory of planned behavior questionnaire for assessing changes in pro-professional behaviors of medical students. *Frontiers in Medicine*, 11. <https://doi.org/10.3389/fmed.2024.1382903>
- Gurer, M. D. (2021). Examining technology acceptance of pre-service mathematics teachers in Turkey: A structural equation modeling approach. *Education and Information Technologies*, 26(4), 4709–4729. <https://doi.org/10.1007/s10639-021-10493-4>
- Gyamfi, S. A. (2016). Identifying Ghanaian pre-service teachers' readiness for computer use: A Technology Acceptance Model approach. *International Journal of Education and Development Using Information and Communication Technology*, 12(2), 105–122.
- Habibi, A., Razak, R. A., Yusop, F. D., Muhaimin, M., Asrial, A., Mukminin, A., & Jamila, A. (2022). Exploring the factors affecting pre-service science teachers' actual use of technology during teaching practice. *South African Journal of Education*, 42(1), Article 1955. <https://doi.org/10.15700/saje.v42n1a1955>
- Habibi, A., Riady, Y., Samed Al-Adwan, A., & Awni Albelbisi, N. (2022). Beliefs and Knowledge for Pre-Service Teachers' Technology Integration during Teaching Practice: An Extended Theory of Planned Behavior. *Computers in the Schools*, 40(2), 107–132. <https://doi.org/10.1080/07380569.2022.2124752>
- Haleem, A., Javaid, M., Qadri, M. A., & Suman, R. (2022). Understanding the role of digital technologies in education: A review. *Sustainable Operations and Computers*, 3, 275–285. <https://doi.org/10.1016/j.susoc.2022.05.004>
- Itani, O. S., Agnihotri, R., & Dingus, R. (2017). Social media use in B2b sales and its impact on competitive intelligence collection and adaptive selling: Examining the role of learning orientation as an enabler. *Industrial Marketing Management*, 66, 64–79. <https://doi.org/10.1016/j.indmarman.2017.06.012>
- Jeong, H., & Hmelo-Silver, C. E. (2010). Productive use of learning resources in an online problem-based learning environment. *Computers in Human Behavior*, 26(1), 84–99. <https://doi.org/10.1016/j.chb.2009.08.001>
- Jokonya, O. (2017). Critical Literature Review of Theory of Planned Behavior in the Information Systems Research. *DEStech Transactions on Computer Science and Engineering*. <https://doi.org/10.12783/dtcse/ameit2017/12297>
- Kafyulilo, A., Fisser, P., & Voogt, J. (2016). Factors affecting teachers' continuation of technology use in teaching. *Education and Information Technologies*, 21, 1535–1554. <https://doi.org/10.1007/s10639-015-9398-0>
- Kliziene, I., Taujanskiene, G., Augustiniene, A., Simonaitiene, B., & Cibulskas, G. (2021). The Impact of the Virtual Learning Platform EDUKA on the Academic Performance of Primary School Children. *Sustainability*, 13(4), Article 2268. <https://doi.org/10.3390/su13042268>
- La Barbera, F., & Ajzen, I. (2020). Control Interactions in the Theory of Planned Behavior: Rethinking the Role of Subjective Norm. *Europe's Journal of Psychology*, 16(3), 401–417. <https://doi.org/10.5964/ejop.v16i3.2056>
- Lemon, N., & Garvis, S. (2015). Pre-service teacher self-efficacy in digital technology. *Teachers and Teaching*, 22(3), 387–408. <https://doi.org/10.1080/13540602.2015.1058594>
- Liu, G., & Ma, C. (2023). Measuring EFL learners' use of ChatGPT in informal digital learning of English based on the technology acceptance model. *Innovation in Language Learning and Teaching*, 18(2), 125–138. <https://doi.org/10.1080/17501229.2023.2240316>
- Lotey, E. K., Arthur, Y. D., Gordon, J. F., & Adu-Obeng, B. (2023). Modeling basic school teachers acceptance of instructional technology in advancing mathematical pedagogy in Ghana. *Contemporary Mathematics and Science Education*, 4(1), Article ep23006. <https://doi.org/10.30935/conmaths/12811>

- Vaske, J. J., Beaman, J., & Sponarski, C. C. (2016). Rethinking Internal Consistency in Cronbach's Alpha. *Leisure Sciences*, 39(2), 163–173. <https://doi.org/10.1080/01490400.2015.1127189>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Wong, G. K. W. (2015). Understanding technology acceptance in pre-service teachers of primary mathematics in Hong Kong. *Australasian Journal of Educational Technology*, 31(6). <https://doi.org/10.14742/ajet.1890>
- Yakubu, M. N., & Dasuki, S. I. (2019). Factors Affecting the Adoption of e-Learning Technologies among Higher Education Students in Nigeria: A Structural Equation Modeling Approach. *Information Development*, 35, 492-502. <https://doi.org/10.1177/0266666918765907>
- Yamane, T. (1967). *Statistics: An Introductory Analysis*. New York: Harper and Row.