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Mathematics learners' adoption of generative artificial intelligence: A structural equation modeling approach

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ABSTRACT

21st-century learners, including in mathematics education, are increasingly utilizing Generative Artificial Intelligence (GenAI). This study examines how various factors influence students' adoption of generative AI in mathematics. It focuses on components of the Unified Theory of Acceptance and Use of Technology (UTAUT) 3 model with external variables such as system accessibility, self-efficacy, knowledge of AI, and perceived privacy concerns. Data were collected from 960 respondents and analyzed using Partial Least Squares-Structural Equation Modeling (PLS-SEM). The results revealed that among the main components of UTAUT 3 model, facilitating conditions, social influence, habit, and knowledge were the strongest and most consistent predictors of students' behavioral intention to use GenAI tools. In contrast, UTAUT constructs such as performance expectancy, effort expectancy, hedonic motivation, personal innovativeness, price value, and perceived privacy concerns did not directly affect behavioral intention. These findings present a shift in the primary drivers of AI adoption, from perceived usefulness and ease of use to factors rooted in familiarity, social influence, and routine engagement. System accessibility, however, significantly affects key constructs, particularly facilitating conditions, performance expectancy, effort expectancy, and social influence. Moreover, self-efficacy significantly affects hedonic motivation, habit, personal innovativeness, price value, and knowledge, implying their role in supporting AI use. The study emphasizes the importance of AI literacy programs, habitual engagement strategies, and socially supportive learning environments to encourage the meaningful integration of generative AI tools into mathematics education.

1. Introduction

As various sectors embrace artificial intelligence (AI), the use of GenAI technologies in education offers an opportunity to enhance academic learning. Rane (2023) researched the application of GenAI tools, particularly the impacts of ChatGPT on mathematics learning. The study revealed promising results, including greater student engagement, improved academic performance, and more positive attitudes toward mathematics. It also demonstrated a direct link between GenAI use and enhanced mathematics achievement among learners. Furthermore, Wardat et al. (2023) added to its advantages by arguing that machine learning models such as ChatGPT enhance the learning experience and help students improve their math skills by providing knowledge of various math concepts. Moreover, AI-generated learning materials support active learning, allowing students to develop a deeper understanding and retention (Aluko et al., 2025). While these studies provide evidence of AI's benefits, particularly for mathematics learners, some also reveal its drawbacks.

Warschauer et al. (2023) reported that AI applications, such as ChatGPT, may be beneficial for teaching students to write and solve math problems, but they also entail disadvantages. While GenAI is effective in assisting student learning and is generally readily available, its use varies. Yan et al. (2024) claimed that relying too heavily on AI tools for academic work reduces students' capacity to develop critical

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thinking and problem-solving skills independently. Therefore, the heavy use of AI tools undermines educational standards and student achievement. Additionally, Daher and Gierdien (2024) found that ChatGPT provided a mathematically incorrect answer to at least one of six problem-solving tasks. Given these disadvantages and students' growing exposure to AI, academic institutions need to integrate AI literacy into the curriculum. This helps guide responsible use while building on students' natural enthusiasm for the technology.

Despite growing evidence that GenAI can personalize feedback, scaffold problem-solving, and increase engagement, current studies in mathematics education seldom quantify why students adopt GenAI rather than simply what GenAI can do. Studies on the UTAUT model 3 and mathematics education remain on the use of ICT, e-learning environments, digital resources, and technology adoption (Bandoh et al., 2024; Gunasinghe et al., 2020; Liu et al., 2025; Mafa & Govender, 2025). Because GenAI is an emerging technology, prior work typically draws on various fields, with few on mathematics education (Nikolic et al., 2024; Setälä et al., 2025). Earlier studies have not fully explored how GenAI is adopted in mathematics education, creating a gap that calls for a model that tests social, competence-based, and infrastructural mechanisms together and that reflects GenAI's distinctive features in mathematics learning, such as problem solving, writing solutions, and critical verification of outputs.

This study fills gaps in understanding the key factors influencing students' intention to use GenAI in mathematics when multiple determinants interact simultaneously. Specifically, it investigates whether traditional expectancy beliefs, such as perceived usefulness and ease of use, or GenAI-specific factors, including AI knowledge, habit, and social influence, most strongly drive students' behavioral intention. To achieve this, the study extends the UTAUT 3 Model by incorporating context-relevant constructs, including self-efficacy, system accessibility, AI knowledge, and perceived privacy concerns, to better reflect the realities of GenAI use in mathematics learning. This extension is justified by the need for a more comprehensive, context-sensitive model that explains students' adoption behavior beyond general technology acceptance, particularly for tasks involving mathematical problem-solving and critical evaluation of AI-generated outputs. Ultimately, the study aims to identify the strongest predictors of GenAI adoption and provide empirical evidence to guide the effective and responsible integration of AI technologies in mathematics education.

2. Literature review

2.1. AI in mathematics education

The rapid integration of generative artificial intelligence (GenAI) in education reflects the increasing alignment of today's learners with emerging technologies, particularly in tertiary settings. This development enables researchers to examine critical factors such as personalized learning, student engagement, and the ethical and technical challenges of AI-driven tools. AI has been widely applied across disciplines, including mathematics (Hwang & Tu, 2021), language learning (Liang et al., 2021), engineering education (Shukla et al., 2019), and medical education (Winkler-Schwartz et al., 2019), highlighting its transformative potential in higher education.

Mathematics, however, remains a challenging subject for many students, often perceived as difficult to understand and master, leading to persistent learning barriers. Ineffective instructional approaches further contribute to these difficulties, as students' comprehension, problem-solving skills, and engagement may be hindered by fast-paced instruction (Obut et al., 2023). In this context, GenAI presents a strategic opportunity to address these challenges by offering adaptive and personalized learning support. AI technologies can identify individual learning gaps and provide tailored assistance, thereby improving students' mathematical performance (Hwang & Tu, 2021). Similarly, AI-based tools function as personal learning assistants that deliver customized educational support (Fitria, 2021), reinforcing the shift toward personalized and flexible learning environments across disciplines (Habib et al., 2023). For instance, features such as instant feedback, evident in tools like Photomath, have been shown to enhance learners' mathematical skills (Vintere et al., 2024). These capabilities are particularly critical in mathematics education, where students frequently encounter complex and abstract problems.

Despite these advantages, the successful integration of GenAI depends on students' willingness to adopt and use these technologies effectively. Understanding the factors influencing adoption is therefore essential in determining how GenAI can support mathematics learners' academic achievement and overall educational experience.

Thus, this body of literature not only highlights the potential of GenAI to enhance learning and educational management but also underscores the need to examine the determinants of its adoption. This study positions itself within this gap by focusing on the factors influencing GenAI use among mathematics learners, providing a foundation for maximizing its effective integration in higher education.

2.2. Unified theory of acceptance and use of technology (UTAUT) model

UTAUT was developed by Venkatesh et al. (2003) to explain users' adoption of technology innovations through eight key constructs. The original model included Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), while later additions—Hedonic Motivation (HM), Price Value (PV), Habit (HB), and Personal Innovativeness (PI)—formed UTAUT-2 and enhanced its predictive power.

In this study, UTAUT-3 is adopted as the primary framework because it captures both cognitive and behavioral aspects of technology use in dynamic digital environments. Prior research, such as Akbar (2021) on e-learning during the COVID-19 pandemic, demonstrates that PE, EE, SI, and FC significantly influence students' adoption of educational technologies, emphasizing the framework's relevance for improving adoption rates in academic settings. UTAUT-3 has also been validated across various contexts, including educational institutions and innovative technologies like augmented reality (Pinto et al., 2022).

Generative AI (GenAI) tools differ from traditional educational technologies due to their interactivity, generativity, and authorship ambiguity, highlighting the importance of habit formation, price/benefit evaluation, and individual innovativeness. UTAUT-3 incorporates habit, hedonic motivation, price value, and personal innovativeness, which align with GenAI's rapid, low-friction, and sometimes entertainment-oriented use in mathematics learning. To better capture GenAI-specific adoption factors, this study extends UTAUT-3 to include self-efficacy, knowledge of AI, system accessibility, and perceived privacy concerns. This integrated approach allows the analysis to examine whether learners' adoption of GenAI is driven by expectancy or by socialization, competence, and habitual engagement. Overall, this model provides a comprehensive framework for identifying and promoting factors that influence user acceptance of emerging educational technologies.

3. Hypothesis development

3.1. UTAUT 3 constructs

The UTAUT-3 identifies nine antecedents that affect actual use of AI in education, namely facilitating conditions (FC), performance expectancy (PE), effort expectancy (EE), social influence (SI), hedonic motivation (HM), price value (PV), habit (HB), personal innovativeness (PI), and behavioral intention (BI).

Facilitating conditions (FC) refer to the extent to which individuals believe that organizational and technical infrastructures support technology use (Venkatesh et al., 2003). Prior studies generally confirm its positive effect on behavioral intention (Foroughi et al., 2023; Perez, 2024; Widyaningrum et al., 2024), although some report non-significant results (Valle et al., 2024; Yakubu et al., 2025), suggesting that support alone may not drive adoption. Thus, this study hypothesizes that:

H10a. FC significantly affects BI.

Performance expectancy (PE) is defined as the degree to which using a system enhances performance (Venkatesh et al., 2003). Evidence shows that AI tools can improve teaching and learning outcomes, influencing users' intention to adopt them (Perez, 2024; Watted, 2025; Wu & Yu, 2023; Yakubu et al., 2025). Thus, this study posits:

H10b. PE significantly affects BI.

Effort expectancy (EE) refers to the perceived ease of using a system (Venkatesh et al., 2003). Studies indicate that ease of use encourages adoption, although concerns about AI accuracy remain (Du & Lv, 2024; Lubowitz, 2023). Thus, this study hypothesizes that:

H10c. EE significantly affects BI.

Social influence (SI) refers to the extent to which individuals perceive that others expect them to use a technology (Venkatesh et al., 2003). Findings on its impact are mixed, with some studies highlighting its importance and others reporting weak effects depending on institutional context (Dwivedi et al., 2021; Kumar et al., 2025; Perez, 2024). Thus, this study hypothesizes that:

H10d. SI significantly affects BI.

Hedonic motivation (HM) refers to the enjoyment derived from using a technology (Brown & Venkatesh, 2005). Research suggests that engaging and interactive AI tools can enhance students' intention to use them (Amer et al., 2020; Phang & Kong, 2024; Romero-Rodriguez et al., 2023). Thus, this study hypothesizes that:

H10e. HM significantly affects BI.

Habit (HB) reflects automatic behavior developed through repeated use. Prior studies confirm that habit strongly predicts continued AI usage in educational contexts (Alhwaiti, 2023; Gajić et al., 2024; Hagger et al., 2023). Thus, this study posits:

H10f. HB significantly affects BI.

Personal innovativeness (PI) refers to an individual's willingness to try new technologies (Agarwal & Prasad, 1998). Studies show that innovative learners are more likely to adopt AI tools (Hussain, 2020; Sadewo et al., 2025). Thus, this study hypothesizes that:

H10g. PI significantly affects BI.

Price value (PV) refers to users' evaluation of cost relative to benefits (Tamilmani et al., 2018). Evidence suggests that affordability influences students' adoption of AI tools, particularly in resource-constrained contexts (Shanthana Lakshmi & Gupta, 2020). Thus, this study posits:

H10h. PV significantly affects BI.

3.2. External factors of GenAI use

Additionally, this study extends the UTAUT 3 model by incorporating external factors influencing the use of GenAI among mathematics learners, including system accessibility, perceived privacy concerns, AI knowledge, and self-efficacy. It specifically examines learners' willingness to use GenAI as a supplementary tool in mathematics education.

System accessibility (SA) refers to the degree to which GenAI tools are available, user-friendly, and accessible to users without barriers (Salloum et al., 2019). In educational contexts, accessibility influences students' engagement, digital equity, and learning outcomes (Selwyn, 2021). When AI tools are accessible, students are more likely to adopt them for academic purposes. In mathematics learning, accessibility enables students to focus on conceptual understanding rather than technical difficulties. Access to reliable internet, devices, and digital literacy further supports the effective use of AI tools (Dwivedi et al., 2021), and has been shown to influence users' willingness to adopt such technologies (Arguson et al., 2025). Thus, system accessibility is a key factor in facilitating AI integration in education. Thus, the study hypothesizes that:

H1. System Accessibility significantly affects FC.

H2. System Accessibility significantly affects PE.

H3. System Accessibility significantly affects EE.

H4. System Accessibility significantly affects SI.

Self-efficacy (SE) refers to an individual's belief in their ability to effectively use AI technologies in learning mathematics. Higher self-efficacy is associated with greater confidence and engagement in the use of digital tools. Prior studies show that self-efficacy influences both initial adoption and sustained use of technology (Ding & Hong, 2024; Sabah, 2016; Wright & Akgunduz, 2018). Learners with higher self-efficacy are more likely to engage actively and adapt to AI-supported learning environments (Chavoshi & Hamidi, 2019). Thus, this study hypothesizes that:

H5. Self-efficacy significantly affects HM.

H6. Self-efficacy significantly affects HB.

H7. Self-efficacy significantly affects PI.

H8. Self-efficacy significantly affects price value.

H9. Self-efficacy significantly affects knowledge of AI.

Knowledge of AI (K) refers to an individual's understanding and ability to use AI technologies effectively. Users with greater knowledge are more likely to perceive AI as useful and relevant to their academic needs. This understanding increases their likelihood of adopting AI tools in education (Venkatesh et al., 2003). Thus, AI literacy plays a crucial role in shaping behavioral intention and meaningful use of AI.

H11. Knowledge of AI significantly affects BI.

Perceived privacy concern (P) refers to users' perceptions of how well their personal data are protected when using GenAI tools. Previous studies indicate that privacy concerns can influence technology adoption, although they are sometimes outweighed by perceived usefulness (Kusyanti et al., 2022; Sheehan, 2002). When users perceive higher risks, they may be less willing to engage with AI technologies. Thus, this study hypothesizes that:

H12. Perceived privacy concerns significantly affect BI.

Overall, this study examines mathematics learners' behavioral intention and actual use of GenAI, as illustrated in the proposed structural model in Fig. 1.

4. Methodology

4.1. Design

This study employed a quantitative survey design to collect data from mathematics learners at secondary and tertiary levels in Cebu, Philippines. The data were collected via an online questionnaire, specifically through Google Forms, for participants' convenience and accessibility. The survey was posted on social media and sent to the email addresses of different schools and universities. The researcher analyzed and visualized the data using advanced statistical techniques, the Partial Least Squares-Structural Equation Modeling (PLS-SEM), to examine the relationships among the UTAUT 3 constructs, other external variables, and their influence on GenAI in mathematics learners.

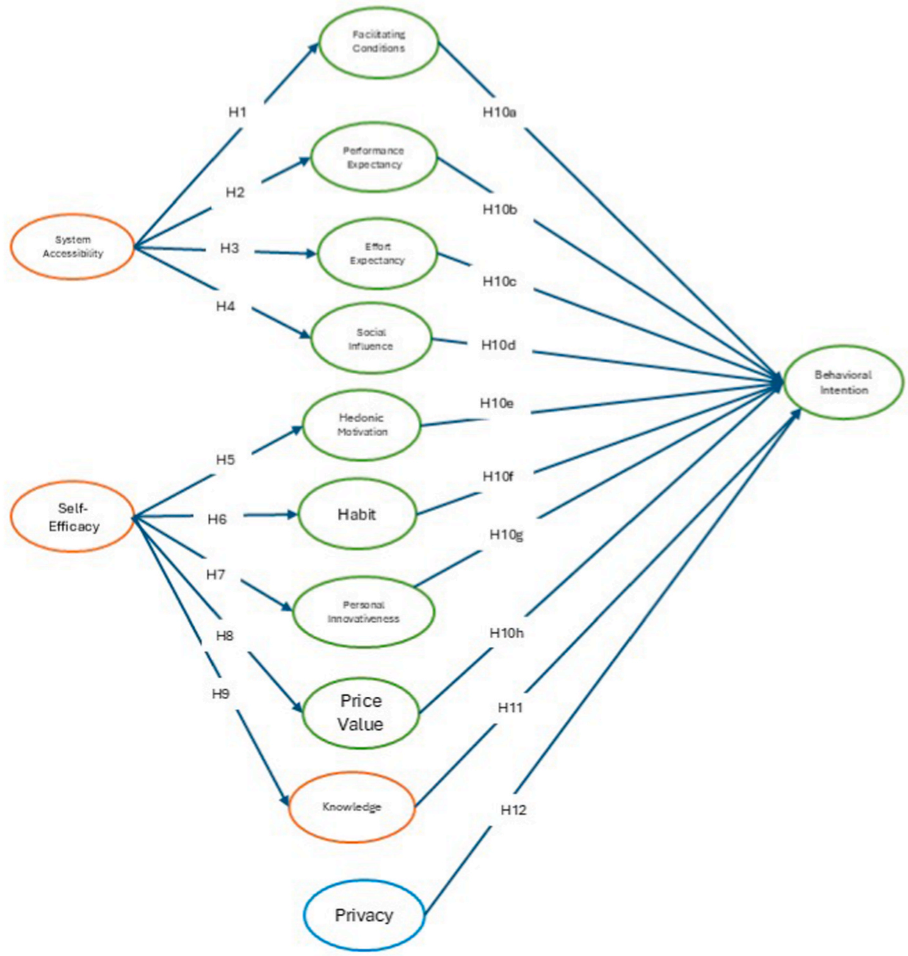

Fig. 1. Proposed Structural Model
(Hypothesized Relationship of System Accessibility and Self-efficacy to the UTAUT 3 Constructs of Mathematics Learners who are GenAI users).

4.2. Respondents

Secondary and tertiary learners from diverse cities and municipalities across the province of Cebu who use AI for math assignments or other math activities are the targeted participants, contributing to a robust, varied database of perspectives and experiences. Moreover, Cebu is an emerging AI hub, with academic institutions offering extensive curricula in AI. Purposive sampling was used to describe AI users in Cebu. Participants were recruited through purposive sampling from both public and private secondary schools and higher education institutions across Cebu. Only students who self-reported having used generative AI tools for mathematics-related activities were included. A total of 978 secondary and tertiary learners who took and are currently taking mathematics responded to the survey. However, 18 responses were excluded because they indicated they do not use AI. Thus, 960 respondents were used in the analysis of this study. Additionally, Hair et al. (2022) suggested a sample size of 619 participants if the minimum path coefficient is 0.05-0.10 and a significance level of 5%. The sample, therefore, provides adequate statistical power for stable parameter estimation.

Table 1 presents the profile of the respondents. This strategy ensured representation across various levels and institution types while focusing on actual users of GenAI in mathematics.

Table 1 presents the demographic characteristics of the 960 participants, including sex, grade level, age, and school type. The sample was female-dominated (69.3%, n = 656), followed by male (31.0%, n = 298), with a small proportion (0.6%, n = 6) preferring not to disclose their gender, consistent with trends in educational research where females are more likely to participate in survey-based studies (García-Retamero & López-Zafra, 2006; Stoet & Geary, 2018). College students comprised the largest group (45.4%, n = 436), followed by Junior High School (33.1%, n = 318) and Senior High School students (21.5%, n = 206), indicating that older students were more accessible or willing to participate, likely due to greater exposure to academic tasks

Table 1
Demographic characteristics of the participants (N = 960).

Category	n	%
Sex		
Male	298	31.00
Female	656	69.30
Prefer not to say	6	0.60
Grade Level		
JHS	318	33.13
SHS	206	21.46
College	436	45.42
Age		
11-14	221	23.02
15-18	421	43.85
19-22	304	31.67
23-26	14	1.46
Type of School		
Private	192	20.00
Public	768	80.00

Legend: JHS = Junior High School; SHS= Senior High School.

and digital tools (Zhao et al., 2021). Most participants were aged 15 to 18 years (43.9%, n = 421), with others aged 19 to 22 (31.7%, n = 304), 11 to 14 (23.0%, n = 221), and 23 to 26 (1.5%, n = 14), corresponding closely to their respective grade levels, consistent with the structured academic progression in the Philippine educational system (UNESCO Institute for Statistics, 2020). The majority attended public schools (80.0%, n = 768), while 20.0% (n = 192) attended private institutions, reflecting national enrollment patterns reported by the Department of Education (2023). Overall, this demographic breakdown provides essential context for interpreting the study's findings in light of participants' gender, age, grade level, and school type.

4.3. Development survey instrument

The study's survey had two sections: the initial section collected demographic details about the respondents. The second section comprises fifty-three (53) statements used to assess the thirteen (13) variables of the proposed research model. Table 2 presents the instruments of the study.

These variables are the constructs of the UTAUT 3 model, PE, EE, SI, FC, HM, PV, and HB, adopted from the modified questionnaire of Xian (2021) and the original source of Venkatesh et al. (2012). The constructs PI and BI were adopted from Thakur and Srivastava (2015) and Tseng et al. (2022), respectively. The proposed external construct, SE, comprises six items adopted from Rahmawati (2019), Alshammari (2020), and Liu et al. (2022). K, with 4 items, was from Nguyen (2021), while P, with 6 items, was from Al-Sharafi et al. (2016). Lastly, SA with five items was adopted from the study of Salloum et al. (2019).

To ensure relevance and validity, this survey used multiple-item scales from existing studies, customized to the specific context of interest, and focused on learners' intentions to use GenAI in mathematics learning. The adapted UTAUT-3 constructs were modified to explicitly reference AI tools (e.g, “this system” was rephrased as “generative AI or GenAI”). This study aimed to capture the detailed viewpoints and opinions of the participants within this domain. Testing the internal consistency within each group of construct indicators was conducted before proceeding to the primary data analysis methods. After establishing internal consistency within and across the constructs, a confirmatory factor analysis (CFA) was performed to assess the suitability of each model fit measure. Additionally, the items' validity and reliability will be tested using SmartPLS.

4.4. Statistical treatment of data

This study employed SmartPLS version 4.1.1.2 to assess the structural model, evaluate model fit indices, and apply PLS-SEM to investigate the research framework. Responses were exported from Google Forms into Microsoft Excel and then coded for analysis in Smart PLS 4. All Likert-scale responses were coded numerically (1-5).

Before analysis, a comprehensive data screening procedure is performed. Cases exhibiting duplicate entries, incomplete responses, or failure to pass the sincerity check are excluded to ensure data quality. The Google Form used required all responses; hence, all respondents submitted complete responses. Furthermore, sincerity was assessed by examining response variability; cases with a standard deviation (SD) of 0 were flagged as potential straight-lining responses. All retained cases (n = 960) demonstrated a standard deviation greater than zero. As a result, no cases were excluded based on sincerity checks. In addition, 18 responses were removed because respondents reported not using artificial intelligence tools, resulting in a final dataset of 960 valid responses. This data refinement process strengthens the validity and reliability of the final dataset.

The subsequent PLS-SEM analysis followed standard two-step procedures: assessment of the measurement model for reliability and validity, and evaluation of the structural model through path analysis,

Table 2
Study Instrument and source.

Variable	Indicators	Source
Performance Expectancy	PE1. Using AI enables me to accomplish my needs more quickly and effectively PE2. Using AI increases equality between all students PE3. Using AI will save me time PE4. Using AI increases the quality of the learning process	Venkatesh et al. (2012) Source: (Venkatesh, Thong, & Xu, 2012) Modified source: (Xian X., 2021)
Effort Expectancy	EE1. Learning how to use AI is easy for me EE2. Using AI in learning will be clear and understandable EE3. I find AI easy to use EE4. It is easy for me to become skillful at using AI	
Social Influence	SI1. People who are important to me think that I should use AI SI2. People who influence my behavior think that I should use AI SI3. People whose opinion that I value, prefer that I use AI	
Facilitating conditions	FC1. I have the resources necessary to use AI. FC2. I have the knowledge necessary to use AI. FC3. AI is compatible with other technologies I use. FC4. I can get help from others when I have difficulties using AI.	
Hedonic Motivation	HM1. Using AI is fun for me HM2. Using AI is very enjoyable HM3. Using AI is very entertaining	
Price Value	PV1. Using AI is reasonably priced PV2. Using AI is a good value for the money PV3. At current price, AI provides a good value	
Habit	HA1. The use of AI becomes a habit for me HA2. I am addicted to using AI HA3. I must use AI HA4. Using AI has become natural to me	
Behavioral intention	BI1. I intent to continue using AI in the future BI2. I will always try to use AI in my daily life BI3. I plan to continue to use AI frequently	Tseng et al. (2022)
Self-efficacy	SE1. I have the necessary skills to use Gen AI in learning mathematics. SE2. I feel confident in finding answers or solutions to mathematics problems by using Gen AI. SE3. I can use Gen AI without being told how it functions. SE4. I can freely navigate the Gen AI in learning mathematics. SE5. I can overcome the obstacles that appear while using Gen AI in learning mathematics. SE6. I'm confident in being able to use Gen AI independently.	(Alshammarı, 2020; Liu et al., 2022; Rahmawati, 2019)
Knowledge	K1. I have sufficient knowledge to use generative AI for learning mathematics. K2. I have sufficient knowledge to handle any problems that may	(Nguyen, 2021)

(continued on next page)

Table 2 (*continued*)

Variable	Indicators	Source
	arise during the use of Gen AI in learning mathematics. K3. I have sufficient knowledge to process answers or information from the Gen AI. K4. I am well-informed about how to deal with problems caused by using Gen AI in learning mathematics.	
Perceived Privacy concerns	P1. I think generative AI shows concerns for the privacy of its users. P2. I feel safe when I send personal information to generative AI. P3. I think generative AI abides by personal data protection laws. P4. I think generative AI only collects user data necessary for its activity. P5. I think generative AI respects the user's rights when obtaining personal information. P6. I think that generative AI will not provide my personal information to other people without my consent.	Al-Sharafi et al. (2016)
System Accessibility	SA1. I access and use the generative AI application without any problem. SA2. The generative AI application can be accessed in school and at home. SA3. The generative AI application is accessible according to my needs. SA4. The chain of communication is suitable to get access to generative AI applications. SA5. I have no difficulty accessing and using the generative AI on the internet.	Salloum et al. (2019)
Personal innovativeness	PI1. I like to try new things PI2. I am usually among the first to try out new technology PI3. I often experiment with new products and services PI4. I am open to trying new technologies	(Thakur & Srivastava, 2015)

including bootstrapping with 5000 resamples. The analysis of the 960 cleaned responses begins with an assessment of the measurement model via confirmatory factor analysis (CFA), which determines whether the observed indicators reliably reflect their corresponding latent constructs. This stage includes the evaluation of convergent validity, to confirm that items within each construct are highly correlated, and discriminant validity, to verify that constructs are conceptually and empirically distinct. Multicollinearity was examined using variance inflation factor (VIF) values, all of which fell below the threshold of 5. Bootstrapping with 5000 resamples was applied to compute standard errors, p-values, and 95% confidence intervals for path coefficients. In addition to significance testing, effect sizes (f2) were calculated to quantify each exogenous variable's contribution to the variance explained in the endogenous constructs.

The use of PLS-SEM was methodologically justified given the study's predictive and exploratory orientation, the presence of a complex research model with multiple latent constructs, and the non-normal distribution of the data. Assessment of univariate normality revealed deviations from normality, with skewness (−0.344) and kurtosis (−0.177) indicating non-normal distributions. Because PLS-SEM does not require normally distributed data, it was deemed appropriate for the objectives and characteristics of the study.

5. Results and discussion

5.1. AI used by mathematics learners

The growing integration of AI in education has led students to explore various AI-powered applications for academic support. In the context of mathematics education, some students increasingly rely on AI tools to assist with problem-solving and task completion. Understanding which AI applications are most commonly used is essential in understanding student preferences and potential gaps in digital learning resources. Table 3 summarizes the frequency of AI applications of 960 mathematics learners, highlighting the dominant role of general-purpose AI platforms alongside more specialized math-focused tools.

Table 3 presents the frequency of AI applications used by 960 mathematics learners, revealing that ChatGPT was the most widely used AI tool (n = 746), followed by Meta AI (n = 321) and Math AI (n = 103). This preference for ChatGPT aligns with its growing popularity in educational settings, where it is valued for its versatility and ability to provide detailed explanations (Kasneci et al., 2023). Other tools, including Cici (n = 34), Symbolab and Socratic (n = 29 each), and Gauthmath (n = 14), were used less frequently. While these platforms support tasks such as equation solving or step-by-step guidance, they are not as widely adopted as generalized AI chat assistants. Notably, math-specific apps such as Woot Math (n = 11), PhotoMath (n = 9), and Step Math (n = 13) were minimally used, likely due to limited accessibility, user familiarity, or perceived effectiveness. The presence of newer AI tools, such as Gemini (n = 17) and Perplexity (n = 12), though small in number, indicates emerging interest in alternative AI platforms for academic support. These findings suggest a clear trend toward multipurpose AI tools, especially those capable of interactive dialogue and contextual problem-solving, reflecting the evolving preferences of today's digital-native students (Mollick & Mollick, 2023). Finally, these results highlight the need for further research on how these tools are integrated into learning and their effectiveness in supporting mathematical understanding.

5.2. Measurement model assessment results

Establishing the reliability and validity of the measurement model was essential in validating the research findings. Internal consistency was assessed using Cronbach's alpha, a standard indicator of reliability, alongside composite reliability (CR), which complements Cronbach's alpha in evaluating the coherence of items within each construct (Netemeyer et al., 2003).

As presented in Table 4, the constructs SA, SE, FC, PE, EE, SI, HM, HA, PI, PV, K, P, and BI demonstrated Cronbach's alpha values between 0.712 and 0.781, with corresponding CR values ranging from 0.758 to 0.900. These results fall within the acceptable range, indicating adequate internal consistency. The model's reliability was further

Table 3
AI apps used by mathematics learners (N = 960).

AI application	Frequency
ChatGPT	746
Meta AI	321
Math AI	103
Woot Math	11
Symbolab	29
Step Math	13
Cici	34
Gauthmath	14
Socratic	29
PhotoMath	9
Gemini	17
Perplexity	12

Table 4
Measurement model assessment results.

Construct	Item	FL	A	CR	AVE
System Accessibility (SA)	SA1	0.697	0.830	0.881	0.597
	SA2	0.774			
	SA3	0.763			
	SA4	0.838			
	SA5	0.784			
Self-Efficacy (SE)	SE1	0.785	0.832	0.833	0.545
	SE2	0.789			
	SE3	0.750			
	SE4	0.712			
	SE5	0.689			
	SE6	0.700			
Facilitating Condition (FC)	FC1	0.910	0.778	0.780	0.818
	FC2	0.899			
Performance Expectancy (PE)	PE1	0.776	0.758	0.760	0.579
	PE2	0.728			
	PE3	0.754			
	PE4	0.784			
Effort Expectancy (EE)	EE1	0.713	0.761	0.771	0.579
	EE2	0.782			
	EE3	0.776			
	EE4	0.770			
Social Influence (SI)	SI1	0.858	0.808	0.808	0.722
	SI2	0.848			
	SI3	0.844			
Hedonic Motivation (HM)	HM1	0.908	0.900	0.905	0.834
	HM2	0.939			
	HM3	0.892			
Habit (HA)	HA1	0.845	0.877	0.883	0.730
	HA2	0.857			
	HA3	0.842			
	HA4	0.874			
Personal Innovativeness (PI)	PI1	0.680	0.763	0.787	0.531
	PI2	0.745			
	PI3	0.843			
	PI4	0.772			
Price Value (PV)	PV1	0.846	0.852	0.866	0.771
	PV2	0.898			
	PV3	0.89			
Knowledge of AI use (K)	K1	0.827	0.834	0.838	0.668
	K2	0.861			
	K3	0.803			
	K4	0.777			
Perceived Privacy Concern (P)	P1	0.720	0.812	0.839	0.508
	P2	0.783			
	P3	0.704			
	P4	0.690			
	P5	0.706			
	P6	0.670			
Behavioral Intentions (BI)	BI1	0.821	0.792	0.797	0.707
	BI2	0.815			
	BI3	0.886			

Legend: FL = factor loadings; AVE = average variance extracted; CFA = Cronbach's alpha; CR = composite reliability; **α** = Cronbach alpha.

supported by strong item loadings ranging from 0.67 to 0.939, indicating satisfactory indicator reliability. In terms of validity, both convergent and discriminant validity were examined. Convergent validity was assessed using the average variance extracted (AVE), with all constructs exceeding the 0.50 threshold. AVE values ranged from 0.508 to 0.834, thereby confirming the adequacy of the latent variables in capturing the variance of their observed indicators.

5.3. Correlation matrices of constructs

The study's discriminant validity was confirmed using the Fornell-Larcker criterion, which requires that the square root of each construct's average variance extracted (AVE) exceed its correlations with other constructs. This method, initially introduced by Fornell and Larcker (1981), is a widely accepted technique for assessing discriminant validity by ensuring that each construct is more strongly associated with its own indicators than with those of other constructs. Applying this criterion strengthened the study's credibility and measurement validity.

As shown in Table 5, the square root of the AVE for each construct, the diagonal value, exceeds its highest correlation with any other construct, thereby satisfying the Fornell-Larcker criterion for discriminant validity. For example, the square root of AVE for BI is 0.84, which is greater than its highest inter-construct correlation with SI at 0.41, followed by HA at 0.39 and SE at 0.36. EE has a diagonal value of 0.76, exceeding its strongest correlation, PE, at 0.61. FC shows a square root of 0.90, which is greater than its correlation with K (0.64). Similarly, HA has a square root of 0.86, surpassing its correlations with PV (0.55) and HM (0.53). HM demonstrates the highest square root value in the model at 0.91, exceeding its highest correlation with PV at 0.63. Other constructs, including K (0.82), P (0.71), PE (0.76), PI (0.76), PV (0.88), SE (0.74), SI (0.85), and SA (0.77), also satisfy the criterion. For instance, SA correlates most strongly with K at 0.48, and SE with K at 0.60, both values lower than their respective AVE square roots. These results confirm that all constructs are statistically distinct, reducing concerns about multicollinearity or conceptual redundancy. Such evidence supports the internal structure and discriminant validity of the measurement model, as recommended by Sarstedt et al. (2022) and Henseler et al. (2021), particularly in models where theoretically related constructs must remain empirically distinguishable.

An additional criterion for evaluating discriminant validity is the Heterotrait-Monotrait (HTMT) ratio of correlations, proposed by Henseler et al. (2015). The HTMT assesses whether constructs are empirically distinct by examining the ratio of between-construct correlations to within-construct correlations. Values approaching 1.0 indicate a lack of discriminant validity, while lower values support its presence. Kline (2011) suggests a conservative threshold of 0.85, beyond which discriminant validity may be compromised. As shown in Table 6, all HTMT values in this study range from 0.21 to 0.805, well below the recommended cutoff. These findings provide additional evidence that the model's constructs are distinct, reinforcing the validity of the measurement framework.

5.4. Hypothesis testing of the structural model

The structural model analysis evaluates the relationships among latent constructs by examining path coefficients and coefficient of determination (R^2) values. PLS-SEM was employed to test the proposed hypotheses and overall conceptual framework. Prior to interpretation, collinearity diagnostics were conducted to detect any multicollinearity among predictor variables, which could distort the accuracy of the estimated path coefficients.

Model fit was assessed using multiple indices. The standardized root mean square residual (SRMR) was 0.06, indicating an acceptable fit, as it falls below the commonly recommended threshold of 0.08. The normed fit index (NFI) was 0.702, indicating moderate fit. While NFI values range from 0 to 1, values exceeding 0.90 are typically interpreted as indicative of a strong model fit. Taken together, these indices suggest that the model exhibits a reasonable degree of empirical adequacy.

R^2 assesses the proportion of variance in an endogenous construct that is explained by its associated exogenous constructs. It serves as a measure of predictive accuracy and indicates the strength of the linear relationship among latent variables. Following the classification proposed by Henseler et al. (2009) and Hair et al. (2011), R^2 values are interpreted as substantial (0.75), moderate (0.50), or weak (0.25). In this study, all R^2 values exceed 0.25, indicating a weak but acceptable level of explanatory power across the model.

In addition, the effect size (f^2) was calculated to evaluate the contribution of each exogenous variable to the variance explained in the endogenous constructs. According to Hair et al. (2017), f^2 values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effects, respectively. Values below 0.02 suggest negligible influence. The results presented in Table 7 show that FC ($f^2 = 0.16$), HA ($f^2 = 0.20$), PV ($f^2 = 0.16$), and PI ($f^2 = 0.25$) exert medium effects on SE. Similarly, EE ($f^2 =$

Table 5
Fornell and larcker criterion.

	BI	EE	FC	HA	HM	K	P	PE	PI	PV	SE	SI	SA
BI	0.84												
EE	0.20	0.76											
FC	0.20	0.45	0.90										
HA	0.39	0.20	0.23	0.86									
HM	0.28	0.32	0.32	0.53	0.91								
K	0.35	0.35	0.64	0.27	0.27	0.82							
P	0.29	0.26	0.28	0.31	0.31	0.42	0.71						
PE	0.30	0.61	0.52	0.30	0.35	0.48	0.35	0.76					
PI	0.17	0.23	0.28	0.32	0.48	0.18	0.21	0.24	0.76				
PV	0.29	0.25	0.26	0.55	0.63	0.25	0.28	0.30	0.42	0.88			
SE	0.36	0.34	0.39	0.37	0.41	0.60	0.43	0.38	0.44	0.37	0.74		
SI	0.41	0.23	0.21	0.35	0.27	0.32	0.29	0.30	0.18	0.24	0.42	0.85	
SA	0.27	0.35	0.45	0.24	0.39	0.48	0.49	0.39	0.32	0.32	0.52	0.28	0.77

Table 6
Heterotrait-Monotrait (HTMT) ratio of correlation.

	BI	EE	FC	HA	HM	K	P	PE	PI	PV	SE	SI	SA
BI													
EE	0.24												
FC	0.26	0.59											
HA	0.46	0.24	0.28										
HM	0.34	0.38	0.38	0.59									
K	0.43	0.43	0.79	0.31	0.31								
P	0.34	0.33	0.39	0.37	0.37	0.52							
PE	0.38	0.81	0.68	0.36	0.43	0.6	0.45						
PI	0.21	0.30	0.36	0.36	0.58	0.22	0.29	0.32					
PV	0.35	0.31	0.32	0.64	0.71	0.29	0.33	0.37	0.51				
SE	0.45	0.41	0.49	0.43	0.47	0.72	0.53	0.48	0.54	0.44			
SI	0.51	0.28	0.27	0.42	0.32	0.39	0.35	0.38	0.21	0.28	0.51		
SA	0.33	0.44	0.56	0.28	0.46	0.58	0.61	0.50	0.40	0.37	0.63	0.34	

Table 7
Coefficient of Determination (R^2 and f^2 coefficient).

	R^2	f^2												
		BI	EE	FC	HA	HM	K	P	PE	PI	PV	SE	SI	SA
BI	0.29													
EE	0.13	0.00												
FC	0.20	0.01												
HA	0.14	0.03												
HM	0.16	0.00												
K	0.37	0.02												
P		0.003												
PE	0.15	0.004												
PI	0.20	0.000												
PV	0.14	0.002												
SE	0.08				0.16	0.20	0.58			0.25	0.16			
SI		0.07												
SA			0.14	0.25					0.18				0.08	

0.14), FC ($f^2 = 0.25$), and PE ($f^2 = 0.18$) demonstrate medium-sized effects on SA. Notably, K exerts a large effect on SE ($f^2 = 0.58$), underscoring its critical role. These findings align with other results in the study, further supporting the validity of the structural model.

Table 8 presents the results of the path analysis, testing 12 hypotheses (H1–H12) regarding factors influencing BI's use of AI tools in mathematics learning.

The findings show that H1 to H4 were all supported, indicating that SA significantly predicts FC ($\beta = 0.449$, t = 13.744, $p < .000$), PE ($\beta = 0.392$, t = 10.505, $p < .000$), EE ($\beta = 0.353$, t = 9.715, $p < .000$), and SI ($\beta = 0.276$, t = 7.869, $p < .000$). Similarly, H5 to H9 were also supported, as SE had significant effects on HM ($\beta = 0.405$, t = 13.437, $p < .000$), HA ($\beta = 0.373$, t = 11.842, $p < .000$), PI ($\beta = 0.444$, t = 13.492, $p < .000$), PV ($\beta = 0.374$, t = 12.840, $p < .000$), and particularly K ($\beta = 0.604$, t = 23.948, $p < .000$), the most substantial effect in the model.

In terms of direct predictors of BI, FC ($\beta = -0.102$, t = 2.480, $p < .05$), SI ($\beta = 0.245$, t = 7.358, $p < .000$), HA ($\beta = 0.200$, t = 5.007, $p < .000$), and K ($\beta = 0.203$, t = 4.877, $p < .000$) were supported, demonstrating the significant roles of facilitating structures, social influences, habitual use, and knowledge in driving AI adoption. However, PE ($\beta = 0.079$, $p = .057$), EE ($\beta = 0.001$, $p = .978$), HM ($\beta = 0.010$, $p = .809$), PI ($\beta = -0.001$, $p = .965$), PV ($\beta = 0.047$, $p = .268$), and P ($\beta = 0.062$, $p = .087$) were not supported due to statistically non-significant results.

It can be noted that not all hypothesized relationships were supported, suggesting a context-specific shift in the determinants of students' intention to use GenAI in learning mathematics. The results imply that knowledge of AI, social influence, and habit are the most influential predictors of students' intention to use AI in learning mathematics. In contrast, traditional UTAUT constructs like performance expectancy and effort expectancy had little to no influence, which may reflect students'

Table 8
Results of the path analysis.

Hypothesis	Path	Beta (β)	T values	p-values	Result
H1	SA - > FC	0.449	13.744	0.00	Supported
H2	SA - > PE	0.392	10.505	0.00	Supported
H3	SA - > EE	0.353	9.715	0.00	Supported
H4	SA - > SI	0.276	7.869	0.00	Supported
H5	SE- > HM	0.405	13.437	0.00	Supported
H6	SE - > HA	0.373	11.842	0.00	Supported
H7	SE- > PI	0.444	13.492	0.00	Supported
H8	SE- > PV	0.374	12.84	0.00	Supported
H9	SE - > K	0.604	23.948	0.00	Supported
H10a	FC - > BI	−0.102	2.48	0.013	Supported
H10b	PE - > BI	0.079	1.902	0.057	NS
H10c	EE - > BI	0.001	0.028	0.978	NS
H10d	SI - > BI	0.245	7.358	0.00	Supported
H10e	HM - > BI	0.01	0.242	0.809	NS
H10f	HA - > BI	0.2	5.007	0.00	Supported
H10g	PI - > BI	−0.001	0.043	0.965	NS
H10h	PV - > BI	0.047	1.108	0.268	NS
H11	K- > BI	0.203	4.877	0.00	Supported
H12	P - > BI	0.062	1.713	0.087	NS

prior familiarity with AI tools and their perception of GenAI as a low-effort resource rather than a novel or complex technology. When learners no longer perceive difficulty or performance risk, expectancy-related beliefs may lose explanatory power (Kumar et al., 2025). Similarly, the non-significance of hedonic motivation and personal innovativeness suggests that GenAI use in mathematics learning is mainly instrumental and task-oriented, driven by efficiency and academic requirements rather than for enjoyment or exploration.

Importantly, the findings must be interpreted in light of potential bias associated with GenAI usage. Variations in students' frequency, depth, and purpose of AI use may influence how constructs are perceived and reported. Heavy or habitual users may underestimate effort or cost because such attributes have become baseline assumptions. In contrast, less experienced users may rely more on peer influence and perceived knowledge to guide adoption decisions. This heterogeneity in GenAI experience may attenuate the observed effects of expectancy- and motivation-based constructs in aggregate analyses. Consistent with recent evidence, the results reinforce that peer dynamics, digital literacy, and frequent usage patterns significantly affect technology adoption more than perceived usefulness or enjoyment (Ali et al., 2023; Islam et al., 2022). Fig. 2 presents the final output of the study.

6. Implications

This section is divided into two equally important components of the discussion on implications. The first component focuses on the study's practical implications, providing evidence-based insights and actionable recommendations intended to benefit the education sector and its key stakeholders.

System accessibility has a strong and consistent impact on facilitating conditions and social influence, both of which significantly affect behavioral intentions to adopt AI learning tools. When access barriers are lowered and supports are visible, learners engage more meaningfully with AI platforms. Moreover, system accessibility may significantly impact performance expectancy and effort expectancy, but these two UTAUT constructs do not significantly affect behavioral intention, contradicting previous studies. These findings may imply that students' adoption of generative AI is less dependent on perceived usefulness or ease of use when accessibility and social encouragement are already assured. Accessibility plays a foundational role in enabling learners to engage meaningfully with AI platforms. This is supported by Lestariningrum et al. (2024), who found that integrating AI into student learning positively and significantly influences academic performance when combined with accessible digital learning materials, while Hussain et al. (2025) found that institutional support, peer influence, and access to resources are significant in fostering AI adoption. Similarly, Valle et al. (2024) found that learners who find AI helpful and recognize its extensive range of short- and long-term benefits are more likely to continue using AI to complete tasks and to enroll immediately in various AI skills-acquisition training programs.

Self-efficacy has a significant impact on habits and knowledge of AI, which, in turn, mediates the effect on behavioral intentions to use AI. Self-efficacy and habit are significant predictors of behavioral intention, reinforcing that repeated and confident use of AI tools leads to habitual, long-term engagement (Venkatesh et al., 2012). However, the strength of these paths may also reflect participants' varied levels of exposure to generative AI: students who use it frequently may have developed stronger habits. In contrast, those with limited exposure may not yet translate confidence into sustained use. Moreover, self-efficacy and knowledge of AI directly affect behavioral intention. Increasing students' understanding of AI and its practical applications can significantly shape their willingness to adopt it (Valle et al., 2024). Integrating AI literacy programs into the curriculum is therefore a strategic approach to encouraging adoption, particularly by bridging differences in learners' prior experiences.

Although self-efficacy significantly influences hedonic motivation, personal innovativeness, and price value, these constructs did not exhibit a statistically significant direct effect on behavioral intention. This finding may appear counterintuitive, since intrinsic enjoyment, openness to innovation, and perceived benefit are typically associated with technology use; however, these factors alone are insufficient to directly predict students' intentions to adopt GenAI technologies in educational contexts. One possible explanation is that, in the context of student users, these variables primarily contribute to shaping favorable attitudes or perceived ease of use, which may only translate into behavioral intention when mediated by more dominant constructs such as habit formation, technological familiarity, or perceived behavioral control (Dwivedi et al., 2021).

These findings support the need to cultivate learners' self-efficacy and habitual engagement with AI tools, transforming positive perceptions into meaningful behavioral outcomes.

Privacy concerns were also examined as potential barriers to individuals engaging with AI tools. However, results showed that perceived privacy concerns do not significantly influence behavioral intentions to use AI. This contradicts Zafar et al. (2024), who noted that perceived privacy concerns can act as barriers to AI adoption, thus the critical importance of trust and data protection in shaping technology acceptance. Similarly, Rana et al. (2024) emphasized the strong connection between user trust and usage behavior, advocating the implementation of security protocols, transparent practices, and credible endorsements to strengthen user confidence. However, the non-significant effect of perceived privacy concerns suggests that, in this context, students may not prioritize data security when using AI tools, possibly because they only want to get answers to their mathematics assignments. They used Gen AI to obtain answers; hence, no private data was shared, implying no privacy concerns. This suggests that while privacy remains theoretically important, its salience may depend on the type and depth of engagement with AI tools.

The second component of this section focuses on the theoretical implications, which highlight the study's contribution to extending and validating existing theoretical frameworks relevant to technology adoption in education. Specifically, this study integrates additional constructs into the UTAUT, offering a more comprehensive model. The extended framework includes system accessibility (Salloum et al., 2019), perceived privacy concerns (Al-Sharafi et al., 2016), self-efficacy (Alshammari, 2020; Liu et al., 2022; Rahmawati, 2019), and knowledge of AI (Nguyen, 2021), which presents key contextual variables affecting the adoption of AI in education. The extended structural equation model aims to provide deeper insights into the multidimensional factors influencing AI integration in the classroom. Notably, the findings revealed that among the four added constructs,

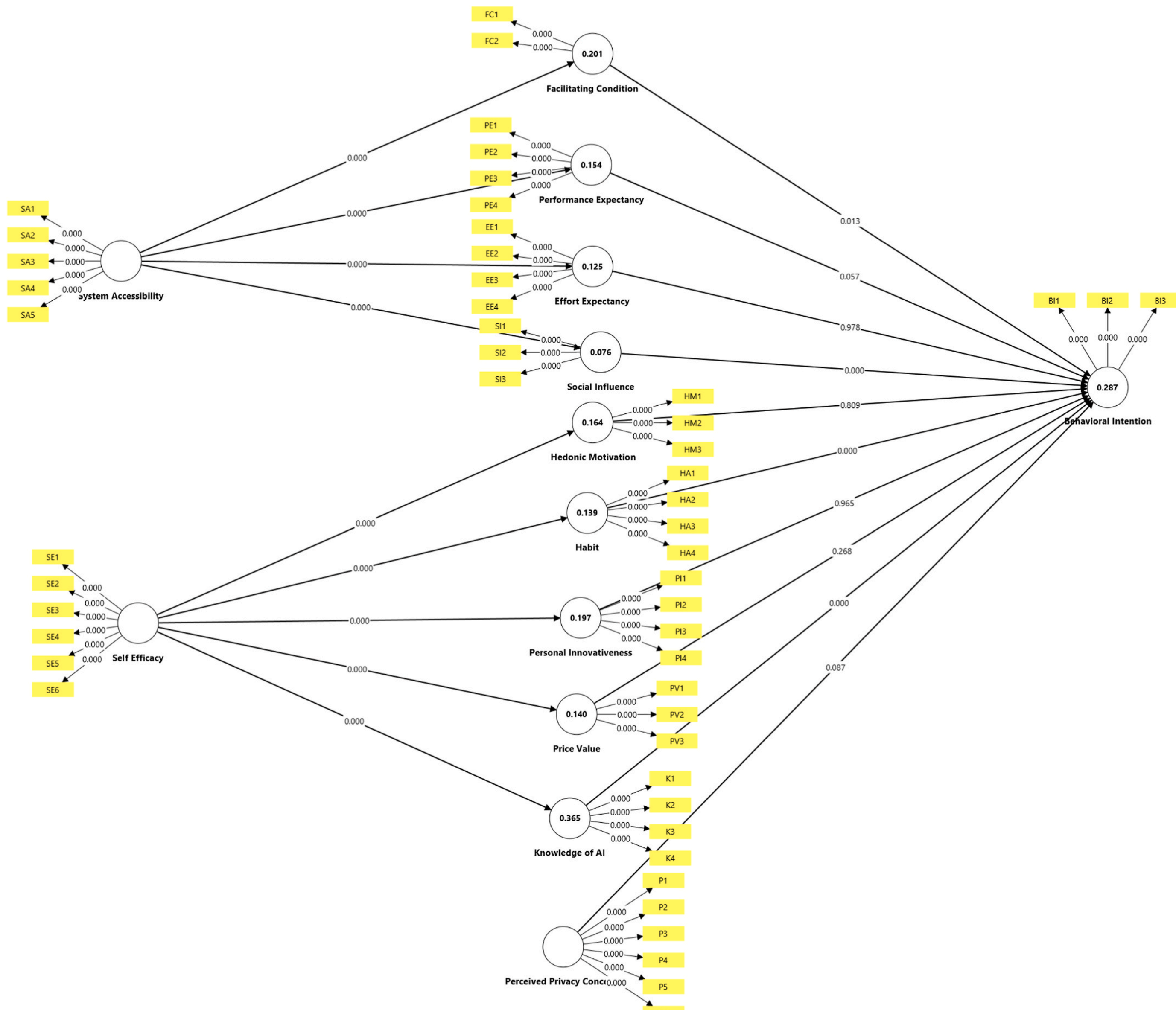

Fig. 2. The final results
(PLS-SEM Result of the Relationship of System Accessibility and Self-efficacy to the UTAUT 3 Constructs of Mathematics Learners who are GenAI users).

only system accessibility, self-efficacy, and knowledge of AI had a statistically significant impact on behavioral intention. Pinto et al. (2022) identified external variables as significant predictors within an extended adoption model, thus reinforcing the theoretical validity of incorporating these constructs into the UTAUT framework.

7. Conclusions

This study investigated students' behavioral intention to use AI tools in mathematics learning by testing 12 hypotheses using a path analysis framework grounded in the UTAUT 3 model with extended constructs. The study findings make several contributions. It provides empirical evidence on how mathematics learners adopt generative AI tools, with knowledge of AI, habit, and social influence as the primary determinants of behavioral intention. At the same time, performance expectancy, effort expectancy, and other traditional UTAUT constructs did not significantly predict behavioral intention in this context. This suggests a paradigm shift where prior familiarity, social context, and habitual engagement precede perceived usefulness or ease of use. Moreover, system accessibility significantly influenced key enabling factors such as facilitating conditions and social influence, emphasizing the foundational role of infrastructure and support systems. Likewise, self-efficacy emerged as a critical construct that enhances knowledge of AI and habitual use, which drives behavioral intention. While constructs such as hedonic motivation, personal innovativeness, and price value were influenced by self-efficacy, they did not directly contribute to intention, suggesting a role as attitudinal rather than behavioral catalysts.

Contrary to previous studies, perceived privacy concerns did not significantly affect behavioral intention. Students may have a context-specific tendency to overlook data protection issues or rely on institutional safeguards. Lastly, the extended UTAUT model provided a framework for understanding AI adoption in educational settings, particularly emphasizing the influence of digital competence, habitual use, and peer ecosystems. However, the non-significant findings is a reminder that adoption drivers are not uniform across contexts or constructs. Lastly, the study demonstrates the value of applying PLS-SEM to test a large-scale structural model with 960 participants, ensuring methodological rigor.

8. Limitations and future directions

While this study offers insights into the factors influencing students' intention to use AI tools in mathematics learning, it has several limitations. First, the study focused on mathematics learners from institutions within Cebu Island, which may limit the generalizability of the findings to other academic disciplines or educational settings. Cultural norms, institutional support, and local policies regarding AI use may differ across regions, shaping adoption patterns that this study does not capture. Second, because the data were collected at a single point in time, the study could not capture how students' perceptions or use of AI might change over time with more experience. Third, because the study relied on self-reported responses, which may be subject to social desirability bias or recall bias, particularly in a rapidly evolving technological domain where respondents may report idealized or normative behaviors rather than actual practices. It is also worth noting that some factors, like performance expectancy and privacy concerns, did not significantly affect this study. However, that does not necessarily mean they are unimportant; they might play a bigger role in different situations or among other groups of learners. Moreover, this study did not control for learners' prior experience with generative AI, which may have shaped responses to constructs such as habit, effort expectancy, or hedonic motivation. Differences between novice and advanced users could influence the relative strength of adoption drivers. Lastly, the study did not include qualitative feedback, such as interviews or open-ended responses, which could have added more depth and context to the findings. Given the fast pace of AI development, learners' reported behaviors may not fully capture evolving practices or the long-term integration of these tools. Future research can build on this work by including diverse student populations, exploring long-term trends, and combining quantitative and qualitative methods to better understand how students engage with AI in education.

CRediT authorship contribution statement

Lislee Valle: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Muchamad Taufiq Anwar:** Writing – original draft, Validation, Resources, Investigation, Data curation. **Nguyen Trong Hien Ton:** Writing – original draft, Validation, Methodology, Investigation, Formal analysis. **Maricar Osabel:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Relgen Obiasada:** Writing – original draft, Supervision, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Doston Pirnazarov:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis.

Ethical statement

The authors confirm that the study does not involve sensitive personal data, medical procedures, or vulnerable populations and poses no more than minimal risk to participants. The study was approved by the Campus Director of Cebu Technological University-Danao Campus. All research activities align with regular educational practices, and participation was voluntary. Informed consent was obtained from all participants prior to data collection. The study strictly adhered to the provisions of the Philippine Republic Act No. 10173, also known as the Data Privacy Act of 2012, ensuring that all information gathered was treated with the utmost confidentiality. Data were collected, stored, and used solely for academic purposes and managed in a secure and ethical manner.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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