Artificial Intelligence in Lifelong and Life-Course Education
EISSN: XXXX-XXXX PISSN: XXXX-XXXX
Vol. 1, No. 1, January 2026

Digital Balance in the AI Era: A Life-Course Perspective on AI Interaction, Digital Well-Being, and Academic Performance among Engineering Students

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ABSTRACT

Purpose – The increasing integration of artificial intelligence (AI) in higher education offers substantial benefits for learning efficiency and personalization, yet it also raises concerns regarding digital ethics, learner autonomy, and digital well-being. From a life-course education perspective, early adulthood represents a critical transitional stage in which patterns of AI interaction may shape long-term learning habits and readiness for lifelong learning. However, empirical evidence examining how multidimensional AI interactions influence academic outcomes through psychological mechanisms remains limited, particularly in developing country contexts. This study investigates the effects of cognitive, affective, and social-ethical interactions with AI on academic performance among Indonesian engineering students, with digital well-being positioned as a mediating mechanism.

Design/methods/approach – A quantitative cross-sectional survey was conducted with 103 engineering students from multiple universities, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM).

Findings – The findings indicate that cognitive interaction with AI significantly enhances academic performance, while affective interaction primarily contributes to digital well-being. Notably, higher levels of digital well-being are associated with reduced academic performance, suggesting a paradox in which increased comfort and convenience from AI may weaken sustained cognitive engagement. Digital well-being significantly mediates the relationship between affective interaction and academic performance, revealing potential risks of emotional overreliance on AI.

Research implications/limitations – These results highlight the importance of balanced and self-regulated AI use in higher education and underscore the need to design AI-supported learning environments that foster cognitive engagement while sustaining digital well-being. From a life-course perspective, the findings suggest that AI interaction patterns formed during early adulthood may have implications for lifelong learning autonomy and educational sustainability.

Originality/value – This study provides empirical evidence on multidimensional AI interaction in higher education from a life-course perspective and emphasizes the importance of ethical and responsible AI integration to safeguard academic performance and student well-being.

OPEN ACCESS

ARTICLE HISTORY
Received: 11-11-2025
Revised: 14-12-2025
Accepted: 10-01-2026

KEYWORDS
Artificial intelligence in education;
Digital well-being;
Engineering students;
Life-course education;
PLS-SEM;

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To cite this article : Author. (2026). Title. Artificial Intelligence in Lifelong and Life-Course Education, 1(1), 1-12. Doi. xxxx

INTRODUCTION

The development of Artificial Intelligence (AI) technology has brought significant changes to higher education by providing more adaptive, faster, and personalized learning (Bimantara et al., 2024). Various platforms such as ChatGPT and Grammarly are increasingly being used by engineering students to support their academic activities, from finding references to completing scientific papers (Tasya et al., 2025). However, this convenience also poses challenges, especially when students utilize AI without understanding its ethical boundaries and how it works, thereby raising the potential for a decline in critical thinking skills, technological dependence, and the risk of academic misconduct (García-López & Trujillo-Liñán, 2025). In this context, digital well-being is an important aspect of maintaining a balance in technology use and ensuring that the learning process remains healthy and productive (Chang et al., 2025).

Student interaction with AI can be viewed through three main dimensions: cognitive, affective, and social-ethical. In the cognitive dimension, the use of AI can assist in information processing and improve critical thinking skills (Huesca & others, 2024). In the affective dimension, AI plays a role in strengthening motivation and learning engagement through adaptive responses tailored to student needs (Tasya et al., 2025). Meanwhile, the social-ethical dimension emphasizes the importance of responsible AI use, including avoiding plagiarism and academic data manipulation (Saputri & Surawan, 2025). These three dimensions show that AI use not only impacts academic outcomes but also the attitudes, motivation, and integrity of engineering students.

Although many studies discuss the role of AI in learning, most still focus on a specific aspect, such as only the cognitive or affective dimensions, thus failing to provide a comprehensive picture of how these three dimensions of interaction work simultaneously (Putri & Panduwinata, 2025; Tasya et al., 2025), In addition, previous studies have not examined the psychological mechanisms that explain the relationship between AI use and academic performance, particularly the role of digital well-being as a mediator (Fan et al., 2025). The socio-ethical aspect has also been relatively unexplored, even though this dimension is very important for engineering students who face ethical risks in the use of technology (Uludağ et al., 2025). This gap highlights the need for an integrative research model that combines the three dimensions of student interaction with AI and incorporates digital well-being as a connecting variable to academic performance.

This study offers a new approach by testing an integrative model that combines the cognitive, affective, and socio-ethical dimensions of engineering students' interactions with AI, while analyzing the mediating role of digital well-being in influencing academic performance. This approach has not been widely studied in the context of higher education in Indonesia, especially among engineering students who have more intensive technology usage characteristics. The research findings are expected to contribute theoretically to the development of educational technology literature and provide practical implications for universities in designing ethical, adaptive, and student-well-being-oriented AI usage policies.

Research Question:

RQ1 : Does the cognitive interaction of engineering students with AI have a positive effect on academic performance?

RQ2 : Does the affective interaction of engineering students with AI have a positive effect on academic performance?

RQ3 : Does the social-ethical interaction of engineering students with AI have a positive effect on academic performance?

RQ4 : Does digital well-being have a positive effect on academic performance?

RQ5 : Does digital well-being mediate the relationship between the cognitive, affective, and social-ethical interactions of engineering students with AI and academic performance?

METHOD

This study uses a quantitative method that emphasizes the collection and analysis of numerical data to test hypotheses and assess relationships between variables objectively (Agusnaya & Nirmala, 2024). The research design applied is cross-sectional, which means that data collection is carried out once at a certain time on predetermined respondents (Abduh et al., 2023). The research was conducted on engineering students from various public and private universities in Indonesia, so that the results reflect the actual conditions of engineering students' interaction with artificial intelligence technology.

The research population consisted of active students of the Faculty of Engineering, while the sample selection used purposive sampling. The inclusion criteria included active students who had experience using AI-based technology in academic activities and were willing to complete the questionnaire. A total of 103 respondents met these criteria and the data can be analyzed further. The questionnaire was distributed online via Google Forms to increase distribution coverage and facilitate participation. The number of respondents exceeded the minimum limit for Partial Least Squares–Structural Equation Modeling (PLS-SEM) analysis, which requires at least 75 respondents based on the Minimum R-Squared method for models with five paths to one latent construct (Tilahun et al., 2023). The research instrument consisted of two parts, namely respondent demographic data and research construct statements measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The initial instrument consisted of 25 items representing five constructs, namely Cognitive Interaction, Affective Interaction, Social-Ethical Interaction, Digital Well-being, and Student Academic Performance. All items were then validated through expert judgment to ensure content suitability with the research context.

The initial stage of analysis showed that three items (AI1, AI5, and DWB5) did not meet the minimum outer loading criterion of 0.70 and were therefore eliminated (Hair et al., 2021). Thus, the final instrument consisted of 22 items that were considered valid and reliable for further analysis. The list of research items is presented in Table 1.

Table 1. Research Instrument

Variable	Code	Item	Source
Cognitive Interaction	CI1–CI5	5	(Filippelli et al., 2026; Liang et al., 2023)
Affective Interaction	AI2–AI4	3	(Xie et al., 2025)
Social-Ethical Interaction	SI1–SI5	5	(Filippelli et al., 2026; Hartwig et al., 2023)
Digital Well-being	DWB1–DWB4	4	(Arslankara et al., 2022; Balaskas et al., 2025)
Student Academic Performance	SAP1–SAP5	5	(Capinding, 2024)

Data collection was carried out through systematic stages, beginning with a literature review and the development of a conceptual framework regarding student interaction with AI, digital well-being, and academic performance (Bećirović et al., 2025; Song et al., 2025). The instrument was then developed, validated by experts, and tested to ensure item clarity. Once deemed feasible, the questionnaire was distributed online to students of the Faculty of Engineering. All responses were selected, coded, and cleaned to ensure data feasibility. This series of processes is summarized in the research procedure in Figure 1.

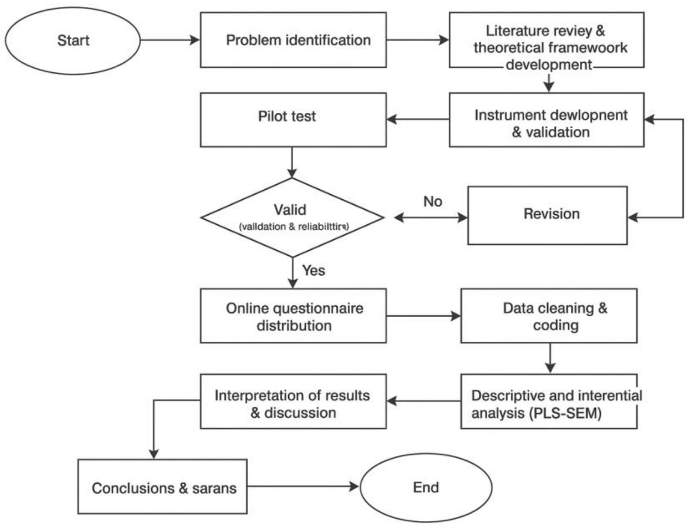

Figure 1. Research Procedures

Data analysis was conducted in two stages using Jamovi and SmartPLS 4. The first stage was descriptive analysis that described the characteristics of respondents, including gender, age, university origin, study program, semester, and intensity of AI use. This preliminary analysis helped provide context before structural testing and supported the interpretation of results (Bećirović et al., 2025; Hair et al., 2021; Yildiz Durak & Onan, 2024). The second stage was inferential analysis using PLS-SEM. The measurement model was evaluated by examining the outer loading values, Cronbach's alpha, composite reliability, convergent validity based on the Average Variance Extracted (AVE ≥ 0.50) value, and discriminant validity using the HTMT < 0.90 value (Cheung et al., 2024). After all criteria were met, structural model testing was conducted using the bootstrapping technique with 5,000 subsamples to obtain t-statistic, p-value, and path coefficient values. The relationship between variables was considered significant if the p-value was < 0.05 and the t-statistic was > 1.96 at a 95% confidence level (Pereira et al., 2024). In addition, the R^2, f^2, and Q^2 values were used to assess the predictive power and contribution of each latent variable in the model.

This study did not require formal ethical approval because it did not involve intervention or the collection of sensitive data. However, all procedures followed the principles of social research ethics, including informed consent, voluntary participation, and protection of respondent anonymity. Data were collected and analyzed anonymously and were used solely for academic purposes. To provide a more comprehensive overview of the relationship between the research variables, the conceptual model used in this study is shown in Figure 2. This model is designed based on the integration of three dimensions of interaction between engineering students and AI technology: cognitive, affective, and socio-ethical interactions, as well as the role of digital well-being in mediating its influence on students' academic performance.

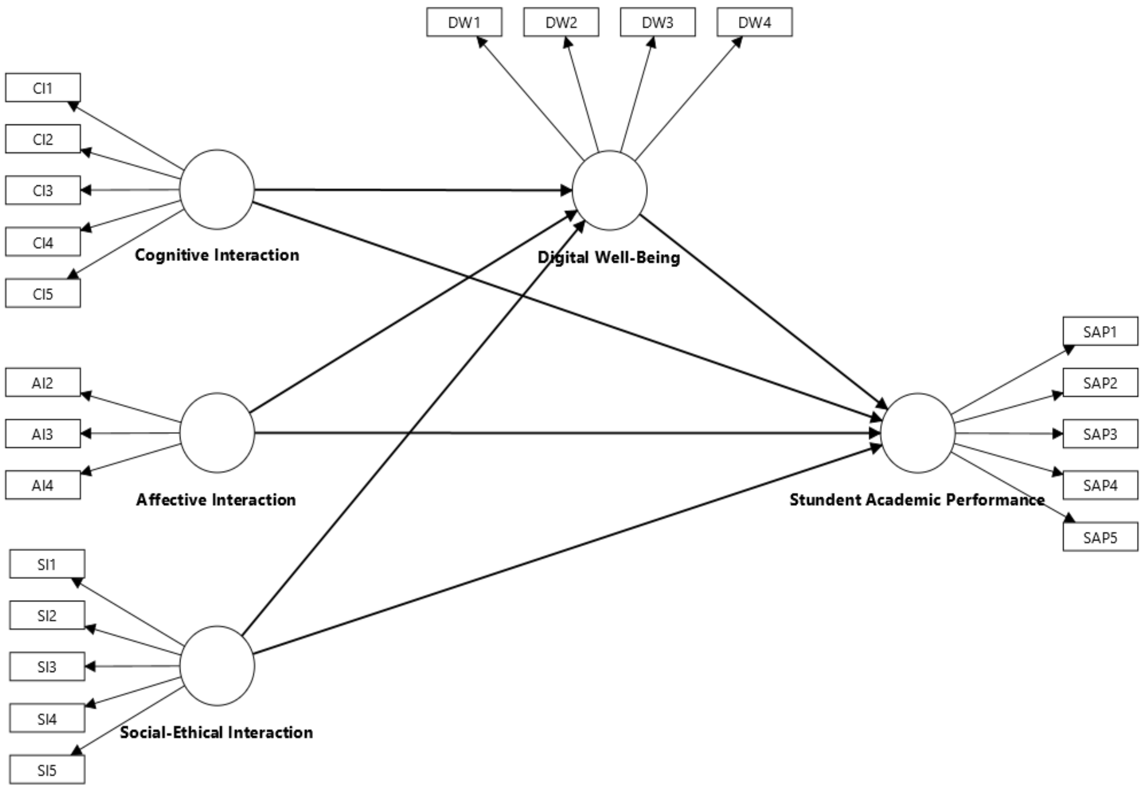

Figure 2. The Model Proposed in This Study

This model forms the basis for the formulation of the following research hypotheses:

H1 : Cognitive interaction has a positive effect on student academic performance.
H2 : Affective interaction has a positive effect on student academic performance.
H3 : Social-Ethical interactions have a positive effect on student academic performance.
H4 : Cognitive interaction has a positive effect on digital well-being.
H5 : Affective interaction has a positive effect on digital well-being.
H6 : Social-Ethical interactions have a positive effect on digital well-being.

H7 : Digital well-being has a positive effect on students academic performance.
H8 : Digital well-being mediates the effect of cognitive interaction on students academic performance.
H9 : Digital well-being mediates the effect of affective interaction on students academic performance.
H10 : Digital well-being mediates the effect of social-ethical interaction on students academic performance.

RESULTS AND DISCUSSION

The research sample consisted of 103 engineering students from various universities in Indonesia. The majority of respondents were aged 18–22 years old, were in their first to seventh semesters, and used AI-based technology almost every day. These conditions indicate that the respondents were digital-native users who were accustomed to interacting with digital technology in their academic activities. A summary of the respondents' characteristics is presented in Table 2.

Table 2. Descriptive Statistics of Respondents

No	Category	Description	Frequency	Percentage
1.	Gender	Male	46	44,7%
		Female	57	55,3%
2.	Age	18 years old	11	10,7%
		19 years old	54	52,4%
		20 years old	25	24,3%
		21 years old	9	8,7%
		22 years old	4	3,9%
3	Semester	I	5	4,9%
		III	83	80,6%
		V	5	4,9%
		VII	10	9,7%
4	Batch	2022	11	10,7%
		2023	6	5,8%
		2024	81	78,6%
		2025	5	4,9%
5	Frequency of Technology Use	Every Day	82	79,6%
		3–5 times a week	13	12,6%
		1–2 times a week	4	3,9%
		Rarely	4	3,9%

In general, the distribution of respondents shows that the engineering students in this study are in the early to intermediate stages of their education and have a very high level of technology adoption. The dominant frequency of AI use on a daily basis reflects an intensive pattern of interaction with digital technology in learning activities. These characteristics are relevant for further analysis in relation to how students utilize AI in the academic process and how this experience can influence their learning behavior.

Outer Model

Convergent Validity and Construct Reliability

The measurement model was evaluated to assess the convergent validity and reliability of each research construct. This test included examining outer loading values, Cronbach's Alpha, Rho_A, Composite Reliability, and Average Variance Extracted (AVE). The complete results of the convergent validity and construct reliability evaluation are presented in Table 3.

Table 3. Results of Convergent Validity and Construct Reliability Evaluation

Construct	Item	Loading	Cronbach's Alpha	Rho_A	Composite Reliability (CR)	AVE
Cognitive Interaction (CI)	CI1	0.830	0.845	0.853	0.890	0.618
	CI2	0.842				
	CI3	0.739				
	CI4	0.709				
	CI5	0.803				
Affective Interaction (AI)	AI2	0.846	0.796	0.797	0.880	0.710
	AI3	0.822				
	AI4	0.859				
Social-Ethical Interaction (SI)	SI1	0.744	0.854	0.860	0.895	0.631
	SI2	0.820				
	SI3	0.838				
	SI4	0.784				
	SI5	0.823				
Digital Well-Being (DWB)	DWB1	0.779	0.800	0.808	0.869	0.625
	DWB2	0.758				
	DWB3	0.812				
	DWB4	0.823				
Student Academic Performance (SAP)	SAP1	0.851	0.900	0.903	0.926	0.715
	SAP2	0.860				
	SAP3	0.872				
	SAP4	0.825				
	SAP5	0.831				

The test results show that all indicators have outer loading values above 0.70, thus fulfilling convergent validity. Each construct also shows Cronbach's Alpha, Rho_A, and Composite Reliability values exceeding the 0.70 threshold, indicating that the internal reliability of all variables is excellent. In addition, the AVE values for all constructs are above 0.50, confirming that the indicators adequately represent the latent constructs. Overall, these findings confirm that the measurement model is of high quality and can be used for structural analysis.

Discriminant Validity

Discriminant validity was evaluated to ensure that each construct in the model had distinct characteristics and did not overlap empirically. This examination was conducted using the Fornell–Larcker criteria, which compared the AVE root value of each construct with its correlation to other constructs. The results of the discriminant validity test are presented in Table 4.

Table 4. Results of the Fornell–Larcker Criterion Discriminant Validity Test

Construct	AI	CI	SI	DWB	SAP
Affective Interaction	0.843				
Cognitive Interaction	0.652	0.786			
Social-Ethical Interaction	0.601	0.688	0.795		
Digital Well-Being	0.806	0.559	0.612	0.790	
Student Academic Performance	0.721	0.886	0.656	0.602	0.845

Based on the results in Table 4, the AVE values of all constructs are above the correlations between constructs, indicating that each variable has unique measurements and there is no overlap between dimensions. This condition confirms that constructs such as Cognitive Interaction, Affective

Interaction, Social-Ethical Interaction, Digital Well-being, and Academic Performance can be clearly distinguished from one another in the context of this study. Thus, the measurement model is declared to meet discriminant validity and is suitable for use in structural analysis in the next stage.

Inner Model

After all constructs met discriminant validity, the analysis proceeded to the inner model testing stage to assess the direction and strength of the relationships between latent variables. This testing was conducted using a bootstrapping procedure with 5,000 subsamples, so that the parameter estimates obtained were more stable and reliable. Through this process, the path coefficient values, t-statistics, and p-values were used to determine whether the relationships between constructs were statistically significant. The effect was considered significant if the p-value was below 0.05. The results of testing the direct effects of each structural path are presented in Table 5.

Table 5. Direct Effect Results

Hypothesis	Path	Path Coefficient	t-Statistic	P-Value	Decision
H1	CI → SAP	0.659	6.242	0.000	Positive and Significant
H2	AI → SAP	−0.023	0.236	0.407	Negative Not Significant
H3	SI → SAP	0.038	0.349	0.364	Positive but Not Significant
H4	CI → DWB	−0.073	0.522	0.301	Negative Not Significant
H5	AI → DWB	0.519	5.138	0.000	Positive and Significant
H6	SI → DWB	−0.192	1.372	0.085	Negative Not Significant
H7	DWB → SAP	−0.165	1.982	0.024	Negative and Significant

Based on the results shown in Table 5, Cognitive Interaction was proven to have a positive and significant effect on Academic Performance, indicating that the cognitive dimension contributes greatly to students' academic achievement. Conversely, Affective Interaction and Social-Ethical Interaction did not show a significant effect on Academic Performance, so these two dimensions cannot explain the variation in academic performance in the research model. In the relationship between variables and Digital Well-being, only Affective Interaction produced a significant effect, while Cognitive Interaction and Social-Ethical Interaction did not show any significant effect. Furthermore, Digital Well-being was found to have a negative and significant effect on Academic Performance, indicating that more comfortable digital conditions do not always correlate with improved academic performance. These results form the basis for understanding the structural dynamics in the research model before proceeding with mediation effect testing. To obtain a more comprehensive picture of the role of Digital Wellbeing as a mediating variable, indirect effect analysis was conducted on the relevant paths. The mediation test results are presented in Table 6.

Table 6. Indirect Effects

Hypothesis	Mediation Path	Path Coefficient	t-Statistic	P-Value	Decision
H8	CI → DWB → SAP	0.012	0.446	0.328	Not Significant
H9	AI → DWB → SAP	−0.086	1.909	0.028	Negative and Significant
H10	SI → DWB → SAP	0.032	1.034	0.151	Not Significant

The test results show that the mediation path in the relationship between Cognitive Interaction and Social-Ethical Interaction on Academic Performance through Digital Well-being is not significant, which means that these two dimensions of interaction do not produce an indirect effect in the model. Meanwhile, the mediating path in the relationship between Affective Interaction → Digital Well-being → Academic Performance shows significant results with a negative direction. Thus, although Affective Interaction has a positive relationship with Digital Well-being, the increase in digital well-being does not contribute to improved academic performance. These findings provide an initial understanding of the more complex relationship patterns between constructs, which are discussed further in the Discussion section.

Discussion

The respondent profile shows that engineering students in this study are a group of digital natives who are very familiar with the use of AI in academic activities. This finding is consistent with (Bećirović et al., 2025; Huesca & others, 2024), who confirm that engineering students are one of the groups that most intensively utilize AI-based technology to understand technical material. However, as noted by Klimova and Pikhart (Klimova & Pikhart, 2025), this intensity of use often has an impact on digital well-being, making the context of this sample important in understanding the dynamics of the relationship between interaction with AI, digital well-being, and academic performance.

Before evaluating structural relationships, the measurement model demonstrated strong reliability and validity. All indicators met the threshold loading > 0.70, Cronbach's Alpha, Composite Reliability, and AVE values were all above the minimum threshold, and discriminant validity was met through the Fornell–Larcker criteria. These conditions are consistent with the recommendations of Hair et al. (2021) and in line with Prinsloo et al. (2024) who emphasize that construct separation is crucial in digital well-being studies. Thus, the measurement model is suitable for interpreting structural relationships as suggested by (Escotet, 2024).

Regarding structural relationships, the results of the study show that H1 is strongly supported, in which Cognitive Interaction has a significant positive effect on Academic Performance. This finding indicates that students who actively evaluate, process, and integrate information from AI show better academic performance. This finding is consistent with (Liang et al., 2023; Singh et al., 2025), who emphasize the dominant role of cognitive processing in technology-based learning. However, H4 is not supported because Cognitive Interaction does not have a significant effect on Digital Well-being. This condition can be explained by the high mental load of intensive AI use, which can actually trigger digital fatigue, as explained by (Zhang et al., 2024).

Unlike cognitive patterns, affective aspects show mixed results. H2 is not supported because Affective Interaction does not significantly affect Academic Performance; although AI can increase comfort or satisfaction, it does not automatically improve academic performance. This is in line with (Chang et al., 2025; Fan et al., 2025), who emphasize that positive emotional experiences will not produce significant academic results without cognitive involvement. However, H5 is supported because Affective Interaction has a significant positive effect on Digital Well-being. Students who experience positive emotions when using AI tend to be more digitally balanced. This is in line with (Balaskas et al., 2025; Xie et al., 2025). Furthermore, H9 is also supported, showing that Digital Well-being mediates the relationship between Affective Interaction → Academic Performance, but with a negative direction. This phenomenon supports the concept of AI-comfort overreliance (Klimova & Pikhart, 2025), where excessive comfort leads to a decrease in cognitive effort, as also explained by (Sun et al., 2025; Wang & Wang, 2024).

On the social-ethical side, the relationship pattern shows that H3 and H6 are not supported because Social-Ethical Interaction does not have a significant effect on either Academic Performance or Digital Well-being. This indicates that ethical awareness has not been internalized as a factor that drives academic performance or digital well-being among students. This finding supports (Hartwig et al., 2023; Knoth et al., 2024), who assert that AI ethical literacy plays a greater role as a moral norm or moderator rather than a direct predictor. Consistent with this pattern, H10 is also not supported because no significant mediation through Digital Well-being was found.

The most notable finding is the significant negative effect of Digital Well-being on Academic Performance (H7 supported). The data shows that the higher the digital comfort felt by students, the lower their academic performance. This indicates a paradox, where the comfort of using AI actually reduces active learning engagement. This phenomenon is consistent with global literature on overreliance on AI Klimova & Pikhart (2025) and the study by Sun et al. (2025), which shows that technological convenience can reduce independent cognitive effort.

From the perspective of model strength, the R^2 value indicates that 46.1% of the variation in Academic Performance can be explained by the interaction construct of AI and Digital Well-being, while 39.2% of the variation in Digital Well-being is explained by the interaction dimension. The positive Q^2 value indicates that the model has good predictive relevance. Meanwhile, the f^2 value shows that Cognitive Interaction contributes the most to Academic Performance, while Affective Interaction contributes the most to Digital Well-being. This f^2 pattern confirms the results of the hypothesis structurally and clarifies the dominant role of cognitive and affective aspects in students' interactions with AI.

Theoretically, this study expands our understanding of the relationship between interaction with AI and academic performance by including Digital Well-being as a mediator, which has rarely been explored in the context of engineering students in Indonesia. The findings regarding the digital well-being paradox make a significant contribution to the literature, showing that being comfortable with AI does not always mean being more academically productive. From a practical standpoint, the implications of this research emphasize the need for universities to design AI literacy curricula that focus not only on technical skills but also on emotional and ethical balance, as well as strategies to prevent over-reliance on technology. AI developers also need to consider features that encourage active engagement, not just convenience.

Overall, this study emphasizes the importance of a holistic approach in understanding student interactions with AI. Academic performance is not only influenced by how AI is used, but also by how students process it cognitively, feel it emotionally, and interpret it ethically. These findings open up opportunities for further research on intervention strategies to improve learning discipline in the AI era and how digital well-being can be managed more adaptively

CONCLUSION

This study demonstrates that cognitive interaction with artificial intelligence is the primary determinant of academic performance among engineering students, while affective interaction mainly contributes to digital well-being without directly enhancing learning outcomes. Social-ethical interaction does not function as a direct predictor of either academic performance or digital well-being within the proposed model. A key finding is the negative effect of digital well-being on academic performance, indicating a paradox in which increased comfort and convenience derived from AI use may reduce sustained cognitive effort and active learning engagement.

From a life-course education perspective, these findings suggest that patterns of AI interaction developed during early adulthood—a critical transitional phase in lifelong learning—may have lasting implications for learners' autonomy, self-regulation, and readiness for continuous learning across the lifespan. While AI has the potential to support lifelong and adaptive learning, unbalanced or emotionally dependent use may undermine the development of durable cognitive and self-regulatory competencies.

Theoretically, this study extends research on artificial intelligence in education by integrating digital well-being as a mediating mechanism within a multidimensional interaction framework. Methodologically, the application of PLS-SEM provides empirical insight into the complex relationships between cognitive, affective, and socio-ethical dimensions of AI interaction in higher education. Practically, the findings highlight the importance of designing AI-supported learning environments and AI literacy initiatives that prioritize cognitive engagement, ethical awareness, and self-regulated learning rather than efficiency and convenience alone.

Despite its contributions, this study is limited by its cross-sectional design, reliance on self-reported data, and focus on engineering students in a single national context. Future research is encouraged to adopt longitudinal or mixed-method approaches, incorporate life-course variables such as self-regulated learning, digital fatigue, and AI literacy, and examine diverse educational stages to deepen understanding of AI-supported lifelong and life-course education.

ACKNOWLEDGMENT

The authors would like to acknowledge the academic support provided by the lecturers and teaching assistants of the Technology Innovation course for their constructive feedback and scholarly guidance during the development of this manuscript. Appreciation is also extended to the Informatics and Computer Engineering Education Study Program, Faculty of Engineering, Universitas Negeri Makassar, for providing an academic environment that supported the completion of this research. The authors declare that all views expressed and conclusions drawn in this article are solely those of the authors and do not necessarily reflect the positions of the affiliated institutions.

AUTHOR CONTRIBUTION STATEMENT

FA conceptualized the study, developed the research framework, and drafted the original manuscript. NAFF contributed to instrument development, data collection, and preliminary data analysis. ADNA conducted statistical analysis using PLS-SEM and interpreted the empirical findings. ABK provided theoretical validation, methodological review, and critical revisions of the manuscript. MMF supervised the research process, refined the theoretical positioning, and finalized the manuscript for publication.

AI DISCLOSURE STATEMENT

The authors used ChatGPT as a language-support tool during the preparation of this manuscript, specifically for grammatical refinement, clarity improvement, and structural editing. All substantive scholarly activities including research design, theoretical development, data collection, statistical analysis, interpretation of results, and formulation of conclusions were conducted entirely by the authors. The authors critically reviewed and edited all AI-assisted content and take full responsibility for the originality, accuracy, and integrity of the published work.

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