

The Role of AI Adoption and Its Relationship with Academic Performance among Industrial Engineering Students

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ABSTRACT

The use of Artificial Intelligence (AI) in higher education is reshaping students' learning behaviors and academic performance. This study investigates how AI adoption, self-efficacy in AI learning, and design thinking mindset influence academic performance among Industrial Engineering students, with self-competence as a mediating factor. Data were collected from 80 undergraduate students at Universitas Atma Jaya Yogyakarta (cohorts 2021–2024) through a validated questionnaire. The respondents included 31.25% freshmen, 23.75% sophomores, 26.25% juniors, and 18.75% seniors. Design Thinking, introduced early through labs and projects, is a key mindset in the Industrial Engineering curriculum and is explicitly applied in the Capstone Project. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the relationships between constructs. The findings indicate that self-efficacy in AI learning has a significant positive effect on both self-competence and academic performance. Similarly, design thinking mindset positively influences academic performance. However, AI adoption did not show a significant direct effect on academic performance. The mediating role of self-competence was not supported, as it did not significantly influence academic performance nor mediate the relationship between self-efficacy or design thinking and academic performance. These results underscore the importance of psychological traits such as self-efficacy and mindset in shaping academic outcomes in AI-integrated learning environments. The study contributes to AI-in-education research and offers insights for curriculum, instructional design, and institutional strategies to support academic success through technology adoption.

Keywords: Artificial Intelligence, Academic Performance, Self-Efficacy, Design Thinking Mindset, PLS-SEM

1. INTRODUCTION

The rapid integration of Artificial Intelligence (AI) in higher education is transforming the way students interact with learning materials, instructors, and problem-solving processes. In particular, AI tools such as ChatGPT and other generative AI systems have become increasingly prevalent in engineering education, offering personalized support and enhancing learning efficiency. These tools are reshaping academic experiences by assisting students in information retrieval, critical thinking, and performance improvement.

Among Industrial Engineering students, AI adoption is especially relevant as it aligns with the analytical and systems-oriented nature of the discipline. The ability to explore, simulate, and analyze information using AI can lead to improvements in academic performance. However, previous studies indicate that the impact of AI in education is not determined solely by access or usage. Psychological and cognitive factors, such as students' self-efficacy and mindset, play crucial roles in moderating the influence of AI on learning outcomes (Ahn, 2024; Almufarreh, 2024; Saritepeci & Durak, 2024).

Self-efficacy is broadly defined as an individual's belief in their ability to accomplish tasks and overcome challenges they face. It reflects the confidence a person has in organizing and executing actions required to achieve specific outcomes (Wilde & Hsu, 2019). Self-efficacy in AI learning refers to students' belief in their ability to effectively learn and operate AI-based tools. Higher self-efficacy may lead to increased motivation, more effective learning strategies, and ultimately better academic results. Design thinking mindset, a structured yet flexible problem-solving approach, is another cognitive trait emphasized in Industrial Engineering education. This mindset encourages creativity, empathy, and iterative learning, all of which are essential when working with emerging technologies like AI.

While both self-efficacy and design thinking mindset may have direct influences on academic performance, they may also exert indirect effects through a mediating variable: self-competence. Self-competence encompasses a learner's belief in their overall capability to successfully perform academic tasks, which may be strengthened by cognitive traits and attitudes toward AI and innovation.

This study investigates the relationships among AI adoption, self-efficacy in AI learning, design thinking mindset, self-competence, and academic performance among Industrial Engineering students. It aims to explore both direct and indirect effects using a structural model. The research is guided by the following hypotheses:

- H1:** AI adoption has a significant positive effect on academic performance.
- H2:** Self-efficacy in AI learning has a significant positive effect on self-competence.
- H3:** Self-efficacy in AI learning has a significant positive effect on academic performance.
- H4:** Design thinking mindset has a significant positive effect on self-competence.
- H5:** Design thinking mindset has a significant positive effect on academic performance.
- H6:** Self-competence has a significant positive effect on academic performance.
- H7:** Self-competence mediates the relationship between self-efficacy in AI learning and academic performance.
- H8:** Self-competence mediates the relationship between design thinking mindset and academic performance.

This research contributes to the growing body of knowledge on AI in education by highlighting the interplay of psychological and behavioral factors in technology-supported learning environments. The findings are expected to offer valuable insights for instructional designers, educators, and policymakers seeking to enhance student performance through strategic AI integration in engineering education.

2. METHOD

The research instrument employed in this study was a questionnaire administered in the Indonesian language. Content validity of the questionnaire was established through a pilot study, involving students to assess the clarity and comprehensibility of the questions, and reviewed by experts in the academic field. Feedback obtained from the pilot study included

suggestions for additional explanations and examples for several statements, which contributed to refining and enhancing the questionnaire prior to its distribution to the main respondents.

The target respondents of this study were students of the Industrial Engineering Program at Universitas Atma Jaya Yogyakarta. This group was selected based on the consideration that students in this program frequently utilize artificial intelligence (AI) in academic activities, particularly in understanding and applying the concept of design thinking. Design Thinking is introduced early in the curriculum through laboratory sessions and project-based learning, and it is explicitly applied in the Capstone Project, making it a core mindset within the Industrial Engineering curriculum. The respondents comprised 31.25% first-year students, 23.75% second-year students, 26.25% third-year students, and 18.75% fourth-year students.

The questionnaire was distributed online using the Google Forms platform. The link was shared via social media to students across all year levels. Data collection was carried out during June and July 2025. The questionnaire was divided into several sections, corresponding to the number of variables studied. Each item employed a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Table 1 shows the list of questionnaires.

Table 1. List of Questionnaires

Variable	Questioner Item	Reference
AI adoption	There is no difficulty to understand the using of AI	Ahn (2024), Imjai et al. (2024), Priamono et al. (2024)
	I can understand the needed of using AI	
	AI is easy and simple to be used	
	I can use AI tools to define the data before analyze it	
	I use management data tools to support the using of AI	
Self-efficacy in AI learning	I feel confident while using AI	
	I use AI as supporting tools during studying	
	AI helps me to obtain the relevant information	
	AI helps me to finish my assignment faster	
	AI helps me to increase my academic productivity	
	AI helps me to finish my assignments better	
Design thinking mindset	I understand the concept of design thinking well	
	I often use AI to create ideas or solutions	
	AI helps me to improve my critical thinking	
	AI helps me to understand the steps of design thinking easily (emphatize, define, ideate, prototype, test)	

	AI helps me to create innovative and creative ideas	
Self-competence	I can handle the academic tasks with AI	
	AI helps me to learn effectively	
	I can determine "when" and "how " to use AI in learning	
	I feel comfort to explore the features of AI by my own	
	I can handle the difficulties topics with AI	
	I understand the limitation of AI and consideration of its using	
Academic Performance	I can finish various subject's assignments well with AI	
	I can finish the assignments with AI efficiently	
	I reach the achievement as my expectation with AI	
	AI helps me to understand the relations among various subjects	
	AI helps me to understand the lecture	

According to Hair (2019), there are 3 stages in conducting an evaluation using PLS SEM, namely preliminary consideration, measurement model assessment, and structural model assessment. In the preliminary consideration stage, it is necessary to check the sample size, distributional assumptions, statistical power, secondary data, and goodness-of-fit. In Measurement model assessment is used to check the robustness (CTA-PLS) which is divided into reflective assessment and formatting. To conduct an analysis of reflective assessment, it is necessary to conduct an analysis related to outer loadings, Cronbach's alpha/composite reliability, AVE, and HTMT. At the formative assessment stage to check the redundancy analysis and significance and relevance of the indicator. In structural model assessment, it is used to check the robustness regarding nonlinearity, endogeneity, and heterogeneity which consists of VIF, Explanatory power and out-of-sample predictive power, significance and relevance of the path coefficients and model comparisons.

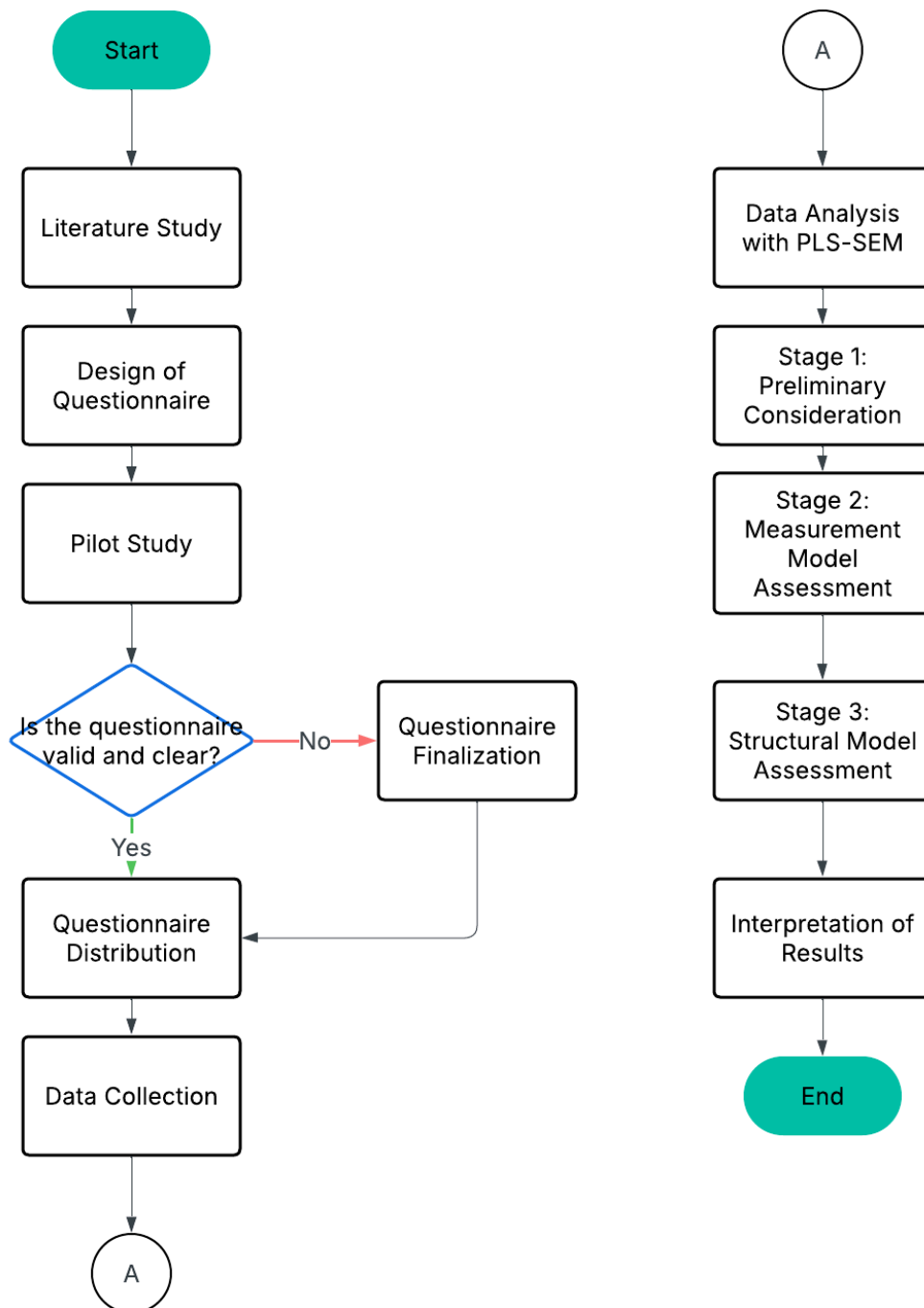


Figure 1. Research Methodology

3. FINDINGS AND DISCUSSION

3.1. Preliminary Consideration

According to Hair (2019), there is a list that outlines key factors to consider when deciding if PLS is a suitable method for SEM. The research points out that they have a small sample size. Also, based on Hair (2019), using a bias-corrected and accelerated bootstrapping method can help deal with this issue to some degree.

3.2. Measurement Model Assessment

According to hair (2019) the first step in evaluating PLS-SEM is examining the measurement models. The first analysis carried out is the Evaluation of the measurement model (Outer model) which aims to see indicators that have a relationship with other variables. The outer model is used to test validity and reliability.

The following is a path diagram between variables in this study.

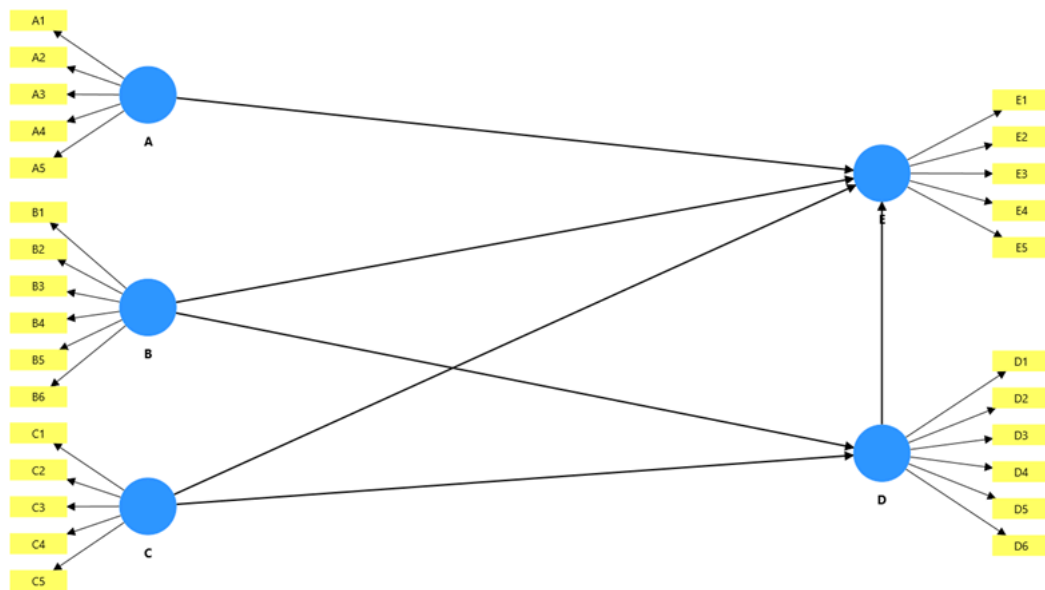


Figure 2. Path Diagram

In the reflective assessment, items with outer loading above 0. 708 are suggested, **meaning** the construct **explains** more than half of the indicator variation, which **shows** the items **have** good reliability. The result of the outer loading based one the original model see on here:

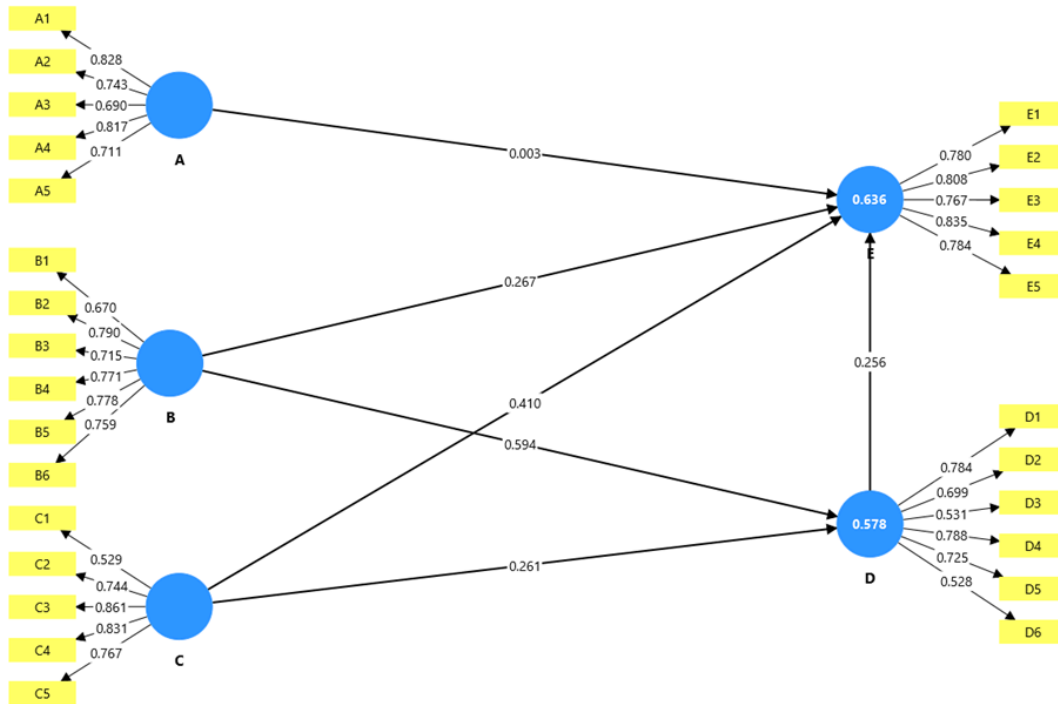


Figure 3. Outer Loading

Based on the outer loading results, one data point from latent variable A is invalid, one from latent variable B is invalid, one from latent variable C is invalid, and three from latent variable D are invalid. Because of this, those data points need to be removed.

Here the result of the outer loading after remove those data points:

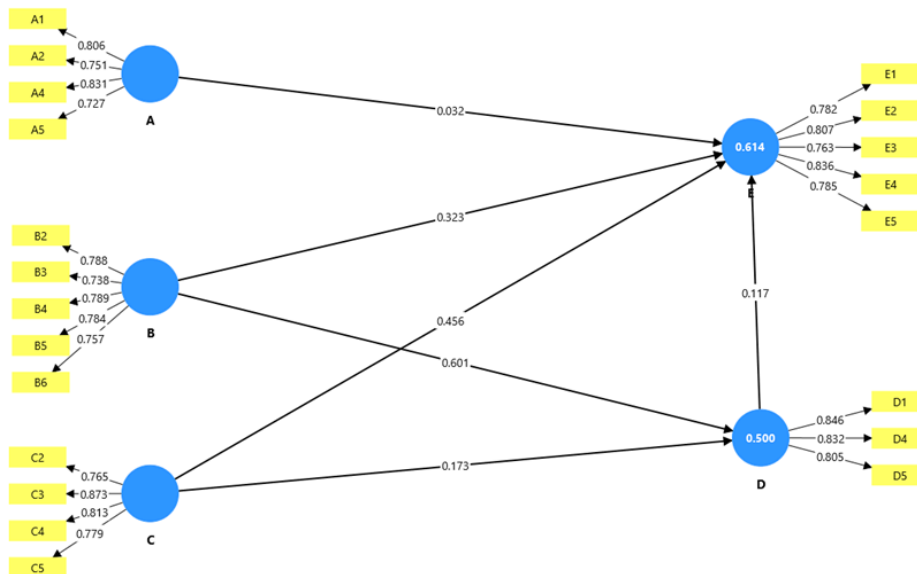


Figure 4. Outer Loading (2)

The next step in checking reflective measurement models is looking at internal consistency reliability. Cronbach's alpha is a way to measure how consistent the items are within a scale. According to Hair (2019), internal consistency reliability is achieved when both Cronbach's alpha and composite reliability values are above 0.70. To check convergent validity for each construct in a reflective model, you can use Average Variance Extracted (AVE) to see how much variance is explained by the items. Based on Hair (2019), an acceptable AVE value should be more than 0.50.

Here are the results for Cronbach's alpha, composite reliability, and Average Variance Extracted (AVE) for the following latent variables: AI Adoption (A), Self-efficacy in AI Learning (B), Design Thinking Mindset (C), Self Competence (D), and Academic Performance (E).

Table 2. Reability and Validity Test

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
A	0.784	0.788	0.861	0.608
B	0.830	0.833	0.880	0.595
C	0.823	0.826	0.883	0.654
D	0.771	0.777	0.867	0.685
E	0.854	0.856	0.896	0.632

The last step to check discriminant validity, which means a construct is clearly different from others in the model, are based on the method proposed by Henseler in 2015 called the heterotrait-monotrait (HTMT) ratio. This method uses correlations between variables. HTMT is calculated by taking the average of correlations between items from different constructs and dividing it by the geometric mean of correlations between items that measure the same construct. If the HTMT value is high, it shows a problem with discriminant validity. According to Hair, 2015 and Henseler 2019, if the HTMT value is above 0.90, it suggests that discriminant validity is not achieved. Researchers can then check if the upper limit of the 95% confidence interval for HTMT is below 0.90 or 0.85. In this research, all off the latent variables have HTMT below 0.90.

Table 3. Hererotrait-Monotrait (HTMT) Ratio

	A	B	C	D	E
A					
B	0.710				
C	0.536	0.624			
D	0.516	0.843	0.606		

E	0.564	0.788	0.819	0.711	
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3.3. Structural Model Assessment

First, it's important to check for collinearity to ensure it doesn't affect the regression results. According to Becker (2015), a VIF value higher than 5 suggests there might be collinearity problems among the predictor variables. In this study, a VIF value below 3 means that collinearity is not a concern.

Table 4. VIF Results

	VIF
A1	2.120
A2	1.855
A4	2.162
A5	1.873
B2	1.825
B3	1.570
B4	1.707
B5	1.679
B6	1.696
C2	1.462
C3	2.469
C4	2.113
C5	1.629
D1	1.596
D4	1.700
D5	1.491
E1	2.006
E2	2.117
E3	1.775
E4	2.348

E5	1.947
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Because collinearity isn't an issue, we look at the R-squared value to see how much variance is explained by each endogenous construct and its measurement in the model. This helps us understand the model's overall explanatory power. According to Henseler (2009) and Hair (2011), an R-squared value of 0.75 is considered substantial, 0.50 is moderate, and 0.25 is weak.

Table 5. R-squared Result

	R-square	R-square adjusted
D	0.500	0.487
E	0.614	0.594

The table above shows that the effect of the variables AI Adoption (A), Self-efficacy in AI Learning (B), and Design Thinking Mindset (C) on Self Competence (D) is 50%. The effect of the same variables on Academic Performance (E) is 61.4%.

Table 6. Direct Hypothesis Test

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
A -> E	0.032	0.039	0.105	0.307	0.759
B -> D	0.601	0.602	0.077	7.842	0.000
B -> E	0.323	0.323	0.116	2.777	0.006
C -> D	0.173	0.178	0.100	1.730	0.084
C -> E	0.456	0.453	0.089	5.150	0.000
D -> E	0.117	0.117	0.103	1.140	0.254

The final step is assess the statistical significance and relevance of Path Coefficient. The results based on the p-value show that the direct hypothesis from AI Adoption (A) to Academic Performance (E) is not supported, the hypothesis from Design Thinking Mindset (C) to Self Competence (D) is not supported, and the hypothesis from Self Competence (D) to Academic Performance (E) is also not supported.

The result from the indirect hypothesis, which goes through the intervening variable Self Competence (D), is rejected.

Table 7. Indirect Hypothesis Test

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
B → D → E	0.070	0.072	0.066	1.068	0.286
C → D → E	0.020	0.021	0.025	0.812	0.417

4. CONCLUSION

This study examined the effects of AI adoption, self-efficacy in AI learning, and design thinking mindset on academic performance, with self-competence as a mediator. Using PLS-SEM analysis on 80 Industrial Engineering students, the following results were obtained:

- **H1** (AI adoption → academic performance): **Not supported**
- **H2** (Self-efficacy → self-competence): **Supported**
- **H3** (Self-efficacy → academic performance): **Supported**
- **H4** (Design thinking → self-competence): **Not supported**
- **H5** (Design thinking → academic performance): **Supported**
- **H6** (Self-competence → academic performance): **Not supported**
- **H7** (Mediation: self-efficacy → self-competence → academic performance): **Not supported**
- **H8** (Mediation: design thinking → self-competence → academic performance): **Not supported**

In summary, **self-efficacy in AI learning** and **design thinking mindset** have a significant direct effect on academic performance. However, **AI adoption** and **self-competence**, including its mediating role, were not significant in this study.

To support academic success in AI-integrated learning environments, it is important to enhance students' self-efficacy through structured training and guided use of AI tools in academic contexts. Design thinking should be further embedded in project-based learning to strengthen its positive impact on academic performance. Additionally, AI adoption strategies should be aligned with pedagogical goals to ensure that technology use meaningfully contributes to learning, rather than serving as a superficial tool. Future research is encouraged to include other influencing factors, such as learning motivation or digital literacy, to gain a more comprehensive understanding of what drives academic achievement in technology-supported education.

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