

Generative AI dependence and decision-making independence in digital society: Evidence from Universitas Airlangga

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Abstract

Dependence on generative artificial intelligence (AI) raises questions about students' ability to maintain independence in decision-making. This study aims to examine the relationship between generative AI dependence and decision-making independence among active students at Universitas Airlangga. A quantitative correlational design was employed with 65 students selected through purposive sampling, using a Likert-scale questionnaire and Pearson correlation analysis. The results revealed a very weak, positive, and statistically nonsignificant relationship between the two variables ($r = 0.103$; $p = 0.416$). This finding indicates that generative AI dependence was not significantly associated with decision-making independence in the study sample. The study contributes to research on AI use in higher education by highlighting the importance of distinguishing technological dependence from students' capacity to make independent decisions.

Keywords: Generative AI dependence; Decision-making independence; Universitas Airlangga students; Pearson correlation; Decision-making autonomy.

Abstrak

Ketergantungan terhadap *artificial intelligence* (AI) generatif menimbulkan pertanyaan mengenai kemampuan mahasiswa mempertahankan kemandirian dalam pengambilan keputusan. Penelitian ini bertujuan menganalisis hubungan antara ketergantungan terhadap AI generatif dan kemandirian pengambilan keputusan pada mahasiswa aktif Universitas Airlangga. Penelitian menggunakan pendekatan kuantitatif korelasional dengan melibatkan 65 mahasiswa yang dipilih melalui teknik *purposive sampling*, menggunakan kuesioner skala Likert dan analisis korelasi Pearson. Hasil menunjukkan hubungan positif yang sangat lemah dan tidak signifikan antara kedua variabel ($r = 0.103$; $p = 0.416$). Temuan ini menunjukkan bahwa ketergantungan terhadap AI generatif tidak terbukti berhubungan secara signifikan dengan kemandirian pengambilan keputusan pada sampel penelitian. Penelitian ini berkontribusi pada kajian penggunaan AI di pendidikan tinggi dengan menekankan pentingnya membedakan ketergantungan teknologi dari kemampuan mahasiswa mengambil keputusan secara mandiri.

Kata Kunci: Ketergantungan AI generatif; Kemandirian pengambilan keputusan; Mahasiswa Universitas Airlangga; korelasi Pearson; Otonomi keputusan.

Introduction

The development of generative artificial intelligence (AI) has transformed how university students search for information, formulate ideas, and complete academic assignments. Unlike conventional search tools, generative AI can produce answers and recommendations through conversational interactions that may influence users' thinking processes. Feuerriegel et al. (2024) explain how generative AI produces new content based on patterns learned from data, while Kasneci et al. (2023) discuss its potential to support learning through explanations, feedback, and academic assistance. Nevertheless, this convenience raises concerns when technological assistance begins to replace students' cognitive effort. Brand et al. (2025) explain that addictive behaviors can be understood through interactions among personal, cognitive, affective, and environmental factors. Therefore, concerns surrounding generative AI use involve not only frequency of use but also the possibility of dependence in relation to students' ability to make decisions independently.

Dependence on generative AI needs to be distinguished from routine use accompanied by critical evaluation. Zhang et al. (2024), in a study involving 300 university students, examined the associations of academic self-efficacy, academic stress, and performance expectations with problematic AI use. At the synthesis level, An et al. (2026) reviewed 54 empirical studies and identified psychological factors, skill gaps, environmental pressures, and the appeal of technology as factors associated with excessive dependence. Their review also identified concerns involving cognitive functioning, learning effectiveness, academic integrity, and psychosocial well-being. Meanwhile, Stanciu and Calugar (2022) demonstrated the relevance of maladaptive cognitions in explaining problematic internet use through the Interaction of Person-Affect-Cognition-Execution (I-PACE) model. These findings indicate that technological dependence is associated with various psychological and behavioral factors, but they do not, in themselves, explain how generative AI dependence relates to students' independence in decision-making.

A more direct empirical basis for examining the relationship between AI dependence and decision-making independence is provided by Le (2026). Based on a survey of 300 university students in Vietnam, the study identified an association between AI dependence and reduced decision-making autonomy, learning engagement, and concerns about privacy and security. However, these findings derive from the Vietnamese higher education context, and their relevance to Indonesian students remains to be examined. In an experiment involving 120 university students, Barcaui (2025) found that knowledge retention among students who used ChatGPT reached 57.5%, lower than the 68.5% recorded by the conventional learning group after 45 days. These findings concern knowledge retention rather than decision-making independence directly. Thus, both studies provide grounds for investigating the

consequences of AI use, but they are insufficient to conclude that AI dependence is invariably associated with lower decision-making independence.

Previous studies have shown that human–AI interactions concern not only efficiency but also how decisions are formed and evaluated. Rastogi et al. (2022) found that de-anchoring strategies accompanied by explanations can help reduce anchoring bias and improve human–AI collaboration performance when a model provides incorrect predictions with low confidence. Through a systematic review of 14 articles, Zhai et al. (2024) identified a tendency among users to rely excessively on AI dialogue systems to select quick solutions, potentially reducing their engagement in critical and analytical thinking. Meanwhile, an experiment by Kern et al. (2022) showed that automated recommendations with humans retaining final decision-making authority were perceived as fairer than decisions delegated entirely to algorithms. These three findings underscore the importance of active human involvement, but they do not directly examine the relationship between generative AI dependence and students' decision-making independence.

In light of this research gap, this study aims to analyze the relationship between generative AI dependence and decision-making independence among active students at Universitas Airlangga. A quantitative correlational design is employed to identify the direction, strength, and statistical significance of the relationship between the two variables without drawing causal conclusions. This focus is important because AI can support academic activities when students continue to evaluate information, consider alternatives, and take responsibility for their choices. Conversely, excessive dependence raises questions about the extent to which students retain independent judgment when using technological recommendations. This study is expected to provide context-specific empirical evidence concerning the relationship between the two variables in Indonesian higher education. Its findings may also inform the development of AI literacy that emphasizes information verification, critical evaluation, and responsibility for decision-making, without assuming that the intensity of AI use necessarily reflects dependence.

Method

This study employed a quantitative approach with a correlational design to examine the relationship between generative artificial intelligence (AI) dependence as the independent variable (X) and decision-making independence as the dependent variable (Y), without testing for causal relationships (Creswell & Creswell, 2023). The study was conducted among active students at Universitas Airlangga, with data collected online from September 17 to 25, 2026. The sample consisted of 65 active students who had previously used generative AI and had used it at least once during the preceding three months. Respondents were selected using a non-probability sampling technique, specifically purposive sampling. The questionnaire was

distributed via WhatsApp using Google Forms and began with informed consent and screening questions. Because respondents were not selected randomly, the findings are not intended to probabilistically represent the entire student population of Universitas Airlangga.

The research instrument was a closed-ended questionnaire using a five-point Likert scale, ranging from Strongly Disagree (1) to Strongly Agree (5). The instrument consisted of 42 items: 15 items measuring generative AI dependence and 27 items measuring decision-making independence. Both variables were operationalized through the adaptation and development of constructs and indicators from relevant sources, taking into account their suitability for the context of university students and generative AI use (Cruchinho et al., 2024). The use of the Likert scale follows the approach of measuring individual responses to a set of statements representing a particular construct (Jebb et al., 2021; Taufique et al., 2026). The dimensions, indicators, and number of items for each variable are presented in Table 1.

Table 1. Operationalization of research variables

Variable	Dimensions and indicators	Number of indicators	Number of items
Generative AI dependence (X)	Unidimensional construct: feelings of vulnerability without access to AI, concerns about relevance and performance, the need to maintain an up-to-date image, seeking external validation, and fear of personal skills becoming obsolete	5	15
Decision-making independence (Y)	Decision-making ability; resistance to conformity and external influence; independence in making decisions	9	27
Total		14	42

Source: Prepared by the authors based on the adaptation and development of instruments from Morales-García et al. (2024) and Risyda et al. (2021).

The data were analyzed using IBM SPSS Statistics, including descriptive statistics, validity testing, reliability testing, assumption testing, and hypothesis testing. Item validity was assessed using Pearson correlations between individual item scores and total scores, with a critical r value of 0.244. Instrument reliability was evaluated using Cronbach's alpha, with an acceptance threshold of 0.60, taking the context of its application into account. Both tests were conducted using the main study data from 65 respondents rather than a separate pilot sample. Normality was assessed using the one-sample Kolmogorov-Smirnov test on the unstandardized residuals, while linearity was evaluated using the Deviation from Linearity significance value. Significance values greater than 0.05 were used as the criteria for meeting both assumptions. The hypothesis was tested using the Pearson product-moment

correlation with a two-tailed test at a significance level of 0.05 to determine the direction, strength, and statistical significance of the relationship between the two variables.

Results and Discussion

Respondent characteristics: Gender, semester, faculty, and generative AI use patterns

This study involved 65 active students at Universitas Airlangga who met the study eligibility criteria: they had previously used generative artificial intelligence (AI) and had used it at least once during the preceding three months. Respondent characteristics were analyzed by gender, semester, and faculty, while generative AI use patterns were examined in terms of frequency of use, platforms used, and purposes of use. This information provides an overview of the respondents' demographic profiles and their experiences with generative AI technology. The distribution of respondents' demographic characteristics is presented in Table 2, while their generative AI use patterns are presented in Table 3. These tables provide a basis for understanding the respondents' backgrounds before examining the relationship between generative AI dependence and decision-making independence.

Table 2. Respondents' demographic characteristics

Characteristic	Category	Frequency	Percentage
Gender	Female	44	67.7%
	Male	21	32.3%
	Total	65	100%
Semester	1	2	3.1%
	3	16	24.6%
	5	42	64.6%
	7	5	7.7%
	Total	65	100%
Faculty	Faculty of Vocational Studies	35	53.8%
	Faculty of Social and Political Sciences	6	9.2%
	Faculty of Economics and Business	4	6.2%
	Faculty of Psychology	3	4.6%
	Faculty of Science and Technology	3	4.6%
	Faculty of Medicine	3	4.6%
	Faculty of Public Health	3	4.6%
	Faculty of Nursing	2	3.1%

Faculty of Humanities	2	3.1%
Faculty of Dental Medicine	1	1.5%
Faculty of Law	1	1.5%
FIKKIA	1	1.5%
Faculty of Fisheries and Marine Sciences	1	1.5%
Total	65	100%

Source: Primary research data, processed in 2026.

As shown in Table 2, 44 respondents (67.7%) were female, while 21 (32.3%) were male. In terms of semester, the majority were in their fifth semester, comprising 42 students (64.6%), followed by 16 students in their third semester (24.6%), five in their seventh semester (7.7%), and two in their first semester (3.1%). Regarding faculty affiliation, the Faculty of Vocational Studies accounted for the largest proportion, with 35 respondents (53.8%), while the remaining respondents were distributed across 12 other faculty or academic-unit categories. This distribution indicates that the sample included students from diverse academic backgrounds, although their representation was uneven. The predominance of students from the Faculty of Vocational Studies and the fifth semester should be considered when interpreting the findings, particularly in assessing how representative the sample is of the overall student population at Universitas Airlangga.

Table 3. Generative AI use patterns

Characteristic	Category	Frequency	Percentage
Frequency of use	Every day	26	40.0%
	5-6 days per week	11	16.9%
	3-4 days per week	20	30.8%
	1-2 days per week	8	12.3%
	Total	65	100%
Platform used	ChatGPT	33	50.8%
	Claude	17	26.2%
	Gemini	14	21.5%
	Microsoft Copilot	1	1.5%
	Total	65	100%
Purpose of use	Assisting with university assignments	—	89.2%
	Finding or understanding information	—	86.2%
	Brainstorming	—	83.1%

Assisting with making or considering decisions	—	49.2%
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Source: Primary research data, processed in 2026.

As shown in Table 3, generative AI use was relatively frequent among the respondents. A total of 26 students (40.0%) used it every day, while 37 students (56.9%) used generative AI at least five days per week. ChatGPT was the most widely used platform, reported by 33 respondents (50.8%), followed by Claude with 17 respondents (26.2%), Gemini with 14 (21.5%), and Microsoft Copilot with one (1.5%). In terms of purpose, generative AI was most commonly used to assist with university assignments (89.2%), find or understand information (86.2%), and engage in brainstorming (83.1%). In addition, 49.2% of respondents used it to assist with making or considering decisions. The percentages for purposes of use do not add up to 100% because respondents could select more than one answer.

Overall, the characteristics presented in Tables 2 and 3 show that the respondents were predominantly female and in their fifth semester, with uneven representation across faculties. Meanwhile, generative AI had become part of most respondents' routines, particularly for supporting academic activities and information seeking. Nearly half of the respondents also reported using AI to help consider decisions. Nevertheless, frequency and purpose of use cannot be treated as direct measures of generative AI dependence. Routine use does not necessarily indicate a high level of dependence, just as using AI to consider decisions does not automatically mean that students have lost their independence. Therefore, the relationship between the two variables must still be established through an analysis of the research instrument scores.

Descriptive statistics of the research variables

Descriptive statistics were used to provide an overview of the scores for generative artificial intelligence (AI) dependence and decision-making independence among the students who participated in the study. The analysis included the number of respondents (N), minimum score, maximum score, mean, and standard deviation. The mean indicates the average respondent score for each variable, whereas the standard deviation describes the dispersion of scores around the mean. The results of the descriptive statistical analysis are presented in Table 4 to summarize the score characteristics of both variables systematically before proceeding to the analysis of the relationship between them.

Table 4. Descriptive statistics of the research variables

Variable	N	Minimum	Maximum	Mean	Standard deviation
Generative AI dependence (X)	65	18	72	48.03	11.07

Decision-making independence (Y)	65	80	135	110.80	13.40
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Source: Primary research data, processed in 2026.

As shown in Table 4, generative AI dependence had a mean score of 48.03 and a standard deviation of 11.07. Respondents' scores for this variable ranged from 18 to 72. Meanwhile, decision-making independence had a mean score of 110.80 and a standard deviation of 13.40, with scores ranging from 80 to 135. These results indicate that the two variables differed in their score ranges and levels of dispersion. However, their mean scores cannot be compared directly to determine which variable is higher or lower because the instruments contain different numbers of items and have different total score ranges. Therefore, the interpretation of descriptive statistics should take into account the measurement characteristics of each variable.

When calculated as the mean score per item, generative AI dependence had an average of 3.20, whereas decision-making independence had an average of 4.10 on the five-point response scale. These values provide an overview of students' average responses to the statements in each instrument. Nevertheless, their interpretation requires consideration of the scoring direction and the meaning of each item. Accordingly, mean scores per item do not automatically indicate respondents' levels of dependence or independence, particularly in the absence of a clearly established classification scheme. These descriptive statistics serve to characterize the research data, while the relationship between generative AI dependence and decision-making independence is examined through correlation analysis aligned with the study's objectives.

Instrument validity and reliability testing

Validity and reliability tests were conducted to evaluate the quality of the research instrument before proceeding with further analyses. The validity test aimed to determine the extent to which each statement item measured the variable under investigation, whereas the reliability test assessed the instrument's internal consistency in measuring that variable. In this study, item validity was assessed by comparing the calculated r value with the critical r value of 0.244. An item was considered valid if its calculated r value exceeded the critical value. Meanwhile, instrument reliability was assessed using Cronbach's alpha, with a minimum threshold of 0.60. Summaries of the validity and reliability test results for both variables are presented in Tables 5 and 6.

Table 5. Summary of instrument validity test results

Variable	Number of items	Range of calculated r values	Critical r value	Result
Generative AI dependence (X)	15	0.301–0.650	0.244	All items valid

Decision-making independence (Y)	27	0.275–0.687	0.244	All items valid
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Source: Primary research data, processed in 2026.

As shown in Table 5, all 15 items measuring generative AI dependence had calculated r values ranging from 0.301 to 0.650. Meanwhile, the 27 items measuring decision-making independence had calculated r values ranging from 0.275 to 0.687. All these values exceeded the critical r value of 0.244. Accordingly, based on the criteria applied in this study, all 42 statement items met the item-validity criterion and were retained in the research instrument. These results indicate that each item correlated with the score of the variable it was intended to measure, in accordance with the established threshold. Nevertheless, these findings constitute evidence of validity based on item correlations and do not, in themselves, establish all aspects of instrument validity.

The reliability test was subsequently used to assess the internal consistency of the statement items for each variable. The analysis employed Cronbach's alpha, with the results presented in Table 6. Higher coefficients indicate stronger internal consistency among the items within an instrument. In this study, an instrument was considered reliable if its Cronbach's alpha coefficient exceeded 0.60. The results for both variables were therefore compared against this threshold to determine whether the instruments demonstrated adequate internal consistency for subsequent analyses.

Table 6. Instrument reliability test results

Variable	Cronbach's alpha	Number of items	Result
Generative AI dependence (X)	0.912	15	Reliable
Decision-making independence (Y)	0.942	27	Reliable

Source: Primary research data, processed in 2026.

As shown in Table 6, generative AI dependence had a Cronbach's alpha coefficient of 0.912, while decision-making independence had a coefficient of 0.942. Both values exceeded the minimum threshold of 0.60 adopted in this study. Therefore, both instruments met the reliability criterion in terms of internal consistency. Overall, the results indicate that all statement items met the item-validity criterion based on item correlations, while both variables demonstrated adequate internal consistency. The instruments could therefore be used in subsequent analyses, including the examination of the relationship between generative AI dependence and decision-making independence among university students.

Classical assumption tests: Normality and linearity

The classical assumption tests in this study comprised normality and linearity tests to assess whether the assumptions required for correlation analysis were satisfied. The normality test examined whether the unstandardized residuals were normally distributed, whereas the linearity test assessed whether the relationship between

generative AI dependence (X) and decision-making independence (Y) followed a linear pattern. Both tests were conducted using data from 65 respondents. The results were used to evaluate whether the data met the assumptions required for the planned statistical analysis. A summary of the normality test results is presented in Table 7, while the linearity test results are presented in Table 8.

Table 7. Normality test results

Test	N	Test statistic	Asymp. Sig. (2-tailed)	Interpretation
Kolmogorov-Smirnov	65	0.079	0.200	Normal

Source: Primary research data, processed in 2026.

As shown in Table 7, the one-sample Kolmogorov-Smirnov test yielded a test statistic of 0.079 and an asymptotic significance value (two-tailed) of 0.200. This significance value exceeded 0.05, indicating insufficient evidence to conclude that the residuals deviated from a normal distribution. Accordingly, based on the criterion applied in this study, the residual normality assumption was considered satisfied. This result supports proceeding with the planned statistical analysis. However, the conclusion concerns the distribution of the model residuals and does not imply that each research variable must independently be considered normally distributed based on this test.

The linearity test was then conducted to assess whether the relationship between generative AI dependence and decision-making independence could be treated as linear. The test examined two components: Linearity and Deviation from Linearity. The Linearity component indicates the statistical significance of the linear component of the relationship, whereas Deviation from Linearity assesses whether the relationship deviates significantly from a linear pattern. In this study, the significance values for Linearity and Deviation from Linearity were 0.498 and 0.989, respectively. A summary of these results is presented in Table 8 to support the assessment of the linearity assumption before conducting the correlation analysis.

Table 8. Linearity test results

Component	F	Sig.
Linearity	0.472	0.498
Deviation from Linearity	0.437	0.989

Source: Primary research data, processed in 2026.

As shown in Table 8, the Linearity component had an F value of 0.472 and a significance value of 0.498, while the Deviation from Linearity component had an F value of 0.437 and a significance value of 0.989. The Deviation from Linearity significance value exceeded 0.05, indicating that no statistically significant deviation from a linear pattern was detected. Therefore, the relationship between generative AI dependence (X) and decision-making independence (Y) could be treated as linear for the subsequent analysis. Overall, the normality and linearity test results indicated that

both assumptions were satisfied according to the criteria applied in this study. Accordingly, the correlation analysis could proceed to examine the relationship between the two research variables.

Hypothesis testing: Pearson correlation

Hypothesis testing was conducted using Pearson product-moment correlation analysis to determine the direction, strength, and statistical significance of the relationship between generative AI dependence and decision-making independence among students at Universitas Airlangga. The analysis involved 65 respondents and used a significance level of 0.05. The correlation coefficient (r) was used to indicate the direction and strength of the relationship between the two variables, while the significance value (p) was used to determine whether the relationship was statistically significant. The Pearson correlation test results are presented in Table 9.

Table 9. Pearson correlation test results

Relationship between variables	Pearson correlation (r)	Sig. (2-tailed)	N
Generative AI dependence (X) × Decision-making independence (Y)	0.103	0.416	65

Source: Primary research data, processed in 2026.

As shown in Table 9, the Pearson correlation analysis yielded a correlation coefficient of $r = 0.103$ and a significance value of $p = 0.416$ ($p > 0.05$). The correlation coefficient indicates a positive but very weak relationship between the two variables. However, because the p value exceeded 0.05, the relationship was not statistically significant. Therefore, H1 was not supported, while H0 could not be rejected. This means that the study did not find sufficient statistical evidence to establish a significant relationship between generative AI dependence and decision-making independence among students at Universitas Airlangga.

These findings indicate that, within the study sample, generative AI dependence was not demonstrated to have a statistically significant relationship with decision-making independence among students at Universitas Airlangga. Although the correlation coefficient indicated a positive direction, this value cannot be used to conclude that greater dependence on generative AI is associated with greater decision-making independence. This is because the relationship was very weak and the test result was not statistically significant. Therefore, the findings should be interpreted proportionately: they do not provide sufficient statistical evidence of a relationship between the two variables in the sample studied, rather than proving that such a relationship does not exist in the broader student population.

The relationship between generative artificial intelligence dependence and decision-making independence among university students

The use of generative artificial intelligence (AI) in academic life raises questions about the extent to which university students can benefit from technology without losing control over their thinking and decision-making processes. This question is relevant to the findings of a study involving 65 active students at Universitas Airlangga, which revealed a very weak positive relationship between generative AI dependence and decision-making independence ($r = 0.103$; $p = 0.416$; $N = 65$). The significance value indicates that the observed relationship was not statistically significant. Thus, the hypothesis concerning a significant negative relationship was not supported by the data. These findings should be interpreted cautiously because AI dependence is not necessarily synonymous with a loss of independence. Abbas et al. (2024) demonstrated that ChatGPT use may be associated with unfavorable academic consequences, whereas Saleh et al. (2025) showed that concerns about dependence are not always strongly associated with the use of AI for learning or with perceived benefits. These differences suggest that the consequences of AI use depend on the behavioral aspects being measured. In the present study, the available evidence only indicates that a relationship between the two variables could not be statistically established.

The frequency of AI use in this study indicates that the technology had become part of the respondents' academic routines. A total of 40% of respondents used AI daily, while 30.8% used it three to four days per week. Nevertheless, the high frequency of use was not accompanied by a statistically significant relationship with decision-making independence. This finding suggests that frequency of access and the ability to make decisions are two distinct aspects. Chan and Hu (2023) found that university students perceived generative AI as a technology offering benefits for learning, although its use also presented several challenges. Their findings help explain why routine AI use cannot automatically be interpreted as surrendering decision-making authority to technology. Students may use AI to obtain information or complete assignments more efficiently while still evaluating the information before making choices. However, the present study did not specifically measure the extent to which respondents verified the accuracy of AI outputs or relied on AI recommendations as the basis for their final decisions. Therefore, frequent AI use is insufficient to establish a decline in decision-making independence, just as a nonsignificant correlation does not demonstrate that all forms of AI use are risk-free.

The respondents' patterns of AI use further clarify this distinction. AI was used to assist with university assignments by 89.2% of respondents, to find information by 86.2%, and to engage in brainstorming by 83.1%, while 49.2% used AI to assist with decision-making. These data indicate that AI was used more extensively to support various academic activities than exclusively to make choices. This pattern should be

considered in relation to how students evaluate technological outputs. Hou et al. (2025a) highlighted the importance of critical thinking in understanding students' reliance on AI for problem-solving. AI use may involve verification and deliberation, but it may also occur without adequate evaluation. In the context of the present study, the overall dependence scores do not establish which of these patterns predominated among individual respondents. For example, students who use AI to develop ideas may still generate and evaluate their own ideas before making decisions. Conversely, using AI to obtain direct answers may reduce engagement in the evaluation process if the outputs are accepted without verification. Because these behavioral patterns were not measured separately, such differences represent one possible explanation for the weak relationship between AI dependence and decision-making independence.

The possibility that AI can support certain activities without automatically undermining independence is also evident when the present findings are compared with experimental evidence. A correlation of 0.103 indicates that this study did not identify a statistically significant relationship between AI dependence and decision-making independence. Meanwhile, Urban et al. (2024) found that students who used ChatGPT produced creative problem-solving solutions with higher quality, elaboration, and originality than those in the control group. This finding demonstrates that AI assistance can improve performance on specific tasks, but it does not, by itself, explain how independently students make decisions. The quality of a product, the ability to evaluate results, and independence in making choices are distinct aspects. This distinction is important to avoid equating the benefits of AI for task completion with a general improvement in independence. In the present study, the dependence and independence scores were not significantly associated; therefore, there is no basis for concluding that AI use either increased or decreased the respondents' decision-making independence. Instead, the findings draw attention to the need to identify the types of tasks students undertake and the thinking processes involved in their use of AI.

In addition to usage patterns, psychological conditions and academic demands may be relevant factors in understanding AI dependence. In this study, the mean score for AI dependence was 48.03, with a standard deviation of 11.07, while the mean score for decision-making independence was 110.80, with a standard deviation of 13.40. These figures describe the distribution of respondents' scores but cannot be used directly to classify dependence or independence as low, moderate, or high without an appropriate classification scheme. Acosta-Enriquez et al. (2025) found that academic stress mediated the relationship between academic self-efficacy and AI dependence, with a significant indirect effect ($\beta = 0.398$; $p < 0.001$). This finding suggests that dependence may be associated with students' academic experiences and beliefs about their own abilities, rather than merely with the frequency of technology use. Nevertheless, the present study did not measure academic stress or self-efficacy.

Consequently, these factors cannot be used to directly explain the observed correlation. Future research should examine whether task demands, academic pressure, and confidence in personal abilities help explain variations in the relationship between AI dependence and decision-making independence.

The nonsignificant relationship identified in this study should also be understood by distinguishing general AI dependence from the behavior of following AI recommendations in specific situations. Klingbeil et al. (2024) found that participants in an experiment could rely excessively on AI advice, including when the advice conflicted with the available contextual information. This finding illustrates the risks that arise when technological recommendations are accepted without adequate evaluation. However, experimental studies of advice-following behavior in specific tasks are not equivalent to questionnaire-based measurements of AI dependence and decision-making independence. This difference in measurement approaches helps explain why dependence-related risks may be observed in experimental settings, whereas the present study found no significant relationship between the two variable scores. The Interaction of Person-Affect-Cognition-Execution (I-PACE) model proposed by Brand et al. (2019) may help interpret the possible roles of personal, affective, cognitive, and executive-function factors in technology use. However, the present study did not directly examine the components of the I-PACE model. The model is therefore used as a conceptual lens, not as evidence that the respondents exhibited addictive behavior or a loss of control in decision-making.

Differences in the constructs measured may also explain why the relationship between AI dependence and academic outcomes does not always follow the same pattern. In the present study, the correlation between AI dependence and decision-making independence was very weak, positive, and nonsignificant ($r = 0.103$; $p = 0.416$). By contrast, Pujiastuti et al. (2025) found a significant negative relationship between dependence on AI chatbots and academic text-reading ability among students in an Indonesian language education program ($r = -0.370$; $p = 0.020$). This difference need not be interpreted as a contradiction because reading ability and decision-making independence are distinct constructs. Dependence on instant answers may be associated with reduced engagement in reading and comprehending texts in depth, but this does not automatically indicate that students have also lost their ability to make choices. Differences in sample characteristics, instruments, and AI-use contexts also limit direct comparisons. Accordingly, the present findings do not rule out the possibility of negative consequences for specific academic abilities. Rather, they indicate that the relationship between AI dependence and academic outcomes should be examined in relation to the specific abilities being measured instead of being generalized as a uniform effect on all aspects of students' cognition.

The sample characteristics constitute another consideration when interpreting the findings. A total of 53.8% of respondents were from the Faculty of Vocational Studies, and 64.6% were in their fifth semester. This composition indicates that the experiences of certain groups were more strongly represented in the data, meaning that the findings may not reflect the entire student population of Universitas Airlangga evenly. Strzelecki and ElArabawy (2024) found that performance expectancy, effort expectancy, and social influence were associated with students' intentions to use ChatGPT, while behavioral intention and facilitating conditions were associated with actual use. These findings suggest that AI-use behavior is also related to perceived benefits and the environment in which the technology is used. In the present study, differences in academic demands across study programs, peer influence, and the availability of facilities were not analyzed as separate factors. Therefore, the nonsignificant relationship may not capture the full range of students' experiences with AI. The predominance of respondents from the Faculty of Vocational Studies and the fifth semester also limits the generalizability of the findings. Future research should include students from a broader range of faculties and semesters to determine whether the relationship between AI dependence and decision-making independence varies according to academic context and respondent characteristics.

Measurement also influences how the correlation findings should be interpreted. The very weak relationship between AI dependence and decision-making independence may not fully capture variations in how students interact with the technology. Morales-García et al. (2024) developed an AI dependence scale for university students with a unidimensional structure supported by exploratory and confirmatory factor analyses and demonstrated measurement invariance across gender. Meanwhile, Hou et al. (2025b) developed an instrument that distinguishes reflective, cautious, unconsidered, and collaborative AI-use behaviors. The scale demonstrated adequate internal reliability, with a Cronbach's alpha of 0.84. These different approaches indicate that measuring general AI dependence and assessing specific behaviors during problem-solving may produce different insights. In the present study, the dependence and independence scores did not provide detailed information about how respondents accepted, evaluated, or rejected AI recommendations. Therefore, future research could combine questionnaires with decision-making scenarios or observations of AI-use processes to examine the relationship between dependence and independence more thoroughly.

Overall, this study found no statistically significant relationship between generative AI dependence and decision-making independence among 65 active students at Universitas Airlangga. The very weak positive correlation ($r = 0.103$; $p = 0.416$) did not support the hypothesis of a significant negative relationship, but it also did not establish that AI dependence is never associated with decision-making independence. Findings from different contexts indicate that the consequences of AI use may vary

according to task type, how students evaluate technological outputs, psychological conditions, and the constructs being measured. The interpretation of these results remains limited by the relatively small sample size, purposive sampling, the predominance of respondents from the Faculty of Vocational Studies and the fifth semester, and the cross-sectional correlational design, which cannot establish causal relationships. Accordingly, the findings are best understood as evidence that the relationship between the two variables was not established in this sample. Future research should use larger and more diverse samples, measure specific patterns of dependence, and examine factors such as critical thinking, academic stress, and trust in AI. Such an approach could clarify the conditions under which AI functions as a tool for supporting thought and those under which its use may reduce students' engagement in decision-making.

Conclusion

The findings indicate that generative artificial intelligence (AI) dependence was not statistically significantly associated with decision-making independence among 65 active students at Universitas Airlangga ($r = 0.103$; $p = 0.416$). The very weak positive correlation indicates that the data do not support the assumption that greater AI dependence is associated with lower decision-making independence. This finding suggests that AI dependence and decision-making independence do not necessarily move in opposite directions. One possible explanation is that students can use AI to seek information, develop ideas, and consider alternatives without fully delegating their final decisions to the technology. However, because this study did not examine AI-use mechanisms in depth, this explanation remains interpretive. Accordingly, the relationship between AI dependence and decision-making independence should be understood in terms of the context of use and how students evaluate AI outputs, rather than solely on the basis of usage frequency.

This study contributes to research on generative AI use in higher education by demonstrating that AI dependence should not automatically be assumed to be associated with lower decision-making independence. In practical terms, the findings underscore the importance of promoting AI use accompanied by critical evaluation, consideration of alternatives, and responsibility for final decisions. Nevertheless, the results should be interpreted in light of several limitations, including the relatively small sample size, purposive sampling, the predominance of respondents from the Faculty of Vocational Studies and the fifth semester, reliance on self-reported data, and the cross-sectional correlational design, which cannot establish causal relationships. Future research should involve larger and more diverse samples, measure specific patterns of dependence, and examine factors such as critical thinking skills, academic stress, self-efficacy, and trust in AI. Longitudinal or experimental approaches could

also be used to clarify how patterns of AI use are associated with the development of students' decision-making independence over time.

References

- Abbas, M., Jam, F. A., & Khan, T. I. (2024). Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students. *International Journal of Educational Technology in Higher Education*, 21, Article 10. <https://doi.org/10.1186/s41239-024-00444-7>
- Acosta-Enriquez, B. G., Arbulú Ballesteros, M. A., Guzman Valle, M. de los A., Morales Angaspilco, J. E., Aquino Lalupú, J. del R., Bravo Jaico, J. L., Reyes, N. C. G., Alarcón García, R. E., & Janampa Castillo, W. E. (2025). The mediating role of academic stress, critical thinking and performance expectations in the influence of academic self-efficacy on AI dependence: Case study in college students. *Computers and Education: Artificial Intelligence*, 8, Article 100381. <https://doi.org/10.1016/j.caeai.2025.100381>
- An, C., Lu, K., & Yang, J. (2026). The dependency trap: A systematic review of the contributing factors and consequences of student over-reliance on generative AI in higher education. *Humanities and Social Sciences Communications*, 13, Article 1604. <https://doi.org/10.1057/s41599-026-08959-2>
- Barcaui, A. (2025). ChatGPT as a cognitive crutch: Evidence from a randomized controlled trial on knowledge retention. *Social Sciences & Humanities Open*, 12, Article 102287. <https://doi.org/10.1016/j.ssaho.2025.102287>
- Brand, M., Müller, A., Wegmann, E., Antons, S., Brandtner, A., Müller, S. M., Stark, R., Steins-Loeber, S., & Potenza, M. N. (2025). Current interpretations of the I-PACE model of behavioral addictions. *Journal of Behavioral Addictions*, 14(1), 1–17. <https://doi.org/10.1556/2006.2025.00020>
- Brand, M., Wegmann, E., Stark, R., Müller, A., Wölfling, K., Robbins, T. W., & Potenza, M. N. (2019). The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors: Update, generalization to addictive behaviors beyond Internet-use disorders, and specification of the process character of addictive behaviors. *Neuroscience & Biobehavioral Reviews*, 104, 1–10. <https://doi.org/10.1016/j.neubiorev.2019.06.032>
- Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, 20, Article 43. <https://doi.org/10.1186/s41239-023-00411-8>
- Creswell, J. W., & Creswell, J. D. (2023). *Research design: Qualitative, quantitative, and mixed methods approaches* (6th ed.). SAGE Publications.

- Cruchinho, P., López-Franco, M. D., Capelas, M. L., Almeida, S., Bennett, P. M., Miranda da Silva, M., Teixeira, G., Nunes, E., Lucas, P., & Gaspar, F. (2024). Translation, cross-cultural adaptation, and validation of measurement instruments: A practical guideline for novice researchers. *Journal of Multidisciplinary Healthcare*, 17, 2701–2728. <https://doi.org/10.2147/JMDH.S419714>
- Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering*, 66, 111–126. <https://doi.org/10.1007/s12599-023-00834-7>
- Hou, C., Zhu, G., & Sudarshan, V. (2025a). The role of critical thinking on undergraduates' reliance behaviours on generative AI in problem-solving. *British Journal of Educational Technology*, 56(5), 1919–1941. <https://doi.org/10.1111/bjet.13613>
- Hou, C., Zhu, G., Sudarshan, V., Lim, F. S., & Ong, Y. S. (2025b). Measuring undergraduate students' reliance on generative AI during problem-solving: Scale development and validation. *Computers & Education*, 234, Article 105329. <https://doi.org/10.1016/j.compedu.2025.105329>
- Jebb, A. T., Ng, V., & Tay, L. (2021). A review of key Likert scale development advances: 1995–2019. *Frontiers in Psychology*, 12, Article 637547. <https://doi.org/10.3389/fpsyg.2021.637547>
- Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., Stadler, M., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, Article 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
- Kern, C., Gerdon, F., Bach, R. L., Keusch, F., & Kreuter, F. (2022). Humans versus machines: Who is perceived to decide fairer? Experimental evidence on attitudes toward automated decision-making. *Patterns*, 3(10), Article 100591. <https://doi.org/10.1016/j.patter.2022.100591>
- Klingbeil, A., Grützner, C., & Schreck, P. (2024). Trust and reliance on AI—An experimental study on the extent and costs of overreliance on AI. *Computers in Human Behavior*, 160, Article 108352. <https://doi.org/10.1016/j.chb.2024.108352>
- Le, T. M. D. (2026). AI dependence in higher education: Effects on students' decision-making autonomy, learning engagement, and privacy concerns. *International Journal of Information and Learning Technology*, 43(4), 371–387. <https://doi.org/10.1108/IJILT-11-2024-0276>

- Morales-García, W. C., Sairitupa-Sanchez, L. Z., Morales-García, S. B., & Morales-García, M. (2024). Development and validation of a scale for dependence on artificial intelligence in university students. *Frontiers in Education*, 9, Article 1323898. <https://doi.org/10.3389/feduc.2024.1323898>
- Pujiastuti, I., Damaianti, V. S., Mulyati, Y., Sastromihardjo, A., & Lestari, D. (2025). Ketergantungan penggunaan AI pada pendidikan tinggi: Ancaman terhadap keterampilan membaca teks akademik. *Diglosia: Jurnal Kajian Bahasa, Sastra, dan Pengajarannya*, 8(2), 473–484. <https://doi.org/10.30872/diglosia.v8i2.1243>
- Rastogi, C., Zhang, Y., Wei, D., Varshney, K. R., Dhurandhar, A., & Tomsett, R. (2022). Deciding fast and slow: The role of cognitive biases in AI-assisted decision-making. *Proceedings of the ACM on Human-Computer Interaction*, 6(CSCW1), Article 83, 1–22. <https://doi.org/10.1145/3512930>
- Risyda, R., Gading, I. K., & Sudarsana, G. N. (2021). Pengembangan skala kemandirian pengambilan keputusan studi lanjut pada siswa. *Jurnal Bimbingan dan Konseling Indonesia*, 6(1), 89–95.
- Saleh, S., Islawati, A., & Niswaty, R. (2025). Benefits, critical responsibility, and dependence concerns in university students' AI use: A descriptive survey for responsible integration. *Jurnal Ilmiah Ilmu Administrasi Publik*, 15(2). <https://ojs.unm.ac.id/iap/article/view/89963>
- Stanciu, D., & Calugar, A. (2022). What is irrational in fearing to miss out on being online. An application of the I-PACE model regarding the role of maladaptive cognitions in problematic internet use. *Computers in Human Behavior*, 135, Article 107365. <https://doi.org/10.1016/j.chb.2022.107365>
- Strzelecki, A., & ElArabawy, S. (2024). Investigation of the moderation effect of gender and study level on the acceptance and use of generative AI by higher education students: Comparative evidence from Poland and Egypt. *British Journal of Educational Technology*, 55(3), 1209–1230. <https://doi.org/10.1111/bjet.13425>
- Taufique, K. M. R., Sabbir, M. M., & Rabbanee, F. K. (2026). A guide to key decision criteria for Likert-scale use in survey research. *Global Business and Organizational Excellence*, 45(5), 493–508. <https://doi.org/10.1002/joe.70032>
- Urban, M., Děchtěrenko, F., Lukavský, J., Hrabalová, V., Svacha, F., Brom, C., & Urban, K. (2024). ChatGPT improves creative problem-solving performance in university students: An experimental study. *Computers & Education*, 215, Article 105031. <https://doi.org/10.1016/j.compedu.2024.105031>
- Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learning Environments*, 11, Article 28. <https://doi.org/10.1186/s40561-024-00316-7>

Zhang, S., Zhao, X., Zhou, T., & Kim, J. H. (2024). Do you have AI dependency? The roles of academic self-efficacy, academic stress, and performance expectations on problematic AI usage behavior. *International Journal of Educational Technology in Higher Education*, 21, Article 34. <https://doi.org/10.1186/s41239-024-00467-0>