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AI ACCEPTANCE AND USE IN MATHEMATICS PRE-SERVICE TEACHERS: A THEORY OF PLANNED BEHAVIOUR APPROACH

Hilman Qudratuddarsi[1*], Jumriani[1], Eli Meivawati[2], Saraswathy a/p Ramasundrum[3]
[1]Mathematics and Science Education Department, Faculty of Teacher Training and Education, Universitas Sulawesi Barat
[2]Elementary School Teacher Education, Faculty of Teacher Training and Education, Universitas Sulawesi Barat
[3]Mathematics and Science Education Department, Faculty of Education, Universiti Malaya, Malaysia

*Corresponding author
hilman.qudratuddarsi@unsulbar.ac.id

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Abstract
Artificial Intelligence (AI) is increasingly integrated into education, including mathematics learning, yet its successful implementation largely depends on teachers' acceptance and readiness. This study aims to examine the determinants of AI acceptance and use among pre-service mathematics teachers by employing the Theory of Planned Behaviour (TPB), which comprises Attitude (AT), Social Norms (SN), Perceived Behavioral Control (PBC), Behavioral Intention (BI), and AI Use (AIU). A quantitative, cross-sectional survey design was used. Data were collected from 427 Generation Z pre-service mathematics teachers enrolled in three Indonesian universities using an online questionnaire. The instrument was adapted from a previously validated TPB-based scale, and data were analyzed using PLS-SEM with SmartPLS. The measurement model demonstrated excellent reliability and validity, and the structural model indicated very good fit (SRMR = 0.044). All hypothesized relationships were supported ($p < 0.001$). SN emerged as the strongest predictor of BI, followed by AT and PBC, while BI was the most powerful determinant of AIU ($\beta = 0.849$). These findings highlight the central role of social influence, positive attitudes, and technological efficacy in shaping pre-service teachers' intentions and actual use of AI. The study implies that teacher education programs should design courses and practicum experiences that foster positive beliefs about AI, enhance digital competence, and leverage supportive social environments to promote meaningful AI integration in mathematics classrooms.

Keywords: Artificial Intelligence Acceptance, Artificial Intelligence Use, Educational technology, Mathematics Pre-service Teacher, Theory of Planned Behaviour,

Abstrak
Artificial Intelligence (AI) semakin banyak dimanfaatkan dalam pendidikan, termasuk pada pembelajaran matematika, namun keberhasilan integrasinya sangat bergantung pada penerimaan dan kesiapan calon guru. Penelitian ini bertujuan menganalisis faktor-faktor yang memengaruhi penerimaan dan penggunaan AI pada calon guru matematika menggunakan kerangka Theory of Planned Behaviour (TPB), yang mencakup Attitude (AT), Social Norms (SN), Perceived Behavioral Control (PBC), Behavioral Intention (BI) dan AI Use (AIU). Penelitian ini menggunakan pendekatan kuantitatif dengan desain cross-sectional. Sebanyak 427 calon guru matematika generasi Z dari tiga universitas di Indonesia berpartisipasi melalui pengisian kuesioner daring. Instrumen diadaptasi dari penelitian terdahulu berbasis TPB dan dianalisis menggunakan PLS-SEM melalui SmartPLS. Hasil menunjukkan bahwa model pengukuran memiliki reliabilitas dan validitas yang sangat baik, serta model struktural menunjukkan kelayakan yang tinggi (SRMR = 0,044). Semua hipotesis didukung secara signifikan ($p < 0,001$). SN muncul sebagai prediktor terkuat BI, diikuti AT dan PBC, sedangkan BI menjadi penentu utama AIU ($\beta = 0,849$). Temuan ini menegaskan pentingnya dukungan sosial, sikap positif, dan efikasi teknologi dalam mendorong niat dan perilaku penggunaan AI. Implikasinya, program pendidikan guru perlu merancang pelatihan dan pengalaman praktik yang menumbuhkan sikap positif, meningkatkan kompetensi digital, dan memanfaatkan pengaruh sosial yang konstruktif terhadap penggunaan AI dalam pembelajaran matematika.

Kata Kunci: *Artificial Intelligence Acceptance, Artificial Intelligence Use, Educational technology, Mathematics Pre-service Teacher, Theory of Planned Behaviour.*

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INTRODUCTION

Artificial Intelligence (AI) has rapidly emerged as one of the most transformative technologies in the 21st century, reshaping how people learn, work, communicate, and solve problems. In education, AI refers to computer-based systems designed to perform tasks that typically require human intelligence—such as reasoning, pattern recognition, decision-making, and adapting to new information (Che Ghazali et al., 2025). These systems manifest through a wide range of digital tools, from intelligent tutoring systems and predictive analytics to automated assessment platforms and generative AI models like ChatGPT (Irwanto, 2025). The integration of AI in educational contexts offers unprecedented opportunities to personalize learning, streamline administrative tasks, enhance feedback mechanisms, and support data-driven instructional decisions (Guo et al., 2024). AI-powered technologies can respond instantly to learners' needs, diagnose learning gaps with greater precision than traditional instruction, and offer adaptive problem-solving pathways. As a result, AI is increasingly viewed as a catalyst for improving student engagement, efficiency, and achievement across various levels of education (D. Wang & Huang, 2025).

In parallel, AI's influence is reshaping pedagogical practices by enabling teachers to leverage data and automation to enrich instruction. For example, AI-driven systems can help educators generate instructional materials, analyze students' performance patterns, and optimize lesson planning, thereby reducing workload and allowing more time for meaningful pedagogical interactions (Ali et al., 2025). AI also supports teachers in cultivating higher-order thinking skills by offering simulations and exploratory tasks that challenge students' reasoning and creativity. Despite its potential, the successful integration of AI in classrooms depends largely on teachers' readiness, willingness, and confidence in using AI tools (Garzón et al., 2025). As AI continues to evolve, understanding how educators—particularly future teachers—perceive, accept, and use AI becomes crucial for shaping effective and ethical AI integration in educational systems. The attitudes and behaviors of pre-service teachers will determine how AI is adopted in future classrooms, which makes empirical research on AI acceptance essential for preparing teacher education programs for the challenges and opportunities of AI-enriched learning environments (Boulhrir & Hamash, 2025; Sperling et al., 2024).

AI has also begun to play a significant role in mathematics education, where problem solving, reasoning, and conceptual understanding are central learning goals. AI-powered tools such as intelligent tutoring systems, computer algebra systems, and automated feedback generators can assist students in exploring mathematical concepts dynamically and interactively (Awang et al., 2025; Van Pham, 2025). These tools offer step-by-step support, adaptive prompts, and immediate error detection, enabling learners to engage in deeper mathematical thinking while receiving tailored assistance based on their individual progress. AI applications in mathematics further enhance visualization of abstract concepts through simulations, graphs, and dynamic representations that make complex ideas more accessible (Mazı, 2025; Panaoura, 2025). For teachers, AI can support instructional planning, assessment, and differentiation, helping them identify specific areas where students struggle and provide targeted interventions. As mathematics education increasingly incorporates such digital advancements, understanding pre-service mathematics teachers' acceptance and use of AI becomes critical for ensuring successful integration in future classrooms (Huclova et al., 2025; Mishra et al., 2025).

The attitudes of pre-service mathematics teachers toward AI hold significant implications for STEM education and digital transformation in schools. As future educators, their perceptions, beliefs, and readiness to use AI will shape how effectively AI is introduced to the next generation of learners (Dewi et al., 2024; Güngör et al., 2025). Mathematics teachers, in particular, operate within a discipline that values analytical reasoning, precision, and structured problem-solving—skills that align closely with the logic and computational foundations of AI (Nurwahid, 2024). As such, their openness to AI can accelerate the adoption of innovative, data-driven teaching practices that enhance conceptual understanding and foster critical thinking (Akendita et al., 2025). Positive attitudes toward AI are associated with stronger motivation to experiment with emerging technologies, willingness to integrate them into instructional routines, and confidence in using AI as a pedagogical ally. Conversely, skepticism or negative perceptions may hinder adoption, limiting students' opportunities to benefit from AI-enhanced learning tools (Açıkyıldız & Şahin, 2025; Aktulun et al., 2024).

Furthermore, pre-service mathematics teachers play a critical role in shaping AI literacy among school-aged learners, especially as AI becomes increasingly embedded in STEM careers. Their beliefs

influence not only their own instructional decisions but also the development of students' digital competencies, computational thinking, and ethical awareness of AI (Cheng et al., 2025; Falebita, 2025). Given that pre-service teachers are still forming professional identities, their attitudes toward AI are particularly malleable and shaped by training, peer influence, and perceived relevance (Ayanwale et al., 2025). As part of the broader STEM education framework, mathematics teachers often serve as key facilitators of technological innovation in schools; thus, their acceptance of AI becomes a determining factor in promoting equitable and effective AI integration. Researching their attitudes provides essential insights for teacher education programs to design training modules, digital literacy courses, and practicum experiences that strengthen AI confidence, understanding, and appropriate use (Yu et al., 2025).

The Theory of Planned Behaviour (TPB) offers a robust framework for examining pre-service teachers' acceptance and use of AI, as it captures the psychological determinants that shape technology-related decision-making (Wang et al., 2025). TPB posits that a person's behavior is driven by three core constructs: Attitude (AT), Social Norms (SN), and Perceived Behavioral Control (PBC), which collectively determine Behavioral Intention (BI) and subsequent actual behavior. This theoretical lens is highly suited to understanding AI adoption because AI tools often require users to evaluate their usefulness, consider social expectations surrounding technology use, and assess their capability to use the technology effectively. By employing TPB, this study captures the cognitive, social, and behavioral dimensions that influence how mathematics pre-service teachers perceive and engage with AI tools. TPB has been widely applied in educational technology research, making it an appropriate and validated model for investigating emerging digital practices such as AI integration (Jiao & Cao, 2024; Zhang, 2025).

Specifically, Attitude (AT) reflects pre-service teachers' positive or negative evaluations of using AI in teaching and learning. A favorable attitude suggests that teachers believe AI can enhance instruction, reduce workload, or support students' learning needs (Anani et al., 2025; Chai et al., 2020). Social Norms (SN) capture the perceived expectations or influences from peers, lecturers, institutions, and the broader educational culture. In collectivist societies such as Indonesia, social norms often play a powerful role in shaping technological decisions, making SN a critical factor in predicting AI acceptance. Meanwhile, Perceived Behavioral Control (PBC) refers to teachers' confidence in their ability to understand, operate, and manage AI tools. Higher PBC indicates that pre-service teachers feel capable of overcoming technical challenges, which increases their likelihood of adopting AI (Chai et al., 2022; Sanusi et al., 2024). Together, these TPB constructs provide a comprehensive explanation for why pre-service mathematics teachers may intend to use and eventually incorporate AI into their future teaching practices. The hypothesis for this study are: H1: AT will have a significant effect on BI to use AI, H2: SN will have a significant effect on BI to use AI, H3: PBC will have a significant effect on BI to use AI, H4: BI will have a strong influence on Artificial Intelligence Use (AIU).

METHOD

Research Design

This study employed a quantitative survey method, focusing on gathering and analyzing numerical data derived from participants' structured answers. As a survey-based investigation, it sought to evaluate pre-service mathematics teachers' acceptance and use of Artificial Intelligence (AI) at a single moment in time, without introducing any interventions or modifying the participant group (Qudratuddarsi, Meivawati, et al., 2024). A cross-sectional design was implemented to obtain a snapshot of their AI acceptance and utilization, while avoiding challenges typically associated with longitudinal research, such as participant attrition or time-related external changes. The quantitative approach ensured objective and reliable findings by enabling statistical analysis of patterns and emerging tendencies.

Research Subject

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design was implemented to obtain a snapshot of their AI acceptance and utilization, while avoiding challenges typically associated with longitudinal research, such as participant attrition or time-related external changes. The quantitative approach ensured objective and reliable findings by enabling statistical analysis of patterns and emerging tendencies.

A total of 427 Generation Z pre-service mathematics teachers participated in this research. Participants were recruited using a convenience sampling technique, which allowed efficient and accessible data collection, although it may slightly reduce the broader generalizability of the results. Nevertheless, the sample remained highly relevant due to their frequent use of technology in both daily activities and academic contexts. The 427 participants were drawn from three universities in Indonesia. In terms of gender composition, 32.78% were male and 67.21% were female, indicating that female participants formed the majority. Regarding academic level, 36.77% were first-year students, 34.66% were in their second year, and 28.57% were third-year students. This distribution reflects a relatively balanced representation across the different stages of study.

Research Instrument

The primary survey instrument utilized in this study was adapted from Habibi et al. (2024), who investigated Chat GPT acceptance and use among Indonesian university students. The instrument is anchored in the TPB framework, a prominent and well-established model for evaluating technology adoption, thereby enhancing its methodological soundness and relevance for the present study. Since the original scale was created in Bahasa Indonesia and had previously undergone comprehensive validation and publication in reputable academic journals, additional translation or linguistic adjustments were not necessary. To ensure its suitability for the current participant group, a pilot test was carried out. Reliability testing for each construct yielded coefficients between 0.86 and 0.95, indicating a very high level of internal consistency and confirming that the instrument reliably captures the intended latent constructs.

Data Collection

Data collection was carried out using Google Forms, which aligns with sustainable, paperless research practices while increasing efficiency and reducing potential data entry errors. The online format also enabled immediate access to participant responses. To promote clear comprehension of the questionnaire items, the researcher was present throughout the data collection process and provided on-the-spot clarification whenever necessary. This presence fostered a supportive atmosphere that encouraged participants to answer honestly (Qudratuddarsi, Ramadhana, et al., 2024). Participation was entirely voluntary, and respondents were clearly informed that their data would remain confidential and would not affect their academic standing. These ethical measures were essential for preserving the accuracy, credibility, and integrity of the dataset.

Data Analysis

Data analysis was conducted using SmartPLS through the PLS-SEM approach, which included assessing both the measurement and structural models (Hair et al., 2022; Vaithilingam et al., 2024). PLS-SEM was selected because it is well suited for examining complex relationships among the five constructs and for predicting Behavioral Intention (BI) and Artificial Intelligence Use (AIU) in a large-sample study. Prior to analysis, data preparation steps were completed, including checking for missing data, coding accuracy, and outliers. The measurement model was then evaluated by examining indicator loadings, reliability, and validity following established guidelines (Habibi, Mailizar, et al., 2024; Habibi, Mukminin, & Sofyan, 2024). After confirming the quality of the measurement model, the structural model was analyzed. Path coefficients, t-statistics, p-values, and effect sizes (f^2) were generated to determine the significance and strength of the hypothesized relationships (Hair et al., 2022; Vaithilingam et al., 2024).

RESULT AND DISCUSSION

Descriptive Statistics and Normality

The descriptive statistics in Table 1 provide an overview of mathematics pre-service teachers' responses toward the constructs of the Theory of Planned Behaviour (TPB), namely Attitude (AT), Perceived Behavioral Control (PBC), Social Norms (SN), Behavioral Intention (BI), and AI Use (AIU). Overall, the mean scores range from 2.64 to 3.43 on a 4-point scale, indicating generally positive but moderate perceptions toward AI acceptance and use. Attitude items (AT1–AT4) recorded the highest means (3.19–3.43), suggesting that participants view AI as useful and beneficial in supporting learning. In contrast, PBC items show slightly lower means (2.67–3.11), reflecting that while students feel somewhat capable of using AI, some still perceive challenges related to skills or confidence. Social Norms (SN) items cluster around means of 2.86–3.03, implying moderate external encouragement from peers, lecturers, or academic settings. Behavioral Intention (BI) and AI Use (AIU) show similar mid-range scores (around 2.86–3.22), suggesting that while students intend to use AI, actual use may still be limited. Normality was assessed through skewness and kurtosis values. All items fall within acceptable thresholds (±1), indicating that the data are approximately normally distributed. This supports the suitability of the dataset for subsequent inferential analyses. Overall, the descriptive results show that mathematics pre-service teachers hold generally positive attitudes toward AI, although confidence, social influence, and actual usage remain moderate.

Table 1
Descriptive Statistics

Items	Mean	Standard deviation	Kurtosis	Skewness
AT1	3.432	0.920	-0.053	-0.208
AT2	3.370	0.911	-0.030	-0.200
AT3	3.194	0.959	-0.278	-0.085
AT4	3.241	0.924	-0.084	-0.161
PBC1	3.108	0.968	-0.184	-0.019
PBC2	2.676	1.009	-0.313	0.195
PBC3	3.000	1.001	-0.280	-0.126
SN1	2.911	0.992	-0.251	0.013
SN2	2.916	1.000	-0.279	0.085
SN3	3.031	0.972	-0.124	-0.073
SN4	2.864	0.992	-0.306	0.059
SN5	2.905	1.008	-0.372	0.062
BI1	3.123	0.908	0.002	-0.110
BI2	3.221	0.933	-0.149	-0.063
BI3	2.867	1.018	-0.309	0.074
BI4	3.034	0.980	-0.171	-0.029
AIU1	3.045	0.968	-0.243	-0.060
AIU2	2.647	1.024	-0.450	0.164
AIU3	2.982	1.020	-0.392	0.040

Loading, Realibility and Convergent Validity

Loading, reliability, and convergent validity are tests used to ensure that survey items accurately and consistently measure the constructs they are intended to represent. These tests to confirm that each item strongly reflects its factor (loading), that the items within a construct are consistent (reliability), and that the construct truly captures the concept it is meant to measure (convergent validity). Table 2 presents the results of the loading values, reliability indices, and convergent validity for the constructs (AT, PBC, SN, BI, and AIU) in this study. All item loadings exceed the recommended threshold of 0.70, indicating that each indicator strongly reflects its intended latent construct. Attitude (AT) items demonstrate particularly high loadings (0.860–0.899), showing that participants consistently perceive the usefulness and positive aspects of AI. Similar strong loadings are observed for Social Norms (SN) (0.869–0.907) and Behavioral Intention (BI) (0.891–0.902), suggesting that these constructs are well represented by

their respective indicators. The Perceived Behavioral Control (PBC) items also show satisfactory loadings (0.777–0.863), with all values surpassing the acceptable cutoff.

For reliability, Cronbach's Alpha (α), rho A, and Composite Reliability (CR) all exceed 0.85 for every construct, demonstrating excellent internal consistency. This means the items within each TPB construct reliably measure the same underlying concept. Composite Reliability values, ranging from 0.868 to 0.946, further confirm the stability and reliability of the measurement model. Convergent validity is supported through Average Variance Extracted (AVE), where all constructs achieve values well above the minimum criterion of 0.50. AT, SN, and BI exhibit particularly high AVE values (0.789–0.789), indicating that a substantial proportion of variance is captured by the constructs rather than measurement error. AVE values for PBC (0.687) and AIU (0.771) also show strong convergence.

Table 2
Loading and Reliability

Factor	Name	Load	Alpha	rho-A	CR	AVE
AT	AT1	0.860	0.911	0.913	0.937	0.789
	AT2	0.896				
	AT3	0.899				
	AT4	0.896				
PBC	PBC1	0.863	0.872	0.881	0.868	0.687
	PBC2	0.844				
	PBC3	0.777				
SN	SN1	0.877	0.928	0.929	0.946	0.778
	SN2	0.869				
	SN3	0.885				
	SN4	0.907				
	SN5	0.872				
BI	BI1	0.891	0.917	0.913	0.937	0.789
	BI2	0.902				
	BI3	0.896				
	BI4	0.893				
AIU	AIU1	0.899	0.852	0.860	0.910	0.771
	AIU2	0.860				
	AIU3	0.875				

Discriminant Validity

Within PLS-SEM analysis, assessing discriminant validity is essential to confirm that each construct is truly distinct from the others (Hair et al., 2022; Vaithilingam et al., 2024). Several techniques can be used to evaluate this aspect, including examining cross-loadings and applying the Fornell–Larcker criterion (Ab Hamid et al., 2017; Hair et al., 2022). Table 3 presents the cross-loading values used to assess discriminant validity in the TPB model. Discriminant validity is achieved when each indicator loads highest on its intended construct compared with other constructs. The results show that items for AT, PBC, SN, BI, and AIU consistently display their strongest loadings on their respective factors. For example, AIU items load highest on AIU, AT items load highest on AT, and so on. This pattern confirms that each TPB construct is empirically distinct, demonstrating good discriminant validity for AI acceptance and use among mathematics pre-service teachers.

The Fornell–Larcker criterion was applied to further assess discriminant validity in the TPB model for AI acceptance and use. This criterion requires that the square root of each construct's AVE be greater than its correlations with other constructs. Meeting this condition indicates that each construct shares more variance with its own indicators than with other variables in the model. The results show that AT, PBC, SN, BI, and AIU all satisfy this requirement, confirming that the constructs are empirically distinct. These findings strengthen the validity of the measurement model in assessing mathematics pre-service teachers' AI acceptance and use.

Table 3
Cross Loadings

	AIU	AT	BI	PBC	SN
AIU1	**0.899**	0.660	0.816	0.563	0.772
AIU2	**0.860**	0.510	0.674	0.565	0.727
AIU3	**0.875**	0.586	0.735	0.548	0.714
AT1	0.564	**0.860**	0.600	0.501	0.580
AT2	0.586	**0.896**	0.651	0.550	0.600
AT3	0.611	**0.899**	0.665	0.569	0.630
AT4	0.619	**0.896**	0.691	0.596	0.640
BI1	0.739	0.663	**0.891**	0.621	0.786
BI2	0.770	0.711	**0.902**	0.594	0.774
BI3	0.764	0.616	**0.896**	0.617	0.779
BI4	0.767	0.643	**0.893**	0.622	0.745
PBC1	0.527	0.578	0.584	**0.863**	0.599
PBC2	0.563	0.515	0.611	**0.844**	0.619
PBC3	0.485	0.458	0.501	**0.777**	0.508
SN1	0.751	0.612	0.747	0.634	**0.877**
SN2	0.716	0.581	0.723	0.583	**0.869**
SN3	0.733	0.626	0.772	0.616	**0.885**
SN4	0.764	0.600	0.771	0.617	**0.907**
SN5	0.741	0.627	0.781	0.624	**0.872**

Table 4
Fornell–Larcker criterion

	AIU	AT	BI	PBC	SN
AIU	0.878				
AT	0.671	0.888			
BI	0.849	0.736	0.895		
PBC	0.635	0.625	0.685	0.829	
SN	0.841	0.691	0.861	0.697	0.882

Structural Model

Table 5 presents the model fit indices and collinearity assessment for the TPB-based structural model examining AI acceptance and use among mathematics pre-service teachers. Prior to interpreting the structural relationships, model fit was assessed using the Standardized Root Mean Square Residual (SRMR), a widely recommended indicator for identifying model misspecification (Hu & Bentler, 1999; Schuberth et al., 2023). According to established guidelines, SRMR values ≤ 0.08 indicate a good model fit, while values between 0.08 and 0.10 are considered acceptable. The SRMR obtained in this study (0.044) is substantially below the recommended cut-off, clearly indicating an excellent level of model fit.

To reinforce the fit evaluation, the squared Euclidean distance (d ULS) and the geodesic distance (d G) were also examined. Although no strict thresholds exist for these indices, lower values generally reflect better model performance. The results—d ULS = 0.371 and d G = 0.284—suggest that the model structure is stable and free from major specification concerns. Additional indices, such as the Chi-square value (1912.012) and NFI (0.899), further support the adequacy of the model. Collinearity was assessed using the Variance Inflation Factor (VIF), which evaluates the degree of redundancy among predictor variables. Following the guidelines of Hair et al., (2022), VIF values below 5 indicate no collinearity issues. All VIF values presented in Table 5—AT (2.073), PBC (2.108), SN (2.456), and BI predicting AIU (1.000)—fall well within acceptable limits. This confirms that the predictors do not exhibit multicollinearity and each contributes uniquely to the model.

Table 5.
VIF and Model Fit

Factor	BI	AIU	Model	Saturated Model
AT	2.073		SRMR	0.044
PBC	2.108		d ULS	0.371
SN	2.456		d G	0.284
BI		1.000	Chi-square	1912.012
			NFI	0.899

Figure 1 illustrates the structural model developed based on the Theory of Planned Behaviour (TPB) to examine AI acceptance and use among mathematics pre-service teachers. The model displays the hypothesized relationships among the five key TPB constructs: Attitude (AT), Perceived Behavioral Control (PBC), Social Norms (SN), Behavioral Intention (BI), and AI Use (AIU). The directional paths represent how AT, PBC, and SN are expected to influence BI, which in turn predicts actual AIU. The model also includes path coefficients and significance indicators that show the strength of each relationship.

Figure 1.
Structural model

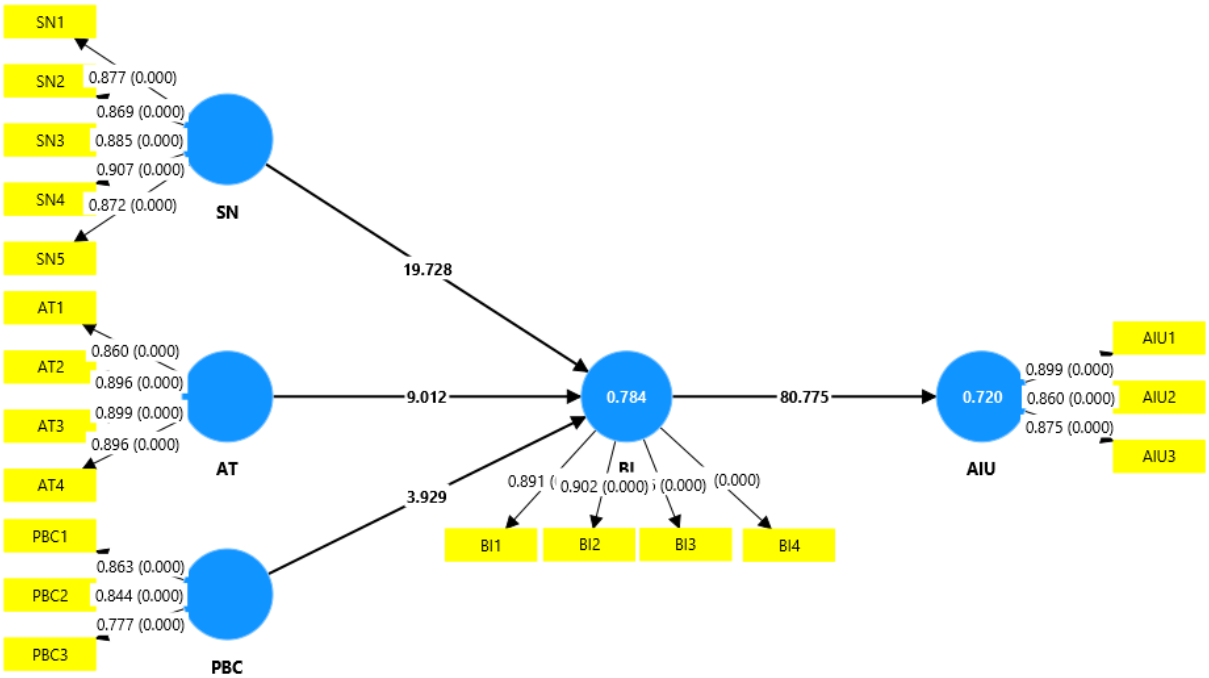


Table 6 presents the structural model results examining the determinants of AI acceptance and use among mathematics pre-service teachers within the TPB framework. The results show that all hypothesized relationships (H1–H4) are statistically significant, with p-values < 0.001, indicating strong empirical support for the proposed model. H1 shows that Attitude (AT) has a positive and significant effect on Behavioral Intention (BI) ($\beta = 0.242$, $t = 9.012$, $f^2 = 0.131$). This suggests that teachers with more favorable perceptions of AI are more likely to intend to use it. This aligns with prior research, such as (Cho et al., 2023; Greitemeyer & Kastenmüller, 2024), who found that positive attitudes played a crucial role in shaping users' intention to switch to ChatGPT. In the current study, students who view AI favorably are more inclined to integrate it into their learning activities, reinforcing the idea that cultivating positive perceptions is essential for encouraging adoption.

H2 indicates that Perceived Behavioral Control (PBC) also influences BI, although with a smaller effect ($\beta = 0.097$, $t = 3.929$, $f^2 = 0.021$), implying that confidence and perceived capability play a modest but meaningful role. This pattern echoes findings by Greitemeyer & Kastenmüller (2024), who reported that a sense of control and confidence in overcoming barriers significantly increased students' intention

to use ChatGPT. Similarly, mathematics pre-service teachers who believe they can manage potential challenges when using AI are more likely to adopt it. Thus, strengthening students' technological efficacy is necessary to maximize AI acceptance.

Table 6.
Structural Model

H	Relationship	β	Mean	SD	T	p	f^2
H1	AT -> BI	0.242	0.243	0.027	9.012	0.000	0.131
H2	PBC -> BI	0.097	0.098	0.025	3.929	0.000	0.021
H3	SN -> BI	0.626	0.625	0.032	19.728	0.000	0.737
H4	BI -> AIU	0.849	0.849	0.011	80.775	0.000	2.575

The strongest predictor of BI is Social Norms (SN), as shown in H3 ($\beta = 0.626$, $t = 19.728$, $f^2 = 0.737$). This large effect size demonstrates that encouragement, expectations, and influence from peers, lecturers, or academic environments strongly shape students' intentions to adopt AI technologies. This is consistent with studies noting the influence of social contexts—particularly in collectivist cultures like Indonesia, where respecting others' perspectives is deeply valued (Alhwaiti, 2023; Guggemos & Seufert, 2021; Marto et al., 2019; Raffaghelli et al., 2022). Encouragement from peers and lecturers, therefore, plays a decisive role in shaping intention.

Finally, H4 reveals that Behavioral Intention strongly predicts actual AI Use (AIU) ($\beta = 0.849$, $t = 80.775$, $f^2 = 2.575$). Behavioral Intention (BI) was identified as the most powerful determinant of actual AI use, supporting earlier findings that stronger intentions lead to higher adoption levels (Cabrera-Sánchez et al., 2021; Habibi, Mukminin, & Sofyan, 2024). This confirms the central role of BI within the TPB framework in predicting real AI-use behavior.

This study has several methodological limitations that should be acknowledged. First, the use of a cross-sectional survey design limits the ability to establish causal relationships, as data were captured at a single point in time. Longitudinal studies may provide deeper insights into how AI acceptance evolves as students gain more exposure to the technology. Second, the application of convenience sampling may restrict the generalizability of the findings, as participants were drawn from only three Indonesian universities and may not represent all pre-service mathematics teachers nationally. Third, the study relied exclusively on self-reported data, which can be influenced by social desirability bias, particularly when assessing attitudes and behavioral intentions toward emerging technologies. Additionally, although PLS-SEM is suitable for complex models, it does not fully eliminate measurement bias or unobserved variables. Future research could incorporate mixed methods, broader samples, and longitudinal approaches to strengthen the robustness of the conclusions.

CONCLUSION

This study demonstrates that the Theory of Planned Behaviour effectively explains AI acceptance and use among pre-service mathematics teachers in Indonesia. All TPB constructs significantly predicted behavioral intention and usage, with Social Norms emerging as the strongest influence, followed by Attitude and Perceived Behavioral Control. Behavioral Intention was the most powerful determinant of actual AI use, indicating that stronger intentions translate directly into greater adoption. These findings highlight the importance of fostering positive beliefs about AI, building technological confidence, and creating supportive social environments within teacher education programs.

To strengthen the study's findings, future research should incorporate qualitative evidence—such as semi-structured interviews or focus groups—to gain deeper insight into how Indonesian Generation Z pre-service mathematics teachers interpret and negotiate AI adoption in their learning and practicum contexts. This approach can unpack *why* Social Norms emerged as the strongest predictor of Behavioral Intention and how attitudes and perceived control are shaped by lecturers, peers, institutional expectations, and access to AI tools.

Building on these findings—particularly the dominant role of Social Norms and the strong intention–use pathway—teacher education institutions should embed AI literacy within mathematics education coursework, create structured and supervised opportunities for hands-on experimentation

with AI tools, and model ethical, responsible AI use through lecturers' and mentors' practices. In parallel, policymakers should issue clear, actionable guidance for AI integration and ensure equitable access to digital infrastructure and training so that pre-service teachers' Perceived Behavioral Control (PBC) is strengthened, not constrained by contextual limitations.

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