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IMPACT OF AI TOOLS ADOPTION ON LEARNING BEHAVIORS AND ACADEMIC ETHICS AMONG INDONESIAN UNIVERSITY STUDENTS: AN APPLICATION OF THE UTAUT MODEL

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Abstract

The rapid adoption of generative artificial intelligence (AI) tools such as Chat GPT, Gemini, and Copilot is transforming the landscape of higher education worldwide. While these tools offer unprecedented efficiency and learning support, their integration raises complex pedagogical and ethical issues. This study investigates how university students' adoption of AI tools influences their learning behavior, academic ethics, and readiness for future employment. Using a modified Unified Theory of Acceptance and Use of Technology (UTAUT) framework, supplemented with variables for perceived risk, trust, and technological competence, we conducted a survey of 320 undergraduate students across Indonesia via a structured online questionnaire. Structural Equation Modelling (PLS-SEM) was used to analyze 14 hypotheses. Results indicate that trust and technological competence significantly drive students' intention to use AI, which in turn predicts actual usage. Additionally, actual AI usage has a strong positive impact on students' learning behavior, ethical awareness, and perceived work readiness. On the mediation pathway, traditional predictors such as performance expectations, social influence, and institutional support were found to significantly influence actual AI use through intention to use AI. These findings highlight a paradigm shift: students are increasingly guided by intrinsic trust and digital competence rather than external factors. This study provides critical insights for educators and policymakers in designing ethical and future-orientated AI.

Keywords: AI Adoption, Intention to Use AI, Actual Use of AI, UTAUT

Introduction

The development of artificial intelligence (AI) technology, particularly generative AI like Chat GPT, is experiencing a surge in usage across various sectors, including in the context of higher education. Among students, the adoption of AI tools has become a globally widespread phenomenon. A study in the United Arab Emirates shows that the use of AI among students is already very common, but there are still ethical concerns and a lack of adequate institutional guidance. Factors such as peer pressure and perceptions of benefits influence students' decisions to use AI tools, reflecting that the adoption process is not only technological but also influenced by psychological and social dynamics (Swidan et al., 2025).

Although many students and prospective educators show enthusiasm for exploring AI technology, there are still doubts regarding its practical application and ethical impact. In California, the majority of prospective teachers are open to the use of generative AI, but they harbor concerns about over-reliance and integrity in the classroom context (Chung, 2024). Meanwhile, in Nigeria, the level of anxiety regarding AI among prospective mathematics teachers is quite high, although the adoption rate is moderate. The research revealed that anxiety towards AI has a weak but significant relationship with usage intensity, with no significant differences between genders (Falebita, 2024).

In the institutional context, the literature highlights the importance of policies and systemic support in ensuring the responsible, ethical, and academic adoption of AI. Awadallah Alkouk & Khlaif (2024) emphasize that higher education institutions need to design adaptive assessment policies so that the use of AI does not undermine academic integrity. Other research highlights that perceptions of risk, trust, and technological proficiency also influence students' readiness to adopt generative AI, particularly in the context of academic evaluation (Oc, Gonsalves, and Quamina, 2024).

Structural barriers also serve as limiting factors in the implementation of AI. A case study in India revealed that although academic libraries are beginning to utilize AI for efficiency and service enhancement, limitations in infrastructure and human resources remain significant challenges (Nimbhorkar 2024). Similarly, at the postgraduate level, doctoral students face technical and ethical challenges in utilizing AI for research, highlighting the importance of adequate training (Aoufir et al., 2025).

The aspects of students' technological readiness and self-efficacy have been shown to influence their perceptions of the ease and benefits of using AI. However, actual adoption does not always align with these perceptions, indicating that attitudes towards AI are a key factor in determining its use (Falebita & Kok, 2025).

Ardito (2024) believes that the school's use of generative AI detection tools in tests does not match current educational trends and actually hides the teaching benefits that new technology should provide.

With these various findings, it is clear that the adoption of AI in higher education holds enormous potential as well as complex ethical and pedagogical challenges. Therefore, this research is important to explore the relationship between the use of AI tools and students' learning behaviors and academic ethics, as well as to examine the extent to which these factors influence their readiness to face the demands of the future job market.

Literature Review

Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT model developed by Venkatesh et al. (2003) is the main theoretical framework in explaining technology adoption behavior. This model states that users' behavioral intentions towards technology are influenced by four main constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. In various studies, UTAUT has proven relevant for analyzing technology acceptance, including in the field of higher education (Venkatesh et al., 2003). In the context of using generative AI in higher education, performance expectancy describes the extent to which students believe that AI helps them complete academic tasks efficiently. Effort expectancy relates to the ease of use of AI tools, while social influence reflects the impact of peers or professors in encouraging AI adoption. Facilitating conditions refer to the technical support and infrastructure from institutions that facilitate the use of this technology (Oc, Gonsalves, and Quamina, 2024).

Perceived Risk in AI Adoption

Adding the perceived risk factor to the UTAUT model is crucial to understand students' worries about AI, especially about data privacy, the truthfulness of information, and maintaining academic honesty (Featherman & Pavlou, 2003). In a recent study, Oc, Gonsalves, and Quamina (2024) showed that perceived risk significantly hinders students' use of generative AI. Concerns about data breaches, misuse of academic information, and the opacity of AI algorithms create resistance to usage, especially for text-based AI like ChatGPT.

The Role of Trust in the Use of AI

Trust is an important dimension for strengthening behavioral intentions toward new technology. Students who have high trust in AI tools and their developers are more likely to adopt this technology in the learning process. The study by Gefen et al. (2003) and confirmed again by Oc, Gonsalves, and Quamina (2024) shows that high trust in AI directly impacts actual usage behavior. On the other hand, trust in educational institutions and lecturers also plays a mediating role in reducing perceived risk and increasing technology adoption.

Relation to Workforce Readiness

Qin and Ma (2022) pointed out that digital readiness involves not just technical skills but also mental and emotional factors like digital mental health, which is affected by how comfortable someone is with technology, their willingness to try new things, and their awareness of digital tools like digital nudging. The three of them play an important role in shaping an individual's readiness to adapt healthily and productively in a highly digitized modern work ecosystem. Therefore, higher education needs to design learning strategies that not only emphasize the use of technology but also equip students with ethics, critical reflection, and adequate digital resilience.

Research conceptual framework

Based on the modified UTAUT theory and previous studies, a conceptual framework is formulated as shown in Figure 1. This model shows that intention to use AI is influenced by six main constructs. Furthermore, the intention affects the actual use of AI, which then impacts the learning behavior, ethical behavior, and job readiness of students.

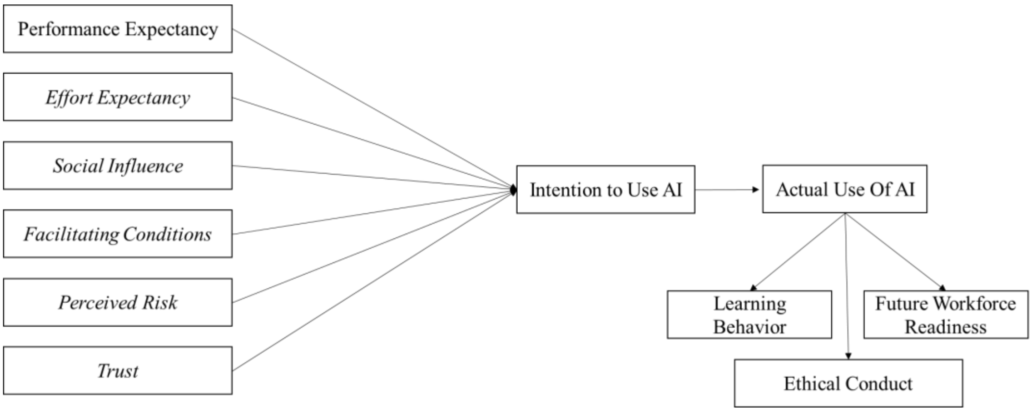

Figure 1. Research conceptual framework

Hypothesis

Based on the conceptual framework that has been developed, 14 hypotheses have been formulated for this research.

H1: There is a relationship between performance expectancy and intention to use AI.
In the UTAUT model, performance expectancy is the main construct that explains that individuals are likely to intend to use technology if they believe that the technology will enhance their performance (Venkatesh et al., 2003).

H2: There is a relationship between effort expectancy and intention to use AI.
Effort expectancy plays a role in shaping behavioral intentions because users tend to choose technology that is easy to use (Venkatesh et al., 2003).

H3: There is a relationship between social influence and intention to use AI.
UTAUT states that social support or pressure from peers and superiors can influence the intention to adopt technology (Venkatesh et al., 2003).

H4: There is a relationship between facilitating conditions and intention to use AI.
Supporting conditions such as infrastructure and institutional policies can influence the intention and ability to use technology (Venkatesh et al., 2003).

H5: There is a relationship between perceived risk and intention to use AI.
Perceived risk reflects concerns about potential losses and can hinder the intention to use digital services (Featherman & Pavlou, 2003).

H6: There is a relationship between trust and intention to use AI.
Trust in technology and its providers is an important factor in determining the acceptance and intention to use technology (Gefen et al., 2003).

H7: There is a relationship between actual use of AI and learning behavior.
Swidan et al. (2025) state that students who actively use AI show improvements in efficiency and learning strategies.

H8: There is a relationship between actual use of AI and ethical conduct.
Direct interaction with AI in an academic context raises ethical reflections, as shown in Chung's study (2024).

H9: There is a relationship between actual use of AI and future workforce readiness.
The use of AI supports students' readiness to face the modern digital work environment (Qin & Ma, 2022).

H10: Intention to Use AI is able to mediate the relationship between effort expectancy and actual AI use.

H11: Intention to Use AI is able to mediate the relationship between Trust and Actual Use of AI.

H12: Intention to Use AI is able to mediate the relationship between social influence and actual AI use.

Methods

This research uses a quantitative approach with an explanatory design to analyze the relationship between various factors in the modified UTAUT model with the use of AI tools by students. This model is expanded by adding outside factors like perceived risk, trust, which research has shown affect how people adopt technology. This approach was chosen because it can explain the causal relationships between the model constructs and provide a comprehensive picture of behavioral intentions and actual use of AI technology in higher education environments. The population in this study consists of active undergraduate students (S1) at universities in Indonesia who have access to and experience using generative AI tools such as Chat GPT, Gemini, Copilot, Grammarly GO, and similar tools. The sampling method uses purposive sampling techniques, with criteria for vocational high school students and active university students throughout Indonesia. Data was

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collected through an online questionnaire distributed using Google Forms. The questionnaire consists of several sections: Section 1 (Personal Data). This section includes questions about personal data, age, gender, major, semester, type of AI used, and average AI usage time per week. Section 2 (Research Questions) consists of 45 research questions that will represent each research variable being studied. All items were measured using a Likert scale, from 1 = strongly disagree to 5 = strongly agree. The obtained data were subsequently analyzed using Partial Least Squares- Structural Equation Modeling (PLS-SEM) with the help of Smart PLS 4 software. This research will ensure ethical principles such as informed consent, anonymity, and data confidentiality. All participants will be asked to consent to voluntary participation before filling out the questionnaire.

Table 1. Operationalization of Research Variables

Variable Type	Code	Variable	Description
Independent Variable	X1	Performance Expectancy	Performance expectations regarding AI usage
	X2	Effort Expectancy	Perception of ease of use
	X3	Social Influence	Social influence (friends, professors)
	X4	Facilitating Conditions	Availability of support & infrastructure
	X5	Perceived Risk	Perceived risks (ethics, privacy, data)
	X6	Trust	Trust in AI and institutions
Mediating Variable	Y1	Intention to Use AI	Intention to use AI tools
Dependent Variable	Y2	Actual Use of AI	Actual behavior in using AI
	Y3	Learning Behavior	Impact on learning behavior patterns
	Y4	Ethical Conduct	Impact on academic ethical behavior
	Y5	Future Workforce Readiness	Students' future job readiness

Results and Discussions

Validity Test

The evaluation of construct reliability in this study was conducted using Cronbach's Alpha to measure the internal consistency among items within each construct. Based on the literature, an adequate Cronbach's Alpha value is in the range of ≥ 0.70, but in the context of exploratory or new constructs, a value approaching 0.60 is still tolerable (Nunnally & Bernstein, 1994). Additionally, according to Truong & McColl (2011), the factor loading value for each item ideally should be more than 0.50 to ensure better and more consistent analysis results. The test results show that most constructs have high Cronbach's Alpha values, indicating a very good level of reliability:

a. Facilitating Conditions ($\alpha = 0.881$), and Future Workforce Readiness ($\alpha = 0.844$) show very strong reliability.
b. Other constructs such as Ethical Conduct ($\alpha = 0.802$), Performance Expectancy ($\alpha = 0.806$), and Intention to Use AI ($\alpha = 0.825$) also meet good reliability standards.
c. Effort expectancy, learning behavior, and trust have α values in the range of 0.78–0.84, indicating stable consistency.
d. Three other constructs, namely Social Influence ($\alpha = 0.672$), Actual Use of AI ($\alpha = 0.609$), and Perceived Risk ($\alpha = 0.583$), are slightly below the 0.70 threshold. However, these values are still considered acceptable in an exploratory context, especially when supported by individual factor loading values exceeding 0.50, as suggested by Truong & McColl (2011). Thus, the overall constructs in the model are deemed to have a reliability level suitable for further analysis in the structural model.

Table 2. Validity Test Results

Category	Cronbach's alpha	Result
Actual Use of AI	0.609	Valid
Effort Expectancy	0.789	Valid
Ethical Conduct	0.802	Valid
Facilitating Conditions	0.881	Valid
Future Workforce Readiness	0.844	Valid
Intention to Use AI	0.825	Valid
Learning Behavior	0.793	Valid
Perceived Risk	0.583	Valid
Performance Expectancy	0.806	Valid
Social Influence	0.672	Valid
Trust	0.837	Valid

Reliability Test

Convergent validity is tested through the Average Variance Extracted (AVE) value. According to the guidelines (Sarstedt et al., 2022), an AVE value ≥ 0.50 indicates that the construct can explain more than half of the variance of its indicators. The analysis results show that all constructs have AVE values above 0.50, ranging from 0.504 (Social Influence) to 0.740 (Intention to Use AI). This result indicates that all constructs have met the convergent validity requirements and are suitable for use in the structural model.

Table 3. Reliability Test Results

Category	Average variance extracted (AVE)	Result
Actual Use of AI	0.549	Reliable
Effort Expectancy	0.612	Reliable
Ethical Conduct	0.614	Reliable
Facilitating Conditions	0.735	Reliable
Future Workforce Readiness	0.681	Reliable
Intention to Use AI	0.740	Reliable
Learning Behavior	0.619	Reliable
Perceived Risk	0.544	Reliable
Performance Expectancy	0.633	Reliable
Social Influence	0.504	Reliable
Trust	0.673	Reliable

Hypothesis Testing

The evaluation of the structural model is conducted to test the causal relationships between constructs within the conceptual framework using path coefficients analysis that shown in Table 4.

Table 4. Path Coefficients

Category	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Direct Effect:					
Actual Use of AI -> Ethical Conduct	0.449	0.455	0.047	9.486	0.000
Actual Use of AI -> Future Workforce Readiness	0.516	0.522	0.052	9.979	0.000
Actual Use of AI -> Learning Behavior	0.583	0.589	0.046	12.591	0.000
Effort Expectancy -> Intention to Use AI	0.055	0.064	0.061	0.895	0.371
Facilitating Conditions -> Intention to Use AI	-0.012	-0.023	0.050	0.234	0.815
Intention to Use AI -> Actual Use of AI	0.638	0.640	0.037	17.444	0.000
Perceived Risk -> Intention to Use AI	0.074	0.068	0.069	1.077	0.281
Performance Expectancy -> Intention to Use AI	0.075	0.079	0.063	1.188	0.235
Social Influence -> Intention to Use AI	0.091	0.093	0.055	1.655	0.098
Mediation Effect:					
Effort Expectancy -> Intention to Use AI -> Actual Use of AI	0.070	0.072	0.041	1.698	0.090
Trust -> Intention to Use AI -> Actual Use of AI -> Learning Behavior	0.173	0.172	0.033	5.289	0.000
Social Influence -> Intention to Use AI -> Actual Use of AI	0.058	0.059	0.035	1.645	0.100
Trust -> Intention to Use AI -> Actual Use of AI	0.296	0.292	0.049	6.079	0.000

Source: Smart PLS 2025

Several relationship paths were found to be statistically significant and insignificant ($p < 0.10$), namely:

a. Actual Use of AI → Ethical Conduct (β = 0.449; t = 9.486; p = 0.000). This indicates that AI also influences ethical behavior, both positively and as a potential risk.
b. Actual Use of AI → Future Workforce Readiness (β = 0.516; t = 9.979; p = 0.000). This affirms the strategic role of AI usage in preparing the workforce readiness of the younger generation.
c. Actual Use of AI → Learning Behavior (β = 0.583; t = 12.591; p = 0.000). This indicates that the actual use of AI has a strong impact on changes in students' learning behavior.
d. Effort Expectancy -> Intention to Use AI (β = 0.055; t = 0.895; p = 0.371).
e. Facilitating Conditions -> Intention to Use AI (β = -0.012; t = 0.234; p = 0.815).
f. Intention to Use AI → Actual Use of AI (β = 0.638; t = 17.444; p = 0.000). This reinforces the assumption that the intention to use AI directly drives actual usage.
g. Trust → Intention to Use AI (β = 0.412; t = 5.931; p = 0.000). This proves that trust in AI and its ecosystem is a key determinant of behavioral intention.
h. Perceived Risk -> Intention to Use AI (β = 0.074; t = 1.077; p = 0.281).
i. Performance Expectancy -> Intention to Use AI (β = 0.075; t = 1.188; p = 0.235).
j. Social Influence -> Intention to Use AI (β = 0.091; t = 1.655; p = 0.098).
k. Effort Expectancy -> Intention to Use AI -> Actual Use of AI AI (β = 0.070; t = 1.698; p = 0.090)
l. Trust -> Intention to Use AI -> Actual Use of AI -> Learning Behavior (β = 0.173; t = 5.298; p = 0.000)
m. Social Influence -> Intention to Use AI -> Actual Use of AI (β = 0.058; t = 1.645; p = 0.100)
n. Trust -> Intention to Use AI -> Actual Use of AI (β = 0.296; t = 6.079; p = 0.000)

Hypothesis Testing Results

Based on the results of the path coefficients testing in table 4, it can be concluded that out of the 14 hypotheses formulated in this research, 10 hypotheses are supported and 4 hypotheses are not. The following table unveils the summary of the hypothesis testing results:

Table 5. Path Coefficients Results

Variables of Influence	**Hypothesis**	**Result**
Actual Use of AI -> Ethical Conduct	H1	Supported
Actual Use of AI -> Future Workforce Readiness	H2	Supported
Actual Use of AI -> Learning Behavior	H3	Supported
Effort Expectancy -> Intention to Use AI	H4	Not Supported
Facilitating Conditions -> Intention to Use AI	H5	Not Supported
Intention to Use AI -> Actual Use of AI	H6	Supported
Perceived Risk -> Intention to Use AI	H8	Not Supported
Performance Expectancy -> Intention to Use AI	H9	Not Supported
Social Influence -> Intention to Use AI	H10	Supported
Mediation Effect:		Supported
Effort Expectancy -> Intention to Use AI -> Actual Use of AI	H11	Supported
Trust -> Intention to Use AI -> Actual Use of AI -> Learning Behavior	H12	Supported
Social Influence -> Intention to Use AI -> Actual Use of AI	H13	Supported
Trust -> Intention to Use AI -> Actual Use of AI	H14	Supported

Source: Data processed by the author

The findings indicate that the actual use of AI positively influences learning behavior, as evidenced by a beta coefficient of 0.583 and a p-value of 0.000. This result shows that the actual use of AI tools significantly enhances students' learning behavior. These findings are in line with Swidan et al. (2025), who assert that students who actively use Chat GPT and similar tools tend to have higher self-directed learning motivation and complete tasks more efficiently.

Next, Actual Use of AI → Ethical Conduct (β = 0.449; p = 0.000). The significant influence of AI usage on students' ethical behavior indicates that active engagement with AI not only supports learning but also encourages students to directly confront ethical dilemmas. This is in line with Chung's (2024) findings, which indicate that prospective teachers in California face a tension between the efficiency of AI use and the importance of academic integrity.

Actual Use of AI → Future Workforce Readiness (β = 0.516; p = 0.000). Actual Use of AI → Future Workforce Readiness (β = 0.516; p = 0.000). This finding reinforces the idea that the use of AI in the academic environment plays a strategic role in equipping students with workforce readiness. The result is consistent with Qin & Ma (2022), who emphasized that the adoption of digital technologies, including AI, correlates with students' mental and professional readiness to face the technology-based world of work.

Intention to Use AI → Actual Use of AI (β = 0.638; p = 0.000). The correlation between Intention to Use AI and Actual Use of AI is significant, with a value of 0.638 and a p-value of 0.000. This strong correlation confirms that intention is the main predictor of actual behavior. The relationship supports the UTAUT theory and the findings of Oc, Gonsalves, & Quamina (2024), who also found that students' intentions regarding the use of AI significantly determine actual adoption, especially in the context of academic evaluation.

Trust → Intention to Use AI (β = 0.412; p = 0.000). Trust in AI and institutions becomes a strong driver in increasing the intention to use AI. This finding aligns with the research of Gefen et al. (2003) and is further supported in the context of higher education by Oc, Gonsalves, & Quamina (2024), which indicates that trust is a crucial factor in adopting new technology.

Meanwhile, the path that is not statistically significant ($p < 0.05$) is Effort Expectancy → Intention to Use AI (β = 0.055; p = 0.371). Although the UTAUT theory states that the perception of ease affects the intention to use technology, in this context, effort expectancy does not have a significant impact. This may be due to the general assumption that students today are already quite accustomed to digital interfaces, so ease of use is no longer the main differential factor. These results differ from the findings of Venkatesh et al. (2003) but align more closely with the contemporary context highlighted by Ardito (2024) that students prioritize pedagogical value over technical aspects.

Facilitating Conditions → Intention to Use AI (β = -0.012; p = 0.815). The insignificance of the influence of institutional support suggests that students may not rely heavily on campus infrastructure to access AI. This finding contrasts with the study by Awadallah Alkouk & Khlaif (2024), which suggests the importance of campus policies and support in promoting AI adoption.

Perceived Risk → Intention to Use AI (β = 0.074; p = 0.281). The insignificance of the perceived risk influence could indicate that students are not very concerned about privacy or data misuse, or perhaps they are not yet fully aware of the risks. This contradicts Featherman & Pavlou (2003), who showed that perceived risk is a barrier to technology adoption, and differs from Oc, Gonsalves & Quamina (2024), who noted students' concerns about generative AI.

Performance Expectancy → Intention to Use AI (β = 0.075; p = 0.235). This result is intriguing because it contradicts the UTAUT model's prediction, where the perception of benefits should drive the intention to use. This may be because students view the benefits of AI as a given rather than the primary motivating factor. These results are not in line with Venkatesh et al. (2003) but indicate a shift in dynamics in the post-generative AI era.

Social Influence → Intention to Use AI (β = 0.089; p = 0.106). Social influence was not found to be significant, which may reflect that students' decisions to use AI are more personal than collective. This result is in line with Chung's (2024) findings, which state that although there is discussion among peers, the final decision remains highly individual.

Conclusion

The results of this study show that the actual use of AI tools significantly shapes learning behavior patterns, ethical awareness, and job readiness among students in the digital era. Among the various factors tested, trust in AI and the level of digital literacy among students proved to be the strongest determinants in driving the intention to adopt this technology. These findings underscore that psychological readiness and personal digital competence play a more significant role than external support such as infrastructure or social influence. Additionally, the desire to use AI has been shown to be the biggest factor in whether students actually use it, which then helps improve their learning and shapes their understanding of ethics in school. Students who actively utilize AI not only demonstrate adaptive capabilities towards technology but also directly confront ethical dilemmas that demand personal reflection and responsibility.

Another interesting finding is that classic factors in the UTAUT model, such as performance expectancy, ease of use, and facilitating conditions, turned out to be insignificant. This reflects a paradigm shift: students are no longer focused on technical aspects but rather on the added value of AI to the quality of learning and future relevance. Similarly, ethical and privacy risks have not yet become a primary consideration, indicating a gap in digital ethics literacy that educational institutions need to bridge promptly. Thus, the development of students' work readiness is not sufficient merely by introducing technological tools but must be accompanied by instilling ethical values, critical thinking skills, and adaptive and visionary higher education policies. Higher education institutions must transform, not only as providers of technology but also as curators of values and digital character for the next generation.

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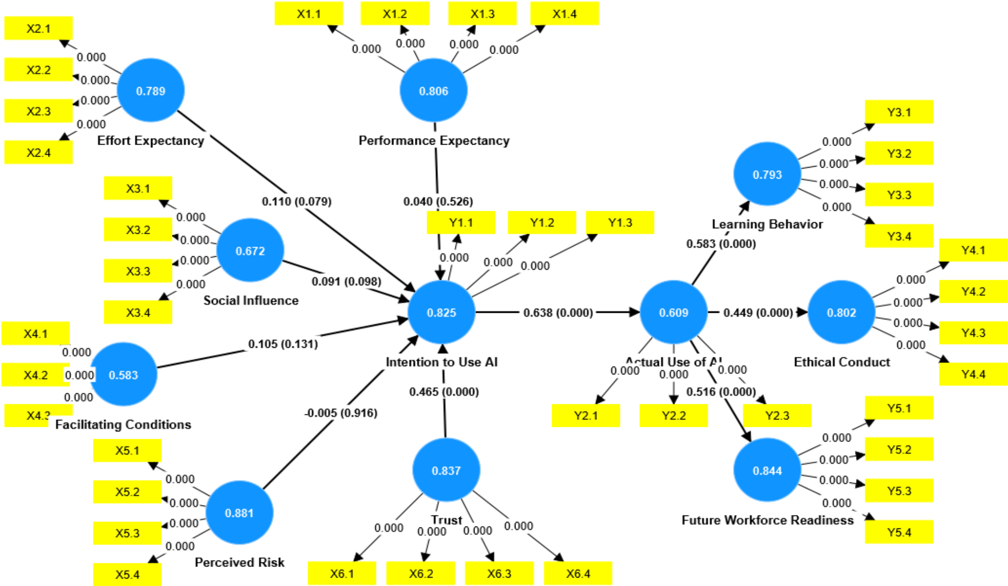
Appendix 1. Bootstrapping results



Appendix 2. Research Questions

Performance Expectancy (PE) X1
1. The use of AI tools helps me understand lecture material more easily.
2. AI tools improve my efficiency in completing academic tasks.
3. I feel that my academic performance has improved due to AI assistance.
4. AI helps me write or organize academic reports better.

Effort Expectancy (EE) X2
1. I found it easy to learn how to use AI tools.
2. Interaction with AI was simple and not confusing.
3. I don't need much effort to use AI for learning.
4. In general, using AI feels comfortable.

Social Influence (SI)X-3
1. My friends encourage me to use AI tools.
2. I use AI because my lecturer or instructor supports its use.
3. I feel social pressure to try or use AI.
4. Many people around me consider it normal to use AI for learning.

Facilitating Conditions (FC)X-4
1. I have sufficient access to tools and networks to use AI.
2. The campus provides support or training related to AI technology.
3. I know where to go for help if I experience difficulties when using AI.

Perceived Risk (PR) 5
1. I am concerned that the results provided by the AI are not accurate.
2. I hesitate to use AI because of plagiarism issues.
3. I am worried that using AI may make me too dependent.
4. I am afraid that the use of AI may negatively impact my academic integrity.

Trust (TR) 6
1. I think AI tools operate in a comprehensible manner.
2. I feel safe using AI for academic purposes.
3. I believe that the results provided by AI are reliable.
4. I trust AI providers to keep my data confidential.

Intention to Use AI (IU) 8.
1. I plan to use AI tools regularly for learning.
2. I will continue to use AI if it is available and allowed.
3. I intend to use AI to help with my academic tasks in the future.

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Actual Use of AI (AU) 9
1. 13. I use AI at least once a week to study.
2. 14. I use AI when working on difficult assignments.
3. 15. I use AI actively during online or self-paced lectures.

Learning Behaviour (LB)10
1. AI helps me learn more independently without relying on lecturers.
2. I have become more accustomed to finding solutions with the help of technology.
3. I focus more on results than process when using AI.
4. Using AI change the way I manage my study time.

Ethical Conduct (EC) 11
1. I make sure not to use AI in exams if they are not authorised.
2. I feel guilty if I rely on AI to complete all assignments.
3. I reread and modify the AI output to suit my abilities.
4. I understand the line between helpful and abusive use of AI in academia.

Future Workforce Readiness (FWR) 12
1. The use of AI makes me better prepared to face challenges in the digital workforce.
2. I believe AI will be an important part of my future work.
3. I feel confident facing new technologies in a professional environment.
4. I am aware that ethics and responsibility will be an important aspect of my work.