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From Usefulness to Trust: How AI Shapes Learning Attitudes in Higher Education

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Abstract
This study also investigates the moderating role of artificial intelligence satisfaction and the mediation role of perceived trust in the relationship. The total sample in this study consisted of 145 respondents who were analysed using partial least squares structural equation modeling (PLS-SEM) and bootstrapping procedures with the help of the SmartPLS version 4 application. The results of the analysis show that perceived usefulness does not have a positive and significant relationship with learning attitudes. Contrarily, perceived trust and artificial intelligence satisfaction have a positive and significant relationship with learning attitudes. The next expression, perceived usefulness has a positive and significant effect on perceived trust. Then, in indirect testing, perceived trust successfully functions as a mediator in the relationship between perceived usefulness and learning attitudes, but not with artificial intelligence satisfaction which acts as a weakening factor in the relationship between perceived usefulness and learning attitudes.

Keywords: Perceived usefulness, Learning attitude, Artificial intelligence satisfaction, Perceived trust

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Introduction

The development of technology that has penetrated the education sector provides benefits in higher education. Technological advancements contribute to solving the problem of learning loss (Hazin et al., 2021), and provision of efficient learning access (Ilyas et al., 2023). For students, technology plays a role in complementing teaching that still uses traditional methods (Tan & Feng, 2023). Therefore, technology's involvement in education today is not only beneficial but also a key component in avoiding and treating learning loss. Notwithstanding its many advantages, technology in the classroom has the potential to lower learning standards. Artificial intelligence (AI)-based learning technologies can lower educational quality by 25%. (Ju, 2023), act of plagiarism and learning disability (Ivanov, 2023). More specifically, AI has a negative impact on a student's cognitive abilities, such as their inability to critically think or analyse problems that are difficult to understand (Shanmugasundaram & Tamilarasu, 2023; Tolan et al., 2021). Consequently, it is crucial for students to use AI technology in a responsible manner during the learning process. One way to achieve this is by creating positive learning environments in the classroom, such as being actively involved and collaborating with classmates.

Students' attitudes toward learning have evolved significantly in recent years. AI in education has the potential to improve students' academic achievement and, consequently, their attitude toward learning (Lee et al., 2022). Students' use of AI can influence their attitudes towards learning, which will lead to continued use of AI (Chang et al., 2022), and improve students' cognitive skills (Su, 2022). Therefore, the presence of AI in learning is an advantage for students to improve their learning attitudes. Students feel that the use of AI in learning tends to help them in learning, one of which is finding reference sources for lecture materials. Wang et al. (2023) mentioned that the perception of AI use among students can increase their participation in learning. Then, Sudaryanto et al. (2023) indicates that the perception of the use of AI is a way for students to adapt to emerging technologies. Thus, AI has succeeded in providing opportunities for students to learn, but also increases anxiety about feeling realistic and intelligent. In addition, trust in the use of AI also plays a role in building students' learning attitudes.
Students' trust in the use of AI has an influence on their intention to use it. This is formed because of the integrated learning by technology and the ability of AI to interpret their searches. Musyaffi et al. (2024) explains that the trust in AI felt by students can influence their acceptance of using AI in the classroom. Meanwhile, explanations that are easy for users to understand are an important factor in building trust in using AI (Conijn et al., 2023; Qin et al., 2020). Perceived use of AI can lead to students' intention to use AI sustainably (Chang et al., 2022). Therefore, AI is often used by students to complete the assigned college assignments. More in depth, Kurniawan et al. (2024) and Neves et al. (2024) emphasized that the use of AI on students tends to have an impact on the decline in academic integrity due to plagiarism. This is due to the low awareness of students regarding the negative impacts of using AI. Therefore, Lund et al. (2024) emphasizes the importance of collaboration between publishers, editors, reviewers, and authors to mitigate the harms of AI in higher education.

Several previous studies have provided findings on the impact of AI use in higher education. However, not many studies have used variables in this study. Lee et al. (2022) and Chang et al. (2022) gives the expression that perceived usefulness has a positive impact on learning attitude with increased learning outcomes. So that it makes their learning attitude intend to use AI sustainably. Then, perceived usefulness has a positive and significant effect on perceived trust Musyaffi et al. (2024) and AI satisfaction (Conijn et al., 2023). This is because of the easy access provided and student satisfaction with the answers given by AI. However, some researchers also convey the negative impacts of using AI on students. Excessive satisfaction and high intensity of use in learning, resulting in damage to academic integrity (Hazin et al., 2021; Ivanov, 2023; Kurniawan et al., 2024; Neves et al., 2024). The imbalance between the positive and negative impacts of AI needs to be understood holistically to ensure sustainability and ethics in its use.

Although previous reviews have looked at the impact of perceived utility on learning attitude, perceived trust, and AI satisfaction, very few studies still take these factors into account. Benefits like better learning outcomes and increased student confidence in technology are the focus of most study. Therefore, the many studies showing the negative impact of AI on learning drive us to confirm in detail. This study attempts to provide readers with an understanding through theoretical and empirical approaches. This study aims to theoretically provide scholars with a comprehensive grasp of student satisfaction and confidence in the use of AI to improve learning. This paper attempts to advise policymakers to anticipate the negative consequences of deploying AI in higher education from an empirical standpoint.

Literature Review and Hypothesis

Perceived Usefulness, Perceived Trust, Learning Attitude

The term "perceived usefulness" describes significant behavioural incentives for system use. Davis et al. (1992) explains that user happiness with a system's outcomes is a measure of user trust. Liaw (2008) shows that students' behavioral intents to use technology, including the usage of artificial intelligence (AI) in higher education, can be influenced by their perceived perception. Kurniawan et al. (2024) highlighted how students frequently use AI to enhance their learning materials. Therefore, perceived trust is the degree to which a person has faith in the usage of technology that is included into education. Kou & Sun (2024) describing how their own experiences have led them to believe that they are trustworthy and dependable, which is a type of reciprocity. As an illustration, consider pupils who feel secure using technology. Alzyoud et al. (2024) confirms that perceived trust has an effect on the acceptance of AI in educational environments. In addition,, Safitri et al. (2023) defines learning attitude as the progress of students to want to learn. Further, Şen (2013) confirm that learning attitude is an important factor in problem solving ability that has a positive impact on students' academic achievement. This is confirmed by Fann (2024) dan Li (2023) indicates that learning using AI can improve positive learning attitudes in students. Thus, the perception of use and perception of trust in the use of AI in learning can build positive attitudes in students.
H1: perceived usefulness influences learning attitude
H2: perceived usefulness influences perceived trust
H3: perceived trust influences learning attitude
H5: perceived trust provides mediation in the relationship between perceived usefulness and learning attitude

Perceived Usefulness, AI Satisfaction, Learning Attitude

Perceived utility, especially artificial intelligence, is the primary driver of technology adoption in education. Additionally, a person's opinion about the employment of technology in education is also known as perceived usefulness. Their positive attitude toward using the technology tends to rise when they complete activities quickly and receive AI-provided replies. As a measure of how satisfied people are with utilizing AI, this has helped to increase AI satisfaction. Seo et al. (2023) and Kashive et al. (2021) shows that students are adapting to technology and that their attitude toward perceived usefulness affects their drive to learn. Students who keep using AI to solve problems are likely to do so consistently. Students' opinions about the application of AI in education can therefore be enhanced by AI satisfaction. Positive and successful learning experiences are also impacted by artificial intelligence (Chen et al., 2024; Huang, 2021). Then, in order to improve the perception of AI, a proactive approach to learning can help promote student participation. Students who feel comfortable utilizing AI are also more likely to be satisfied with the new technology. Zhai et al. (2021) suggests that favourable attitudes toward learning are impacted by the use of technology in the classroom, particularly in higher education. Positive and proactive learning in the classroom is thus influenced by perceived usefulness, AI satisfaction, and learning attitude.
H4: AI satisfaction m influences terhadap learning attitude
H6: AI satisfaction moderates the relationship between perceived usefulness and learning attitude

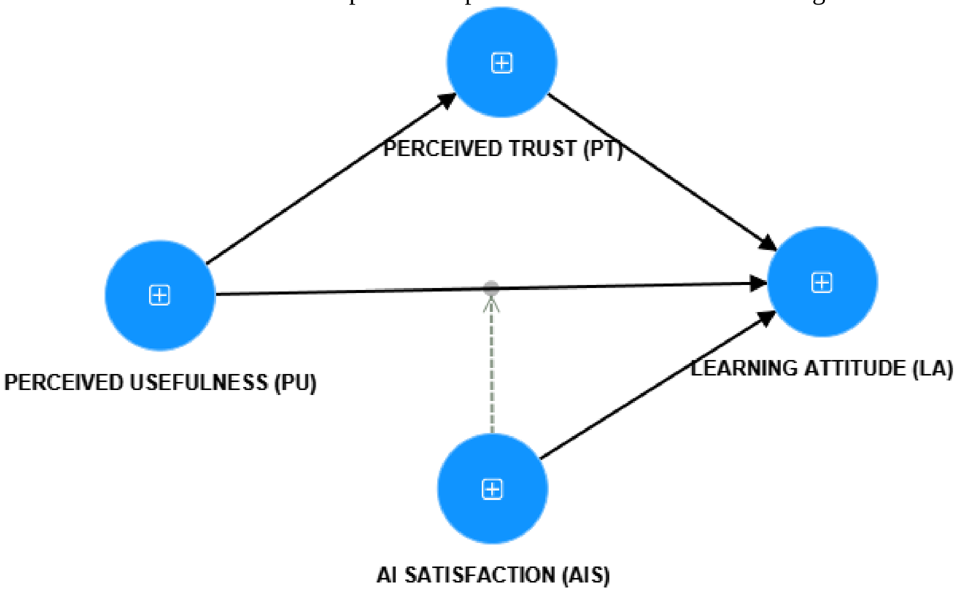

Figure 1. Conceptual framework

Materials and Methods

Research Design

An explanatory quantitative technique was used to perform the investigation. This is consistent with the study's goal of analysing the connections between all the variables. The specific goal of this study is to investigate how students' attitudes toward learning relate to how AI is perceived. Furthermore, this study seeks to explore the connection between students' perceptions of AI trust and the moderating of AI satisfaction.

Population and Sample

Students enrolled in local schools made up the research population for this study, which was carried out in South Sulawesi between September and November of 2024. An online calculator was used to determine the bare minimum of responders needed from (Soper, 2021). Four latent variables, seventeen observable variable items, an effect size of 0.3, and a probability level of 0.05 are all included in the computation. The A-priori Sample Size Calculator for Structural Equation Model indicates that 91 respondents are the bare minimum required. As a result, the study's questionnaire will be completed by at least 91 students. A Google Form-distributed online survey employing the snowball sampling technique was used to collect data. Respondent criteria include: 1) students enrolled in South Sulawesi, both at private and public universities; 2) students beginning college in 2021 and continuing until 2023; and 3) students who have employed artificial intelligence in their education at least once. In the context of cutting-edge learning, particularly regarding the application of artificial intelligence technology, these criteria were selected to guarantee that respondents possess pertinent academic expertise. According to these standards, the information gathered should provide fresh and pertinent student viewpoints on the application of technology in higher education.

Instruments and Data Procedure

A Four-point Likert scale, with 1 denoting "strongly disagree" and 4 denoting "strongly agree," was employed in this study's questionnaire to gather data from participants. Four latent variables—AI satisfaction (AIS), learning attitude (LA), perceived trust (PT), and perceived usefulness (PU)—were employed in this investigation. Every latent variable used in this investigation was taken from an existing study. Research led to the adoption of AIS. Almufarreh (2024) with a Cronbach's alpha value of 0.88, the statements "I use AI to greatly improve my ability to learn" and "For me, AI greatly facilitates and increases the effectiveness of learning" are used as instances. Next, in the LA variable, using Jia & Tu (2024) Using one instance "I am active in seeking additional information to improve my understanding of the course”. Cronbach's alpha for the LA variable is 0.88. The PT variable is associated with Rahim et al. (2022) "I use AI-Chatbot if the information provided is accurate" is an example item. Cronbach's alpha for this variable is.89. Lastly, the PU variable is related to Wang et al. (2021) the example sentence "I use AI to achieve the learning objectives set" and obtain a Cronbach's alpha value of.86 instead. Table 2 displays all the test findings. After that, the data distribution results were processed with the aid of the Structural Equation Modeling (SEM-PLS) technique in the SmartPLS version 4 statistical tool. PLS-SEM is utilized in this study for data processing methods because to its dependability in generating predictions regarding the link between each variable. In the meantime, the latent variables in this study are assessed using the inner model and outer model tests. As a latent variable, the inner model test seeks to assess and perceive its reliability. The outer model test then seeks to determine the significance and impact of each previously developed hypothesis.

Results

Respondent Characteristics

The results of the questionnaire distribution show that out of the 91 determined samples, there are 145 respondents who have filled out the questionnaire with various characteristics presented in Table 1. Based on gender, there are 95 female respondents and 50 male respondents. Meanwhile, 124 respondents are under 23 years old, 11 respondents are over 29 years old, and the remaining 10 respondents are in the age range of 23 to 27 years. In addition, 125 respondents are pursuing undergraduate education, 14 respondents are pursuing diploma and doctoral education, while 6 other respondents are pursuing master's education. Lastly, regarding the intensity of AI usage among students, 83 respondents often use AI, 30 respondents very often use it, and the remaining 32 respondents rarely to very rarely use AI in their learning. Thus, the sample in this study has been fulfilled and can proceed to the testing stage.

Table 1. Profile of respondents

Characteristics	**Frequency**	**Percentage**
Gender		
Men	50	34%
Women	95	66%
Age (*years old*)		
<23	124	86%
23-25	6	4%
25-27	4	3%
>29	11	8%
Current Education		
Diploma	7	5%
Bachelors	125	86%
Magister	6	4%
Doctoral	7	5%
Year of Entrance		
2021	18	12%
2022	33	23%
2023	94	65%
Al Use Intensity		
Very Rarely	1	1%
Rarely	31	21%
Often	83	57%
Very Often	30	21%
Total	**145**	**100%**

The outer model testing aims to evaluate items up to the construct on the latent variables used in this research. The testing is conducted by evaluating outer loading, validity, and reliability. First, the outer loading test aims to evaluate the research items by examining the values of each variable. (lihat Tabel 2). A construct can be considered valid if it has a value greater than the threshold of 0.7. Secondly, the validity and reliability testing of the construct is conducted by examining the values of Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE) for each variable. Each test has a threshold that must be met: the values of CA and CR must be greater than 0.7, while AVE must be greater than 0.5. (lihat Tabel 3). Finally, the discriminant validity test aims to ensure that there is a difference between the model and the latent variables used in this study. In this study, discriminant validity is tested using cross-loading values by comparing the item values with other items horizontally. (see in Table 4).

Table 2. Outer loading value

Item	**Artificial Intelligence Satisfaction (AIS)**	**Learning Attitude (LA)**	**Perceived Trust (PT)**	**Perceived Usefulness (PU)**
1	0.87	0.80	0.82	0.89
2	0.87	0.86	0.94	0.90
3	0.81	0.80	0.87	0.85
4	0.76	0.83	0.82	
5	0.82	0.79		

Table 2 shows the outer loading values for each item in the latent variable. The results show that the AIS variable has the smallest outer loading value on item 4 (0.76 > 0.7) and the largest on items 1 and 2 with the same value, namely (0.87 > 0.7). The LA variable has the smallest outer loading on item 5 (0.79 > 0.7) and the largest on item 2 (0.86 > 0.7). Next, the PT variable has the smallest outer loading values on items 1 and 4 (0.82 > 0.7) and the highest on item 2 (0.94 > 0.7). Finally, the PU variable has the smallest outer loading value on item 3 (0.85 > 0.7) and the highest on item 2 (0.90 > 0.7). Thus, all items on the latent variables have outer loading values greater than the estimated value of 0.7. Therefore, all items have valid values, allowing for further testing. In the validity and reliability testing, the AIS variable has CA values (0.88 > 0.7), CR values (0.89 > 0.7), and AVE values (0.69 > 0.5). Next, the LA variable has CA values (0.88 > 0.7), CR values (0.88 > 0.7), and AVE values (0.67 > 0.5). The PT variable yields CA values (0.89 > 0.7), CR values (0.89 > 0.7), and AVE values (0.75 > 0.5). Finally, the PU variable has CA values (0.86 > 0.7), CR values (0.86 > 0.7), and AVE values (0.78 > 0.5). All the latent variables used in this study have exceeded the specified thresholds, thus it can be concluded that these variables have good validity and reliability. (lihat tabel 3).

Table 3. Validity and reliability value

Variabel	CA	CR	AVE
Artificial Intelligence Satisfaction (AIS)	0.88	0.89	0.69
Learning Attitude (LA)	0.88	0.88	0.67
Perceived Trust (PT)	0.89	0.89	0.75
Perceived Usefulness (PU)	0.86	0.86	0.78

Cross-loading testing is intended to test the discriminant validate of all latent variables (AIS, LA, PT, and PU) presented in Table 4. The results of the discriminant validate test in this study indicate that all items in the construct have a greater value compared to the values around them. Thus, the discriminant validate test has been successfully fulfilled.

Table 4. Validity discriminant variabel

Item	Artificial Intelligence Satisfaction	Learning Attitude	Perceived Trust	Perceived Usefulness
AIS-1	**0.87**	0.63	0.58	0.69
AIS-2	**0.87**	0.49	0.44	0.70
AIS-3	**0.81**	0.54	0.51	0.56
AIS-4	**0.76**	0.46	0.47	0.64
AIS-5	**0.83**	0.53	0.49	0.81
LA-1	0.43	**0.80**	0.38	0.31
LA-2	0.51	**0.87**	0.49	0.35
LA-3	0.53	**0.81**	0.40	0.41
LA-4	0.52	**0.83**	0.48	0.43
LA-5	0.63	**0.79**	0.52	0.51
PT-1	0.46	0.44	**0.83**	0.51
PT-2	0.57	0.54	**0.95**	0.51
PT-3	0.60	0.46	**0.88**	0.48
PT-4	0.47	0.49	**0.83**	0.44
PU-1	0.77	0.43	0.49	**0.90**
PU-2	0.73	0.47	0.46	**0.91**
PU-3	0.68	0.43	0.52	**0.86**

Inner Model

After the outer loading criteria are met, the process proceeds to testing the inner model, which aims to evaluate the values and relationships among the developed hypotheses. Testing is done by looking at the T value and β value for each hypothesis. If the T value exceeds the 1.96 threshold, then the relationship is significant, and the hypothesis can be accepted. Conversely, if the T value is less than 1.96, then there is no significant relationship. (more details in Table 5).

Table 5. Direct and indirect hypothesis testing

Hipotesis	B	T Value	P Values	Effect Size	Conclusions
H1: PU → LA	0.14	1.36	0.17	0.01	H1 rejected
H2: PU → PT	0.55	6.81	0.00	0.44	H2 accepted
H3: PT → LA	0.26	2.66	0.00	0.08	H3 accepted
H4: AIS →LA	0.55	4.33	0.00	0.17	H4 accepted
H5: PU → PT → LA	0.14	2.38	0.01	0.02	H5 accepted
H6: AIS*PU → LA	-0.06	0.63	0.52	0.01	H6 rejected

NOTE: artificial intelligence satisfaction (AIS); learning attitude (LA); perceived trust (PT); perceived usefulness (PU); hypotheses (H)

The results of hypothesis testing are presented in Table 5. It was found that PU (β: 0.14; T: < 1.96) has no significant relationship with LA with a small effect size (0.01). PU (β: 0.55; T: > 1.96) has a positive and significant relationship with PT with a large effect size (0.44). PT (β: 0.25; T: > 1.96) also has a positive and significant relationship with LA with a small effect size (0.08). In addition, AIS (β: 0.55; T: > 1.96) has a positive and significant relationship with LA with a medium effect size (0.17). This study also examines the role of PT variables as mediators and AIS as moderators. The results show that PT exerts an indirect influence (β: 0.14; T: > 1.96) on the PU to LA relationship with a low moderation effect (0.02). However, in the moderation test, it was found that AIS had a value (β: -0.06; T: < 1.96) that weakened the relationship of PU to LA and showed no significant effect (0.01).

Discussion

Perceived Usefulness, Perceived Trust, Learning Attitude

Statistical test results show that perceived usefulness does not have a positive and significant effect on learning attitude. This proves that the use of AI in the learning process lowers their learning attitude. The convenience provided by AI, provides dependence on its users so that it can reduce students' learning attitude. In addition, if students use AI to find answers or complete their assignments, it will reduce their motivation to learn. Study from Yani (2024) and Ju (2023) emphasized that the convenience offered by AI provides a dependency that has an impact on decreasing student motivation to learn. More deeply, Alasgarova & Rzayev (2024) mentioned that the utilization of AI in learning can interfere with the function of autonomy in the body, causing a lack of honesty in students. Students who are too dependent on AI lose their motivation to explore the material in depth. Morales-García et al. (2024) argue the reliance on AI has the effect of lowering students' cognitive skills, thus reducing their ability to explore the material. However, Li (2023) and Wu et al. (2024) denial that perceived ease of use of AI can promote positive learning attitudes, especially in higher education. Therefore, it is important for students to maintain a balance between AI and ethics in its use.

Then, the test results found that perceived usefulness has a positive and significant impact on perceived trust. This refers to the efficiency of using AI for students which can increase trust in the use of AI. Students who are confident in the accuracy of the answers provided by AI chatbot, tend to have high motivation in achieving their academic performance. Choung et al. (2023) opined that high trust in students in the use of AI, has a great impact in influencing the intention to use. Furthermore, Sun & Zhou (2024) emphasizes that the use of generative AI such as Chat-GPT, perplexity, humanta AI and so on, is able to improve students' academic quality and encourage independent learning attitudes. The contribution made by AI in learning greatly helps students to learn more efficiently by getting accurate answers from generative AI. In line with this, Ahmed et al. (2024) confirms that Generative AI offers better opportunities in learning with the personalization of learning. Thus, the utilization of AI in learning is not only about the use, but also the trust to use the technology.

Furthermore, the results of testing the outer model also show that PT has a positive and significant effect on LA. The positive effect is formed by students' trust in the use of AI as a learning resource that can be trusted and avoid plagiarism. The use of AI in learning is strongly related to the quality of information sources obtained. Prokhorova et al. (2024) confirmed if students feel satisfaction in using AI to find information about lecture material quickly. Similarly, Ahmed et al. (2024) argued that AI plays a positive role in building learning attitudes by providing a more interactive and motivating experience. Moreover, the results of generative AI writing that match students' expectations have an impact on motivation to explore the material in more depth. Therefore, AI can build a proactive learning attitude in understanding and applying the material. Leong et al. (2024) and Davis et al. (1992) opined that the use can help students to find the material they want by using AI-based instruction. Thus, the use of AI in learning is very effective in fostering students' learning attitude, especially their engagement in classroom learning. This is related to the understanding of the material being studied.

PT successfully moderates the relationship between PU and LA. The positive impact of PU on PT increases students' trust in AI through the efficiency and accuracy of the answers provided. This student trust strengthens the relationship with more positive learning attitudes. PT also shapes students' perceptions of AI as a learning resource that is trustworthy and safe from plagiarism. This trust encourages students to explore the material more deeply and understand the broader context. Overall, PT strengthens the effectiveness of AI use in fostering proactive learning attitudes, increasing engagement in learning, and promoting better learning outcomes. In line with this, Ralhan (2024) and Oseremi Onesi-Ozigagun et al. (2024) supports that the integration of responsible and unethical use of AI will encourage students to avoid plagiarism in higher education. Furthermore, Amoozadeh et al. (2024) mentioned that students' trust in the use of AI in learning is able to build their engagement in the learning process. In addition, Leong et al. (2024) dan Ahmed et al. (2024) gave the opinion that the proactive attitude of students cannot be separated from the role of AI to provide personalization in learning.

Perceived Usefulness, AI Satisfaction, Learning Attitude

The positive relationship of AIS to LA was established by the benefits that students perceived in using AI for learning. This finding confirms that AI is successful in building positive learning attitudes. Students feel that the use of AI in learning, makes it easier for them to prepare content, materials, improve learning abilities, and valuable benefits from the use of AI. Students' use of AI encourages them to create a positive learning attitude (Li, 2023; Wu et al., 2024), improve cognitive ability (Su, 2022), which has an impact on student learning outcomes (Chang et al., 2022). In addition, the use of AI on students also has an impact on the effectiveness of time in understanding the material independently. The wise use of AI in students will raise awareness about their mastery of course material. Thus, AI acts as a catalyst that can build commitment to student learning success.

Although the previous test results show that PU has a positive impact on both AIS and LA, the moderation test shows that AIS can weaken the relationship between PU and LA. This finding indicates that students who depend on the use of AI may weaken their intrinsic motivation and thus reduce their critical thinking ability. Furthermore, the ease of finding answers from AI causes students to be less motivated in exploring the material in depth. Research in line with these findings states that the excessive use of AI has an impact on the decline of critical thinking skills (Shanmugasundaram & Tamilarasu, 2023; Tolan et al., 2021), reduced students' critical thinking skills (Hazin et al., 2021; Ivanov, 2023), and the destruction of academic integrity such as plagiarism (Ivanov, 2023; Kurniawan et al., 2024). Therefore, while AI can help students with their work, it is important to be aware of its negative impact on their cognitive and psychomotor abilities.

The findings presented earlier contradict some previous studies. Kurniawan et al. (2024) dan Neves et al. (2024) argues that the high intensity of AI use will lead to a decline in academic integrity such as plagiarism. Then, Ivanov (2023) explained that the high use of AI has an impact on the decline in students' cognitive abilities. Therefore, Husna et al. (2024) emphasizes the need for self-control in the use of AI as an effort to avoid the adverse effects of its use. In terms of self-determination theory (SDT), which explains that lecturer support and student expertise in the use of AI play an important role in encouraging students' intrinsic motivation and independent learning (Chiu et al., 2023; Zhou & Zhang, 2024). In depth, SDT lends support to these findings with the question that internal motivation plays a key role in students' satisfaction with AI use.

Conclusions

This study highlights the impact of AI use among university students in Indonesia, particularly in South Sulawesi. The author provides valuable insights for researchers by examining the relationship between the variables of perceived usefulness, AI satisfaction, perceived trust, and learning attitude. The results of this study emphasize the importance of maintaining a balance in the use of AI in learning. Although AI offers convenience to its users, dependence on AI may decrease intrinsic motivation and critical thinking ability. Self-control in AI use is very important for students to avoid negative impacts on academic integrity. The practical implication for teachers in higher education is the importance of building ethical use of AI among students, for example by including ethical use of AI curriculum in the learning process. This is needed as a preventive measure to avoid the negative impact of AI for students. The implementation of this study has limitations in the variables studied and the number of samples used. A sample limited to students in South Sulawesi may limit the generalization of findings to students in other regions. In addition, this study is also limited to the variables used. Therefore, future research can expand the scope of the study area and consider other factors that may affect students' motivation in using AI in learning.

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Author(s) Contribution Rate

Jeranah (34%): conceptualization, methodology, formal analysis, original draft preparation, and project administration. Novian Candra Kurniawan (33%): data curation, investigation, visualization, and manuscript review. Asdar Ahmad (33%): supervision, validation, interpretation of findings, and review/editing of the manuscript. All authors read and approved the final version of the manuscript.

Ethical Approval

For this study, ethical approval was obtained from the Ethics Committee of Malang State University (No. 19.8.32/UN32.14/PM/2024, dated August 23, 2024).

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