Abjadia : International Journal of Education, 10 (2): 306-317 (2025)
DOI: 10.18860/abj.v10i2.32579

2443-0587 (ISSN Online)
2528-3979 (ISSN Print)
abjadia
International Journal of Education
أبجدية
مجلة علمية دولية في التربية
Research and Publication Center
Tarbiyah and Teaching Training Faculty
State Islamic University of Maulana Malik Ibrahim
Malang Indonesia
http://ejournal.uin-malang.ac.id/index.php/abjadia
e-mail: abjadia@uin-malang.com

EXPLORING THE RELATIONSHIP BETWEEN PERSONALITY TRAITS AND STUDENTS' ATTITUDES TOWARD ARTIFICIAL INTELLIGENCE IN EDUCATIONAL CONTEXTS

Sulaiman Abdul Rasid [1*], M. Fadli Al Azhari [2]
[1,2] Institut Agama Islam Negeri Ponorogo, Indonesia

Abstract

The use of artificial intelligence (AI) in higher education continues to increase, but there are still limited studies examining the role of student personality in utilizing this technology for self-development. This study aims to examine the influence of personality dimensions on the use of AI and its impact on self-development in learning. The method used is a quantitative approach with the Partial Least Squares-Structural Equation Modeling (PLS-SEM) analysis technique. A total of 131 students who actively use AI in the academic process became respondents in this study. The results of the analysis show that personality has a significant effect on self-development ($\beta = 0.267$; $p < 0.05$) and on the theory of planned behavior ($\beta = 0.385$; $p < 0.05$). The use of AI also has a significant effect on learning effectiveness ($\beta = 0.639$; $p < 0.05$), and is an important mediator in the self-development process ($\beta = 0.328$; $p < 0.05$). This model shows strong predictive power with R^2 values of 0.792 for self-development and 0.738 for Theory of Planned Behavior. The main contribution of this study is to provide a conceptual and practical basis for the development of technology-based learning designs that are responsive to students' personalities in the era of digital education.

Keywords: Personality Dimensions, AI Acceptance Self-Development, Higher Education, Learning Effectiveness

***CorrespondenceAddress:**	sulaiman.abdul.rasid@iainponorogo.ac.id

	Received	Revised	Accepted	Published
Article History	2025-04-14	2025-05-20	2025-05-28	2025-06-30

INTRODUCTION | مقدمة

The development of artificial intelligence (AI) technology has brought about major changes in higher education, especially in the way students learn, access information, and develop their potential (Ding et al., 2025). AI is the ability of machines to imitate human cognitive functions such as learning, reasoning, and problem solving. Tools such as ChatGPT, Bard, and Claude are now widely used by students as learning assistants, writers, or even as self-reflection tools.(Crompton & Burke, 2023; Lounsbury et al., 2008)

In this context, it is important to understand how personality traits relatively stable psychological characteristics that shape a person's thinking and behavior play a role in influencing attitudes toward AI and how students use this technology in their self-development process (Harteis et al., 2020). One of the common approaches used in measuring personality is the Big Five Personality Traits or OCEAN, which includes five main dimensions: Openness to Experience openness to new experiences, Conscientiousness thoroughness and discipline, Extraversion tendency to be sociable, Agreeableness cooperative and empathetic nature, and Neuroticism emotional stability. (Kovbasiuk et al., 2024; Razafiarivony & Odhiambo, 2025)

The use of AI technology by students is no longer just a technical tool, but has become part of a complex and personal learning process. Therefore, it is necessary to examine how students' personality characteristics affect the way they adapt, regulate themselves, improve cognitive abilities, and build academic efficacy through the help of AI (Acosta-Enriquez et al., 2024; Mauti & Ayieko, 2024). Although there have been several studies that highlight the relationship between personality and technology adoption, most are still general and have not specifically examined how the five personality dimensions affect the use of AI in the context of student self-development. Moreover, in Indonesia, research on the relationship between personality, AI, and student self-development is still very limited. This indicates an important gap that needs to be filled through more focused empirical studies (Lan & Zhou, 2025; Vieriu & Petrea, 2025a).

This study has a unique contribution because it not only examines the relationship between personality and AI use, but also links it directly to the process of student self-development. In addition, this study will also explore the ethical dimensions of AI use, especially how personality differences can affect perceptions and moral responsibilities in using technology wisely. With this approach, the study is expected to provide conceptual and practical contributions to the development of more adaptive, inclusive, and character-centered learning strategies for students.

METHOD | منهج

Research Design

This study uses a quantitative approach to examine the influence of personality traits of AI-using students on self-development in learning. The data analysis method used is Partial Least Squares–Structural Equation Modeling (PLS-SEM) because it is able to handle complex latent variable relationships, including mediation effects, and is suitable for small to medium sample sizes. Purposive sampling technique was used to select respondents, namely students who actively use AI technology in academic activities (Harwisaputra et al., 2024; Purnomo et al., 2024a; Rasid et al., 2024). The number of respondents in this study was 131 students, in accordance with the minimum sample requirements in PLS-SEM (Hair et al., 2021). Construct validity testing was carried out through confirmatory factor analysis, while instrument reliability was tested using Cronbach's Alpha and Composite Reliability (CR). All testing and analysis were carried out using SmartPLS software.

Research Sample and Procedure

This study involved 131 students as participants, selected based on their active use of artificial intelligence (AI) in the learning process. The sampling technique applied was purposive sampling, which means respondents were chosen based on specific criteria aligned with the goals of the research. In this case, participants were students who had experience using AI for academic purposes and demonstrated a clear commitment to self-development. Purposive sampling was chosen to ensure that the data collected came from individuals who truly understood the context of AI usage and its relevance to personal growth. This approach allowed the researcher to gather more focused and meaningful data.

Although the sample was not selected randomly, the total of 131 respondents is considered adequate for quantitative research, particularly when using Partial Least Squares-Structural Equation Modeling (PLS-SEM). This method is known for its flexibility in analyzing complex models and does not require normally distributed data. It is also well-suited for studies with medium to small sample sizes. In the structural model of this study, there are three major paths leading to the dependent variable, self-development. (Hair et al., 2021) According to general guidelines for PLS-SEM, the minimum sample size should be ten times the number of such paths, which means at least 30 participants. Therefore, with 131 students, the sample size is sufficient to ensure valid analysis and support broader generalization of the findings.

This study involved 131 students as participants, who were selected based on Students Who Use Artificial Intelligence (AI) Actively in the Learning Process in Lectures in Completing Assignments. The sampling technique applied was random sampling, which means that respondents were selected based on certain criteria that were in line with the objectives of the study. In this case, participants were students who had experience using AI for academic purposes and showed a clear commitment to self-development. Random sampling was chosen to ensure that the data collected came from individuals who truly understood the context of AI use and its relevance to personal growth.

This approach allows researchers to collect more focused and meaningful data. Although the sample was not selected randomly, a total of 131 respondents was considered sufficient for quantitative research, especially when using Partial Least Squares-Structural Equation Modeling (PLS-SEM). This method is known for its flexibility in analyzing complex models and does not require normally distributed data. This method is also suitable for research with medium to small sample sizes. In the structural model of this study, there are three main paths leading to the dependent variable, self-development. (Hair et al., 2021) According to general guidelines for PLS-SEM, the minimum sample size should be ten times the number of paths, which means at least 30 participants. Therefore, with 131 students, the sample size is sufficient to ensure valid analysis and support broader generalization of the findings.

Data Collection Techniques

Data collection in this study was carried out using a closed-ended questionnaire based on a Likert scale. The instrument was designed to measure four main variables: personality trait (X^1), use of AI (X^2), self-development (Y), and the Theory of Planned Behavior (Z). Each variable was assessed through a series of statements rated on a 5-point Likert scale, where respondents indicated their level of agreement, ranging from strongly disagree (1) to strongly agree (5).

The use of the Likert scale enabled the researcher to quantitatively capture participants' attitudes, perceptions, and behavioral tendencies toward each variable. The questionnaire items were carefully developed based on specific indicators of each construct to ensure the validity and reliability of the data collected.

Table 1. The Construct of the Research Variables

No	Variable	Indicators	Construct	References
1	X1: Personality Traits	Technology openness.	C1	(Bewersdorff et al., 2025; Wang & Li, 2024; Weng et al., 2024)
2		Usage responsibility.	C2	
3		Emotion management.	C3	
4		Learning initiative.	C4	
5		Information evaluation.	C5	
6		Technology adaptation.	C6	
7		Exploration comfort.	C7	
8		Utilization consistency.	C8	
9		Stress control.	C9	
10		Sharing interaction.	C10	
11	X2:AI Utilization	Concept understanding.	B1	(Ji et al., 2025; Parsakia, 2023; Sardi et al., 2025)
12		Material summarization.	B2	
13		Academic references.	B3	
14		Comprehension checking.	B4	

No	Variable	Indicators	Construct	References
15		Learning strategies.	B5	
16		Analytical skills.	B6	
17		Information organization.	B7	
18		Task completion.	B8	
19		Information searching.	B9	
20		Routine usage.	B10	
21	Y: Planned Behavior Theory	Understanding belief.	A1	(Ma'amor et al., 2024; Nazaretsky et al., 2025; Stein et al., 2024)
22		Academic support.	A2	
23		Environmental encouragement.	A3	
24		Learning effectiveness.	A4	
25		Optimal skills.	A5	
26		Learning control.	A6	
27		Self-confidence.	A7	
28		Usage motivation.	A8	
29		Self-development.	A9	
30		Social engagement.	A10	
31	Z: Self-Development	Decision confidence.	E1	(Katona & Gyonyoru, 2025; Rogers, 2004; Sasikala & Ravichandran, 2024; Vieriu & Petrea, 2025b)
32		Critical skills.	E2	
33		Independent learning.	E3	
34		Adaptability ability.	E4	
35		Time management.	E5	
36		Learning goals.	E6	
37		Improvement motivation.	E7	
38		Learning discipline.	E8	
39		Effective strategies.	E9	
40		Skill enhancement.	E10	

Research Hypothesis

H-DIR1: Personality Trait Has a Positive Influence on Self-Development.
H-DIR2: Personality Trait Has a Positive Influence on the Theory of Planned Behavior.
H-DIR3: AI Utilization Has a Positive Impact on Self-Development.
H-DIR4: AI Utilization has a positive effect on the Theory of Planned Behavior.
H-DIR5: Self-Development has a positive influence on the Theory of Planned Behavior.
H1: Personality Trait Mediates the Effect of Self-Development on the Theory of Planned Behavior.
H2: AI Utilization mediates the influence of Self-Development on the Theory of Planned Behavior.

RESULT | نتائج

PLS-SEM Analysis: Outer Model

Evaluation of the measurement model is crucial to ensure that indicators used to measure constructs or latent variables align with research objectives and maintain high quality. Construct validity verification is the primary purpose of measurement model evaluation (Purnomo et al., 2024b). By analyzing the relationships between indicators and constructs, researchers can confirm that measurements accurately reflect the desired construct aspects. Through analysis of factor loadings, reliability, and discriminant validity, researchers can determine which indicators should be included in the analysis and which should be removed (Azhari & Effendi, 202).

Convergent validity in PLS-SEM demonstrates how effectively the indicators or manifestation variables used to measure a construct correspond to the actual construct. Higher convergent validity indicates better quality of construct measurement. Researchers can test consistency among indicators used to measure the same construct using convergent validity measures. Convergent validity helps ensure that interpretations of PLS-SEM analysis results truly reflect the intended construct. This is essential for ensuring research accuracy and findings. Table 1 below presents the results of convergent validity, reliability, and AVE testing from the PLS algorithm output.

Evaluation of Measurement Models

Based on the results of the validity and reliability analysis, it can be concluded that each construct in this study meets the required validity criteria. In terms of convergent validity, all indicators have a factor loading value above 0.70, indicating that each indicator strongly contributes to the construct being measured. Furthermore, the Average Variance Extracted (AVE) values for all variables exceed 0.50, meaning that more than 50% of the variance from the indicators can be explained by the corresponding construct. This confirms that the constructs used in this study meet the requirements for convergent validity.

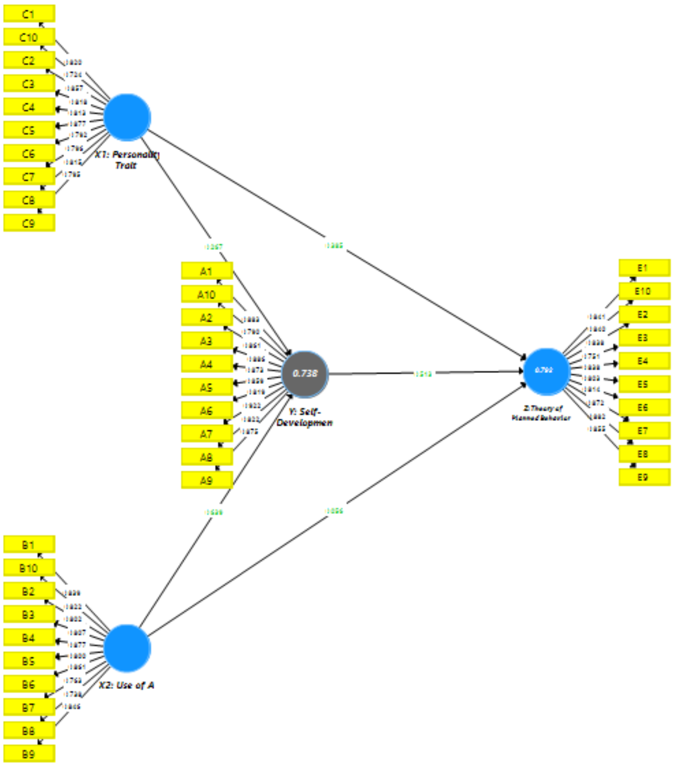

Figure 1. Evaluation of the Measurement Model

From the reliability perspective, the Cronbach's Alpha (CA) and rho_A values for each construct are above 0.70, demonstrating that the research instrument has good internal consistency. Additionally, the Composite Reliability (CR) values, which also exceed 0.70 for each construct, confirm that all variables have a high level of reliability and can be consistently used to measure the intended concepts. Specifically, the Personality Trait (X_1) construct has an AVE of 0.659 with a high level of reliability (CA = 0.942, CR = 0.951), indicating that the indicators effectively represent students' personality traits. The Use of AI (X_2) construct also demonstrates high validity and reliability, with an AVE of 0.667 and a CR of 0.952, confirming that its indicators consistently measure AI usage in learning. The Self-Development *(Y)* construct has the highest AVE value of 0.739, reinforcing that its indicators are highly representative of students' self-development. Additionally, the Theory of Planned Behavior (*Z*) construct also exhibits strong validity and reliability, with an AVE of 0.696 and a CR of 0.958, confirming that this construct is well-measured in the study.

Table 2. Outer Model: Convergent Validity and Reliability

No	Variable	Indicator	Conver Validity		Consistency Reliability		
			FL (λ>0.70)	AVE (>0.50)	CA (α>0.70)	rho_A (ϕ>0.70)	CR (δ>0.70)
1		C1	0.820				
2		C2	0.857				
3		C3	0.818				
4		C4	0.813				
5	X1: Personality Trait	C5	0.877	0.659	0.942	0.946	0.951
6		C6	0.792				
7		C7	0.796				
8		C8	0.815				
9		C9	0.795				
10		C10	0.724				
11		B1	0.839				
12		B2	0.802				
13		B3	0.807				
14		B4	0.877				
15	X2: AI Utilization	B5	0.800	0.667	0.944	0.948	0.952
16		B6	0.861				
17		B7	0.763				
18		B8	0.738				
19		B9	0.846				
19		B10	0.822				
20		A1	0.882				
21		A2	0.860				
22		A3	0.886				
23		A4	0.874				
24	Y: Self-Development	A5	0.859	0.739	0.961	0.962	0.966
25		A6	0.819				
26		A7	0.922				
27		A8	0.823				
28		A9	0.875				
19		A10	0.792				
20		E1	0.841				
21		E2	0.837				
22		E3	0.749				
23		E4	0.836				
24	Z: Theory of Planned Behavior	E5	0.803	0.696	0.951	0.952	0.958
25		E6	0.815				
26		E7	0.873				
27		E8	0.883				
28		E9	0.856				
29		E10	0.841				

Based on these results, it can be concluded that all indicators used in this research are valid and reliable. With strong convergent validity and high reliability, this research model can be considered to have a high-quality measurement framework. This ensures that the obtained analytical results can be trusted in assessing the influence of personality traits and AI usage on students' self-development through the Theory of Planned Behavior.

Table 3. Discriminant Validity: The Fornell Larcker and HTMT

Variable	*X1*	*X2*	*Y*	*Z*
X1	0.812**			
X2	0.803* 0.759**	0.817**		
Y	0.782* 0.751**	0.872* 0.841**	0.860**	
Z	0.846*	0.814*	0.886*	

	0.813**	0.778**	0.849**	0.834**

*NB: Fornell Larcker** And HTMT**

The discriminant validity test using the Fornell-Larcker criterion compares the square root of each construct's AVE with the correlations between constructs. The results show that most AVE square roots—X_1 (*0.812*), X_2 (*0.817*), Y (0.860), and *Z* (*0.834*)—are higher than their respective inter-construct correlations. Two exceptions were noted: the correlation between X_2 and Y (*0.842*), and between *Y* and *Z* (*0.849*), which slightly exceed their corresponding AVE values. Nevertheless, the overall findings indicate that the model still meets the requirements for discriminant validity.

Discriminant validity was also evaluated using the HTMT (Heterotrait-Monotrait Ratio) approach, which determines how distinct each construct is from the others in the model. A value below 0.90 generally indicates acceptable discriminant validity. The results show HTMT values of 0.803 between X_1 and X_2, 0.782 between X_1 and *Y*, 0.846 between X_1 and Z, 0.872 between X_2 and Y, 0.814 between X_2 and Z, and 0.886 between *Y* and *Z*. Since all values are below the 0.90 threshold, it can be concluded that the constructs are conceptually distinct and do not significantly overlap. Therefore, the model fulfills the discriminant validity criteria based on the HTMT method.

PLS-SEM Analysis: Evaluation of Structural Model (Inner Model)

Path Analysis and Hypothesis Testing

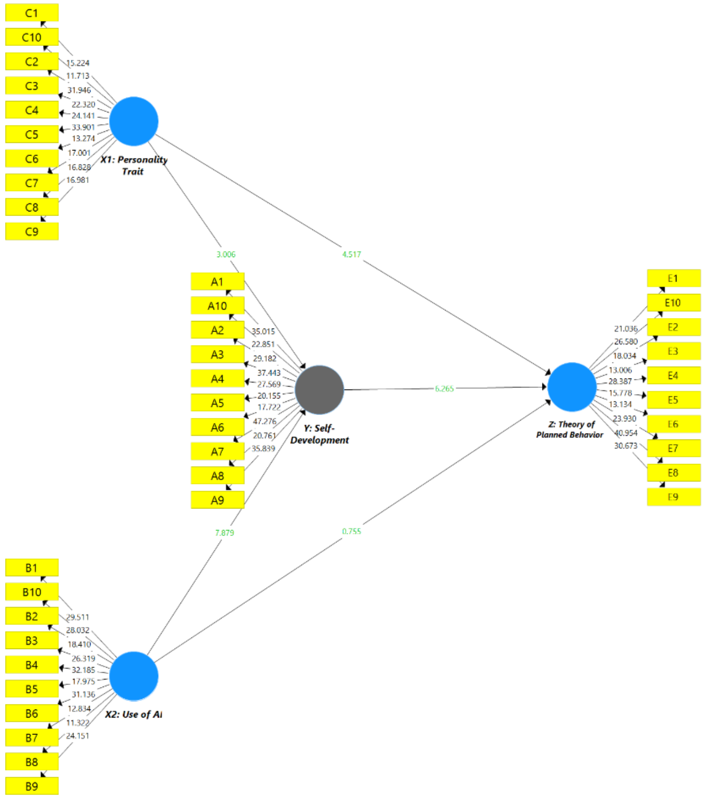

Figure 2. Evaluation of Structural Model

Path analysis and hypothesis testing, including direct and indirect effects (mediation), are essential components for understanding the mechanisms of relationships between variables. This testing allows researchers to identify the extent to which independent variables directly influence dependent variables, and whether there are mediator variables that strengthen or explain some of the influence. In the context of this study, the mediating role of self-experience in the relationship between principal leadership and self-development with teacher competence provides deeper insight into the factors that influence teacher competence. Understanding the dynamics of these relationships is invaluable for developing more targeted and effective strategies for improving educator quality.

The analysis results indicate that only Y and Z have reported R^2 values. Variable Y shows an R^2 of 0.792, while variable Z has a value of 0.738. Both are classified as having a moderate level of influence. Although these values are relatively high, in social research they are still considered moderate due to the possibility of other influencing factors that are not captured within the current model. An R^2 value of 0.792 for variable Y suggests that approximately 79.2% of the changes in the dependent variable can be explained by this variable. Likewise, an R^2 of 0.738 for *Z* indicates that around 73.8% of the variation is influenced by *Z*. These values reflect a strong contribution, but given the complexity of social phenomena, the "moderate" label is applied to provide a balanced and realistic interpretation of the model's explanatory power.

Tabel 4. Measurement of Structural Model: R^2, f^2, Q^2

Variable	R^2		f^2		Construct Cross-Validated (Q^2)				
					Redundancy		Communality		Predictive
	Value	Decision	Value	Decision	SSE	Q^2	SSE	Q^2	Power
X1			0.114	Small	1310.000		562.299	0.571	Strong
X2			0.662	Large	1310.000		539.422	0.588	Strong
Y	0.792	Moderate			614.104	0.531	436.302	0.667	Strong
Z	0.738	Moderate			611.225	0.533	493.632	0.623	Strong
X1			0.276	Medium					
X2			0.003	Very Small					
Y			0.334	Medium					

The analysis results indicate that X_1 has an f^2 value of 0.114, categorized as small, meaning its influence on Y is relatively limited. In contrast, X_2 has an f^2 value of 0.662, which is considered large, showing that X_2 makes a strong contribution in explaining Y. For the variable *Z*, X_1 scores 0.276, placing it in the medium category, which means it plays a meaningful role in influencing *Z*. Meanwhile, X_2 only scores 0.003, falling into the very small category, indicating its effect on *Z* is practically negligible. *Y*, with a value of 0.334, is also in the medium range, suggesting it has a significant role in explaining variations in *Z*.

Based on the Q^2 calculation results, all variables in the model fall into the strong category, indicating that the model has excellent predictive capability. The variable X1 has a Q^2 value of 0.571, reflecting a reliable level of predictive accuracy for X_1. The Q^2 value for X_2 is 0.588, also within the strong range, showing that the model is highly capable of explaining X2. Additionally, *Y* shows the highest Q^2 value at 0.667, indicating that the model performs very well in predicting *Y*. Finally, *Z* has a Q^2 value of 0.623, which also falls into the strong category, confirming the model's ability to explain *Z* accurately. In summary, the Q^2 values across all four constructs demonstrate that the model possesses a consistently strong and dependable level of predictive power.

Tabel 5. Results of Path Coefficients: Direct Effects

Hypothesis	**Path Analysis**	**β-Values (+/-)**	**Sample Mean**	**SDV**	**T-Statistics (>1,96)**	**P-Values (<0,05)**	**Decision**
H-DIR1	X1→Y	0.267	0.268	0.088	3.028	0.003	Accepted
H-DIR2	X1→Z	0.385	0.386	0.089	4.305	0.000	Accepted
H-DIR3	X2 → Y	0.639	0.642	0.078	8.230	0.000	Accepted
H-DIR4	X2 →Z	0.056	0.063	0.083	0.677	0.499	Rejected
H-DIR5	Y→ Z	0.513	0.507	0.083	6.189	0.000	Accepted

The direct effect analysis shows that variable X_1 has a positive and significant influence on variable Y. This is reflected in the path coefficient of 0.267, a t_{value} of 3.028, and a p_{value} of 0.003, which is below the 0.05 significance level. This means that higher X_1 values are associated with increased AI usage in learning (Y). Furthermore, X_1 also has a significant effect on Z, with a coefficient of 0.385, t_{value} of 4.305, and p-value of 0.000, indicating that X_1 contributes to enhancing students' self-development.

In addition, X_2 shows a significant positive effect on Y, as indicated by a high coefficient of 0.639, t_{value} of 8.230, and p-value of 0.000. This suggests that X_2 positively drives AI usage. However, the relationship between X_2 and Z is not significant, with a low coefficient of 0.056, t_{value} of 0.677, and p_{value} of 0.499, indicating that X_2 does not directly impact self-development. On the other hand, variable Y significantly affects Z, with a coefficient of 0.513, t_{value} of 6.189, and p_{value} of 0.000. This confirms that AI usage (Y) plays a direct role in supporting self-development (Z). Overall, both X_1 and X_2 influence Y, but only X_1 and Y have a direct effect on Z.

Tabel 6. Results of Path Coefficients: Indirect Effects

Hypothesis	Path Analysis	β-Values (+/-)	Sample Mean	SDV	T-Statistics (>1,96)	P-Values (<0,05)	Decision
HI	X1 → Y→Z	0.137	0.134	0.045	3.070	0.002	Accepted
H2	X2→Y→Z	0.328	0.327	0.074	4.419	0.000	Accepted

Based on the results of indirect effect analysis in Table 7, the path from X_1 to Z through Y shows a coefficient value of 0.137, with a $t_{statistic}$ of 3.070 and a p_{value} of 0.002. Since the $t_{statistic}$ is greater than 1.96 and the p-value is below 0.05, it can be concluded that the indirect path from X_1 to Z through Y is significant. Therefore, hypothesis H1 is accepted. Furthermore, for the indirect path from X_2 to Z through Y, the coefficient is 0.328, with a $t_{statistic}$ of 4.419 and a p_{value} of 0.000. These values indicate that the indirect effect of X_2 on Z through Y is also significant. Hence, hypothesis H2 is accepted.

DISCUSSION | مناقشة

The results of the study show that personality traits play an important role in influencing the use of AI technology and the process of student self-development. The five main dimensions in the Big Five openness, conscientiousness, extraversion, agreeableness, and neuroticism contribute differently to how students adapt, learn, and face academic challenges. For example, students with high levels of openness tend to be more open to exploring new technologies such as AI, while conscientiousness plays a role in discipline and consistency in learning (Bleidorn et al., 2021a; Buss, 1989).

The use of AI in the context of learning has been shown to have a positive impact on a more personal, adaptive, and efficient learning experience. Students can use AI to obtain fast feedback, organize learning materials systematically, and deepen their understanding of complex concepts. However, the effectiveness of this use is greatly influenced by the personality characteristics of each individual. Therefore, personalization of AI-based learning that considers personality profiles is crucial in increasing the effectiveness of student learning and self-development.

This finding is in line with previous studies that emphasize the importance of the suitability between individual character and the technological approach used in education. Compared to previous research, this study makes a novel contribution by highlighting how the integration of

AI and personality can shape a more targeted self-development path (Bleidorn et al., 2021b; Verduyn & Brans, 2012). This underscores the need for flexible, adaptive, and data-driven pedagogical strategies to create a more inclusive and transformative learning ecosystem.

CONCLUSSION | خاتمة

This study shows that student personality has a significant influence on the use of AI technology and self-development in learning. Dimensions such as openness and conscientiousness encourage the effective use of AI, which in turn improves students' learning and adaptability. The research model has strong predictive power, emphasizing the importance of integration between individual factors and technology in supporting student development. Therefore, AI-based learning designs need to be personalized according to personality profiles to maximize learning outcomes and readiness to face future challenges. This study also highlights the importance of an ethical and responsible approach to the use of AI in higher education, and opens up opportunities for further, more in-depth studies.

BIBLIOGRAPHY | مراجع

Acosta-Enriquez, B. G., Arbulú Pérez Vargas, C. G., Huamaní Jordan, O., Arbulú Ballesteros, M. A., & Paredes Morales, A. E. (2024). Exploring attitudes toward ChatGPT among college students: An empirical analysis of cognitive, affective, and behavioral components using path analysis. *Computers and Education: Artificial Intelligence*, *7*, 100320. https://doi.org/10.1016/j.caeai.2024.100320

Azhari, M. F. A., & Effendi, M. (2024). Analysis Of Students' Self Awareness In Mediating The Influence Of Management Information Systems And Action Card Systems On Reinforcement Of Learning. *Abjadia : International Journal of Education*, *9*(2), Article 2. https://doi.org/10.18860/abj.v9i2.27835

Bewersdorff, A., Hornberger, M., Nerdel, C., & Schiff, D. S. (2025). AI advocates and cautious critics: How AI attitudes, AI interest, use of AI, and AI literacy build university students' AI self-efficacy. *Computers and Education: Artificial Intelligence*, *8*, 100340. https://doi.org/10.1016/j.caeai.2024.100340

Bleidorn, W., Hopwood, C. J., Back, M. D., Denissen, J. J. A., Hennecke, M., Hill, P. L., Jokela, M., Kandler, C., Lucas, R. E., Luhmann, M., Orth, U., Roberts, B. W., Wagner, J., Wrzus, C., & Zimmermann, J. (2021a). Personality Trait Stability and Change. *Personality Science*, *2*(1), e6009. https://doi.org/10.5964/ps.6009

Bleidorn, W., Hopwood, C. J., Back, M. D., Denissen, J. J. A., Hennecke, M., Hill, P. L., Jokela, M., Kandler, C., Lucas, R. E., Luhmann, M., Orth, U., Roberts, B. W., Wagner, J., Wrzus, C., & Zimmermann, J. (2021b). Personality Trait Stability and Change. *Personality Science*, *2*(1), e6009. https://doi.org/10.5964/ps.6009

Buss, A. H. (1989). Personality as traits. *American Psychologist*, *44*(11), 1378–1388. https://doi.org/10.1037/0003-066X.44.11.1378

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, *20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Ding, N., Chen, M., & Hu, L. (2025). Examining the impact of big five personality traits on generation Z designers' subscription to paid AI drawing tools using SEM and FsQCA. *Scientific Reports*, *15*(1), 17587. https://doi.org/10.1038/s41598-025-02926-8

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). An Introduction to Structural Equation Modeling. In J. F. Hair Jr., G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, & S. Ray (Eds.), *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook* (pp. 1–29). Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7_1

Harteis, C., Goller, M., & Caruso, C. (2020). Conceptual Change in the Face of Digitalization: Challenges for Workplaces and Workplace Learning. *Frontiers in Education*, *5*. https://doi.org/10.3389/feduc.2020.00001

Ji, Y., Zhong, M., Lyu, S., Li, T., Niu, S., & Zhan, Z. (2025). How does AI literacy affect individual innovative behavior: The mediating role of psychological need satisfaction, creative self-efficacy, and self-regulated learning. *Education and Information Technologies*. https://doi.org/10.1007/s10639-025-13437-4

Katona, J., & Gyonyoru, K. I. K. (2025). Integrating AI-based adaptive learning into the flipped classroom model to enhance engagement and learning outcomes. *Computers and Education: Artificial Intelligence*, *8*, 100392. https://doi.org/10.1016/j.caeai.2025.100392

Kovbasiuk, A., Triantoro, T., Przegalińska, A., Sowa, K., Ciechanowski, L., & Gloor, P. (2024). The personality profile of early generative AI adopters: A big five perspective. *Central European Management Journal*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/CEMJ-02-2024-0067

Lan, M., & Zhou, X. (2025). A qualitative systematic review on AI empowered self-regulated learning in higher education. *Npj Science of Learning*, *10*(1), 1–16. https://doi.org/10.1038/s41539-025-00319-0

Lounsbury, J. W., Steel ,Robert P., Gibson ,Lucy W., & and Drost, A. W. (2008). Personality traits and career satisfaction of human resource professionals. *Human Resource Development International*, *11*(4), 351–366. https://doi.org/10.1080/13678860802261215

Ma'amor, H., Achim, N., Ahmad, N. L., Roszaman, N. S., Anuar, N. N. K., Azwa, N. C. A. K., Rahman, S. N. A., & Hamjah, N. A. A. (2024). The Effect of Artificial Intelligence (AI) on Students' Learning. *Information Management and Business Review*, *16*(3S(I)a), 856–867. https://doi.org/10.22610/imbr.v16i3S(I)a.4178

Mauti, J. M., & Ayieko, D. S. (2024). Ethical Implications of Artificial Intelligence in University Education. *East African Journal of Education Studies*, *8*(1), Article 1. https://doi.org/10.37284/eajes.8.1.2583

Nazaretsky, T., Mejia-Domenzain, P., Swamy, V., Frej, J., & Käser, T. (2025). The critical role of trust in adopting AI-powered educational technology for learning: An instrument for measuring student perceptions. *Computers and Education: Artificial Intelligence*, *8*, 100368. https://doi.org/10.1016/j.caeai.2025.100368

Parsakia, K. (2023). The Effect of Chatbots and AI on The Self-Efficacy, Self-Esteem, Problem-Solving and Critical Thinking of Students. *Health Nexus*, *1*(1), Article 1. https://doi.org/10.61838/kman.hn.1.1.11

Purnomo, A. K., Munir, M., & Daryono, R. W. (2024a). The Role of Self-Awareness in Mediating the Influence of Islamic Boarding School Policies and Regulations on the Competency

Development of Santri: PLS-SEM Approach. *AL-ISHLAH: Jurnal Pendidikan*, *16*(3), Article 3. https://doi.org/10.35445/alishlah.v16i3.5179

Purnomo, A. K., Munir, M., & Daryono, R. W. (2024b). The Role of Self-Awareness in Mediating the Influence of Islamic Boarding School Policies and Regulations on the Competency Development of Santri: PLS-SEM Approach. *AL-ISHLAH: Jurnal Pendidikan*, *16*(3), Article 3. https://doi.org/10.35445/alishlah.v16i3.5179

Rasid, S. A., Mukhibat, M., & Daryono, R. W. (2024). Evaluation of the Independent Curriculum in Special Schools to Enhance Participation of Children with Special Needs. *Al-Hayat: Journal of Islamic Education*, *8*(2), 817–832.

Razafiarivony, M.-A., & Odhiambo, J. N. (2025). Exploring Students' Personality Traits and Attitudes toward Artificial Intelligence and its Adoption in Higher Education Learning Experience. *Pan-African Journal of Education and Social Sciences*, *6*(1), Article 1. https://doi.org/10.56893/pajes2025v06i01.02

Rogers, L. W. (Louis W. (2004). *Self-Development and the Way to Power*. https://www.gutenberg.org/ebooks/13142

Sardi, J., Darmansyah, Candra, O., Yuliana, D. F., Habibullah, Yanto, D. T. P., & Eliza, F. (2025). How Generative AI Influences Students' Self-Regulated Learning and Critical Thinking Skills? A Systematic Review. *International Journal of Engineering Pedagogy (iJEP)*, *15*(1), Article 1. https://doi.org/10.3991/ijep.v15i1.53379

Sasikala, P., & Ravichandran, R. (2024). Study on the Impact of Artificial Intelligence on Student Learning Outcomes. *Journal of Digital Learning and Education*, *4*(2), Article 2. https://doi.org/10.52562/jdle.v4i2.1234

Stein, J.-P., Messingschlager, T., Gnambs, T., Hutmacher, F., & Appel, M. (2024). Attitudes towards AI: Measurement and associations with personality. *Scientific Reports*, *14*(1), 2909. https://doi.org/10.1038/s41598-024-53335-2

Verduyn, P., & Brans, K. (2012). The relationship between extraversion, neuroticism and aspects of trait affect. *Personality and Individual Differences*, *52*(6), 664–669. https://doi.org/10.1016/j.paid.2011.12.017

Vieriu, A. M., & Petrea, G. (2025a). The Impact of Artificial Intelligence (AI) on Students' Academic Development. *Education Sciences*, *15*(3), Article 3. https://doi.org/10.3390/educsci15030343

Vieriu, A. M., & Petrea, G. (2025b). The Impact of Artificial Intelligence (AI) on Students' Academic Development. *Education Sciences*, *15*(3), Article 3. https://doi.org/10.3390/educsci15030343

Wang, L., & Li, W. (2024). The Impact of AI Usage on University Students' Willingness for Autonomous Learning. *Behavioral Sciences*, *14*(10), 956. https://doi.org/10.3390/bs14100956

Weng, X., Xia, Q., Ahmad, Z., & Chiu, T. K. F. (2024). Personality traits for self-regulated learning with generative artificial intelligence: The case of ChatGPT. *Computers and Education: Artificial Intelligence*, *7*, 100315. https://doi.org/10.1016/j.caeai.2024.100315