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SELF-EFFICACY AND PRE-SERVICE TEACHERS BEHAVIORAL INTENTION TO USE GENERATIVE AI FOR LEARNING: A PLS-SEM APPROACH

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Abstrak

Perkembangan *generative artificial intelligence* dalam pendidikan tinggi menuntut mahasiswa calon guru memiliki keyakinan diri, persepsi kemudahan, persepsi manfaat, dan sikap positif untuk menggunakannya secara bertanggung jawab dalam pembelajaran. Penelitian ini bertujuan menganalisis pengaruh *self-efficacy*, *perceived ease of use*, *perceived usefulness*, dan *attitude toward using* terhadap *behavioral intention to use generative AI for learning*. Penelitian menggunakan pendekatan kuantitatif dengan desain survei eksplanatori. Responden penelitian adalah 149 mahasiswa calon guru di Sekolah Tinggi Keguruan dan Ilmu Pendidikan Muhammadiyah Kalabahi, Kabupaten Alor, Nusa Tenggara Timur. Data dikumpulkan menggunakan angket berskala Likert dan dianalisis menggunakan *partial least squares structural equation modelling*. Hasil penelitian menunjukkan bahwa *self-efficacy* berpengaruh positif terhadap *behavioral intention to use*. *Perceived ease of use* berpengaruh positif terhadap *perceived usefulness* dan *attitude toward using*. *Perceived usefulness* dan *attitude toward using* berpengaruh positif terhadap *behavioral intention to use*. *Perceived ease of use* juga berpengaruh tidak langsung terhadap *behavioral intention to use* melalui *attitude toward using* dan *perceived usefulness*. Nilai *R-square behavioral intention to use* sebesar 0,748 menunjukkan bahwa model memiliki daya jelas yang kuat. Temuan ini menegaskan bahwa intensi penggunaan *generative AI* dibentuk oleh keyakinan diri, kemudahan penggunaan, manfaat yang dirasakan, dan sikap positif terhadap teknologi.

Kata kunci: Kecerdasan buatan, efikasi diri, calon guru,

Abstract

The development of generative artificial intelligence in higher education requires pre-service teachers to have self-efficacy, perceived ease of use, perceived usefulness, and positive attitudes to use it responsibly for learning. This study aims to analyze the effects of self-efficacy, perceived ease of use, perceived usefulness, and attitude toward using on behavioral intention to use generative AI for learning. This study employed a quantitative approach with an explanatory survey design. The respondents were 149 pre-service teachers at Sekolah Tinggi Keguruan dan Ilmu Pendidikan Muhammadiyah Kalabahi, Alor Regency, East Nusa Tenggara. Data were collected using a Likert-scale questionnaire and analyzed using partial least squares structural equation modelling. The results showed that self-efficacy positively influenced behavioral intention to use. Perceived ease of use positively influenced perceived usefulness and attitude toward using. Perceived usefulness and attitude toward using positively influenced behavioral intention to use. Perceived ease of use also indirectly influenced behavioral intention to use through attitude toward using and perceived usefulness. The R-square value of behavioral intention to use was 0.748, indicating that the model had strong explanatory power. These findings confirm that pre-service teachers' intention to use generative AI is shaped by self-efficacy, perceived ease of use, perceived usefulness, and positive attitudes toward technology.

Keyword: *generative AI*; *self-efficacy*; Pre-Service Teacher

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INTRODUCTION

The development of generative artificial intelligence, or generative AI, has transformed the ways in which students access information, understand learning materials, develop ideas, compose academic writing, and complete learning tasks (Barrett & Pack, 2023; Liu et al., 2024; Mirea et al., 2025). In higher education, generative AI functions not only as a technological tool but also as part of a digital learning environment that requires the ability to use technology critically, productively, and responsibly (Batista et al., 2024; Nguyen, 2025). For pre-service teachers, this ability is particularly important because they are being prepared to become educators who are not only capable of using technology, but who also understand how technology can be pedagogically employed to support learning processes (Crompton & Burke, 2023; Zawacki-Richter et al., 2019)

Generative AI has the potential to assist students in designing learning ideas, explaining concepts, preparing teaching materials, obtaining initial feedback, and developing independent learning strategies (Mittal et al., 2024; Moundridou et al., 2024). However, this potential does not automatically ensure that students will have the intention to use it in learning. Technology acceptance is influenced by various psychological and perceptual factors, such as self-efficacy, ease of use, perceived usefulness, and attitudes toward technology. Within the technology acceptance framework, behavioral intention is considered important because it reflects users' tendency to accept and continue using a technology over time (Davis, 1989; Venkatesh et al., 2003).

Theoretically, this study is grounded in the Technology Acceptance Model, which explains that technology acceptance is influenced by perceived usefulness and perceived ease of use. A technology is more likely to be accepted when users perceive it as useful and easy to use (Davis, 1989). In the context of generative AI-based learning, perceived usefulness refers to the extent to which students believe that generative AI can support their learning processes, whereas perceived ease of use refers to the extent to which the technology is perceived as easy to learn and use. These two constructs are important because users' initial perceptions of technology can shape their attitudes and intentions to use it (Alshammari & Babu, 2025; Shahzad et al., 2024; Strzelecki, 2024).

In addition to ease of use and usefulness, self-efficacy is also an important factor in explaining the intention to use generative AI (Mun & Hwang, 2025). Computer self-efficacy refers to individuals' beliefs in their ability to use computer technology to accomplish specific tasks, and this construct has been shown to be related to users' responses to technology (Compeau & Higgins, 1995). In the use of generative AI, self-efficacy relates to students' beliefs that they are able to formulate prompts, understand AI-generated outputs, evaluate the accuracy of information, and use AI in accordance with learning objectives (Anders & Dux Speltz, 2025; Li et al., 2025). The higher students' self-efficacy, the more likely they are to be ready to use generative AI in learning activities (Collie et al., 2024; Ramnarain et al., 2025).

Previous studies have shown that the acceptance of generative AI in education cannot be separated from self-efficacy, perceived usefulness, perceived ease of use, and attitudes toward technology. Collie et al. (2024) explained that generative AI self-efficacy is associated with perceived value and the integration of AI into educational work. (Ramnarain et al., 2025) also showed that pre-service teachers' intention to use generative AI needs to be understood in relation to their readiness to employ technology in learning activities. Meanwhile, studies on ChatGPT acceptance in higher education indicate that perceived usefulness and perceived ease of use are important factors in explaining students' intention to use the technology (Almogren et al., 2024; Alshammari & Babu,

2025).

The main research gap in this study lies in the need for empirical testing of the relationships among self-efficacy, perceived ease of use, perceived usefulness, attitude toward using, and behavioral intention to use generative AI among pre-service teachers. Existing studies on technology acceptance have explained the importance of ease of use and usefulness in shaping intention to use; however, empirical testing that positions self-efficacy alongside technology acceptance constructs in the context of generative AI for learning still requires further strengthening. In fact, pre-service teachers need psychological and pedagogical readiness so that the use of generative AI is not merely technical, but also supports learning processes effectively and responsibly (Collie et al., 2024; Crompton & Burke, 2023; Ramnarain et al., 2025).

Based on this gap, this study aims to analyze the effects of self-efficacy, perceived ease of use, perceived usefulness, and attitude toward using on behavioral intention to use generative AI for learning. Specifically, this study examines the effect of self-efficacy on behavioral intention to use, the effect of perceived ease of use on perceived usefulness and attitude toward using, the effect of perceived usefulness on behavioral intention to use, and the effect of attitude toward using on behavioral intention to use. This study also examines the indirect effect of perceived ease of use on behavioral intention to use through attitude toward using and perceived usefulness (Davis, 1989; Venkatesh et al., 2003).

The background of the problem, the gap between current conditions and ideal expectations, and the objectives of the study are therefore formulated into the following hypotheses:

H1: Self-efficacy has a positive effect on behavioral intention to use generative AI for learning.

H2: Perceived ease of use has a positive effect on perceived usefulness of generative AI for learning.

H3: Perceived ease of use has a positive effect on attitude toward using generative AI for learning.

H4: Perceived usefulness has a positive effect on behavioral intention to use generative AI for learning.

H5: Attitude toward using has a positive effect on behavioral intention to use generative AI for learning.

H6: Perceived ease of use has an indirect effect on behavioral intention to use through attitude toward using.

H7: Perceived ease of use has an indirect effect on behavioral intention to use through perceived usefulness.

METHOD

This study uses a quantitative approach with an explanatory survey design. This design was chosen because the research aims to test the relationship between latent variables that explain the intentions of prospective teacher students in using generative artificial intelligence for learning. A quantitative approach is appropriately used to test theoretical models built from psychological and perceptual constructs, while explanatory surveys are used to explain the influence between variables based on respondents' empirical data (Hair et al., 2019; Ivankova et al., 2006).

The research was carried out on prospective teacher students at the Muhammadiyah Kalabahi Teacher Training and Education College, Alor Regency, East Nusa Tenggara. The respondents to the study were 149 prospective teacher students, consisting of 81 males and 68 females. All respondents were prospective teacher students who were relevant to the context of using learning technology, especially generative AI to support learning activities.

The research instrument was prepared in the

form of a closed questionnaire using the Likert scale. The constructs measured consisted of self-efficacy, perceived ease of use, perceived usefulness, attitude toward using, and behavioral intention to use. The instruments for each variable are adopted and adjusted from previous research instruments that are relevant to the acceptance of technology and the use of learning technology. The self-efficacy indicator is adapted from the concept of computer self-efficacy developed by Compeau & Higgins (1995), with adjustments in the context of using generative AI for learning. The perceived ease of use and perceived usefulness indicators are adapted from the Technology Acceptance Model developed by Davis (1989). Meanwhile, the indicators of attitude toward using and behavioral intention to use were adapted from a study of technology acceptance that describes the attitude and intention of user behavior in accepting new technology (Davis, 1989; Venkatesh et al., 2003). All instrument items are customizable contextual to be relevant to the use of generative AI by prospective teacher students in learning activities.

Self-efficacy measures pre-service teachers' beliefs in their ability to use generative AI to support learning. Perceived ease of use measures students' perceptions that generative AI is easy to learn and use. Perceived usefulness measures students' perceptions that generative AI is beneficial in supporting learning activities. Attitude toward using measures students' positive attitudes toward the use of generative AI. Behavioral intention to use measures students' intention to use generative AI in learning (Compeau & Higgins, 1995; Davis, 1989; Venkatesh et al., 2003).

Data were analyzed using partial least squares structural equation modelling (PLS-SEM). PLS-SEM was selected because it is appropriate for prediction-oriented research involving multiple latent constructs and for explaining the variance of endogenous constructs in a structural model (Hair et al., 2019). In addition, PLS-SEM enables the simultaneous evaluation of both the measurement model and the structural model, particularly when a study focuses on testing relationships among latent variables and assessing the model's ability to explain users' behavioral intention toward technology use (Hair et al., 2019, 2021).

The analysis was conducted in two stages. The first stage involved the evaluation of the measurement model to assess construct validity and reliability. This evaluation included outer loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and discriminant validity. Indicators were considered to meet convergent validity when their outer loading values exceeded 0.70 and AVE values exceeded 0.50. Constructs were considered reliable when Cronbach's alpha and composite reliability values were above 0.70. Discriminant validity was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). HTMT was used because it is considered more sensitive in detecting discriminant validity in latent construct-based models (Fornell & Larcker, 1981; Henseler, 2017).

The second stage involved the evaluation of the structural model to test the research hypotheses. The structural model was assessed by examining path coefficients, t-statistics, p-values, confidence intervals, R-square values, and indirect effects. The significance of the relationships was tested using the bootstrapping procedure. Relationships among variables were considered significant when the p-values were below 0.05. The R-square value was used to assess the extent to which exogenous variables explained the variance of endogenous constructs. In this study, the endogenous constructs consisted of perceived usefulness, attitude toward using, and behavioral intention to use (Hair et al., 2019)

RESULT

Containing 149 research respondents at the Muhammadiyah Kalabahi Teacher Training and Education College, Alor Regency, East Nusa Tenggara. Based on gender, the respondents consisted of 81 males and 68 females. Details of respondent characteristics are presented in Table 1.

Table 1. Respondent Characteristics

Gender	**Quantity**	**Percentage**
Male	81	54,36%
Women	68	45,64%

Evaluation of the measurement model was carried out to assess the validity and reliability of the construct. The results of *the outer loading* test showed that all indicators had values above 0.70. The lowest *outer loading* value is found in the SE5 indicator of 0.713, while the highest value is found in the BI2 indicator of 0.927. Thus, all indicators meet the criteria of convergent validity.

Table 2. Outer Loading Value

Construct	**Indicator**	**Outer Loading**
Attitude Toward Using	ATU1	0,891
Attitude Toward Using	ATU2	0,871
Attitude Toward Using	ATU3	0,894
Behavioral Intention to Use	BI1	0,909
Behavioral Intention to Use	BI2	0,927
Behavioral Intention to Use	BI3	0,899
Perceived Ease of Use	PEOU1	0,872
Perceived Ease of Use	PEOU2	0,859
Perceived Ease of Use	PEOU3	0,914
Perceived Ease of Use	PEOU4	0,826
Perceived Usefulness	PU1	0,796
Perceived Usefulness	PU2	0,840
Perceived Usefulness	PU3	0,884
Perceived Usefulness	PU4	0,862
Perceived Usefulness	PU5	0,794
Self-efficacy	SE1	0,867
Self-efficacy	SE2	0,880
Self-efficacy	SE3	0,854
Self-efficacy	SE4	0,843
Self-efficacy	SE5	0,713

The reliability of the construct was tested using *Cronbach's alpha*, *composite reliability* rho_a, *composite reliability* rho_c, and *average variance extracted* or AVE. The results of the analysis showed that the entire The construct has *Cronbach's alpha* value above 0.70, *composite reliability* above 0.70, and AVE above 0.50. Thus, the entire construct meets the criteria of internal reliability and convergent validity.

Table 3. Reliability and Validity of Constructs

Construct	**Cronbach's Alpha**	**rho_a**	**rho_c**	**AVE**
Attitude Toward Using	0,862	0,862	0,916	0,784
Behavioral Intention to Use	0,899	0,900	0,937	0,832
Perceived Ease of Use	0,891	0,897	0,924	0,754
Perceived Usefulness	0,892	0,892	0,921	0,699
Self-efficacy	0,889	0,900	0,919	0,695

Discriminant validity was tested using the Fornell-Larcker criteria. Based on the Fornell-Larcker criteria, the square root value of AVE of each construct is greater than the correlation with the other construct. These results show that the validity of the discrimination based on the Fornell-Larcker criteria is met.

Table 4. Criteria Fornell-Larcker

Construct	**ATU**	**BI**	**PEOU**	**PU**	**SE**
Attitude Toward Using	0,886				
Behavioral Intention to Use	0,804	0,912			
Perceived Ease of Use	0,685	0,597	0,868		
Perceived Usefulness	0,818	0,762	0,721	0,836	
Self-efficacy	0,732	0,796	0,582	0,713	0,834

The evaluation of the structural model was carried out by looking at the values of the path coefficient, *t-statistics*, and *p-values*. The test results show that all direct relationships in the model have a positive and significant direction. The results of the direct relationship test are presented in Table 5.

Table 5. *Direct Contact Test Results*

H	**I**	**t**	**p**	**Result**
H1	*Self-efficacy* → *Behavioral Intention to Use*	4,674	<0,001	Accepted

H	I	t	p	Result
H2	*Perceived Ease of Use → Perceived Usefulness*	9,826	<0,001	Accepted
H3	*Perceived Ease of Use → Attitude Toward Using*	9,066	<0,001	Accepted
H4	*Perceived Usefulness → Behavioral Intention to Use*	2,097	0,036	Accepted
H5	*Attitude Toward Using → Behavioral Intention to Use*	3,941	<0,001	Accepted

*H=hipotesis, I= Intervariable Relationships, t= t-statistics, p= p-value

Based on Table 6, the largest direct influence was found in the relationship *between Perceived Ease of Use* and *Perceived Usefulness* with a coefficient of 0.721. The next direct effect was *Perceived Ease of Use* on *Attitude Toward Using* of 0.685, *Self-efficacy* on *Behavioral Intention to Use* of 0.403, *Attitude Toward Using* on *Behavioral Intention to Use* of 0.364, and *Perceived Usefulness* on *Behavioral Intention to Use* of 0.176.

The *R-square* value is used to see the ability of exogenous variables to explain endogenous constructs. The results of the analysis showed that *the R-square value of Behavioral Intention to Use* was 0.748, *Perceived Usefulness* was 0.520, and *Attitude Toward Using* was 0.470. Details of *the R-square* value are presented in Table 7.

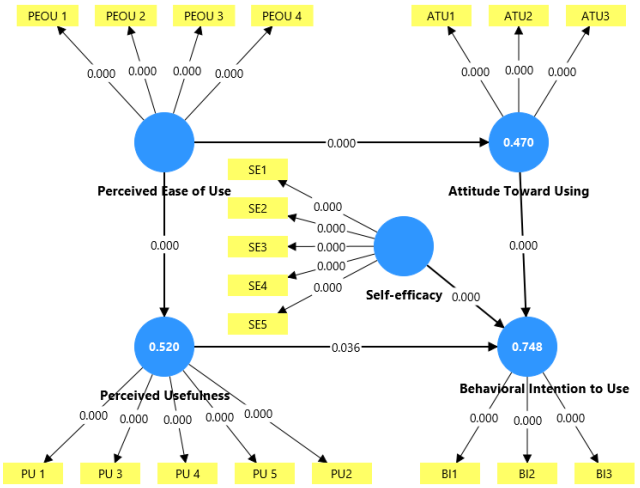

Figure 1. Structural Model Framework

Table 6. R-square value

Construct Endogen	R-square	R-square Adjusted
Attitude Toward Using	0,470	0,466
Behavioral Intention to Use	0,748	0,743
Perceived Usefulness	0,520	0,516

The *R-square* value of 0.748 on *Behavioral Intention to Use* shows that *self-efficacy*, *perceived usefulness*, and *attitude toward using* are able to explain 74.8% of the variation in student intentions of prospective teachers in using *generative AI* for learning. Furthermore, *perceived ease of use* was able to explain 52.0% of the variation in *perceived usefulness* and 47.0% variation in *attitude toward using*.

In addition to direct influences, this study also examined indirect influences. The results of the analysis showed that *Perceived Ease of Use* had an indirect effect on *Behavioral Intention to Use* through *Attitude Toward Using* with a coefficient of 0.249, t-statistics 3.394, and p-values of 0.001. In addition, *Perceived Ease of Use* also has an indirect effect on *Behavioral Intention to Use* through *Perceived Usefulness* with a coefficient of 0.127, t-statistics 2.006, and

p-values of 0.045.

Based on the results of hypothesis testing, all research hypotheses are accepted. Thus, the model shows that *self-efficacy*, *perceived ease of use*, *perceived usefulness*, and *attitude toward using* have a role in explaining *the behavioral intention to use generative AI* for learning in prospective teacher students.

DISCUSSION

The findings of this study indicate that pre-service teachers' intention to use generative AI for learning is primarily shaped by their self-efficacy, attitude toward using, and perceived usefulness. The R-square value of 0.748 for behavioral intention to use suggests that the model has strong explanatory power in accounting for pre-service teachers' intention to use generative AI. Thus, the use of generative AI in learning should not be understood merely as a matter of technological availability, but also as closely related to students' psychological readiness and their initial experiences when interacting with the technology (Collie et al., 2024; Davis, 1989; Strzelecki, 2024; Venkatesh et al., 2003).

The effect of self-efficacy on behavioral intention to use indicates that pre-service teachers who feel capable of using generative AI tend to have stronger intentions to employ it in learning. This finding is important because generative AI is not a technology that operates neutrally apart from users' skills. Students need to understand how to formulate prompts, critically interpret AI-generated outputs, verify the accuracy of information, and adapt AI responses to their academic needs. Therefore, self-efficacy serves as an initial foundation before students are willing to use generative AI more actively. This finding is consistent with Collie et al. (2024), who showed that generative AI self-efficacy is associated with perceived value and the integration of AI into educational work. In the context of pre-service teachers,, Ramnarain et al. (2025) also emphasized that acceptance of generative AI should be understood in relation to pre-service teachers' pedagogical readiness to use technology in teaching and learning processes.

The next finding shows that perceived ease of use has a strong effect on perceived usefulness. This means that students are more likely to recognize the benefits of generative AI when they perceive the technology as easy to learn and use. This relationship reinforces the basic logic of the Technology Acceptance Model, which proposes that ease of use can shape users' perceptions of a technology's usefulness. In learning contexts, technology perceived as easy to use is more readily accepted because students do not need to invest excessive effort simply to understand how it works. At this point, the benefits of generative AI become more concrete: it can help students generate ideas, explain concepts, produce summaries, obtain initial feedback, and support the completion of academic tasks. This finding is in line with Strzelecki (2024), who found that the acceptance of ChatGPT in higher education is influenced by perceived ease of use and perceived usefulness.

In addition to influencing perceived usefulness, perceived ease of use also affects attitude toward using. This finding suggests that an initial experience that is easy and not burdensome can foster students' positive attitudes toward generative AI. In practice, students who perceive AI as accessible, easy to direct, and useful for learning needs are more likely to view the technology positively. Such a positive attitude does not emerge merely because AI is considered advanced, but because students directly experience that the technology can be used without substantial barriers. Alshammari & Babu (2025) also found that perceived ease of use and perceived usefulness play a role in shaping students' intention to use ChatGPT. This strengthens the finding of the present study that the acceptance of generative AI should begin with user experiences that are simple, clear, and relevant to learning needs.

The effect of perceived usefulness on behavioral intention to use is also significant,

although its coefficient is smaller than those of self-efficacy and attitude toward using. This result indicates that perceived usefulness remains important, but it is not the only factor that drives students' intention to use generative AI. Students may recognize that AI is useful, yet they may not necessarily have a strong intention to use it if they lack confidence or do not hold a positive attitude toward the technology. This finding shows that the acceptance of generative AI is layered. The usefulness of the technology needs to be accompanied by ease of use and users' self-confidence. Kasneci et al. (2023) emphasized that large language models offer considerable opportunities to support learning, but their use still requires literacy, critical oversight, and an understanding of the technology's limitations.

Attitude toward using was found to be one of the important factors influencing pre-service teachers' intention to use generative AI. Students who hold a positive attitude toward AI are more likely to intend to use it in learning. However, a positive attitude should not be interpreted as uncritical acceptance. In academic contexts, what is needed is a positive attitude accompanied by caution. Students should view generative AI as a learning aid, not as a substitute for thinking, reading, writing, and reasoning. In this way, AI can be used to strengthen learning rather than undermine academic integrity. This view is consistent with Zawacki-Richter et al. (2019), who emphasized that the implementation of AI in higher education needs to consider pedagogical, ethical, and institutional dimensions, rather than focusing solely on technological aspects.

The indirect effect of perceived ease of use on behavioral intention to use through attitude toward using and perceived usefulness provides a more complete explanation of how students form their intention to use generative AI. Ease of use does not directly drive intention; rather, it operates through two pathways. First, ease of use leads students to perceive AI as more useful. Second, ease of use fosters a more positive attitude. In this study, the pathway through attitude had a larger coefficient than the pathway through usefulness. This suggests that a comfortable and easy experience of using AI is more powerful in encouraging intention when that experience helps form a positive attitude. Therefore, learning about generative AI for pre-service teachers should not merely explain the benefits of AI, but should also provide direct experiences that enable students to feel capable, comfortable, and safe in using it (Davis, 1989; Venkatesh et al., 2003).

Overall, this study confirms that the acceptance of generative AI among pre-service teachers is shaped by the combination of self-efficacy, ease of use, perceived usefulness, and attitude toward using. These findings extend the understanding of technology acceptance in learning by showing that pre-service teachers need more than access to technology. They need learning experiences that build self-confidence, demonstrate the practical value of AI, and cultivate a critical yet positive attitude toward its use. Therefore, teacher education institutions need to design generative AI training that is both practical and pedagogically grounded, for example through exercises in prompt formulation, verification of AI-generated outputs, the use of AI in designing learning plans, and discussions on the ethical boundaries of AI use in academic tasks (Crompton & Burke, 2023; Kasneci et al., 2023; Ramnarain et al., 2025; Zawacki-Richter et al., 2019).

CONCLUSION

This study concludes that the intention of prospective teacher students to use generative AI for learning is influenced by self-efficacy, perceived usefulness, and attitude toward using. Self-efficacy was found to have a positive effect on behavioral intention to use, indicating that students who possess stronger confidence in their ability to use generative AI are more likely to develop stronger intentions to integrate it into learning activities. In addition, perceived ease of use positively influenced both

perceived usefulness and attitude toward using, suggesting that ease of use constitutes an important foundation for shaping students' perceptions of usefulness and positive attitudes toward the technology.

The findings further indicate that perceived usefulness and attitude toward using positively affect behavioral intention to use. This means that pre-service teachers are more likely to use generative AI when they perceive the technology as beneficial for learning and hold a positive attitude toward its use. The indirect effect of perceived ease of use on behavioral intention to use through attitude toward using and perceived usefulness demonstrates that ease of use is not merely a technical aspect of user experience, but also an important factor in shaping users' perceptions and attitudes.

Overall, the research model explained 74.8% of the variance in behavioral intention to use. This finding confirms that pre-service teachers' acceptance of generative AI cannot be sufficiently explained by perceived usefulness alone, but should be understood as the result of the interaction among self-efficacy, perceived ease of use, perceived usefulness, and attitude toward using. Therefore, efforts to strengthen the integration of generative AI in teacher education should focus on practical, ethical, and pedagogically grounded training, enabling students to use AI productively, critically, and responsibly in learning

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