Analyzing academic acceptance of artificial intelligence using extended technology acceptance model

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ABSTRACT

This study aims to analyze the acceptance of artificial intelligence (AI) technology among Indonesian academics using extended technology acceptance model (TAM). The analysis involved general extended technology acceptance model for e-learning (GETAMEL) independent variables, which include subjective norm (SN), experience (EXP), enjoyment (ENJOY), computer anxiety (CA), and self-efficacy (SE), as well as mediator variables: perceived usefulness (PU) and perceived ease of use (PEOU). This study uses technology innovations (TI) as moderator variable and behavioral intention (BI) as a dependent variable. The analysis reveals that SN has a significant influence over PU but not PEOU. ENJOY and SE have a significant positive influence over both PU and PEOU, while EXP and CA don't have a significant influence over both variables. PU and PEOU have a significant positive influence over BI. TI strengthens the relation between PU and BI, but weakens the relation between PEOU and BI. This finding provides an important outlook for developing a strategy to increase the acceptance of AI technology in the academic environment through an approach that takes into account the factors of pleasure, self-confidence, and TI.

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1. INTRODUCTION

Technology has had a significant impact on teaching management, educational innovation, and learning behavior analysis [1]. Artificial intelligence (AI) is described as a technology that allows computers to imitate human cognitive abilities such as thinking, learning, and problem-solving. In the context of education, AI gradually changes the lecturer's role. Lecturers can now utilize AI-based teaching tools to track student learning and provide personalized support in a timely manner. Accordingly, artificial intelligence in education (AIEd) has become an important issue with the advancement of communication and computer technology. From an educational perspective, AI technology can be utilized to analyze and predict students' academic achievements and provide personalized instructions, as well as automatic feedback that is helpful in evaluation [2].

AIEd is a cross-disciplinary field that is very dependent on technology. Despite its increasing integration into education, the use of AI technology in teaching still faces various challenges. An AIEd application may fail if the lecturer doesn't understand its role and function within the education system [2].

On the other hand, the lecturers who understand the function and attributes of AI technology can adopt the right application in their class to increase motivation, involvement, and learning achievement of their students [3]. In this context, understanding the lecturer's perspective on the use of AI in teaching is very important. The attitude and intention of lecturers to use AI will greatly affect the application of this technology in the learning process [4].

In educational research, the technology acceptance model (TAM) is often used to explain the attitudes and intentions of teacher behavior towards the use of new technology [5]–[7]. Furthermore, previous studies on AI-based educational technologies also highlight several challenges in technology adoption, including the need for digital literacy, adequate training, and users' readiness to integrate AI tools into learning activities [8]. Adoption of novel technology by lecturers in teaching is a complex problem that requires strong motivation and intentions. Without such, the unused technology will be left useless [2], [6].

Research on technology acceptance often uses general extended technology acceptance model for e-learning (GETAMEL) to understand the factors that influence technology adoption. Main factors such as perceived ease of use (PEOU) and perceived usefulness (PU) are greatly influential in determining individual attitudes towards technology. According to Teo and Zhou [9], the comfort and usefulness of technology affect individual attitudes, especially in the use of digital services. Research by authors [10], [11] also shows that the perception of technological benefits is positively related to attitudes towards their use. In organizations, information accessibility, and ease of use of information technology influence individuals' views on the usefulness of the technology, which in turn impacts the intention to use behavioral intention (BI). Understanding the relation between PEOU and PU factors helps to determine the technology usage behavior. This study aims to analyze the acceptance of AI technology among academics using the extended TAM in order to identify the reasons for its adoption.

Although previous studies have explored technology acceptance in e-learning and AI adoption contexts [12]–[14], limited studies have specifically integrated the GETAMEL with technology innovativeness (TI) as a moderating variable in the context of AI adoption among university students. Most prior studies mainly focused on conventional e-learning systems and general digital technologies, whereas AI-based educational technologies possess more adaptive, interactive, and autonomous characteristics that may influence students' perceptions differently [15]–[22]. Furthermore, empirical evidence regarding AI technology acceptance among Generation Z students in developing countries, particularly Indonesia, remains limited. Therefore, this study aims to investigate the acceptance of AI technology among Indonesian undergraduate students using the extended GETAMEL with TI as a moderating variable. This study contributes to the literature by extending the application of GETAMEL in the AI education context and providing empirical evidence from Generation Z students in Indonesian higher education institutions.

2. LITERATURE REVIEW

2.1. The general extended technology acceptance model for e-learning

Adoption of e-learning is influenced by several external factors that shape academics' perceptions and attitudes [13]. Self-efficacy (SE) is academics' belief in their ability to use e-learning technology; the higher their self-confidence, the more positive their view of the ease and benefits of e-learning. SN refers to social influences from the surrounding environment, such as friends and family; their support makes academics more likely to find e-learning useful. Enjoyment (ENJOY), or a sense of ENJOY, increases academic engagement because they find e-learning enjoyable. On the other hand, computer anxiety (CA) i.e., the negative feeling towards computer technology, can hinder the adoption of e-learning as it makes academics view technology as difficult and useless. Previous experience (EXP) with e-learning also plays an important role; positive EXP increase self-confidence and positive views of the technology [13], [14]. All these factors together influence whether academics will adopt e-learning and how they perceive its ease and usefulness [23].

2.2. Subjective norm

Subjective norm (SN) is a person's perception of social pressure from important people around them to do or not do something [24]. In the context of e-learning, SN means the extent to which academics feel pressure from their environment to use e-learning systems. Research shows that SN has a significant relation with PU and PEOU of technology [13], [25]. Although some studies show that SN doesn't always have a significant effect on the intention to use technology, many other studies have found a positive and significant impact. This study combines previous findings on the relation between SN and PU, PEOU, and intention to use e-learning [13], [25], [26].

H1: SN has a significant influence on PU in e-learning.
H2: SN has a significant influence on PEOU in e-learning.

2.3. Experience
EXP in using technology such as computers and the internet significantly influences perception of the ease and benefits of e-learning [13]. Academics who frequently use technology feel more comfortable and confident with it, they consider e-learning easier to use and more useful. Familiarity with technology reduces anxiety and increases comfort in operating the e-learning system. In addition, factors of ENJOY, suitability to needs and learning styles, and high levels of interactivity also play an important role in strengthening positive perceptions of e-learning. Positive technology EXPs increase academics' intention to continue using e-learning in the future, since they feel confident and comfortable with the technology. Overall, EXP using technology is a key factor in determining academics' attitudes and behaviors toward e-learning [27], [28].
H3: EXP has a significant influence on PU in e-learning.
H4: EXP has a significant influence on PEOU in e-learning.

2.4. Enjoyment
ENJOY plays an important role in the usage of e-learning systems. When users feel happy when using it, they are more likely to see the system as easy to use and useful. This positive EXP helps reduce the psychological and cognitive barriers that often occur when learning new technology. In addition, ENJOY also increases users' intention to continue using the system in the future. This is important as consistent use of educational technology can improve digital skills and understanding of the material [13]. While perceived ease and usefulness of the system are also important, user ENJOY has a greater impact on driving long-term engagement. Therefore, the development and implementation of e-learning systems must pay attention to this factor by creating intuitive interfaces, engaging interactive features, and content presented in a fun way. Continuous evaluation and improvement are also needed to ensure that the system remains relevant, engaging, and fun for users [28]–[30].
H5: ENJOY has a significant influence on PU in e-learning.
H6: ENJOY has a significant influence on PEOU in e-learning.

2.5. Computer anxiety
CA is the discomfort, worry, or fear that arises when using computers or other technology. It can be caused by many things, such as fear of damaging the equipment or worrying about looking ridiculous. Such anxiety can have a major impact on how people accept new technologies, such as the use of e-learning in colleges [13]. While some studies suggest that tech anxiety affects how people view the usefulness of technology, not all studies agree. However, it is important to acknowledge that tech anxiety can affect how people perceive technology in general. Further research is needed, especially in relation to mobile technology. For example, there are differences in how technology anxiety affects academics in using mobile technology for learning. This suggests that CA may influence how academics view the ease of use of technology, but has no effect on their interest in the technology [14], [31], [32].
H7: CA has a significant influence on PU in e-learning.
H8: CA has a significant influence on PEOU in e-learning.

2.6. Self-efficacy
In information technology, SE refers to a person's ability to use technology in order to complete a specific task. SE not only affects how easy users feel about technology, but also affects their attitudes towards using technology [25]. In the educational context, SE is the academics' belief in their ability to use technology, which is critical to integrating technology into learning [33]. Research shows that academics with higher SE tend to be more successful in integrating technology into their teaching. For example, in the flipped teaching method, academics' SE influences their attitudes towards the use of technology [34].
H9: SE has a significant influence on PU in e-learning.
H10: SE has a significant influence on PEOU in e-learning.

2.7. Technology acceptance model variable
When a person feels that a technology, such as AI, has great benefits, they are more likely to accept it. The feeling of convenience and usefulness of the technology influences an individual's attitude towards its use, such as the speed and ease of using digital services [9]. Research shows that the greater the PU of a technology, the more positive an individual's attitude toward its use [10], [11]. Factors such as PEOU and PU are key in the TAM, where PEOU and PU directly influence BI. In an organizational context, the accessibility of information and ease of use of information technology also influence how individuals perceive the usefulness of the technology. By understanding the relation between PEOU and PU, as well as

other factors that influence technology adoption, research can determine technology usage behavior and the reasons behind selecting a particular technology.
H11: PU has a significant influence on BI in e-learning
H12: PEOU has a significant influence on BI in e-learning

2.8. Technology innovation as moderator

TI plays an important role in linking user perceptions of technology with its adoption and use. In the context of e-learning use, TI serves as a major moderator between factors, such as SN, ENJOY, EXP, CA, SE, and PU and PEOU [14]. TI, especially those involving AI, are not only increasing confidence and PEOU but are also streamlining the learning process with more personalized and interactive features. This is changing the way users interact with e-learning, increasing the adoption of technology in the learning environment. Thus, TI not only enhances user EXP but also moderates the relationship between psychological factors and user perceptions of e-learning, making it more accessible and usable [9], [15]–[22].
H13: TI moderates the influence between PU and BI.
H14: TI moderates the influence between PEOU and BI.

3. METHOD

This study will examine how factors in the GETAMEL can influence the BI of academics in Indonesia in utilizing AI in the teaching and learning process. PU and PEOU will mediate this relationship. In turn, the relationship will be moderated by TI.

3.1. Population and sample

This study expects a fairly broad level of generalization to undergraduate students in Indonesia. It is not known for sure how many undergraduate students in Indonesia are due to limited access. Therefore, the population can be stated as unknown. Rouquette and Falissard [35] recommends sample sizes in a confirmatory analysis using a rough scale as follows: 50–very poor; 100–poor; 200–adequate; 300–good; 500–very good; 1000 or more–excellent. Osborne and Costello [36] states that the larger the sample size, the better, as a larger sample size can reduce the magnitude of error. Therefore, this study will use a minimum sample size of 250 respondents to be able to represent the population well. The final number of respondents collected in this study was 253 undergraduate students from various higher education institutions in Indonesia, which exceeded the minimum sample requirement for structural equation modeling (SEM) analysis. All respondents in this study were members of Generation Z, a demographic group considered highly relevant to this research due to their close interaction with digital technology and AI applications in educational settings. Demographically, the respondents came from 19 cities/regencies with a high concentration of higher education institutions across 13 provinces in Indonesia, thereby providing broad representation of Indonesian undergraduate students. This distribution supports the generalizability of the study findings in the context of AI technology acceptance in Indonesian higher education.

3.2. Data types and sources

This study will use primary data obtained directly by distributing online questionnaires through Google Form. The questionnaire will contain several questions that represent each indicator in the variable and respondents can choose the most appropriate statement. The measurement of response statements is conducted using a five-point Likert scale. The operational definitions of the study variables are presented in Table 1.

3.3. Data analysis method

This study uses SEM analysis. SEM is useful for non-experimental research where the model for testing the theory has not been developed thoroughly [37]. The stages of SEM research explained as follows.

i) Develop a structural model (inner model) by designing a model of the relation between latent variables based on a predetermined hypothesis. The structural model describes the causal relation between latent variables.
ii) Develop a measurement model (outer model) to determine reflective or formative indicators for each latent variable. The measurement model describes the relation between the latent variables and the measured indicators.
iii) Constructing a path diagram by transforming the structural model and measurement model into a path diagram. This diagram visualizes the relation between latent variables and indicators, as well as between latent variables.
iv) Check the data and assumptions to ensure that SEM assumptions are met.
v) Perform SEM-PLS model estimation to estimate model parameters.

vi) Evaluate the validity and reliability of the measurement model through convergent validity and discriminant validity.
vii) Furthermore, to minimize the potential common method bias in self-reported Likert-scale data, this study also considered Harman's single-factor test.
viii) Evaluation of the structural model by assessing the goodness of fit of the structural model using R-square (R^2), and testing the strength and direction of the relation between latent variables.
ix) Test the hypothesis by looking at the values of the t-statistic and p-values. The hypothesis is considered significant if the t-statistic ≥ t-table (usually 1.96 for alpha 5%) and p-values <0.05.

The conceptual framework of this study is illustrated in the form of a path diagram, as shown in Figure 1.

Table 1. Operational definition of a variable

Variable	Indicator	Items	References
GETAMEL	SN	People who influence my behavior will think that I should use AI.	[13], [38], [39]
		People who are important to me will think that I should use AI.	
	EXP	I enjoy using computer.	[40], [41]
		I feel comfortable using internet.	
		I feel comfortable to save and search for files.	
	ENJOY	In my opinion the usage of AI is fun.	[42]–[44]
		The actual process of using AI is fun.	
		I have fun using AI.	
	CA	Computer doesn't scare me at all.	[13], [45], [46]
		Computer makes me feel uncomfortable.	
		Working with computer makes me anxious.	
	SE	I am confident in using AI even though there is no one around to show me how to do it.	
		I am confident that I can use AI even though I have never used such system before.	
		I am confident in using AI even though I only have the software manual as a reference.	
PU	Faster	Using AI will allow me to complete learning tasks faster.	[26], [47], [48]
	Improving performance	Using AI will improve my learning performance.	
	increasing effectiveness	Using AI will increase my effectiveness in learning.	
PEOU	Easy to operate	Learning to use AI will be easy for me.	
	Easy setup	I will find it easy to make AI do what I want.	
	Easy to understand	My interactions with AI will be clear and understandable.	
TI	Looking for a way to try	If I hear about a new information technology, I will find a way to try it.	[14], [49]
	Try first	Among my peers I'm usually the first to try new information technologies.	
	Love to experiment	I like to experiment with new information technologies.	
BI	Interested in using	Assuming I have access to AI, I intend to use it.	[42]–[44]
	Ready to use	Given that I have access to AI, I expect I will use it.	
	Planning to use	I plan to use AI in the future.	

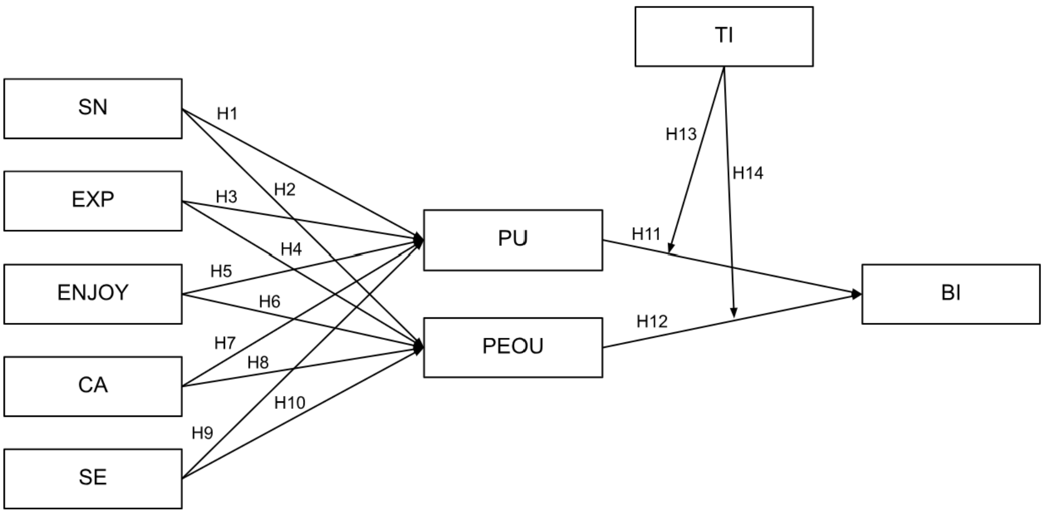

Figure 1. Path diagram conceptual framework

4. RESULTS AND DISCUSSION
4.1. Result

In the early stages, the researcher tried to present the results of the outer model test in this study. Some important information is displayed, such as the standardized factor loading value, Cronbach's alpha (α), composite reliability (CR), and average variant extract (AVE). First, the factor loading value in this study tends to be above the specified standard, namely 0.6, this condition indicates that there is a correlation between indicators in the construct [50], as presented in Table 2.

Table 2. Model measurement

Items	Standardized factor loading	α	CR	AVE
SN		0.709	0.871	0.772
SN1	0.849			
SN2	0.908			
EXP		0.714	0.838	0.663
EXP1	0.788			
EXP2	0.822			
EXP3	0.776			
ENJOY		0.885	0.929	0.814
ENJOY1	0.907			
ENJOY2	0.936			
ENJOY3	0.862			
CA		0.846	0.894	0.738
CA1	0.825			
CA2	0.823			
CA3	0.926			
SE		0.823	0.894	0.738
SE1	0.862			
SE2	0.841			
SE3	0.873			
PU		0.833	0.900	0.751
PU1	0.831			
PU2	0.880			
PU3	0.887			
PEOU		0.777	0.870	0.691
PEOU1	0.849			
PEOU2	0.847			
PEOU3	0.797			
TI		0.761	0.857	0.667
T1	0.863			
TI2	0.721			
TI3	0.859			
BI		0.879	0.926	0.806
BI1	0.915			
BI2	0.917			
BI3	0.860			

Furthermore, the α value is used to see the lower value of a construct reliability, the α value can be said to be reliable if it is more than 0.6 [51]. As shown in the Table 2 the α value for each variable is more than 0.6, thus all variables in this model have good reliability. Then, the CR value is also used to measure the reliability of a construct. Similar to α, CR can be said to be good if it has a value of more than 0.6. Based on Table 2, the overall CR value of the variables is above 0.6. Therefore, all variables have good reliability.

Discriminant validity aims to ensure that each construct in the research model is truly different from each other and doesn't overlap. In other words, the constructs used must be able to measure different concepts in the study. One method used to test discriminant validity is the Fornell-Larcker criterion. This criterion states that the square root of the AVE for each construct must be greater than the correlation between constructs, as presented in Table 3. From the table, it can be concluded that all variables have good discriminant validity, as the square root of AVE for each variable is greater than the correlation between variables. This shows that the constructs used in this study are different from each other and each construct is able to capture different phenomena in the research model. In addition, the result of Harman's single-factor test showed that no single factor dominated the total variance, indicating that common method bias was not a serious concern in this study.

Table 3. Discriminant validity test

	SN	EXP	ENJOY	CA	SE	PU	PEOU	TI	BI
SN	**0.879**								
EXP	0.301	**0.796**							
ENJOY	0.405	0.510	**0.902**						
CA	0.035	-0.238	-0.081	**0.859**					
SE	0.249	0.435	0.498	-0.177	**0.859**				
PU	0.370	0.386	0.612	-0.052	0.474	**0.866**			
PEOU	0.293	0.423	0.602	-0.070	0.636	0.594	**0.831**		
TI	0.253	0.468	0.349	-0.046	0.414	0.325	0.451	**0.817**	
BI	0.457	0.537	0.659	-0.120	0.549	0.640	0.641	0.500	**0.898**

Next is the R^2 and predictive relevance (Q^2) tests, as presented in Table 4 (R^2 and Q^2 test), which aim to assess the strength of the research model in explaining the dependent variable and the model's ability to predict data that is not used in the model estimation. R^2 is a coefficient of determination that measures how much of the variability of the dependent variable can be explained by the independent variables in the model. The higher the R^2 value, the better the model is at explaining the variability of the dependent variable. In general, R^2 values above 0.25 are considered moderate, and above 0.50 are considered high. Q^2 calculated using the Stone-Geisser method to evaluate the model's predictive ability. A positive Q^2 value indicates that the model has good predictive ability. A Q^2 value above 0.30 is considered good.

Table 4. R-square and predict relevance test

Variable	R^2	Q^2
PU	0.430	0.309
PEOU	0.517	0.343
BI	0.578	0.459

Based on the Table 4, PU has an R^2 value of 0.430 and a Q^2 value of 0.309. This means that 43% of the variability in PU can be explained by the independent variables in the model. With a Q^2 value of 0.309, this model has a quite good predictive ability for PU. PEOU has an R^2 value of 0.517 and a Q^2 of 0.343. This shows that 51.7% of the variability in PEOU can be explained by the independent variables in the model. The Q^2 value of 0.343 indicates that the model has good predictive ability for PEOU. BI has an R^2 value of 0.578 and a Q^2 of 0.459. This indicates that 57.8% of the variability in BI can be explained by the independent variables in the model. The Q^2 value of 0.459 indicates that the model has very good predictive ability for BI. The results of the SEM test using partial least squares (PLS), as presented in Figure 2. This test aims to identify the relation between various constructs in the research model, including independent, mediator, moderator, and dependent variables.

SN, ENJOY, and SE have a significant positive influence on PU, while EXP and CA are not significant on PU. So H1, H5, and H9 are accepted while H3 and H7 are rejected. Furthermore, ENJOY and SE have a significant positive influence on PEOU, while SN, EXP, and CA tend to be insignificant. Thus, H6 and H10 are accepted, while H2, H4, H8 are rejected. PU and PEOU show a significant positive influence on BI, so that H11 and H12 are accepted.

For moderator analysis using the TI variable, the TI variable is able to moderate PU to BI, with a positive coefficient value indicating that TI strengthens the relation between PU and BI. The TI variable is also able to moderate PEOU to BI, although the coefficient value shown is negative, indicating that TI weakens the relation between PEOU and BI. Thus, H13 and H14 are accepted.

4.2. Discussion

In the results above, several GETAMEL variables such as ENJOY and SE have a significant positive relation with PU and PEOU. On the other hand, the SN variable only has a significant positive effect on PU and is insignificant on PEOU. Meanwhile, the EXP and CA variables don't have a significant effect on PU or PEOU. The TAM shows that both PU and PEOU have a significant positive effect on BI.

Furthermore, IT variables are able to moderate the relation between PU and PEOU towards BI, but weakens the relation from PEOU to BI, and strengthen the relation between PU and BI.

Further discussion regarding the results, SN has a significant positive effect on PU but doesn't have a significant effect on PEOU. This finding can be explained since SN, which reflects social pressure from significant others, makes individuals more likely to view AI technology as beneficial and performance-enhancing, as supported in the studies conducted by [13], [29]. However, PEOU is more influenced by internal factors such as individual EXP and skills in using technology, thus social pressure doesn't have a significant impact on PEOU, in line with [14], [26], [52].

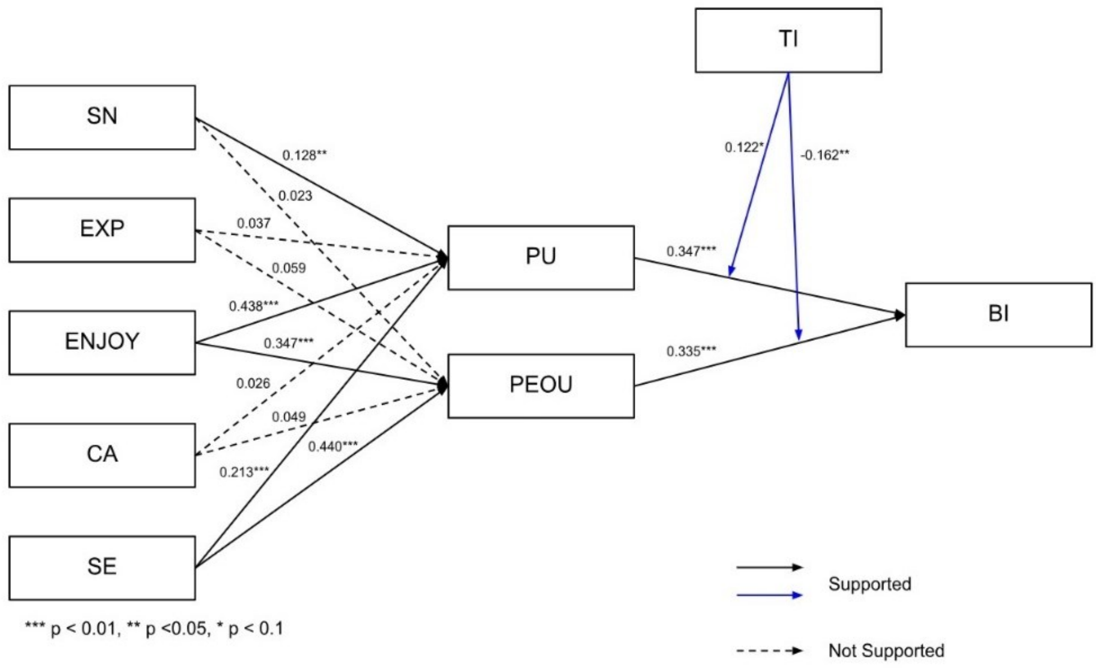

Figure 2. SEM results

The next results regarding ENJOY and SE show that both have a significant positive effect on PU and PEOU. ENJOY increases PU and PEOU, since when individuals enjoy using AI technology, they're more likely to view it as a useful and easy-to-use tool. This result is consistent with the researches done by [13], [28] which showed that ENJOY in using technology can increase positive perceptions of its usefulness. Meanwhile, SE, which reflects self-confidence in the ability to use technology, also strengthens PU and PEOU. Individuals who are confident in their abilities tend to view AI technology as more useful and easier to operate, consistent with [46] theory which states that SE increases the perception of ease and effectiveness of technology usage [53], [54].

The research results show that EXP and CA don't have a significant effect on PU and PEOU. The lack of influence of EXP may be explained by the possibility that the EXP in using computers and internet doesn't directly influence the PU and PEOU of the more specific and complex AI technologies. This result is in line with studies conducted by [26], [55] which showed that general EXP with technology doesn't always translate into acceptance of new technology. Meanwhile, CA which reflects discomfort and fear of using computers, may not have a significant effect because individuals who already have high anxiety tend to avoid using new technology from the start, thus not forming clear perceptions about its usefulness and ease-to-use [13], [56], [57].

For the TAM results, the PU and PEOU variables have a significant positive effect on BI to use AI technology. This finding can be explained by the TAM model which states that when individuals perceive AI technology as useful and easy-to-use, they're more likely to adopt it. PU influences BI as individuals who see AI technology as a tool that can improve their performance and efficiency will be more motivated to use it. PEOU also has a significant influence since if AI technology is considered easy to operate and understand, individuals will feel more comfortable and confident in using it, which ultimately increases their intention to adopt it. This result is in line with the studies done by [58]–[61] which showed that PU and ease of use are the main determinants of BI towards technology adoption.

For the analysis of moderation relationships, the results of the study show that TI moderates the relation between PU and PEOU with BI in two different directions. TI strengthens the PU relation with BI, meaning that individuals with a high propensity to try new technologies will be more motivated to use AI technology if they see it as useful [62], [63]. This can be explained as innovative individuals tend to be more enthusiastic and open to the potential benefits of new technologies, thus high perceptions of usefulness will further encourage their intention to adopt the technology [64], [65].

In contrast, TI weakens the relation between PEOU and BI, suggesting that highly innovative individuals may be less affected by the ease-of-use of technology. They may be more interested in the advanced features and capabilities of the technology than in its ease of operation, so even if they find AI technology easy to use, this doesn't significantly increase their intention to adopt it. This finding is in line with the research of Akar [66], which showed that technology innovators are often more interested in the added value than in its mere convenience.

5. CONCLUSION

This study demonstrates that ENJOY, PU, and PEOU are the main factors influencing Indonesian undergraduate students' intention to adopt AI technologies. SN significantly influences PU, while SE has a significant positive effect on both PU and PEOU. In contrast, EXP and CA do not significantly influence PU or PEOU. The findings also show that TI strengthens the relationship between PU and BI but weakens the relationship between PEOU and BI, indicating that TI students place greater emphasis on the usefulness of AI than on its ease of use. Overall, these findings support the extended TAM in explaining AI technology acceptance among Indonesian undergraduate students. Future research should include more diverse samples, incorporate additional variables, and employ longitudinal designs to further examine changes in AI technology acceptance over time.

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C : **C**onceptualization
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Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

No conflict of interest is declared. The authors affirm that there are no known financial, personal, or professional conflicts of interest that could have influenced the content or findings of this manuscript. Furthermore, the authors confirm the absence of any non-financial competing interests, including political, religious, ideological, academic, or intellectual affiliations that might be perceived as affecting the integrity of this work.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [AH], upon reasonable request.

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