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Research paper

Determinants of Behavioral Intention to Use Generative AI: The Role of Trust, Personal Innovativeness, and UTAUT II Factors

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Abstract

This study examines the key determinants influencing Indonesian university students' behavioral intention to use generative AI, focusing on the roles of trust, personal innovativeness, and factors from the Unified Theory of Acceptance and Use of Technology II (UTAUT II). The study employed a survey research method, collecting 480 valid responses. Data analysis was conducted using descriptive statistics and PLS-SEM to identify significant predictors of generative AI adoption. The findings indicate that performance expectancy, facilitating conditions, hedonic motivation, personal innovativeness, price value, and trust significantly influence students' intention to adopt generative AI, while effort expectancy and social influence were found to be insignificant. The study contributes to theory by extending UTAUT II with trust and personal innovativeness in the context of generative AI adoption. Practically, it offers insights for policymakers to enhance the adoption of AI by focusing on factors that matter most to students.

Keywords: *Generative AI; UTAUT; personal innovativeness; trust; education*

1. Introduction

The integration of Information and Communication Technology (ICT) into education has become essential in modern learning environments, as digital tools and resources have reshaped how knowledge is shared, acquired, and applied (Timotheou et al., 2023). ICT has revolutionized traditional teaching methods, offering greater accessibility, flexibility, and interactivity that enable students and educators to engage with educational content more effectively (Prakash et al., 2023). The inseparability of ICT and education is evident in various applications, from online learning platforms and digital classrooms to educational software and interactive multimedia content (Bilynska et al., 2024). As a result, the presence of ICT in education has shifted from a supplementary role to a fundamental component in the learning process.

With the rapid advancement of artificial intelligence (AI), particularly generative AI (GenAI), the educational landscape is experiencing unprecedented transformation (Alasadi & Baiz, 2023). GenAI, capable of producing text, images, audio, and even video, has opened new possibilities in personalized tutoring, automated content creation, and interactive learning experiences (Yehia, 2025). These technologies allow for customized educational approaches that cater to individual learning styles and needs, enhancing students' engagement and understanding (Zhan et al., 2025). However, the proliferation of GenAI also brings challenges. Concerns about academic integrity, over-reliance on AI-generated content, and potential biases in AI models raise questions about the ethical and responsible use of AI in educational settings (Bittle & El-Gayar, 2025). As GenAI becomes more prevalent, educators and institutions must balance its benefits with the potential drawbacks to foster a healthy learning environment.

The impact of GenAI is felt across all levels of education, from early childhood to higher education (Nguyen & Truong, 2025). In kindergarten and primary school settings, AI tools can provide engaging learning experiences through interactive storytelling, visual aids, and gamified learning applications, capturing young learners' attention and curiosity (Zhao et al., 2024). At the secondary level, GenAI supports students in exploring complex subjects, offering personalized assistance in subjects like math, science, and language arts. In tertiary education, where students engage in more advanced research and analytical tasks, GenAI tools like ChatGPT and DALL-E assist in generating ideas, drafting essays, and creating visual presentations, streamlining the learning process (Farrelly & Baker, 2023). While each educational stage benefits uniquely from GenAI, the universal challenge remains ensuring that these tools are used to enhance learning rather than replace critical thinking and creativity.

While studies on AI adoption in education have proliferated, each country possesses unique cultural, educational, and technological characteristics that can influence AI acceptance and usage. Consequently, findings from AI adoption studies conducted in other regions may not be directly applicable to Indonesia, where the educational landscape and students' attitudes toward technology may differ significantly. Understanding these contextual nuances is crucial for developing insights that accurately reflect the Indonesian student experience.

Most existing research on AI adoption in education has primarily focused on text-based GenAI, such as ChatGPT (e.g., Salloum et al., 2024; Duong et al., 2025; Shahzad et al., 2025), with limited attention given to the broader spectrum of GenAI tools, including those that generate audio, video, code, and images. This narrow scope restricts our understanding of the full potential and challenges of GenAI in supporting diverse educational needs. Although some research on GenAI adoption has been conducted in Indonesia, previous studies have generally been limited in their scope, focusing on a restricted set of variables and respondent groups (e.g., Idris, Pujani & Yeni, 2024). Notably, these studies have often overlooked critical factors such as trust and personal innovativeness, which may play a significant role in shaping students' behavioral intentions toward GenAI. This study aims to address these gaps by examining the key factors that influence Indonesian students' intention to use GenAI, with a specific focus on trust, personal innovativeness, and a comprehensive set of Unified Theory of Acceptance and Use of Technology II (UTAUT II) (Venkatesh, Thong & Xu, 2012) factors across various AI modalities. Specifically, the study aims to answer the following research question: "What are the key determinants influencing Indonesian university students' behavioral intention (BI) to use GenAI, and how do trust (TR), personal innovativeness (PI), and UTAUT II factors contribute to this intention?"

This research is significant as it provides a deeper understanding of the factors driving GenAI adoption among Indonesian students, contributing valuable insights to both academia and educational practitioners. By examining a comprehensive set of variables, including trust and personal innovativeness alongside UTAUT II factors, this study addresses previously overlooked aspects that may influence students' willingness to adopt AI technologies. In an era where GenAI is increasingly integrated into educational environments, understanding these determinants is crucial for developing effective strategies to enhance AI acceptance and utilization in diverse learning contexts. Furthermore, the inclusion of various GenAI modalities—text, audio, video, code, and image—ensures a holistic approach, allowing for a more nuanced perspective on how different AI tools can support educational outcomes.

2. Literature Review

AI is a broad field encompassing technologies designed to perform tasks that typically require human intelligence, such as problem-solving, decision-making, and pattern recognition (Banh & Strobel, 2023). Within AI, a subset called Machine Learning, focuses on systems that can learn from data and improve their performance over time without being explicitly programmed for each specific task. Machine Learning includes various techniques, such as decision trees and support vector machines, which identify patterns and make predictions based on the data they process (Jain & Srihari, 2025). A more advanced area within Machine Learning is Deep Learning, which involves neural networks with multiple layers that can analyze complex and large datasets. Deep Learning algorithms, like convolutional and recurrent neural networks, have been highly effective in fields like image recognition, speech processing, and natural language understanding, where they detect intricate patterns and nuances in the data (Di, Peng & Chen, 2025).

GenAI, a specialized branch within Deep Learning, focuses on creating new, meaningful content such as text, images, and audio by learning from existing data patterns (Feuerriegel et al., 2024). GenAI models, including large language models and generative adversarial networks, can produce human-like text, realistic images, and other creative outputs. This technology has seen widespread adoption in content creation, artistic applications, and interactive tools, enabling systems to assist and augment human creativity and productivity by generating novel content based on learned knowledge (De Freitas, Nave & Puntoni, 2025).

According to Wood & Moss (2024), GenAI can significantly impact education by facilitating real-world applications, enhancing teaching strategies, supporting continuous learning, and fostering personal and professional. In terms of real-world applications, GenAI can be integrated into educators' current roles, supporting tasks such as lesson planning, content generation, and assessment development (Wood & Moss, 2024). By embedding AI into workflows, educators can streamline their teaching processes, making time for more direct student engagement and personalized feedback (Khairullah et al., 2025). AI's practical applications also include automating routine administrative tasks, which allows teachers to focus more on instructional quality and student outcomes.

Enhanced teaching strategies is another area where GenAI shines, particularly in creating adaptive learning environments (Wood & Moss, 2024). AI systems can assess student progress in real-time, adapting content and instruction based on individual needs (Vafadar & Amani, 2024). This capability aligns with instructional design methodologies, where the focus is on using data-driven insights to tailor educational experiences. GenAI also supports innovative teaching methods, such as using AI-generated simulations or case studies, which can make abstract concepts more tangible and relatable for students. This adaptability can lead to more inclusive learning experiences, where students of varying abilities and learning styles receive support suited to their specific needs.

Another benefit is in continuous learning, where GenAI enables educators to assess and refine their teaching methods (Wood & Moss, 2024). By analyzing data from AI-driven platforms, educators can identify areas for improvement, pursue professional development opportunities, and explore advanced instructional design techniques that incorporate AI. Furthermore, GenAI can be a tool for lifelong learning among educators (Masrek et al., 2024), helping them stay updated with evolving technologies and instructional methodologies, and ultimately, enhancing their instructional delivery (Vafadar & Amani, 2024).

Personal and professional growth for educators is also enhanced by AI's role in promoting improved time management, fostering critical thinking, and deepening their understanding of instructional design principles (Wood & Moss, 2024). As AI tools assist with administrative tasks and provide resources for planning, educators gain more time to focus on their development. Additionally, by interacting with advanced AI systems, educators can cultivate critical thinking skills, learning how to evaluate AI-generated outputs critically and use them effectively in their classrooms (Vafadar & Amani, 2024).

However, there are challenges associated with integrating GenAI into education (Wood & Moss, 2024; Vafadar & Amani, 2024). One major obstacle is adapting to new AI tools, as many educators may initially be unfamiliar or uncomfortable with this technology. Overcoming skepticism towards AI is essential for its successful adoption, requiring both practical demonstrations of AI's educational benefits and training programs to build educator confidence. Additionally, the rapid evolution of AI tools demands continuous learning and adaptation, which may feel overwhelming to some educators. This challenge is compounded by the need to ensure that AI-generated content aligns with educational standards and ethical considerations, especially regarding the accuracy and reliability of AI-generated information (Nguyen, 2025).

Numerous studies have reported how GenAI has been used by students to support their learning process (Ch'ng, 2024; Liu, Zhang & Biebricher, 2024; Paul, Tretheway & Liu, 2024; Pérez-Colado et al., 2024). These studies reveal that students in many countries are increasingly aware of GenAI and are gradually embracing these technologies. Table 1 presents the use of GenAI by students across different modalities: text, audio, video, image, and code. It includes descriptions, examples of AI tools, and how students utilize these tools to support learning, such as drafting essays (text), creating narrated presentations (audio), producing visual content (video), generating illustrations (image), and assisting in coding tasks (code).

Table 1: The Use of GenAI by Students

Modality	Description	Example of Tools	How Students Use to Support Learning
Text	Generates written content such as essays, summaries, and explanations	ChatGPT, Jasper	Students use it to draft essays, summarize articles, and receive explanations on complex topics
Audio	Produces audio outputs, such as spoken lectures or language practice	Murf, Descript	Students use it to convert text to speech for listening practice or to create narrated presentations.
Video	Creates video content, including animations and tutorials	Synthesia, Pictory	Students use it to produce visual explanations for presentations, study guides, or project summaries.
Image	Generates visual content, such as illustrations, diagrams, or infographics	DALL-E, Midjourney	Students use it to create images for projects, presentations, or to visualize complex ideas.
Code	Generate or assist in writing programming code for assignments or projects	GitHub Copilot, CodeGPT	Students use it to get help with coding tasks, debug programs, or understand coding concepts.

3. Theoretical Framework and Hypothesis Development

This study adopts the UTAUT II as the guiding theoretical framework to investigate students' behavioral intention to use GenAI tools. Compared to earlier models such as the Technology Acceptance Model (TAM) (Davis, 1989) or the Diffusion of Innovation (DOI) (Rogers, 2023), UTAUT II offers a more comprehensive approach, integrating both extrinsic (e.g., performance expectancy, facilitating conditions) and intrinsic (e.g., hedonic motivation) motivators of technology acceptance. Its flexibility and proven predictive power across educational and emerging technology contexts (Venkatesh, Thong, & Xu, 2012; Venkatesh, 2022) make it particularly suited for studying complex and novel technologies like GenAI. As illustrated in Figure 1, this framework has been extended by incorporating two additional constructs—trust and personal innovativeness—reflecting psychological and dispositional factors that play a crucial role in the adoption of GenAI.

To better address the unique characteristics of GenAI—such as lack of transparency in underlying algorithms and the rapid pace of innovation—this study extends UTAUT II by including two additional constructs: TR and PI in IT. Drawing on McKnight, Choudhury & Kacmar (2002) and McKnight et al. (2011), trust is conceptualized here as users' beliefs in the integrity, competence, and benevolence of the GenAI system itself—not its developers or institutions. In the context of AI, trust is crucial because users often lack full visibility into how content is generated. Meanwhile, personal innovativeness, as defined by Agarwal and Prasad (1998), reflects an individual's predisposition to try out new technologies early. This trait-based construct captures user readiness and curiosity, which are essential to understanding engagement with emerging tools like GenAI. The inclusion of these constructs is both theoretically and contextually grounded, as recent studies have demonstrated their relevance in AI adoption (Al-Kfairy, 2024; Bouteraa et al., 2024). The extended framework includes eight constructs hypothesized to influence behavioral intention:

Performance Expectancy (PE) is defined as the belief that using GenAI will enhance academic performance (Venkatesh et al., 2003). Prior research has consistently shown this to be a primary driver of technology use in educational settings (e.g., Camilleri, 2024).

H1: PE has a positive and significant relationship with intention to use GenAI.

Effort Expectancy (EE) refers to the perceived ease of using GenAI tools. While some studies report a significant effect (Fu et al., 2024), others—particularly in digitally literate populations—do not (Idris, Pujani & Yeni, 2024). This study retains the construct to test its contextual relevance in Indonesian higher education.

H2: EE has a positive and significant relationship with BI to use GenAI.

Social Influence (SI) describes the extent to which peer or institutional opinions affect adoption decisions (Venkatesh et al., 2003). Although recent findings are mixed (e.g., significant in Nepal, but not in Egypt or Indonesia), it remains a core UTAUT variable, included here to examine its role in a GenAI context.

H3: SI has a positive and significant relationship with BI to use GenAI.

Facilitating Conditions (FC) represent the availability of technical and institutional support for using GenAI (Venkatesh et al., 2003). Multiple studies have confirmed its importance in educational technology adoption (Habibi et al., 2024; Bhat et al., 2024).

H4: FC has a positive and significant relationship with BI to use GenAI.

Hedonic Motivation (HM) refers to the enjoyment derived from using GenAI tools. This construct captures the intrinsic engagement aspect of AI use, especially relevant for creative and exploratory learning (Fu et al., 2024).

H5: HM has a positive and significant relationship with BI to use GenAI.

Price Value (PV), distinct from PE, reflects users' perceptions of GenAI's value relative to its cost (Venkatesh et al., 2012). This is particularly relevant where freemium or subscription-based models exist.

H6: PV has a positive and significant relationship with BI to use GenAI.

Trust (TR), as noted earlier, captures confidence in GenAI systems' reliability and ethical functioning (McKnight et al., 2002; McKnight et al., 2011). Its inclusion strengthens the model's capacity to account for psychological risk-reduction mechanisms.

H7: TR has a positive and significant relationship with BI to use GenAI.

PI in IT explains individual differences in willingness to try GenAI early and independently (Agarwal & Prasad, 1998). Its addition helps account for psychological readiness that UTAUT II alone may not capture.

H8: PI in IT has a positive and significant relationship with BI to use GenAI.

By combining the established predictive power of UTAUT II with the context-sensitive constructs of trust and personal innovativeness, this framework provides a robust and theoretically grounded lens to examine GenAI adoption behavior in higher education.

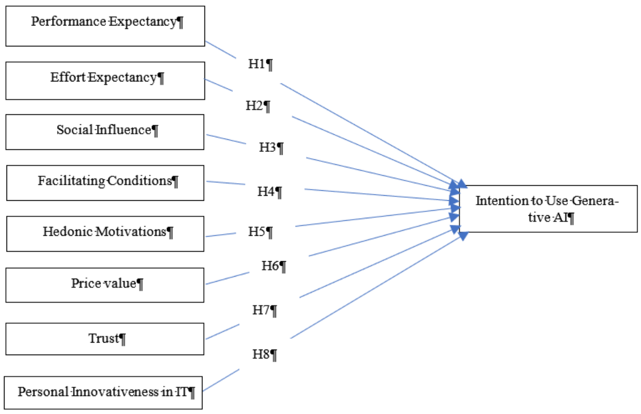

Fig. 1: Theoretical Framework

4. Research Methodology

This study employed a survey research method to investigate the determinants influencing university students' intention to use GenAI. Data was collected through an online questionnaire, developed and administered using SurveyMonkey, which allowed for efficient distribution and response collection from many students. The measurement items for the constructs were adapted from established scales in past studies, specifically from research by Camilleri (2024), Budhathoki et al. (2024), Hsu and Silalahi (2024), Fu et al. (2024), Hwang, Yoon Hwang, and Hoe-Chang (2024), Paulussen (2024), Surya Bahadur et al. (2024), Idris, Pujani, and Yeni (2024), and Habibi et al. (2024). These sources provided validated items, ensuring that the constructs used in this study were reliable and consistent with prior research on technology acceptance.

Before full data collection, the questionnaire was pre-tested with three faculty members: one professor and two senior lecturers. This pre-test helped refine the questionnaire for clarity and relevance. Following this, a pilot test was conducted with 45 respondents to assess the reliability of the measurement items. The Cronbach's alpha values for all constructs were above 0.7, indicating satisfactory internal consistency and reliability. The target population for this study was university students in Indonesia. Due to the lack of a formal sampling frame, a convenience and purposive sampling approach was used, targeting students who were likely to have some familiarity with GenAI tools.

For data analysis, descriptive statistics were calculated using SPSS (Version 24.0) to summarize the demographic profile and initial patterns in the data. Structural equation modeling (PLS-SEM) was performed using SmartPLS (Version 4.0) to test the research hypotheses and assess the relationships between the constructs. A reflective model was used in the analysis, consistent with prior studies in this field (e.g. Masrek et al., 2020), to represent the direction of causality from the latent variables to the observed measures.

5. Findings

5.1 Assessment of the Threats of Common Method Variance

To confirm that the collected data did not suffer from common method variance, a correlation analysis was performed following the guidelines of Bagozzi, Yi & Phillips (1991). Common method bias is indicated by a high correlation among primary constructs ($r > 0.9$). However, as shown in Table 2, common method variance was not a concern, as the correlations among constructs were all below the 0.9 threshold (Bagozzi, Yi, & Phillips, 1991).

Table 2: Correlation Among Constructs

	BI	EE	FC	HM	PE	PI	PV	SI	TR
BI	1								
EE	0.601	1							
FC	0.649	0.598	1						
HM	0.684	0.688	0.672	1					
PE	0.626	0.684	0.635	0.642	1				
PI	0.650	0.508	0.51	0.54	0.494	1			
PV	0.641	0.552	0.648	0.647	0.574	0.478	1		
SI	0.578	0.555	0.688	0.589	0.578	0.372	0.603	1	
TR	0.644	0.519	0.578	0.593	0.597	0.428	0.65	0.603	1

Legend: BI – Intention to Use GenAI, EE – Effort Expectancy, FC – Facilitating Conditions, HM – Hedonic Motivations, PE – Performance Expectancy, PI – Personal Innovativeness in IT, PV – Price Value, SI – Social Influence, TR - Trust

5.2 Demographic Profiles

Table 3 provides an overview of the demographic characteristics of the respondents involved in the study. The table includes variables such as gender, age, academic level, and field of study. Most respondents are female, representing 58% of the sample, while males constitute 42%. In terms of age distribution, the majority are between 18 and 24 years old, reflecting a younger demographic primarily consisting of undergraduate students. The academic levels represented in the sample range from undergraduate to postgraduate, with a predominant number of undergraduate students (approximately 70%). The respondents' fields of study are diverse, including areas such as social sciences, engineering, and business, with social sciences being the most common field. This demographic breakdown helps to contextualize the findings, highlighting that the sample largely consists of younger, undergraduate students from a variety of academic disciplines.

Table 3: Demographic Profiles of Respondents

		Frequency	Percent
Gender	Male	141	29.4
	Female	339	70.6
Age (years old)	Less than 21	264	55.0
	21 - 25	189	39.4
	26 - 30	2	0.4
	31 - 35	5	1.0
	36 - 40	8	1.7
	41 - 45	6	1.3
	46 - 50	1	0.2
	51 - 55	3	0.6
	Above 55	2	0.4
Marital Status	Single	471	98.1
	Married	8	1.7
	Divorced	1	0.2
Program level enrolled	Diploma	13	2.7
	Bachelor	433	90.2
	Master	20	4.2
	PhD / Doctor of Philosophy	14	2.9
Type of University	State / Government University	456	95.0
	Private	8	1.7
	Polytechnique	6	1.3
	Institute	10	2.1
Field of Study	Science and Technology (e.g. Computer Science, Information Technology, Engineering, Mathematics, Natural Sciences)	20	4.2
	Business and Economics (e.g., Business, Management, Economics, Finance)	152	31.7
	Social Science and Humanities (e.g., Library Science, Mass Communication, Arts and Design, etc)	251	52.3
	Medical and Health Science (e.g., Medicine, Pharmacy, Dentistry, etc)	12	2.5
	Others	45	9.4

Table 4 presents the types of GenAI tools used by respondents, classified by modality. The results show that text or writing tools (e.g., ChatGPT, Jasper AI) are the most frequently used, with 95.8% of respondents reporting utilization in this category. Other AI modalities, such as graphic design (25.2%), music or audio (16.25%), video or animation (11.67%), coding or programming (4.16%), and 3D modeling (0.025%), demonstrate lower usage rates among respondents, indicating a primary preference for text-based GenAI applications.

Table 4: GenAI Utilization

Modality	Frequency	Percentage
Text / Writing (Example ChatGPT, Jasper AI, Copy.ai)	460	95.80
Graphic Design (Example DALL-E, Midjourney, Stable Diffusion)	121	25.20
Music / Audio (Example Soundraw, AIVA, Amper Music)	78	16.25
Video / Animation (Example Runway ML, Synthesia, Pictory)	56	11.67
Coding / Programming (Example GitHub Copilot, OpenAI Codex, CodeT5)	20	4.16
3D Modeling (Example DreamFusion, Point-E)	12	0.025

Table 5 details the purposes for which respondents use GenAI. The most common purpose is assisting with academic assignments, with 86.9% of respondents indicating this use. Other significant purposes include preparing presentation or project materials (27.5%) and enhancing personal creativity (23.8%). Less common uses involve trying out new technology (20.0%), developing new skills (13.8%), and entertainment or personal exploration (11.9%), suggesting that GenAI is predominantly applied for academic and creative tasks.

Table 5: Purpose of Utilization

Purposes of Utilization	Frequency	Percentage
Assisting with academic assignments	417	86.9
Enhancing personal creativity	114	23.8
Entertainment or personal exploration	57	11.9
Preparing presentation or project materials	132	27.5
Trying out new technology	96	20.0
Developing new skills	66	13.8
Others	26	5.4

5.3 Measurement Model Assessment

Table 6 presents the Factor Loadings, Composite Reliability, and Average Variance Extracted (AVE) for the constructs. Factor loading reflects the strength of the correlation between an observed variable (indicator) and its corresponding latent construct. Generally, high factor loadings (above 0.7) indicate that the indicator is a reliable measure of the latent variable. However, Ramayah et al. (2018) suggest that a factor loading as low as 0.6 can be considered acceptable, provided that composite reliability exceeds 0.7 and AVE is above 0.5. Composite reliability assesses the internal consistency of the indicators associated with a latent construct. A value above 0.7 is typically deemed satisfactory, indicating that the indicators consistently reflect the construct (Hair et al., 2019). AVE measures the proportion of variance explained by a latent construct relative to the total variance, including measurement error. An AVE greater than 0.5 suggests that the construct explains more than half of the variance in its indicators, thereby confirming good convergent validity (Hair et al., 2019). Based on the results presented, no issues were observed with the convergent validity of the constructions.

Table 6: Convergent Validity Assessment

Construct	Item Code	Factor Loading	Composite Reliability	Average Variance Extracted
Intention to use GenAI (BI)	BI1	0.865	0.909	0.714
	BI2	0.840		
	BI3	0.836		
	BI4	0.838		
Effort Expectancy (EE)	EE1	0.811	0.866	0.619
	EE2	0.838		
	EE3	0.805		
	EE4	0.685		
Facilitating Conditions (FC)	FC1	0.854	0.881	0.651
	FC2	0.858		
	FC3	0.819		
	FC4	0.685		
Hedonic Motivations (HM)	HM1	0.861	0.92	0.742
	HM2	0.891		
	HM3	0.907		
	HM4	0.782		
Performance Expectancy (PE)	PE1	0.802	0.905	0.704
	PE2	0.859		
	PE3	0.863		
	PE4	0.831		
Personal Innovativeness in IT (PI)	PI1	0.799	0.915	0.729
	PI2	0.878		
	PI3	0.891		
	PI4	0.845		
Price Value (PV)	PV1	0.851	0.899	0.69
	PV2	0.821		
	PV3	0.817		
	PV4	0.833		
Social Influence (SI)	SI1	0.763	0.889	0.666
	SI2	0.828		
	SI3	0.856		
	SI4	0.816		
Trust (TR)	TR1	0.809	0.899	0.69
	TR2	0.847		
	TR3	0.838		
	TR4	0.827		

Discriminant validity ensures that each construct in a model is distinct from others, capturing unique aspects not represented by other constructs (Hair et al., 2019). A common method for assessing discriminant validity is the Heterotrait-Monotrait Ratio (HTMT), which compares correlations between constructs. An HTMT value below 0.85 (or 0.90, depending on the context) suggests adequate discriminant validity (Hair et al., 2019). As shown in Table 7, all inter-constructed correlations fall below the recommended threshold, indicating no issues with discriminant validity in this model.

Table 7: Discriminant Validity Assessment

	BI	EE	FC	HM	PE	PI	PV	SI	TR
BI									
EE	0.719								
FC	0.769	0.733							
HM	0.779	0.810	0.790						
PE	0.723	0.817	0.757	0.733					
PI	0.746	0.606	0.606	0.613	0.568				
PV	0.744	0.667	0.779	0.747	0.672	0.553			
SI	0.679	0.688	0.833	0.689	0.682	0.438	0.713		
TR	0.741	0.621	0.694	0.681	0.697	0.488	0.766	0.712	

Legend: BI – Intention to Use GenAI, EE – Effort Expectancy, FC – Facilitating Conditions, HM – Hedonic Motivations, PE – Performance Expectancy, PI – Personal Innovativeness in IT, PV – Price Value, SI – Social Influence, TR - Trust

The model fit was evaluated using several key indicators provided by SmartPLS. The Standardized Root Mean Square Residual (SRMR) for both the saturated and estimated models was 0.055, which is well below the commonly accepted threshold of 0.08, indicating a good fit between the model and the data (Hair et al., 2019). Additionally, the d_ULS value was 2.001, and the d_G value was 0.746, both providing further evidence of an acceptable model fit. The Chi-square value for the model was 2175.616, while the Normed Fit Index (NFI) was 0.813. Although NFI values closer to 1 suggest a better model fit, an NFI of 0.813 is generally considered acceptable, suggesting that the model structure aligns reasonably well with the data.

5.4 Structural Model Assessment

Table 8 presents the results of the structural model analysis, detailing the path coefficients, statistical significance, confidence intervals, effect sizes, and measures of the model's explanatory and predictive power. The f^2 values illustrate the individual impact of each predictor on the dependent variable, Behavioral Intention (BI). Following Cohen's (1988) guidelines, most f^2 values are relatively low (e.g., 0.009, 0.007, 0.032), indicating small effect sizes. This suggests that while each predictor contributes to explaining BI, their individual effects are modest. However, PE → BI exhibits a moderately higher effect size ($f^2 = 0.172$), indicating a more substantial role in influencing BI than the other predictors.

The R^2 value for BI is 0.666, as shown in Table 6, meaning that 66.6% of the variance in BI is explained by the model's predictors, including EE, FC, HM, PE, PI, PV, SI, and TR. According to Hair et al. (2019), an R^2 value of this magnitude suggests substantial

explanatory power, indicating that the model effectively captures a significant amount of variability in BI, thereby underscoring the robustness of the predictors in explaining BI to use GenAI.
The Q^2 value for BI, calculated through the blindfolding procedure, is 0.466. Since Q^2 is greater than zero, it demonstrates the model's predictive relevance for BI (Chin, 1998). This positive Q^2 value indicates that the model has adequate predictive accuracy, enabling it to generalize effectively to predict future observations of BI. The relatively high Q^2 value of 0.466 further reinforces the model's applicability and practical relevance. The results of hypothesis testing indicate that most hypotheses are supported, as evidenced by significant p-values (below 0.05) and confidence intervals that do not include zero (BCI LL and BCI UP). Specifically, Hypotheses H4 (FC → BI), H5 (HM → BI), H1 (PE → BI), H7 (PI → BI), H6 (PV → BI), and H8 (TR → BI) are supported, indicating that these constructs have significant positive effects on BI. However, H2 (EE → BI) and H3 (SI → BI) are not supported, with p-values above 0.05, suggesting that EE and SI do not have a statistically significant impact on BI.

Table 8: Hypothesis Testing

Path	β	t-value	p-value	BCI LL	BCI UP	f^2	R^2	Q^2	Hypothesis
H2: EE → BI	0.032	0.669	0.252	-0.048	0.107	0.009			Not supported
H4: FC → BI	0.093	1.728	0.042	0.004	0.181	0.032			Supported
H5: HM → BI	0.171	3.368	0	0.088	0.257	0.007			Supported
H1: PE → BI	0.076	1.674	0.047	0	0.149	0.172	0.666	0.466	Supported
H7: PI → BI	0.302	8.402	0	0.24	0.358	0.013			Supported
H6: PV → BI	0.102	1.917	0.028	0.015	0.192	0.005			Supported
H3: SI → BI	0.061	1.303	0.096	-0.011	0.143	0.053			Not supported
H8: TR→ BI	0.195	4.451	0	0.123	0.265	0.009			Supported

Legend: BI – Intention to Use GenAI, EE – Effort Expectancy, FC – Facilitating Conditions, HM – Hedonic Motivations, PE – Performance Expectancy, PI – Personal Innovativeness in IT, PV – Price Value, SI – Social Influence, TR – Trust, BCI LL - Bias-Corrected Confidence Interval Lower Limit, Bias-Corrected Confidence Upper Limit (BCI UL)

5.5 Importance-Performance Map Analysis (IPMA)

The Importance-Performance Map Analysis (IPMA) provides insights into the relative importance and performance of each construct influencing the BI to use GenAI among Indonesian university students. PI and PE emerge as the most important and high-performing constructs, indicating that students who are open to new technologies and believe in the effectiveness of GenAI are more likely to adopt it. Thus, fostering an innovative mindset and highlighting the practical benefits of GenAI could significantly drive adoption.
As illustrated in Fig. 2, the IPMA visually maps the total effects (importance) against performance scores for each construct, clearly showing PI and PE positioned at the upper-right quadrant as priority areas for intervention. This visual representation emphasizes that focusing on these two constructions could yield the greatest impact on BI, while also providing a comparative view of how other constructs perform relative to their importance.
Other constructs like EE, FC, and HM play supportive but secondary roles, suggesting that while ease of use, available resources, and enjoyment influence students' BI, they are not primary drivers. PV and SI are relatively less critical, while TR has a moderate impact. These findings indicate that strategies aiming to enhance PI and PE may be most effective in promoting GenAI adoption among students in Indonesia.

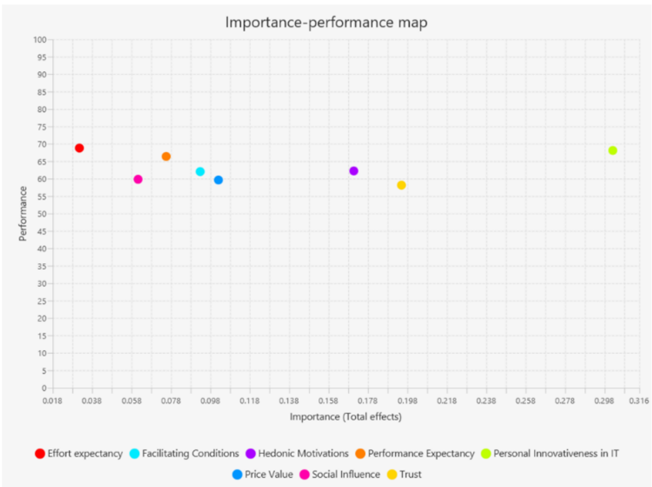

Fig. 2: Importance-performance map

6. Discussion

The study aims to address the following research question: "What are the key determinants influencing Indonesian university students' BI to use GenAI, and how do trust, personal innovativeness, and UTAUT II factors contribute to this intention?" To achieve this, eight hypotheses were developed, and the subsequent sections discuss the results of each hypothesis test.

6.1 Performance Expectancy (PE) and Behavioral Intention (BI)

The findings support H1, confirming that PE plays a key role in positively shaping BI to use GenAI. This aligns with previous studies, such as Camilleri (2024) and Budhathoki et al. (2024), who also reported that students' expectations of enhanced performance significantly influence their intention to adopt AI tools like ChatGPT. This result confirms that when students believe GenAI will improve their academic

performance, they are more likely to intend to use it. This suggests that GenAI is perceived as a valuable tool for enhancing productivity and academic success, encouraging adoption among students.
In the Indonesian higher education context, students often face high academic pressure (Siregar et al., 2025), with performance metrics such as grades and standardized assessments playing a critical role in their educational journey. In this environment, tools like GenAI that can assist with information retrieval, idea generation, and academic writing are perceived as valuable for improving academic outcomes. Additionally, the increasing integration of digital tools in coursework and institutional support for technology-enhanced learning reinforces the belief that emerging tools like GenAI can meaningfully contribute to academic success. These factors likely amplify the perceived usefulness of GenAI, making PE a particularly influential driver of adoption among Indonesian students.

6.2 Effort Expectancy (EE) and Behavioral Intention (BI)

The analysis shows that EE does not significantly impact BI, leading to the rejection of H2. While this result is consistent with findings from Idris, Pujani, and Yeni (2024) and Bouteraa et al. (2024), who similarly reported no significant relationship between ease of use and AI adoption intentions, it raises important questions about the contextual factors influencing this outcome. One plausible explanation is the high level of digital familiarity among university students in Indonesia, particularly those in urban areas or with prior exposure to digital learning tools. In such settings, ease of use may be assumed or taken for granted, thus diminishing its role as a differentiating factor in adoption decisions.
Culturally, Indonesian students may also exhibit adaptive digital behaviors due to increased integration of technology in education during the post-pandemic period, leading them to approach new platforms like GenAI with confidence, regardless of perceived complexity (Musa & Ishak, 2025). In addition, Indonesia's collectivist culture may shape how students perceive and navigate new technologies. In collectivist learning environments, students often rely on collaborative problem solving, peer support, and group-oriented learning approaches, which can help reduce the perceived difficulty of adopting GenAI tools (Tiffany & Rosman, 2024). This shared responsibility and community-based approach may lessen the salience of effort expectancy as a barrier because challenges are often addressed collectively rather than individually. Methodologically, it is worth noting that GenAI tools like ChatGPT are designed to be user-friendly (Ma et al., 2025), which may result in low variance in perceived effort expectancy among respondents—potentially weakening its predictive power in the model. Demographically, the sample largely comprised digitally literate university students, many of whom belong to younger age groups that are highly familiar with online platforms and adaptive to new technologies. Such demographic characteristics may minimize the perceived difficulty of using GenAI, as these students are accustomed to navigating complex digital tools with minimal support. Collectively, these cultural, contextual, and design-related factors may help explain why effort expectancy did not emerge as a significant determinant in this study.

6.3 Social Influence (SI) and Behavioral Intention (BI)

Contrary to expectations, SI does not significantly affect BI, resulting in the rejection of H3. This outcome aligns with the findings of Jain, Shah, and Jiwani (2024), who reported a similarly weak influence of social pressure on ChatGPT usage in Egypt. A possible cultural explanation lies in the increasingly individualistic orientation of technology adoption among students (Xavier & Korunka, 2025), where decisions to engage with tools like GenAI are guided more by perceived personal benefit than by peer norms or authority endorsements.
In the Indonesian higher education context, students may prioritize self-directed learning and individual exploration of technology, especially given the wide availability of GenAI tools outside formal institutional channels (Rabuandika, 2025). Moreover, methodological factors may also contribute to this result—specifically, if GenAI adoption is still at an exploratory phase, peer influence may not yet have matured into a dominant social norm, limiting the salience of social pressure at this stage (Kariodimedjo, 2025). It is also plausible that the novelty and self-service nature of GenAI tools encourage private experimentation over socially-influenced usage, further weakening the role of social influence in predicting BI.
Another plausible explanation for the limited role of social influence lies in the digital disparities that persist across Indonesia. As highlighted by Lito, Samudro, and Soesilo (2025), significant gaps in internet accessibility, device availability, and digital infrastructure exist between urban and rural regions. These disparities may lead to fragmented patterns of GenAI exposure and adoption, where students in well-resourced areas engage with GenAI tools more frequently and develop independent usage habits, while those in under-resourced regions may have limited opportunities to explore such technologies. Demographically, the sample primarily consisted of university students from varied socioeconomic backgrounds, with younger, digitally experienced students in urban institutions likely relying less on peer or authority influence when experimenting with new technologies. In contrast, students in less connected or resource-constrained environments may have limited exposure to peer-driven norms around GenAI use. Consequently, the lack of uniform access and shared experiences could weaken the development of strong peer norms around GenAI use, thereby reducing the overall influence of social pressure on behavioral intention.

6.4 Facilitating Conditions (FC) and Behavioral Intention (BI)

The results support H4, indicating that FC has a significant positive impact on BI. This finding aligns with the studies by Habibi et al. (2024) and Mägi (2024), which demonstrated that access to necessary resources, training, and technical support significantly influences the intention to adopt ChatGPT. In this context, the availability of supportive infrastructure appears to reduce perceived barriers, encouraging students to engage with GenAI tools for academic purposes. This underscores the importance of institutional support, such as training sessions and accessible resources, in promoting the adoption of GenAI.
While universities in major urban centers often benefit from strong internet connectivity, advanced digital infrastructure, and active institutional investment in educational technologies, many institutions in rural or under-resourced regions face challenges in providing comparable levels of support. These gaps can affect students' ability to access and effectively utilize GenAI tools. Moreover, the variation in institutional readiness to integrate emerging technologies—driven by differences in funding, administrative priorities, and faculty digital literacy—further influences students' perceptions of the support available (Muawanah, Marini, & Sarifah, 2024). Consequently, initiatives aimed at improving equitable access to digital infrastructure, offering GenAI-focused training programs, and embedding technical support within universities are critical for maximizing the influence of facilitating conditions on students' adoption of GenAI across diverse Indonesian higher education contexts (Haetami, 2025).

6.5 Hedonic Motivation (HM) and Behavioral Intention (BI)

The analysis confirms H5, revealing that HM significantly influences BI. This result is consistent with prior findings by Fu et al. (2024) and Bhat et al. (2024), who found that enjoyment and pleasure derived from using ChatGPT positively impact students' adoption intentions. It suggests that students are motivated to use GenAI not only for functional purposes but also because they find it engaging and enjoyable. This implies that the intrinsic pleasure associated with using GenAI may be a key driver of its adoption.

In the Indonesian higher education context, the role of HM may be further amplified by the cultural and pedagogical shifts occurring in recent years (Yetti, 2024). Traditional lecture-based instruction has gradually been complemented by more interactive and student-centered approaches, where enjoyment and engagement are emphasized to improve learning outcomes. GenAI tools, with their ability to provide creative outputs, personalized feedback, and interactive content, align well with these evolving pedagogical strategies, making their use inherently enjoyable for students. Furthermore, the growing popularity of digital content creation among Indonesian youth—spanning social media, gaming, and online collaboration platforms—may heighten students' appreciation for the playful and exploratory aspects of GenAI (Sirmayanti et al., 2022). This convergence of academic and recreational digital practices suggests that hedonic motivation could be a particularly strong driver of adoption in Indonesia, where students are increasingly blending learning with creative and leisure-oriented technology use.

6.6 Price Value (PV) and Behavioral Intention (BI)

H6 is supported, indicating a significant positive relationship between PV and BI. This finding is in line with studies by Parveen et al. (2024) and Al-Abdullatif & Alsubaie (2024), which showed that when students perceive a favorable balance between the benefits of using GenAI and its associated costs, their intention to adopt the technology increases. This implies that students are more likely to use GenAI if they perceive its benefits as worth any potential costs. Practical implications suggest that educational institutions could offer affordable or subsidized access to GenAI tools to encourage broader adoption among students who may otherwise be hesitant due to cost concerns.

In Indonesia, many students, particularly those from rural or lower-income backgrounds, are highly cost sensitive when considering the adoption of new technologies (Kustanto, 2024), including GenAI tools that may require subscription fees or reliable high-speed internet access. At present, access to GenAI tools is largely dependent on students' resources, as most universities have yet to formally integrate or subsidize these technologies within their academic systems. This reality creates variations in how students evaluate the value of GenAI relative to its costs, with affordability becoming a key determinant of adoption. Moreover, cultural factors such as the strong emphasis on resourcefulness and cost effectiveness in Indonesian households may also influence students' adoption decisions (Rahmatunnisya et al., 2024), with GenAI tools being more readily embraced when perceived as offering clear academic and personal benefits at minimal financial burden. Thus, policies that promote affordable access and communicate the tangible academic value of GenAI could significantly enhance its adoption across diverse student populations.

6.7 Personal Innovativeness (PI) in IT and Behavioral Intention (BI)

The results support H7, demonstrating that PI positively and substantially affects BI. This finding is consistent with Sabeh (2024) and Bouteraa et al. (2024), who observed that individuals with higher levels of innovativeness are more inclined to adopt ChatGPT. This suggests that students who are open to experimenting with new technologies are more likely to engage with GenAI in their learning. This insight highlights the role of personal characteristics in technology adoption; promoting GenAI as an innovative and cutting-edge tool may appeal to students who are naturally inclined to explore new technologies.

In the Indonesian context, the influence of PI on GenAI adoption may be further shaped by the country's evolving digital ecosystem and educational landscape. Rapid government initiatives to promote digital transformation in higher education, such as the Merdeka Belajar (Freedom to Learn) program, have encouraged students to explore innovative tools and approaches in their academic work (Hunaepi & Suharta, 2024). This policy environment fosters a culture of experimentation, particularly among students in urban universities with greater exposure to technology integration. However, there are disparities across institutions, as students in rural or under-sourced areas may have fewer opportunities to develop and express personal innovativeness due to limited access to advanced digital infrastructure. Thus, while PI emerges as a strong predictor of GenAI adoption overall, its impact may be amplified among students in well-connected and innovation-oriented academic environments, reflecting the uneven pace of digital readiness across Indonesia's higher education sector.

6.8 Trust (TR) and Behavioral Intention (BI)

Finally, H8 is supported, with TR showing a significant positive impact on BI. This finding aligns with studies by Lai et al. (2024) and Amin, Kim, and Noh (2024), which highlighted the importance of trust in determining students' intention to use ChatGPT. In this context, students are more likely to adopt GenAI if they trust its reliability, integrity, and overall performance. Such trust, however, extends beyond technical functionality to encompass broader ethical considerations. Concerns about academic integrity—such as the potential for plagiarism or misuse of AI-generated content—and awareness of algorithmic biases are central to shaping students' confidence in these tools (Petricini, Zipf & Wu, 2025). Thus, fostering trust requires not only ensuring system reliability but also providing assurances that GenAI use aligns with ethical academic practices and delivers unbiased, credible outputs. Institutions can enhance this trust by implementing transparent policies, promoting responsible use guidelines, and educating students about the ethical implications of GenAI, thereby creating a secure and trustworthy environment for its adoption.

Trust in emerging technologies often depends not only on the systems themselves but also on the institutions endorsing them (Masrek et al., 2014). If universities are perceived as taking proactive measures—such as providing clear guidelines for ethical use, ensuring data privacy, and incorporating GenAI into academic integrity frameworks—students are more likely to view these tools as credible and safe for academic purposes. Moreover, cultural values emphasizing collective responsibility and respect for authority may influence how students evaluate institutional messages about GenAI, with well-communicated policies from universities potentially enhancing adoption. Therefore, cultivating trust involves a holistic approach that combines technical reliability with institutional transparency, cultural sensitivity, and active student engagement.

7. Conclusion

7.1 Contributions

This study contributes to the theoretical advancement of the UTAUT II framework by integrating trust and personal innovativeness as additional predictors of BI to use GenAI. These extensions strengthen the model by capturing dimensions that the original UTAUT II does not fully address, particularly in the context of emerging and complex technologies such as generative AI. Trust introduces a relational and risk-oriented dimension, which is especially relevant when users interact with AI systems whose processes and decisions are often opaque. Meanwhile, personal innovativeness brings in a dispositional element, capturing individual variability in openness to adopt novel technologies beyond social or performance-driven factors (Khan, Masrek & Mahmood, 2019). The inclusion of these constructs enhances the model's explanatory power, as evidenced by the high R^2 value, and reveals new dynamics in technology adoption—such as the importance of psychological readiness and confidence in the technology itself—that are not explicitly accounted for in the original UTAUT II. Together, these additions provide a more holistic and context-sensitive framework for understanding technology adoption in AI-mediated learning environments.

Empirically, this study provides valuable insights into the significance of factors such as PE, PI, and TR in influencing students' intentions to adopt GenAI. While these findings contribute meaningfully to the growing body of research on AI adoption in education—particularly within the Indonesian context—they should be interpreted with caution. Given the use of a convenience sampling method, the results may not be fully representative of all Indonesian university students, especially those from underrepresented regions or diverse academic backgrounds. Therefore, the conclusions drawn here should be viewed as indicative rather than definitive, and future studies employing more rigorous sampling strategies are encouraged to validate and extend these findings across broader student populations.

From a practical standpoint, the findings offer significant implications for advancing the adoption of GenAI within Indonesia's higher education landscape. To encourage meaningful integration, efforts must go beyond general encouragement and focus on concrete, actionable strategies that foster both personal innovativeness among students and institutional trust in AI technologies. Embedding GenAI orientation modules into first-year programs can help cultivate students' confidence, creativity, and willingness to experiment with new technologies—key elements of personal innovativeness. At the same time, building trust in GenAI systems requires institutional transparency, including clear communication about how student data is used, the reliability of AI outputs, and safeguards against misuse.

The effectiveness of these efforts depends on addressing the specific roles and responsibilities of different stakeholders. For instance, university IT departments should ensure reliable access to GenAI platforms by improving digital infrastructure, particularly in regions where internet connectivity remains limited. Lecturers and instructional designers can be supported with professional development programs that demonstrate how to integrate GenAI meaningfully into coursework, such as designing AI-assisted assignments or using AI tools for formative assessment. At the policy level, the Ministry of Education could introduce funding incentives for AI-enhanced teaching initiatives and embed GenAI competency indicators into national accreditation criteria to institutionalize innovation.

Contextualizing these recommendations within Indonesia's educational and cultural realities further enhances their relevance. Given regional disparities in digital access and GenAI awareness, a one-size-fits-all approach may not be effective. Institutions should localize tools and materials in Bahasa Indonesia and account for varying degrees of digital literacy. Promoting culturally aligned awareness campaigns can help reduce skepticism and build public trust in AI applications within education (Bao, Liu & Dai, 2025).

To ensure the long-term managerial significance of GenAI adoption, institutions must establish clear mechanisms for monitoring and evaluation. This includes implementing AI usage dashboards to track engagement, gathering student feedback on usability and perceived effectiveness, and analyzing academic performance data to assess the impact of GenAI on learning outcomes. Such evidence-based approaches will enable continuous improvement, support strategic decision-making, and strengthen both students' personal innovativeness and institutional trust in AI-enhanced education.

7.2 Limitations and Suggestions for Future Studies

This study is limited by its reliance on non-probability convenience sampling, which inherently restricts the generalizability of the findings (Shamsudin, Hassim, & Abd Manaf, 2024). While the data provide valuable insights, the sample may not adequately capture the diversity of Indonesian university students across various geographic regions, institutional types, and demographic profiles. To address this limitation, future research should adopt more robust sampling strategies, such as stratified random sampling, which allows proportional representation of key subgroups (e.g., by region, university type, or academic discipline). This approach would enhance the representativeness of the sample and strengthen the external validity of the results.

To advance the field further, future studies should also pursue more ambitious research directions. Longitudinal designs would be valuable for capturing changes in students' perceptions, attitudes, and behaviors toward GenAI over time, especially as institutional support, tool availability, and societal norms evolve. Additionally, cross-cultural comparative studies could reveal how cultural values, education systems, and digital ecosystems shape GenAI adoption differently across countries or regions.

Another important avenue is the inclusion of mediating and moderating variables to better explain the pathways through which key constructs influence BI. For example, digital literacy (Saad, Mohamad & Tsong, 2021), prior experience with AI, or perceived ethical risks may serve as moderators that strengthen or weaken the effects of core predictors like performance expectancy or trust. Similarly, constructs such as attitude toward GenAI or perceived usefulness could act as mediators that help uncover indirect relationships in the adoption process. These additions would increase the explanatory depth of the model and yield richer theoretical and practical insights.

Expanding the model to include domain-specific perspectives could also enhance its relevance. Future studies may explore how GenAI adoption differs across academic disciplines—for instance, in creative arts, computer science, or healthcare—where the use cases and ethical concerns may vary considerably. Examining how institutional culture, assessment practices, or academic integrity policies influence GenAI usage would contribute to a more context-sensitive understanding of AI integration in education.

Data Availability Statement

The raw data supporting the findings of this article are available from the authors upon reasonable request, without any undue restriction.

Ethics Statement

Ethical review and approval were not mandated for this study involving human participants, as per local legislation and the institutional policies of Universitas Islam Negeri Sumatera Utara, Sumatera, where the research was conducted. Nevertheless, in adherence to professional scholarly standards, a cover letter accompanied the questionnaire. The letter clearly stated the purpose of the research, emphasized the voluntary nature of participation, assured participants of confidentiality, and included the researcher's contact information for any inquiries. All information requested in the questionnaire was non-sensitive and aligned with the data reported in the findings.

Competing Interest Statement

The authors of this publication declare there are no competing interests.

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