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RESEARCH ARTICLE

An Extended UTAUT Model of E-Learning Resource Adoption Among Mathematics Teachers

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Abstract

The study examines e-learning resource adoption in mathematics education using the extended Unified Theory of Acceptance and Use of Technology model, including personal innovativeness, perceived risks, and e-learning self-efficacy. Data from 282 pre-service and in-service mathematics teachers in Philippines were analyzed using Covariance-Based Structural Equation Modeling to explore their intentions to integrate e-learning resources in teaching. Results showed that personal innovativeness positively influences effort expectancy and performance expectancy, indicating that innovative teachers find e-learning tools easier and more useful. e-learning self-efficacy enhances social influence and facilitating conditions, while performance expectancy and facilitating conditions are the strongest drivers of behavioral intention. Social influence shows an inverse relationship, suggesting more independent adoption decisions. Demographic factors such as age, respondent type, and teaching experience significantly moderate technology adoption behavior. In-service teachers are more influenced by ease and usefulness, while facilitating conditions and social influence matter more for pre-service teachers. The main takeaway from this paper is that improving digital

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competence, fostering teaching innovation, and strengthening technological infrastructure are key to promoting e-learning adoption in mathematics education.

Keywords: *e-Learning, Perceived Risks, Personal Innovativeness, Self-efficacy, Structural Equation Modeling, UTAUT*

1. Introduction

The integration of digital technologies has become a key feature of modern education, fundamentally transforming instructional design and the delivery of learning (Ma et al., 2019). As educational institutions adapt to increasingly diverse learner needs, technology-driven approaches are being adopted to enhance accessibility and instructional efficiency (Qiao et al., 2021). In this broader shift, e-learning has emerged as a structured educational method that supports flexible and self-paced learning environments (Bai et al., 2018). E-learning environments often utilize multimedia resources and interactive digital platforms to boost learner engagement and understanding (Sarker et al., 2019). Additionally, the widespread adoption of e-learning in schools is motivated by its cost-effectiveness, scalability, and ability to provide personalized learning experiences (Castro, 2019).

The adoption of e-learning resources among mathematics teachers has gained attention in recent years (Moreno-Guerrero et al., 2020). As technology continues to evolve, educators are exploring innovative ways to enhance mathematics instruction by utilizing digital tools and resources. E-learning platforms offer a range of interactive modules, simulations, and virtual manipulatives that can enhance students' understanding of mathematical concepts (Akugizibwe & Ahn, 2020). By incorporating these resources into their teaching practices, mathematics teachers can offer personalized learning experiences and cater to the diverse needs of their students (Moreno-Guerrero et al., 2020). The exploration of e-learning resource adoption among mathematics teachers holds immense potential for transforming mathematics education and fostering student engagement and achievement.

The incorporation of technology into mathematics education has been widely recognized as a promising avenue to enhance instructional practices, improve student engagement, and foster a deeper understanding of mathematical concepts (Seufert et al., 2021; Roman et al., 2021; Maass et al., 2019). However, despite the potential benefits, mathematics teachers often encounter barriers and problems while using e-learning resources (Wang et al., 2022; Adarkwah, 2021). Understanding the underlying factors that influence their decision-making process is crucial for developing effective strategies to encourage the use of e-learning resources in mathematics classrooms. Some studies have identified factors such as ease of use, perceived usefulness, and attitude as predictors of e-learning adoption, but the relationships among these factors and their impact on e-learning adoption in mathematics education remain unclear (Al-Adwan et al., 2021). According to recent studies, the incorporation of technology in education has witnessed a surge in popularity, with e-learning emerging as a prominent approach in various academic disciplines (Vershitskaya et al., 2020; Daultani, 2021; Meskhi, 2019). However, the successful adoption and implementation of e-learning resources among mathematics teachers remains a complex challenge, requiring a deeper investigation into the factors that influence their decision-making process.

The Unified Theory of Acceptance and Use of Technology (UTAUT) serves as the framework for explaining the factors influencing technology acceptance (Venkatesh et al., 2003). Although widely used in studying technology adoption in education, its application to mathematics education and e-learning resource adoption is not yet fully understood in the current literature. Most research tends to focus on general or higher education (Xue et al., 2024), with insufficient attention to mathematics teachers, whose pedagogical needs demand high interaction, visualization, and immediate feedback. Additionally, UTAUT models are often analyzed without including domain-specific factors such as e-learning self-efficacy, perceived risk, and personal innovativeness, which are especially important in mathematics teaching. As a result, there is a gap in empirically validated, context-specific models that effectively explain the adoption of e-learning among mathematics teachers, particularly in settings with limited resources.

The aim of this study is to investigate the impact of e-learning resource adoption among mathematics teachers, utilizing an extended Unified Theory of Acceptance and Use of Technology (e-UTAUT) adapted from the UTAUT model by Venkatesh et al. (2003). As the integration of technology becomes increasingly prevalent in educational settings, it is essential to understand the factors that affect the use of e-learning resources (Almaiah et al., 2020). By extending the UTAUT model to incorporate additional constructs such as personal innovativeness, perceived risk, and e-learning self-efficacy, therefore, this study investigates the relationships between the e-UTAUT constructs and their influence on e-learning resource adoption among mathematics teachers. The study proposed a structural model based on the identified gap and tested using Covariance-Based Structural Equation Modeling (CB-SEM). The methodology enabled us to examine how various factors, such as personal innovativeness, perceived risk, and e-learning self-efficacy, interact within the UTAUT framework. Because CB-SEM can handle complex, simultaneous relationships, it was the perfect tool to see what actually drives math teachers to adopt e-learning resources. The findings provide a clear understanding of what makes a digital transition successful. For teachers, it highlights exactly where to focus their professional development. For administrators, it gives a data-backed roadmap for setting policies and investing in good infrastructure. Thus, this study aims to provide educators with the tools they need to enhance teaching quality and support students' success in the digital math classroom.

The rest of the paper is organized into the following sections: Section 2 presents the literature review and hypothesis development, while Section 3 describes the study's methodological procedures. Section 4 presents the results of the CB-SEM analysis, while Section 5 discusses these findings. Section 6 provides the conclusion, while Section 7 provides the recommendations.

2. Literature Review and Hypothesis Development

This section provides the theoretical underpinnings that anchor the proposed model and the relevant literature supporting the arguments for establishing the hypotheses leading to behavioral intention in adopting e-learning resources in mathematics education.

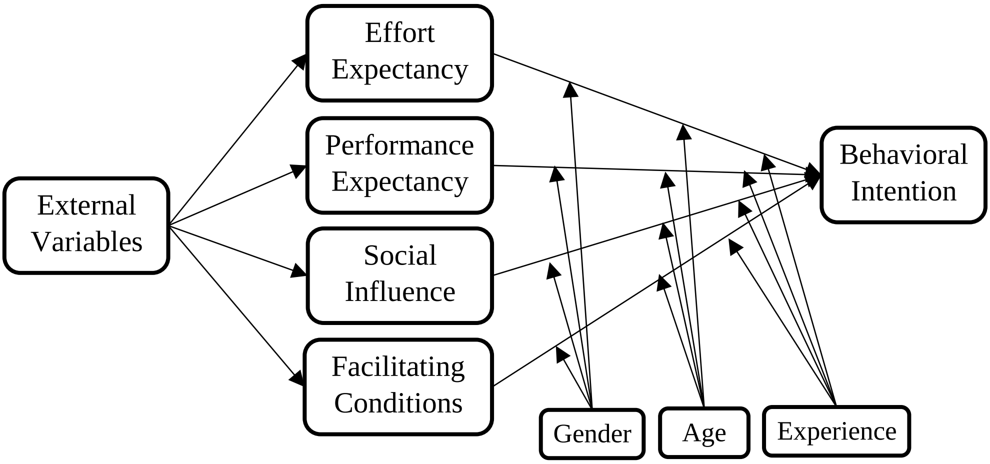
2.1 Theoretical Foundations of the Proposed Model

The Unified Theory of Acceptance and Use of Technology (UTAUT) offers a comprehensive framework for understanding how individuals accept and use technology. Performance expectancy, effort expectancy, social influence, and facilitating conditions are the four primary factors influencing technology adoption, as developed by Venkatesh et al. (2003). These factors have been widely studied in various contexts of technology adoption, including e-learning. Building upon the UTAUT model, the researcher proposes an extended UTAUT model that includes three additional constructs: personal innovativeness, perceived risks, and e-learning self-efficacy. The e-UTAUT (Extended Unified Theory of Acceptance and Use of Technology) is an extension of the original UTAUT model, specifically focusing on the acceptance and use of technology in educational settings. It expands upon the core constructs of UTAUT and incorporates additional factors that are relevant to technology adoption in educational contexts.

Several studies have supported extending the UTAUT model with additional factors. For example, personal factors like ICT competence, motivation, and attitudes affected e-learning adoption differently for learners and instructors in developing countries (Kim & Park, 2017). During the COVID-19 pandemic, the UTAUT model revealed that performance expectancy, effort expectancy, social influence, and facilitating conditions influenced intentions to adopt e-learning (Jameel et al., 2022). Both studies highlight the importance of technology readiness and the significant impact of personal innovativeness on teachers' use of e-learning technologies. Perceived risks were also identified as influential, especially concerning potential negative outcomes (Chao, 2019). E-learning self-efficacy, or teachers' confidence in integrating e-learning resources into mathematics teaching, is another critical factor (Guoyan et al., 2021). These constructs are essential in understanding the complexities of e-learning resource adoption in mathematics education. Researchers recognize the value of the e-UTAUT model for understanding technology adoption in education. It has been widely used to explore factors influencing teachers' acceptance and use of classroom technology (Teng et al., 2022), demonstrating its relevance in studying the adoption of e-learning resources among educators.

Furthermore, numerous studies (e.g., Almaiah & Alyoussef, 2019; Batucan et al., 2022; Teng et al., 2022) highlight the importance of the e-UTAUT model in their investigations into the adoption of mobile learning among teachers. The e-UTAUT model provides a comprehensive framework that incorporates various factors, including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and price value. This model enables a more comprehensive understanding of teachers' acceptance and use of mobile learning technologies (Teng et al., 2022). In this study, the UTAUT model, developed by Venkatesh et al. (2003), serves as the foundational framework to investigate the impact of technology-related constructs on the adoption of e-learning resources among mathematics teachers. Additionally, it will be expanded upon by incorporating additional constructs to capture the unique complexities and dynamics of technology adoption in mathematics education.

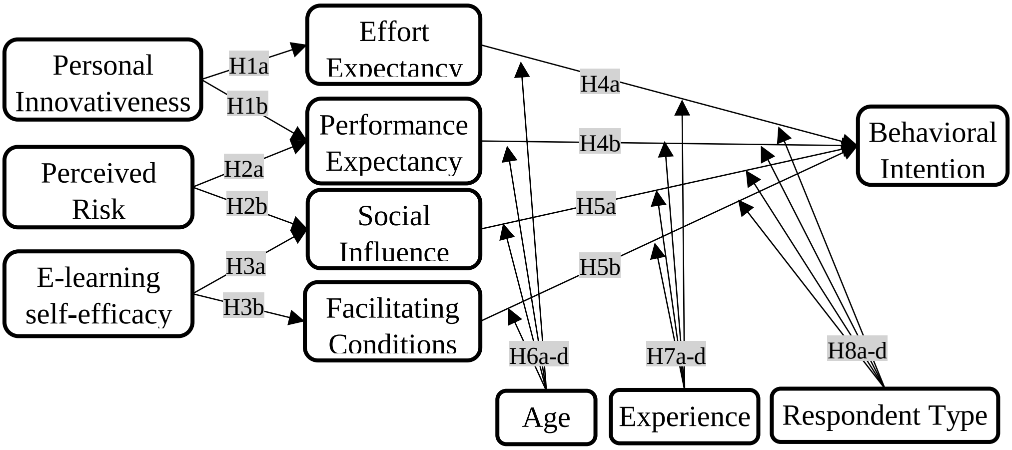
Figure 1
The e-UTAUT Theoretical Framework



2.2 The Proposed Model

The implementation of e-learning resources in education has become increasingly important, and mathematics education is no exception. To better understand the factors influencing the adoption of e-learning resources among mathematics teachers, this study proposes an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model. In addition to the original UTAUT constructs, the extended model incorporates personal innovativeness, perceived risk, and e-learning self-efficacy.

Figure 2
Proposed Structural Model



2.3 Hypothesis Development

Hypothesis development is organized from the most exogenous variables and progresses toward the most endogenous in the model. Each subsection presents (1) the definition of the latent factor, (2) a review of literature that supports or challenges the hypothesized path, and (3), in the absence of existing literature, the argument is built upon relevant theoretical foundations.

2.3.1 Personal Innovativeness (PI)

Personal innovativeness is defined as an individual's readiness and willingness to adopt and embrace new technologies (Setiawan et al., 2021). In this study, personal innovativeness relates to the degree to which mathematics teachers exhibit a propensity to adopt e-learning technology for planning and teaching mathematics. Previous research has highlighted the importance of personal innovativeness in the adoption of technology. For instance, personal innovativeness has been shown to influence teachers' adoption of e-learning technologies (Mazman Akar, 2019). These findings highlight the role of personal innovativeness as a determinant of technology acceptance and usage among teachers. The inclusion of this construct as an extended component in the extended UTAUT model provides valuable insights into the factors influencing mathematics teachers' adoption of e-learning technology.

H1: *Personal Innovativeness will positively affect the (a) effort expectancy and (b) performance expectancy of mathematics teachers in e-learning adoption.*

2.3.2 Perceived Risks (PR)

Perceived risk is an additional construct integrated into the extended UTAUT model. It refers to individuals' perceptions of potential negative consequences or uncertainties associated with adopting and using technology (Teng et al., 2022). Within the realm of e-learning resource adoption among mathematics teachers, perceived risks may include concerns about the reliability of the technology, potential negative impacts on student learning, or challenges in adapting to new teaching methods. Perceived risk significantly negatively moderated the relationship between performance expectancy and behavioral intention (Chao, 2019). Previous research has acknowledged the significance of perceived risk in the adoption of technology. For instance, Liao et al. (2022) highlighted that perceived risk influenced users' adoption of mobile technology. These findings underscore the importance of understanding the influence of perceived risk on e-learning resource adoption and can provide insights into the barriers and challenges faced by mathematics teachers when integrating technology into their instructional practices.

H2: *Perceived risks will positively affect the (a) performance expectancy and (b) social influence of mathematics teachers in e-learning adoption.*

2.3.3 E-Learning Self-efficacy (SE)

E-learning self-efficacy is a vital construct within the extended UTAUT model, focusing on teachers' beliefs in their ability to effectively use e-learning resources in mathematics instruction. Teachers with higher SE to embrace and utilize technology for teaching purposes more readily (Almaiah & Alyoussef, 2019). These teachers possess the confidence and competence to effectively navigate and utilize e-learning resources. Investigating the impact of e-learning self-efficacy on the adoption of e-learning resources among mathematics teachers can provide valuable insights into the role of teachers' perceived capabilities in technology integration.

H3: *E-Learning self-efficacy will positively affect (a) social influence and (b) facilitating conditions of mathematics teachers in e-learning adoption.*

2.3.4 Effort Expectancy (EE)

Effort expectancy (EE) is a key construct within the UTAUT framework, representing users' perceptions of the ease and minimal effort required to use technology (Venkatesh et al., 2003). EE specifically pertains to the extent to which these teachers perceive that using e-learning technology for planning and teaching mathematics will be effortless and require little exertion. Previous research has highlighted the significance of EE in the acceptance and utilization of technology. For instance, perceived ease of use, which aligns closely with effort expectancy, influenced intentions to adopt and use technology (Wijaya et al., 2022). Similarly, EE was critical in determining teachers' actual usage of technology in education (Balkaya & Akkucuk, 2021). These findings underscore the importance of investigating the role of effort expectancy in shaping mathematics teachers' adoption and utilization of e-learning technology for planning and teaching mathematics.

H4: *(a) Effort expectancy will positively affect behavioral intention to use e-learning resources among mathematics teachers.*

2.3.5 Performance Expectancy (PE)

Performance expectancy (PE) is a fundamental construct in the UTAUT framework, representing users' perceptions of how technology adoption will improve their job performance (Venkatesh et al., 2003). In the specific context of this study, focusing on mathematics teachers, PE refers to the degree to which these teachers perceive that the utilization of e-learning technology will enhance their planning and instructional practices in mathematics. Prior research has highlighted the significance of PE in influencing technology acceptance and usage among educators. For instance, higher levels of PE positively influenced teachers' intentions to utilize and adopt technology in their teaching (Nikolopoulou et al., 2021). Furthermore, some researchers (e.g., Wijaya et al., 2022; Zacharis & Nikolopoulou, 2022) confirmed that performance expectancy played a crucial role in actual technology usage by teachers. These studies emphasize the importance of investigating the role of performance expectancy in shaping mathematics teachers' integration and acceptance of e-learning technology into their instructional practices.

H4: *(b) Performance expectancy will positively affect behavioral intention to use e-learning resources among mathematics teachers.*

2.3.6 Social Influence (SI)

Social influence (SI) is a construct within the UTAUT framework, representing users' perceptions of the support and influence of important individuals in their social network towards technology adoption (Venkatesh et al., 2003). In this study, which focuses on mathematics teachers, SI specifically denotes the extent to which these teachers perceive support from colleagues or administrators in using e-learning technology for planning and teaching mathematics. Previous research has emphasized the role of social influence in the acceptance of technology. For instance, studies by Leow et al. (2021) and Alasmari & Zhang (2019) found that the influence and support of colleagues significantly influenced users' intentions and actual adoption of technology. These findings point to the importance of examining the influence of social factors on mathematics teachers' adoption and integration of e-learning technology for planning and teaching mathematics.

H5: *(a) Social influence will positively affect behavioral intention to use e-learning resources among mathematics teachers.*

2.3.7 Facilitating Conditions (FC)

Facilitating conditions (FC) is a critical construct within the UTAUT framework, representing users' perceptions of the availability and adequacy of resources and support necessary to facilitate the use of technology (Venkatesh et al., 2003). In the context of this study, which focuses on mathematics teachers, FC specifically refers to the extent to which these teachers perceive having access to the necessary resources, such as training and technical support, to effectively utilize e-learning technology for planning and teaching mathematics. Previous research has highlighted the significance of facilitating conditions in technology adoption. For instance, a study by Lutfi (2022) found that access to resources and support had a positive influence on users' intentions and actual usage of technology. Similarly, facilitating conditions played a crucial role in teachers' adoption and acceptance of technology in education (Adov et al., 2020). These findings draws attention to of examining the influence of FC on mathematics teachers' adoption and integration of e-learning technology for planning and teaching mathematics.

H5: *(b) Facilitating conditions will positively affect behavioral intention to use e-learning resources among mathematics teachers.*

2.3.8 Behavioral Intention

The behavioral intention of mathematics teachers to adopt e-learning resources is primarily influenced by performance expectancy, effort expectancy, social influence, and facilitating conditions. Studies show that teachers are more likely to integrate digital tools in mathematics instruction when they believe these resources will improve their teaching effectiveness and when they perceive them as user-friendly (Venkatesh et al., 2003; Mailizar et al., 2021). Moreover, social influence, such as encouragement from school leaders and peers, can form the motivation to adopt e-learning platforms, especially in collectivist contexts like the Philippines (Salloum et al., 2019). Facilitating conditions, including access to infrastructure, technical support, and professional training, further strengthen BI by reducing barriers to adoption (Alqahtani & Rajkhan, 2020). These findings highlight that mathematics teachers' intention to adopt e-learning resources is not only shaped by individual perceptions of usefulness and ease but also by institutional and social supports embedded within the e-UTAUT framework.

2.3.9 Moderating Variables (Age, Experience, Respondent Type)

Age is an important moderator in technology adoption. Younger educators may demonstrate greater confidence in navigating new tools, while older educators might have more entrenched teaching practices (Venkatesh et al., 2003; Scherer et al., 2019). Such generational differences can alter how UTAUT predictors impact their intention to use e-learning resources.

Experience with technology, both in teaching and personal contexts, can influence perceptions of ease of use, usefulness, and external support systems (Dwivedi et al., 2019). Educators with more experience may rely less on facilitating conditions, whereas novices may depend heavily on them. Lastly, respondent type (e.g., preservice teacher, in-service teacher) may influence the relevance and perceived benefits of e-learning resources. Different professional roles come with varying responsibilities, expectations, and exposure to digital tools, which can shape how the UTAUT predictors relate to adoption intentions.

H6: *Age moderates the impact of (a) effort expectancy, (b) performance expectancy, (c) social influence, and (d) facilitating conditions on the behavioral intention to use e-Learning resources in teaching Mathematics.*

H7: *Experience moderates the impact of (a) effort expectancy, (b) performance expectancy, (c) social influence, and (d) facilitating conditions on the behavioral intention to use e-Learning resources in teaching Mathematics.*

H8: *Respondent type moderates the impact of (a) effort expectancy, (b) performance expectancy, (c) social influence, and (d) facilitating conditions on the behavioral intention to use e-Learning resources in teaching Mathematics.*

3. Methods

The study employs a quantitative survey design, utilizing multivariate data analysis to explore how mathematics teachers engage with technology. The study chose CB-SEM as the primary analytical tool because it allows for the concurrent examination of complex, interconnected relationships among latent variables. This makes it an ideal method for testing theory-based models, such as UTAUT, and establishing how various factors influence one another within our proposed framework. A critical component of this methodology is the sample size. We collected 282 responses (see subsection 2.5), a number that provides a robust foundation for our analysis. This section outlines the methodology, covering everything from research design to ethical considerations.

3.1. Research Participants

A total of 282 participants, including both pre-service (third- or fourth-year students) and in-service mathematics teachers, representing a range of experience levels, were involved in the study. These individuals are currently employed in various public and private educational institutions across the Philippines. During the data quality audit, four responses were excluded because they failed the sincerity test. Data collection was conducted through online survey forms, resulting in a final analysis dataset consisting of 282 respondents. Table 1 reveals an overview of the demographic characteristics of these participants.

Table 1
Demographic Characteristics of Participants

Category		*n*	%
Sex	Male	83	29.43
	Female	199	70.57
Age	18 - 21 years old	99	35.11
	22 - 25 years old	84	29.79
	26 years old and above	99	35.11

Respondent Type	In-service Teachers	114	40.43
	Pre-service Teachers	168	59.57
Three major island groups of the Philippines	Luzon	41	14.54
	Visayas	206	73.05
	Mindanao	35	12.41

3.2. Research Instruments

The survey instrument used in this study comprises two sections. The first section focuses on gathering demographic details and exploring the teaching experiences of the respondents. On the other hand, the second section of the survey consists of fifty-seven (57) statements designed to evaluate the eight constructs derived from the proposed research model. These constructs are PE with seven (7) items, EE with seven (7) items, SI with six (6) items, FC with six (6) items, PI with six (6) items, PR with ten (10) items, SE with eight (8) items, and BI with seven (7) items. Respondents rated their agreement with each statement on a five-point Likert scale, where 1 indicates "Strongly Disagree" and 5 indicates "Strongly Agree."

To ensure the relevance and validity of the survey instrument, multi-item scales were carefully selected from various previous studies. These scales were further modified to specifically suit the area of interest, which is the examination of teachers' beliefs on the adoption of e-learning resources in the context of teaching mathematics. By adapting these scales, the study aims to capture the nuanced perspectives and opinions of the participants in relation to this specific domain.

3.3. Data Analysis

To investigate the relationships between the constructs of the e-UTAUT, Pearson correlation was used to explore the associations between each construct. The data were examined using SPSS Statistics 24 software to assess the measurement model and conduct CFA. SEM was then utilized to establish the hypothesized model, facilitating the examination of intricate predictive relationships among the variables. Lastly, the AMOS software was utilized to estimate the structural model and evaluate its fit to the data, according to the suggested fit measures by Hair (2009).

The first step involved assessing the measurement model through CFA to evaluate if the measurement items for each construct loaded as expected onto their respective constructs. This assessment included examining convergent validity, ensuring that the items within each construct were strongly related, and discriminant validity, which ensured that the constructs were distinct from each other. Convergent validity was established when the measurement items within a construct exhibited high correlations, indicating that they measured the same underlying construct.

Discriminant validity was established when the correlation between constructs was lower than the correlation within each construct, indicating that the constructs were distinct from one another.

After confirming the measurement model, the next step involved estimating the structural model using SEM analysis. Structural equation modeling allowed for the examination of complex relationships among variables and provided estimates of the strength and significance of these relationships. The structural model helped test the hypothesized relationships between the constructs and provided insights into the direct and indirect effects of the variables. During the estimation of the structural model, fit measures were assessed to evaluate how well the model fits the data. Acceptable fit measures, as suggested by Hair (2009), were used as criteria for evaluating the model. These fit measures may include indices such as the chi-square goodness-of-fit statistic, comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). These measures provided information about the overall fit of the model to the data, the amount of variance explained, and the differences between the model and the observed data.

3.4. Ethical Consideration

The paper received institutional ethics clearance on October 09, 2023. The study was classified as 'Exempted' due to its low-risk nature, with rigorous adherence to ethical protocols ensuring the protection of participants' rights. These protocols included informed consent, confidentiality, anonymity, voluntary participation, and secure data handling. Before answering the survey, respondents will receive an informed consent form outlining the study's purpose, procedures, potential risks and benefits, confidentiality, and their right to withdraw at any time without explanation. The research team consistently upheld these ethical standards throughout data collection, analysis, reporting, and publication.

4. Results

This section presents the data analysis and interpretation of the outcomes, such as (1) respondents' behavioral rating on the following constructs, (2) the hypothesis testing through CB-SEM, and (3) the analysis of the moderating effect. In CB-SEM results, the following tables are presented and discussed in this section: (a) preliminary analysis, (b) testing the Model by CFA, (c) testing the relationships among Latent Variables, (d) Structural Equation modeling results, and the moderating effect.

4.1 Respondents' Behavioral Ratings on the Constructs

The second sub-problem focused on the behavioral rating of the respondents on the following variables: performance expectancy, effort expectancy, social influence, facilitating conditions, personal innovativeness, perceived risks, e-learning self-efficacy, and behavioral intention, as illustrated in Table 2.

Table 2

Summary Table of Respondents' Perception of the Variables

Constructs	Aggregate Mean	Interpretation
Performance Expectancy	6.18	Strongly Agree
Effort Expectancy	5.64	Agree
Social Influence	5.63	Agree
Facilitating Conditions	5.58	Agree
Personal Innovativeness	6.04	Agree
Perceived Risks	3.67	Neither Agree nor Disagree
E-learning Self-Efficacy	5.41	Agree
Behavioral Intention	5.80	Agree

4.2 Preliminary Analysis

The initial analysis aimed to assess the internal consistency reliability of each construct through Cronbach's alpha, based on the original survey items. The reliability coefficients ranged between 0.830 and 0.939, indicating that all measures are reliably consistent internally (Awang, 2012). Table 12 examines multicollinearity and discriminant validity through a correlation matrix visual analysis.

Table 3
Zero-order Correlations and Descriptive Statistics of the Study Variables

Study Variables	PI	PR	SE	EE	PE	SI	FC	BI
PI	1							
PR	0.608**	1						
SE	0.545**	0.586**	1					
EE	0.459**	0.585**	0.632**	1				
PE	0.496**	0.522**	0.542**	0.646**	1			
SI	-0.218**	-0.189**	-0.018	-0.053	-0.213**	1		
FC	0.374**	0.564**	0.505**	0.678**	0.620**	-0.097	1	
BI	0.505**	0.508**	0.536**	0.560**	0.653**	-0.103	0.711**	1
Mean	6.04	3.67	5.41	5.64	6.18	5.63	5.58	5.80
Standard Deviation	0.69	1.28	0.87	0.82	0.73	0.86	0.85	0.78

***Correlation is significant at the 0.01 level (2-tailed).*

The correlation analysis showed significant results at the 0.01 alpha level, indicating strong statistical relationships between the constructs. The correlations ranged from -0.218 to 0.711, highlighting a mix of negative and positive relationships across different variables. The highest positive correlation was observed between BI and FC at 0.711, indicating a strong relationship between the ease of using e-learning resources and the intention to use them. All other coefficients range from 0.459 to 0.678, illustrating moderate to strong relationships among the constructs. The lowest correlation was between SI and Personal Innovativeness (PI) at -0.218, suggesting a slight inverse relationship between the influence of social circles and personal innovation in using e-learning resources.

Interestingly, SI exhibited a significant inverse relationship with several core constructs, including Personal Innovativeness and Performance Expectancy. This suggests that for this group of mathematics teachers, technology adoption is driven more by individual agency and perceived utility than by social or external pressures. The negative correlation with innovativeness may indicate that 'early adopters' in the math department operate independently of peer trends, prioritizing pedagogical fit over social conformity.

4.3 Measurement Model

This study employed Pearson correlation coefficient analysis to support the path analysis within the SEM. Following the guidelines set by Schober et al. (2018), the study classified correlations as negligible (0.00–0.09), weak (0.10–0.39), moderate (0.40–0.69), strong (0.70–0.89), and very strong (0.90–1.00).

Table 4

CFA results of the Final Measurement Model

Constructs	Items	Estimate	CR	AVE	Cronbach's Alpha
Performance Expectancy	PE7	0.624	0.896	0.592	0.901
	PE6	0.701			
	PE5	0.828			
	PE4	0.894			
	PE3	0.813			
	PE2	0.723			
Effort Expectancy	EE7	0.636	0.891	0.542	0.892
	EE6	0.750			
	EE5	0.579			
	EE4	0.764			
	EE3	0.779			
	EE2	0.799			
	EE1	0.815			
Social Influence	SI6	0.820	0.872	0.533	0.871
	SI5	0.776			
	SI4	0.708			
	SI3	0.768			
	SI2	0.645			
	SI1	0.644			
Facilitating Conditions	FC6	0.656	0.876	0.590	0.865
	FC4	0.650			
	FC3	0.876			
	FC2	0.842			
	FC1	0.787			
Perceived Risks	PR2	0.600	0.927	0.588	0.939
	PR3	0.675			
	PR4	0.729			
	PR5	0.836			

	PR6	0.853			
	PR7	0.924			
	PR8	0.78			
	PR9	0.744			
	PR10	0.707			
E-learning Self-Efficacy	SE1	0.775	0.901	0.569	0.899
	SE2	0.817			
	SE3	0.719			
	SE4	0.868			
	SE5	0.697			
	SE7	0.756			
	SE8	0.620			
Behavioral Intention	BI1	0.617	0.878	0.508	0.889
	BI2	0.642			
	BI3	0.648			
	BI4	0.760			
	BI5	0.779			
	BI6	0.812			
	BI7	0.708			
Perceived Innovativeness	PI2	0.768	0.885	0.607	0.883
	PI3	0.773			
	PI4	0.769			
	PI5	0.782			
	PI6	0.802			

Convergent validity is demonstrated in two ways: the factor loadings must be significant and higher than 0.5 (Bagozzi & Yi, 1988), and then the AVE for each of the factors is >0.5 (Fornell & Larcker, 1981). The analysis revealed that AVE values ranged from 0.508 to 0.607, supporting strong convergent validity. Additionally, all factor loadings were acceptable ranging from 0.579 to 0.924. Composite Reliability (CR) indices affirm the scale's reliability for each construct, all of which exceed 0.6 (Bagozzi & Yi, 1988), with values ranging from 0.872 to 0.927. The overall measurement model demonstrated a very satisfactory fit, with indices including CFI (0.909), TLI (0.901), RMSEA (0.054), and SRMR (0.0644).

4.4 Relationship Between the Latent Variable

This study employed Pearson correlation coefficient analysis to support the path analysis within the SEM. Following the guidelines set by Schober et al. (2018), the study classified correlations as negligible (0.00–0.09), weak (0.10–0.39), moderate (0.40–0.69), strong (0.70–0.89), and very strong (0.90–1.00).

Table 5

Correlation results among the constructs in CFA

Factors	PI	PR	SE	EE	PE	SI	FC	BI
PI	1							
PR	-0.268**	1						
SE	0.503**	-0.0981	1					
EE	0.435**	-0.204**	0.564**	1				
PE	0.485**	-0.212**	0.384**	0.613**	1			
SI	0.455**	-0.0259	0.505**	0.586**	0.558**	1		
FC	0.497**	-0.0494	0.686**	0.578**	0.445**	0.604**	1	
BI	0.608**	-0.1117	0.711**	0.508**	0.507**	0.536**	0.534**	1

***Correlation is significant at the 0.01 level (2-tailed).*

Table 5 provides the correlation matrix for the constructs analyzed in the CFA, indicating both negative and positive significant correlations at the 0.01 alpha level. These correlations ranged from -0.268 to 0.711, demonstrating a variety of relationships among the constructs. Notably, the highest positive correlation was between the constructs of SE and BI at 0.711, suggesting a strong positive relationship. On the negative side, the most significant negative correlation was observed between PI and PR, with a correlation coefficient of -0.268, indicating an inverse relationship between these two variables.

All other coefficients fell within the moderate range, from -0.204 to 0.686. This wide range of correlations underscores the complexity of the relationships between the different variables studied. Specifically, the dependent variable, BI, showed significant correlations with all seven other variables.

4.5 The Path Analysis

The final model fit indices are satisfactory, with a chi/df of 1.802, CFI of 0.911, and TLI of 0.903, while RMSEA of 0.053 indicates an excellent fit between the hypothesized model and the observed data

(Hair, 2009). The significance of each hypothesized structural path is examined using standardized path coefficients and their corresponding p-values.

Figure 3
The Final Model of the Study

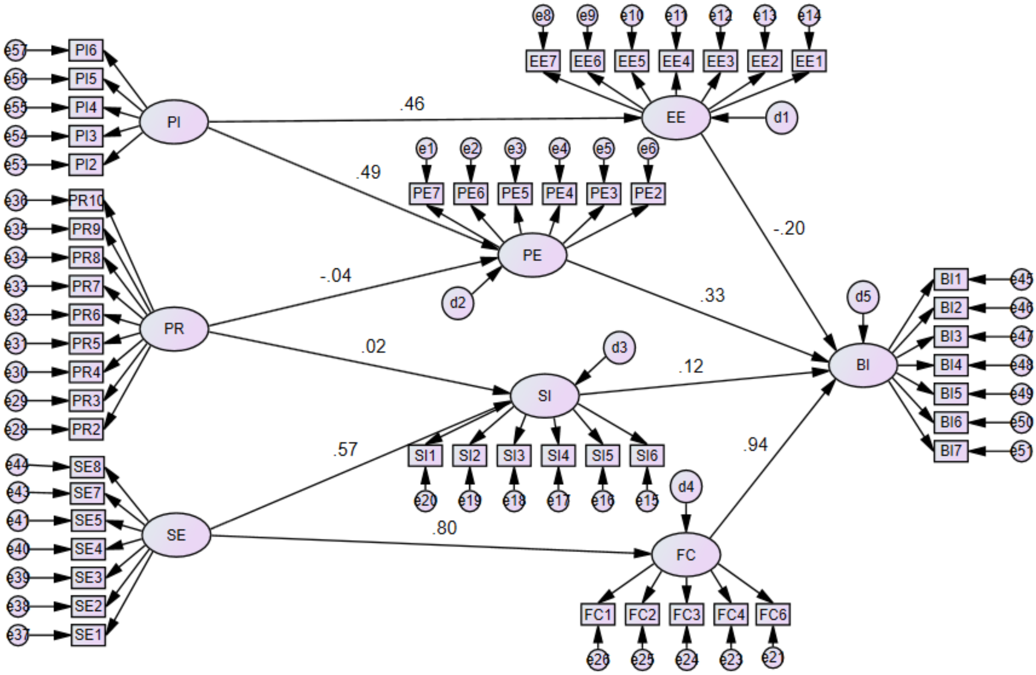


Table 6
SEM results

Hypothesis	Path Analysis	Estimate	SE	CR	Remarks
H1a	PI --> EE	0.473***	0.148	3.203	Supported
H1b	PI --> PE	0.335***	0.051	6.55	Supported
H2a	PR --> PE	-0.02	0.029	-0.701	Not Supported
H2b	PR --> SI	0.018	0.052	0.355	Not Supported

H3a	SE --> SI	0.636***	0.073	8.654	Supported
H3b	SE --> FC	0.858***	0.089	9.591	Supported
H4a	EE --> BI	-0.193	0.089	-2.167	Not Supported
H4b	PE --> BI	0.473***	0.115	4.101	Supported
H5a	SI --> BI	0.092	0.055	1.686	Not Supported
H5b	FC --> BI	0.767***	0.115	6.645	Supported

*Note: *** $p < 0.001$, * $p < 0.05$*

Figure 3 shows that seven paths are significant at $p < 0.001$, one at $p < 0.05$, and three paths are not significant. As shown in Table 6, PI has a significant influence on both EE and PE, with path coefficients of 0.473 and 0.335, respectively. This suggests that individuals who are more receptive to new technologies are likely to have higher expectations of the e-learning system's efficiency and effectiveness. This finding is consistent with studies showing that personal innovativeness enhances adoption intentions through positive perceptions of performance and effort expectancy and that technological awareness significantly influences user adoption decisions (Kumari et al., 2023; Sair & Danish, 2018).To effectively leverage this insight, developers and educators should consider designing e-learning systems that cater to varying levels of technological sophistication among users, ensuring that these systems are not only advanced but also user-friendly, thereby enhancing their appeal to a broader audience. This strategy could maximize the adoption and sustained usage of e-learning platforms across different user demographics.

Similarly, SE demonstrates a strong positive effect on SI and FC, with coefficients of 0.636 and 0.858, respectively, indicating that individuals' confidence in their ability to use the e-learning system enhances their perception of social support and the availability of resources for using the system. Research suggests relationships between self-efficacy and both social influence and facilitating conditions, with studies highlighting how enhanced self-efficacy can positively impact perceptions of social support and resource availability in educational settings (Sung et al., 2015; Wang & Chu, 2023). These insights underscore the importance of interventions designed to boost self-efficacy, thereby improving user engagement and educational outcomes in e-learning environments.

Notably, the path from EE to BI is significant but negative (β = -0.193), implying that while users may find the system easy to use, this does not necessarily translate to a higher intention to use it. This could be interpreted as users prioritizing functionality and outcomes over simplicity. Contrary findings in the literature suggest that, even when users acknowledge the ease of using e-learning systems, other factors, such as perceived usefulness, may have a stronger influence on their intention to use these systems. For instance, alternative paths to behavioral intention emphasize the complexity of user adoption behavior in educational technologies (Amin & Zaman, 2021; Wang & Chu, 2023). This highlights the importance of addressing multiple facets of user experience, such as perceived effectiveness and relevance, to enhance the likelihood of e-learning adoption.

PE and FC are the strongest predictors of BI to use the e-learning system, with coefficients of 0.473 and 0.767, respectively, underscoring the importance of PE and FC in the adoption process. This finding is consistent with research indicating that performance expectancy and facilitating conditions critically influence behavioral intentions across different technologies and contexts, reinforcing the need for systems to meet users' performance expectations and provide the necessary support (Antwi-Boampong et al., 2022; Zacharis & Nikolopoulou, 2022). This implies that to drive user adoption, enhancements in system performance and support infrastructure should be prioritized.

On the other hand, the non-significant paths from PR to PE and SI suggest that in this e-learning context, users might not view risks as a major factor influencing their expectations of the system's performance or the social pressures to use it. This contrasts with studies that have shown perceived risks significantly deter technology adoption by affecting performance expectations and the influence of social circles (Almaiah et al., 2022; Koenig-Lewis et al., 2015). This implies that the target users may have a high level of trust in the system, or the perceived benefits may overshadow any concerns about risks, indicating an opportunity to focus on reinforcing these positive perceptions rather than mitigating non-significant concerns.

Furthermore, the path from SI to BI was also not significant, suggesting that SI may not be a decisive factor in determining behavioral intention in this instance. This finding aligns with research by Hunde et al. (2023), which also found that the influence of social factors on behavioral intentions to use e-learning was minimal among health science students. This suggests that in certain educational contexts, particularly those where individual learning needs and preferences prevail, social influence may not play a significant role. Therefore, it could be beneficial for educational institutions to tailor their e-learning systems more towards individual learning styles and benefits, rather than focusing heavily on social advocacy or peer influence strategies.

4.6 Analysis of the moderating effect

The UTAUT model states that the influence of its core predictors on technology adoption and use varies across different user demographics and context factors, acting through four primary moderators: gender, age, and experience (Venkatesh et al., 2003). Extending this framework, the current study examines age, experience, and respondent type as moderating variables. This choice is informed by the need to investigate how these factors might influence e-learning adoption among educators, distinguishing between pre-service and in-service educators to uncover potential differences in technology adoption patterns.

Table 7

Moderating Variable – Age

Age	18-21 yrs. old		22-25 yrs. old		26 and above yrs. old	
	β	CR	β	CR	β	CR
EE --> BI	0.099	0.985	0.054	0.48	0.163	1.659
PE --> BI	-0.01	-0.082	0.335	1.923	0.483**	2.742
FC --> BI	0.505***	3.997	0.217	1.792	0.188	1.895
SI --> BI	0.426**	3.164	0.179	1.176	0.184	1.23

Note: *** $p < 0.001$, ** $p < 0.01$

As shown in Table 7, the influence of age on the relationship between key e-learning adoption predictors and BI showcases notable variations across different age groups. For EE leading to BI, the relationship appears to strengthen with age, moving from a non-significant $\beta = 0.099$ for the 18-21 years group to a modest $\beta = 0.163$ for individuals aged 26 and above. This trend suggests that older users might slightly prioritize ease of use over younger counterparts when deciding to adopt e-learning systems. However, the overall impact remains limited across age groups. PE's impact on BI is not significant in the youngest and middle age groups but becomes significant ($\beta = 0.483$, $p < 0.01$) for those aged 26 and above. This indicates a clear trend: as age increases, so does the importance of perceived benefits and outcomes from using e-learning systems in influencing their intention to use such platforms.

In contrast, FC exhibits a decreasing trend in influence with age. While younger users (18-21 years old) show a strong and significant reliance on FC for adopting e-learning (β = 0.505, p < 0.001), this influence notably diminishes for the older age groups, maintaining a positive yet weaker effect. Similarly, SI shows a strongly significant effect for the youngest group (β = 0.426, p < 0.01), underscoring the impact of peer opinions and societal norms on their decision to adopt e-learning. However, this effect lessens with age, transitioning to non-significant levels for older groups.

Table 8

Moderating Variable – Respondent Type

Respondent Type	In-service		Pre-service	
	β	CR	β	CR
EE --> BI	0.443***	3.225	-0.077	-1.002
PE --> BI	0.44***	3.258	0.206*	2.532
FC --> BI	0.073	0.756	0.467***	4.909
SI --> BI	0.224*	2.096	0.309***	3.675

Note: *** p < 0.001, * p< *0.05*

Table 8 shows the analysis of respondent type, distinguishing between in-service and pre-service educators, and reveals notable differences in how various factors influence their behavioral intention toward e-learning adoption. For in-service educators, EE and PE both have a significant and strong positive impact on BI, with coefficients (β) of 0.443 and 0.44, respectively, and both at ρ < 0.001. This suggests that for these experienced educators, both the ease of use and the perceived benefits of e-learning platforms are crucial factors in determining their willingness to adopt such technologies.

Moreover, for pre-service educators, PE has a positive impact on BI (β = 0.206, p < 0.05), suggesting that the perceived benefits of e-learning systems are also important for them; in contrast, EE shows a negative and non-significant relationship (β = -0.077). This might indicate that for pre-service educators, who are likely more familiar with digital technologies, the ease of use of e-learning systems is not a significant barrier or facilitator to adoption. Interestingly, FC and SI play a more significant role for pre-service educators, with coefficients of 0.467 and 0.309, respectively, both of which are significant at $p < 0.001$. This highlights that for these individuals, the availability of resources, support, and social endorsement is more critical in influencing their decision to adopt e-learning.

Table 9

Moderating Variable – Teaching Experience

Teaching Experience	Below five (5) years		Above five (5) years	
	β	CR	*β*	CR
EE --> BI	-0.03	-0.443	0.684*	2.682
PE --> BI	0.281***	3.65	0.233	1.672
FC --> BI	0.411***	4.927	0.141	1.105
SI --> BI	0.308***	4.097	0.19	1.444

Note: *** $p < 0.001$, * $p < 0.05$

The analysis of Table 9 focuses on teaching experience as a moderating variable. For respondents with less than five years of teaching experience, EE does not significantly influence BI, indicated by a path coefficient of -0.03. This group appears to place less importance on the ease of use of e-learning platforms when making decisions about adopting such technologies. Conversely, EE has a significant positive impact on BI for those with more than five years of experience (β = 0.684, p < 0.05), suggesting that the ease of using e-learning technologies becomes increasingly important with more teaching experience.

PE shows a significant positive influence on BI for educators with less than five years of experience (β = 0.281, p < 0.001). However, the influence is somewhat stronger for this group compared to their more experienced counterparts (β = 0.233). This indicates that while perceived benefits from e-learning technologies are important for all educators, they hold slightly more sway among those with fewer years of experience. FC demonstrates a strong positive relationship with BI among those with less teaching experience (β = 0.411, p < 0.001), suggesting that access to resources and support plays a critical role in their decision to adopt e-learning technologies. For educators with more than five years of experience, this relationship, although still positive, is not significant (β = 0.141), suggesting a possible adaptation to or better navigation of the e-learning environment over time, which reduces the perceived need for facilitating conditions. SI is significantly positive for both groups, with a stronger effect observed among less experienced educators (β = 0.308, p < 0.001) compared to those with more experience (β = 0.19). This suggests that the opinions of significant others, such as colleagues and industry leaders, have a greater impact on the decision-making of newer educators regarding the adoption of e-learning.

5. Discussion

This study investigates the adoption of e-learning resources among mathematics teachers by examining the influence of effort expectancy, performance expectancy, social influence, facilitating conditions, personal innovativeness, perceived risks, and e-learning self-efficacy on their behavioral intentions. Conducted across various regions in the Philippines, it employs SEM within an extended UTAUT framework to analyze these relationships. The insights gained contribute to the formulation of a proposed training program designed to help teachers effectively integrate e-learning into their teaching methodologies. This plan is intended to enhance mathematics education through the strategic use of technology. The study encompasses a diverse group of 282 respondents, including both pre-service and in-service teachers.

This study reveals a strong positive perception among participants towards various constructs related to the adoption and use of e-learning platforms. Notably, PE received the highest aggregate mean score of 6.18, indicating that respondents strongly agree on the benefits and effectiveness of e-learning in enhancing their performance. This is closely followed by PI, with a mean of 6.04, indicating a high level of agreement on the willingness to adopt new technologies for learning. Other constructs, such as EE, SI, FC, SE, and BI, all fell within the 'Agree' range, suggesting a positive attitude towards the ease of use, the influence of social circles, the support available for e-learning, the belief in their e-learning capabilities, and the intention to use e-learning platforms, respectively. However, PR associated with e-learning was the only construct about which participants were undecided, with a mean score of 3.67, indicating neither agreement nor disagreement, which highlights potential concerns or uncertainties about the drawbacks or challenges of e-learning.

The path analysis conducted to examine the relationships between various constructs revealed several significant findings. Seven paths were statistically significant, while three paths were not. Specifically, H1a, H1b, H3a, H3b, H4a, H4b, and H5a were found to be significant. These findings highlighted the importance of personal innovativeness and e-learning self-efficacy in shaping teachers' perceptions and intentions regarding the adoption of e-learning. On the other hand, the paths H2a, H2b, and H5b were found to be not significant. Indicating that perceived risks and social influence might not have a strong direct impact on teachers' performance expectancy and their behavioral intentions toward e-learning adoption.

Besides, the significance of the path from EE to BI being negative (H4a) is particularly intriguing, suggesting that higher effort expectancy may reduce the intention to use e-learning. In contrast, the significant positive paths from PI to both EE and PE (H1a and H1b) highlight the role of innovativeness in overcoming potential barriers to e-learning adoption. Teachers who are more innovative may perceive e-learning technologies as both easier to use and more beneficial, which, in turn, positively impacts their intention to adopt these technologies.

The analysis of moderating variables revealed varying impacts across different demographics, indicating that age, type of respondent, and length of teaching experience influence the connections between key factors. For age groups, significant interactions were observed in the paths from PE to BI among those aged 26 and above and from FC to BI across all age groups, with the strongest effect in the 18-21 years category. SI to BI also showed significant moderation for the 18-21- and 22-25-year categories, indicating varied impacts of these constructs on behavioral intention across different age groups. In terms of respondent type, in-service teachers demonstrated a stronger connection in all paths leading to BI compared to pre-service teachers, notably in the paths from EE to BI and from PE to BI, where the relationships were significantly stronger. This suggests that in-service teachers' intentions to use technology in their teaching practices are more influenced by their perceptions of ease and effort than those of pre-service teachers. Additionally, FC and SI to BI were significantly stronger for pre-service teachers, indicating that these factors could be more crucial in shaping their behavioral intentions to adopt technology.

Lastly, when examining teaching experience, those with less than five years of experience showed a notably strong relationship between FC and SI, highlighting the significance of supportive conditions and social norms for this group. Conversely, for those with more than five years of experience, the effect of EE on BI was significantly stronger, suggesting that the intentions of experienced teachers are more influenced by the effort they perceive in using technology in their teaching practices.

6. Conclusion

This study addresses the research gap in understanding e-learning adoption among mathematics teachers by extending the Unified Theory of Acceptance and Use of Technology (e-UTAUT) model to better explain factors influencing their technology acceptance. By integrating novel constructs, including Personal Innovativeness (PI), Perceived Risk (PR), and E-Learning Self-Efficacy, with the traditional UTAUT variables, the study provides a comprehensive framework for examining the integration of technology in mathematics education. To validate the model, the study employed a quantitative survey design, yielding 282 responses, which were analyzed using Covariance-Based Structural Equation Modeling (CB-SEM). This multivariate approach enabled the simultaneous examination of complex direct and indirect relationships, tailored to mathematics instruction.

The findings show that PI influence both effort expectance (EE) and performance expectancy (PE), suggesting that teachers with a natural inclination toward innovation find e-learning tools more straightforward to use and more effective. E-Learning Self-Efficacy emerged as a predictor of social influence (SI) and facilitating conditions (FC), indicating that confidence in digital skills can enhance perceptions of social support and technical infrastructure. Notably, the correlation analysis revealed an inverse relationship for Social Influence, suggesting that for these educators, adoption is often an independent, merit-based decision rather than one driven by peer pressure. Although perceived risks did not significantly hinder performance beliefs, factors such as PE and FC remained the most critical drivers of actual behavioral intention (BI).

These results offer a strategic roadmap for both teachers and administrators. For educators, the study promotes professional growth by building self-efficacy, a foundation for navigating digital resources effectively. For administrators, the evidence supports a shift toward targeted infrastructure spending and policies that foster a sustainable community of practice. Because Performance Expectancy is a primary driver, institutions should focus on demonstrating the tangible benefits of e-learning for math-specific pedagogy. Furthermore, mitigating perceived risks through clear data privacy communication and reliable technical support can alleviate lingering apprehensions, ensuring that technology is seen as a supportive tool rather than an administrative burden.

While these insights provide a valuable foundation, the study is naturally constrained by its cross-sectional design, which offers a static snapshot of teacher perceptions at a single point in time. To build on this work, future research should adopt longitudinal approaches to track how technology adoption matures over time. Such studies would be vital for understanding how educators' attitudes shift as e-learning platforms become more sophisticated and integrated into the daily classroom environment. Additionally, researchers should explore the ambivalent view of perceived risks found in this study by investigating specific security concerns in greater detail. It is recommended that schools cultivate an innovative culture by rewarding early adopters and integrating self-efficacy training into standard professional development. Continuous research will be essential to keep pace with the rapidly evolving digital landscape and to ensure that instructional quality in mathematics continues to improve.

References

Adarkwah, M. A. (2021). "I'm not against online teaching, but what about us?": ICT in Ghana post Covid-19. *Education and information technologies*, *26*(2), 1665-1685.

Adov, L., Pedaste, M., Leijen, Ä., & Rannikmäe, M. (2020). Does it have to be easy, useful, or do we need something else? STEM teachers' attitudes towards mobile device use in teaching. *Technology, pedagogy and education*, *29*(4), 511-526.

Akugizibwe, E., & Ahn, J. Y. (2020). Perspectives for effective integration of e-learning tools in university mathematics instruction for developing countries. *Education and Information Technologies*, *25*(2), 889-903.

Al-Adwan, A. S., Albelbisi, N. A., Hujran, O., Al-Rahmi, W. M., & Alkhalifah, A. (2021). Developing a holistic success model for sustainable e-learning: A structural equation modeling approach. *Sustainability*, *13*(16), 9453.

Alasmari, T., & Zhang, K. (2019). Mobile learning technology acceptance in Saudi Arabian higher education: an extended framework and A mixed-method study. *Education and Information Technologies*, *24*(3), 2127-2144.

Almaiah, M. A., & Alyoussef, I. Y. (2019). Analysis of the effect of course design, course content support, course assessment and instructor characteristics on the actual use of E-learning system. *Ieee Access*, *7*, 171907-171922.

Almaiah, M. A., Al-Khasawneh, A., & Althunibat, A. (2020). Exploring the critical challenges and factors influencing the E-learning system usage during COVID-19 pandemic. *Education and information technologies*, *25*(6), 5261-5280.

Almaiah, M. A., Al-Rahmi, A. M., Alturise, F., Alrawad, M., Alkhalaf, S., Lutfi, A., ... & Awad, A. B. (2022). Factors influencing the adoption of internet banking: An integration of ISSM and UTAUT with price value and perceived risk. *Frontiers in Psychology*, *13*, 919198.

Alqahtani, A. Y., & Rajkhan, A. A. (2020). E-learning critical success factors during the covid-19 pandemic: A comprehensive analysis of e-learning managerial perspectives. *Education sciences*, *10*(9), 216.

Amin, M. K., & Zaman, M. (2021). Assessing the Adoption Behavior of E-Learning in a Developing Country in South East Asia: Predicting an Alternative Path to Behavioral Intention to Use. *International Journal of Education and Development using Information and Communication Technology*, *17*(3), 38-56.

Antwi-Boampong, A., Boison, D. K., Doumbia, M. O., Boakye, A. N., Osei-Fosua, L., & Owiredu Sarbeng, K. (2022). Factors affecting port users' behavioral intentions to adopt financial technology (fintech) in ports in sub-saharan africa: A case of ports in Ghana. *FinTech*, *1*(4), 362-375.

Awang, Z. (2012). *Research methodology and data analysis second edition*. UiTM Press.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the academy of marketing science*, *16*(1), 74-94.

Bai, X., He, Y., & Kohlbacher, F. (2018). Older people's adoption of e-learning services: A qualitative study of facilitators and barriers. *Gerontology & geriatrics education*, *41*(3), 291-307.

Balkaya, S., & Akkucuk, U. (2021). Adoption and use of learning management systems in education: The role of playfulness and self-management. *Sustainability*, *13*(3), 1127.

Batucan, G. B., Gonzales, G. G., Balbuena, M. G., Pasaol, K. R. B., Seno, D. N., & Gonzales, R. R. (2022). An extended UTAUT model to explain factors affecting online learning system amidst COVID-19 pandemic: The case of a developing economy. *Frontiers in Artificial Intelligence*, *5*, 768831.

Castro, R. (2019). Blended learning in higher education: Trends and capabilities. *Education and information technologies*, *24*(4), 2523-2546.

Chao, C. M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in psychology*, *10*, 1652.

Daultani, Y., Goswami, M., Kumar, A., & Pratap, S. (2021). Perceived outcomes of e-learning: identifying key attributes affecting user satisfaction in higher education institutes. *Measuring Business Excellence*, *25*(2), 216-229.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information systems frontiers*, *21*(3), 719-734.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

Guoyan, S., Khaskheli, A., Raza, S. A., Khan, K. A., & Hakim, F. (2021). Teachers' self-efficacy, mental well-being and continuance commitment of using learning management system during COVID-19 pandemic: a comparative study of Pakistan and Malaysia. *Interactive learning environments*, *31*(7), 4652-4674.

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.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2009). Multivariate data analysis 7th edition Pearson prentice hall. *JOUR*.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, *6*(1), 1-55.

Hunde, M. K., Demsash, A. W., & Walle, A. D. (2023). Behavioral intention to use e-learning and its associated factors among health science students in Mettu university, southwest Ethiopia: Using modified UTAUT model. *Informatics in Medicine Unlocked*, *36*, 101154.

Jameel, A. S., Karem, M. A., & Ahmad, A. R. (2021, June). Behavioral intention to use e-learning among academic staff during COVID-19 pandemic based on UTAUT model. In *International Conference on emerging technologies and intelligent systems* (pp. 187-196). Cham: Springer International Publishing.

Kim, B., & Park, M. J. (2017). Effect of personal factors to use ICTs on e-learning adoption: comparison between learner and instructor in developing countries. *Information Technology for Development*, *24*(4), 706-732.

Koenig-Lewis, N., Marquet, M., Palmer, A., & Zhao, A. L. (2015). Enjoyment and social influence: predicting mobile payment adoption. *The Service Industries Journal*, *35*(10), 537-554.

Kumari, V., Bala, P. K., & Chakraborty, S. (2023). An empirical study of user adoption of cryptocurrency using blockchain technology: Analysing role of success factors like technology awareness and financial literacy. *Journal of Theoretical and Applied Electronic Commerce Research*, *18*(3), 1580-1600.

Lee, W., & Shin, S. (2019). An empirical study of consumer adoption of Internet of Things services. *International Journal of Engineering and Technology Innovation*, *9*(1), 1-11.

Leow, L. P., Phua, L. K., & Teh, S. Y. (2021). Extending the social influence factor: Behavioural intention to increase the usage of information and communication technology-enhanced student-centered teaching methods. *Educational Technology Research and Development*, *69*(3), 1853-1879.

Liao, Y. K., Wu, W. Y., Le, T. Q., & Phung, T. T. T. (2022). The integration of the technology acceptance model and value-based adoption model to study the adoption of e-learning: The moderating role of e-WOM. *Sustainability*, *14*(2), 815.

Lutfi, A. (2022). Factors influencing the continuance intention to use accounting information system in Jordanian SMEs from the perspectives of UTAUT: Top management support and self-efficacy as predictor factors. *Economies*, *10*(4), 75.

Ma, J., Li, C., & Liang, H. N. (2019). Enhancing students' blended learning experience through embedding metaliteracy. *Education Research International*, *2019*(1), 6791058.

Maass, K., Geiger, V., Ariza, M. R., & Goos, M. (2019). The role of mathematics in interdisciplinary STEM education. *Zdm*, *51*(6), 869-884.

Mailizar, M., Almanthari, A., & Maulina, S. (2021). Examining teachers' behavioral intention to use E-learning in teaching of mathematics: An extended TAM model. *Contemporary educational technology*, *13*(2), ep298.

Mazman Akar, S. G. (2019). Does it matter being innovative: Teachers' technology acceptance. *Education and Information Technologies*, *24*(6), 3415-3432.

Meskhi, B., Ponomareva, S., & Ugnich, E. (2019). E-learning in higher inclusive education: needs, opportunities and limitations. *International journal of educational management*, *33*(3), 424-437.

Moreno-Guerrero, A. J., Aznar-Díaz, I., Cáceres-Reche, P., & Alonso-García, S. (2020). E-learning in the teaching of mathematics: An educational experience in adult high school. *Mathematics*, *8*(5), 840.

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2021). Habit, hedonic motivation, performance expectancy and technological pedagogical knowledge affect teachers' intention to use mobile internet. *Computers and Education Open*, *2*, 100041.

Ong, C. S., & Lai, J. Y. (2006). Gender differences in perceptions and relationships among dominants of e-learning acceptance. *Computers in human behavior*, *22*(5), 816-829.

Qiao, P., Zhu, X., Guo, Y., Sun, Y., & Qin, C. (2021). The development and adoption of online learning in pre-and post-COVID-19: Combination of technological system evolution theory and unified theory of acceptance and use of technology. *Journal of Risk and Financial Management*, *14*(4), 162.

Roman, T. A., Brantley-Dias, L., Dias, M., & Edwards, B. (2021). Addressing student engagement during COVID-19: Secondary STEM teachers attend to the affective dimension of learner needs. *Journal of Research on Technology in Education*, *54*(sup1), S65-S93.

Sair, S. A., & Danish, R. Q. (2018). Effect of performance expectancy and effort expectancy on the mobile commerce adoption intention through personal innovativeness among Pakistani consumers. *Pakistan Journal of Commerce and social sciences (PJCSS)*, *12*(2), 501-520.

Salloum, S. A., Al-Emran, M., Shaalan, K., & Tarhini, A. (2019). Factors affecting the E-learning acceptance: A case study from UAE. *Education and information technologies*, *24*(1), 509-530.

Sarker, M. F. H., Mahmud, R. A., Islam, M. S., & Islam, M. K. (2019). Use of e-learning at higher educational institutions in Bangladesh: Opportunities and challenges. *Journal of Applied Research in Higher Education*, *11*(2), 210-223.

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & education*, *128*, 13-35.

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation coefficients: appropriate use and interpretation. *Anesthesia & analgesia*, *126*(5), 1763-1768.

Setiawan, B., Nugraha, D. P., Irawan, A., Nathan, R. J., & Zoltan, Z. (2021). User innovativeness and fintech adoption in Indonesia. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(3), 188.

Seufert, S., Guggemos, J., & Sailer, M. (2021). Technology-related knowledge, skills, and attitudes of pre-and in-service teachers: The current situation and emerging trends. *Computers in human behavior*, *115*, 106552.

Sung, H. N., Jeong, D. Y., Jeong, Y. S., & Shin, J. I. (2015). The relationship among self-efficacy, social influence, performance expectancy, effort expectancy, and behavioral intention in mobile learning service. *International Journal of u-and e-Service, Science and Technology*, *8*(9), 197-206.

Tarhini, A., Elyas, T., Akour, M. A., & Al-Salti, Z. (2016). Technology, demographic characteristics and e-learning acceptance: A conceptual model based on extended technology acceptance model. *Higher Education Studies*, *6*(3), 72-89.

Teng, Z., Cai, Y., Gao, Y., Zhang, X., & Li, X. (2022). Factors affecting learners' adoption of an educational metaverse platform: An empirical study based on an extended UTAUT model. *Mobile Information Systems*, *2022*(1), 5479215.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Vershitskaya, E. R., Mikhaylova, A. V., Gilmanshina, S. I., Dorozhkin, E. M., & Epaneshnikov, V. V. (2020). Present-day management of universities in Russia: Prospects and challenges of e-learning. *Education and Information Technologies*, *25*(1), 611-621.

Wang, X. Y., Li, G., Malik, S., & Anwar, A. (2022). Impact of COVID-19 on achieving the goal of sustainable development: E-learning and educational productivity. *Economic Research-Ekonomska Istraživanja*, *35*(1), 1950-1966.

Wang, Z., & Chu, Z. (2023). Examination of higher education teachers' self-perception of digital competence, self-efficacy, and facilitating conditions: An empirical study in the context of China. *Sustainability*, *15*(14), 10945.

Wijaya, T. T., Cao, Y., Weinhandl, R., Yusron, E., & Lavicza, Z. (2022). Applying the UTAUT model to understand factors affecting microlecture usage by mathematics teachers in China. *Mathematics*, *10*(7), 1008.

Zacharis, G., & Nikolopoulou, K. (2022). Factors predicting University students' behavioral intention to use eLearning platforms in the post-pandemic normal: an UTAUT2 approach with 'Learning Value'. *Education and Information Technologies*, *27*(9), 12065-12082.

Xue, L., Rashid, A. M., & Ouyang, S. (2024). The unified theory of acceptance and use of technology (UTAUT) in higher education: A systematic review. *Sage Open*, *14*(1), 21582440241229570.