Computer and Decision Making

An International Journal

www.comdem.org
eISSN: 3008-1416



Generative AI, Critical Thinking, and Human Agency A Computational Study of Decision-Making in Digital Environments

Yosuf Mohamed Ismail Ahmed Hassan[1*], Ilona Israilova[2], Mehdi Safaei[3], Mavlyanova Shahnoza Zakirovna[4]

[1*]School of Computer Science- Taylor's University, Email: yosufmohamed99@gmail.com, ORCID ID: 0009-0005-3582-2594
[2]Associate Professor, Tashkent State Medical University, Email: ilona1israilova@gmail.com, ORCID ID: 0000-0001-7275-4897
[3]Faculty of Economics, Administrative and Social Sciences, Logistics Management Department, Istanbul Gelisim University, Istanbul, Türkiye, Email: msafaei@gelisim.edu.tr, ORCID ID: 0000-0003-3740-9486
[4]Professor, Doctor of Medical Sciences, Republican Specialized Scientific and Practical Medical Center of dermatovenerology and cosmetology of the Ministry of Health of the Republic of Uzbekistan, Tashkent, 100109, Almazar district, 3 Farobi St.; Head of the scientific laboratory for the study of dermatosis problems; Email: shahnoza_m@mail.ru, ORCID: 0000-0003-2256-5383

ARTICLE INFO

Article history:
Received 19 June 2026
Received in revised form 03 August 2026
Accepted 07 September 2026
Available online 30 September 2026

Keywords: Generative AI; Critical Thinking; Human Agency; Cognitive Dependence; Academic Decision-Making

ABSTRACT

This study explored the connections between use of generative artificial intelligence (GenAI), critical thinking, human agency, cognitive dependence, trust in AI, and academic decision-making in a digital learning environment. The method used was a quantitative cross-sectional design, based on a survey of 2,613 university students and 30 variables related to demographic characteristics and five behavioral constructs. The study used descriptive statistics, Cronbach's alpha, Pearson's correlation, multiple linear regression, and predictive machine-learning models to analyze composite scores. The results revealed a generally high level of GenAI use in academic activities, with a mean score of 3.80, and critical thinking responses and AI-assisted academic decision-making both scoring 3.75. Academic decision-making was strongly associated with cognitive dependence and trust in AI, while there was a lesser bivariate association with reduced critical thinking. The overall variance in academic decision-making was accounted for by 40.8% of the variance in the multiple regression, with standardized cognitive dependence being the strongest predictor followed by AI usage and trust. Moderate discrimination was also observed for predictive classification, with the best ROC-AUC score of 0.748 for XGBoost. The overall findings suggest a growing integration of GenAI into students' academic reasoning and decision-making, with increased reliance potentially compromising autonomous cognitive engagement and agency-related behaviors. The study points to the importance of responsible AI literacy, verification practices and learning designs, which guarantee critical thinking and autonomous decision-making.

1. Introduction

In recent years, generative artificial intelligence, or GenAI, and conversational AI systems like ChatGPT have rapidly found their way into the higher education sector and into other digital learning environments. The technologies produce explanations, summaries, recommendations, written content, and problem-solving support, and are becoming more appealing to students who are finishing academic tasks (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). Recent research shows that students are employing GenAI in the preparation of written assignments, in brainstorming, for

[*] *Corresponding author.*
E-mail address: yosufmohamed99@gmail.com

information retrieval, study planning, research support, and to clarify complex concepts (Chan & Hu, 2023; Labadze et al., 2023). While they enhance access, efficiency, and individualized learning, there have been questions about becoming too reliant on the devices, cheating, and the loss of independent cognitive effort (Cotton et al., 2024; Farrokhnia et al., 2024). The educational implications of GenAI are thus not limited to productivity, but should also account for the potential impact on students' cognitive abilities, judgements, autonomy, and independent processing of complex information (Grassini, 2023; Kasneci et al., 2023).

Judgement and algorithmic recommendations are becoming more intertwined in decision-making in digital environments. AI systems ease the burden of information processing by quickly providing information solutions, alternatives and recommendations, but may lead to overdependence on AI outputs when making decisions (Araujo et al., 2020). The study of AI-supported decision-making shows that besides the performance of AI systems, users' perceived credibility, convenience, and confidence about algorithmic support also affect reliance on AI (Cao & Huang, 2022). In the educational setting, GenAI impacts preparation for assignments, research topic planning, study strategies, problem solving, and academic priorities. This help can help with making decisions more efficiently but also limit students' ability to consider other options themselves. The rise of generative conversational AI therefore poses relevant issues of suitable human supervision and the need for nuanced human judgment in the context of AI support (Dwivedi et al., 2023).

Critical thinking requires the ability to critically analyze evidence, challenge assumptions, compare options and make reasoned conclusions. GenAI helps with these processes by offering explanations, other angles, and instant feedback. However, to what extent it influences the learner depends greatly on how the learner interacts with the produced content. There is empirical evidence that ChatGPT impacts the cognitive abilities of university undergraduates, providing positive outcomes when actively used rather than as a replacement for individual thinking (Essel et al., 2024). Another issue is that there are concerns that by using AI-generated text repeatedly, students' critical thinking suffers as they accept the output without checking or considering it (Essien et al., 2024). Furthermore, systematic reviews highlight the potential for GenAI to both translate to improved learning opportunities and introduce the risks of shallow processing, reliance, and decreased intellectual effort (Bhullar et al., 2024; Castillo-Martínez et al., 2024).

Human agency describes human beings' ability to act intentionally, be autonomous, and make decisions based on their own thinking and aspirations. Agency plays a crucial role in an AI-assisted learning environment, as students need to decide whether to accept, challenge, adapt, or discard AI-driven suggestions. GenAI enhances agency as it provides greater access to information and aids in self-directed learning, however, overreliance diminishes confidence in independent problem-solving and decision-making (Chan & Hu, 2023; Kasneci et al., 2023). As a result, verifying behaviour, independent judgment, confidence without AI and resistance to uncritical dependence may be considered signs of human agency.

While previous studies have explored the adoption of ChatGPT, the benefits it brings to learning, cognition, academic integrity, and reliance on AI have been studied individually; there has been comparatively little empirical research that has brought them together under one computational framework. The existing literature is mostly conceptual, exploratory, and review-based (Albadarin et al., 2024; Baig & Yadegaridehkordi, 2024). This makes quantitative analysis with the aim of identifying the relation between patterns of GenAI usage and cognitive independence and decision behaviour at the same time necessary.

The current study seeks to explore the connections among critical thinking, human agency, decision making, and use of Generative AI in digital academic settings. In particular, the study aims to investigate the patterns of using GenAI, its association with critical thinking, signs of human agency and cognitive dependence, its impact on academic decision-making, and the key factors predicting decision behaviour dependency on GenAI.

2. Materials and Methods

2.1 Research Design

The design of this study was a quantitative, cross-sectional design that explored the relationships between the use of Generative AI, critical thinking, human agency, cognitive dependence, and academic decision-making in digital learning environments. Secondary survey data were analysed using descriptive, inferential and predictive methods. The data were observational and taken once, so there was no emphasis on causal inference, rather on associations and prediction.

2.2 Dataset and Participants

The number of variables in the dataset was 30 and the number of students was 2,613 who are university students (Arifen et al., 2026). Five variables characterised the participants as: gender, age, type of university, academic level, and academic discipline. The other variables that were measured included generative AI usage, cognitive dependence, trust in AI, critical thinking, and academic decision-making. Five items were included in each of the five behavioral constructs for a scale that ranged from 1 = Strongly Disagree to 5 = Strongly Agree. The data consisted of students in public and private universities and covered various academic fields.

2.3 Study Variables and Construct Measurement

The use of generative AI was assessed using questions related to the regular use of AI in academic activities, assistance with assignments, planning of study, research activities and completion of tasks. The students' critical thinking was tested by their perceptions of a decrease in their ability to think deeply, analyze, research independently, solve problems, and generate their own ideas. Human agency was indirectly measured through measures of independent thought, confidence without AI, verification behaviour, cognitive reliance, and reliance on AI recommendations. The academic decision-making aspect was assessed by analyzing academic decisions, study decisions, academic research-topic selection, performance-related academic research-topic selection, and academic decision support. To include more explanatory constructs in the model, latent constructs were added to the model, such as trust in AI which affects both dependence and decision behavior.

2.4 Data Preparation

The data were examined for missing data, duplications, and inconsistent responses and coding. The responses were recoded on a Likert scale of 1 to 5. Composite scores were obtained for generative AI usage, cognitive dependence, trust in AI, critical thinking and academic decision-making by taking the mean scores of the respective items. The direction of items in this scale, which was explored in greater depth, was particularly interesting because higher item score values on the critical-thinking scale were associated with a higher perceived reduction in independent cognitive activity. Therefore, human agency was determined by indicators of relevance, dependence, confidence and verification, and independent thinking, instead of as a directly measured scale.

2.5 Statistical Analysis

Descriptive statistics were utilized to describe the characteristics of the participants and major study variables. Categorical variables were presented as frequencies and percentages; continuous and composite measures were presented as means and standard deviations. Cronbach's alpha was used to determine the internal consistency of multi-item constructs. Pearson correlation analyses were performed to explore the relationships between the use of generative AI, cognitive dependence, trust in AI, decreased critical thinking and academic decision-making. Multiple linear regression was then tested with academic decision-making as the outcome measure and the various study constructs as predictor measures, as appropriate, with demographic variables as control measures.

2.6 Predictive Analysis

To better capture students with relatively higher AI-driven academic decision-making, a complementary machine-learning analysis was performed. This academic decision-making composite scale was dichotomized into high and low AI dependence with a sample-based cut-off. Three classifiers (logistic regression, decision tree classifier, random forest) and XGBoost were tested. Stratified sampling was applied to the data to split it into training and testing sets and categorical variables were

encoded appropriately. The following metrics of model performance were used: accuracy, precision, recall, F1-score, and ROC-AUC. The predictive analysis was employed to assess the classification performance and reveal patterns of multi-variables that showed higher dependence on generative AI in academic decision-making.

3. Results

3.1 Participant and Dataset Characteristics

The total number of subjects for this analysis was 2,613 students attending university aged 18–28 years, with a mean age of 22.61 years (SD = 2.84). Of the respondents, 59.4% were male and 40.6% were female. The majority of participants were undergraduate students (60.7%) while 55.3% studied at private universities. It is worth noting that no data were missing from the dataset so there was no imputation of missing values for analysis. As illustrated in Table 1, the sample was dominated by undergraduate students, although postgraduate students also constituted a substantial proportion. Representation from both public and private universities provided variation in participants' educational environments.

Table 1. Participant Characteristics of the Study Sample

Characteristic	**Category/Statistic**	**n**	**%**
Gender	Male	1,551	59.4
	Female	1,062	40.6
University type	Private university	1,445	55.3
	Public university	1,164	44.5
	Other	4	0.2
Academic level	Undergraduate	1,587	60.7
	Postgraduate	1,026	39.3
Age	Mean ± SD	22.61 ± 2.84	—
	Range	18–28 years	—

3.2 Patterns of Generative AI Usage

The composite score on the five-point scale for generative AI use was relatively high across all five academic use indicator scores with a mean of 3.80 ± 0.64. Regular academic use had the highest mean (M = 3.91) followed by Assignment writing (M = 3.86). Also above the scale midpoint were research-related use (M = 3.77), study planning (M = 3.75), and reliance on AI for quicker completion of academic tasks (M = 3.71). As seen in Figure 1, there is a consistently high usage of AI in academic activities. The trend indicates that generative AI was not just used for one specific function but was integrated into writing, planning, research, and overall academic processes.

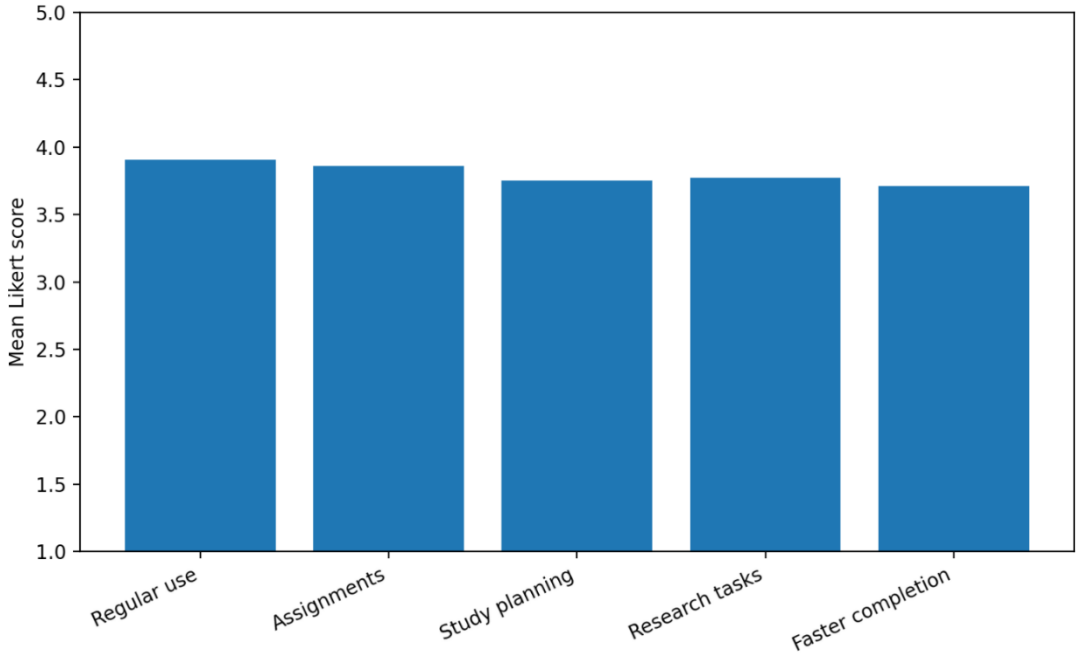

Figure 1. Mean Scores for Generative AI Usage Across Academic Activities

3.3 Critical Thinking Responses

The total score of the reduced-critical-thinking construct was 3.75 ± 0.68, which is a relatively frequent perception of AI reducing independent cognitive effort. The highest mean was for analyzing less when using material generated by AI (M = 3.87), while the lowest mean (but still quite high) was for preference for AI explanations over conducting independent research (M = 3.67). All of the critical-thinking indicators were above the neutral score of 3.00 as seen in Table 2. The findings therefore suggest a general trend towards perceived offloading to AI in terms of reduced analytical engagement with the AI-generated responses, although caution should be exercised in interpreting the composite score given the moderate to low level of internal consistency of this scale.

Table 2. Descriptive Statistics for Reduced Critical-Thinking Indicators

Critical-thinking indicator	**Mean**	**SD**
AI reduces the need to think deeply	3.71	1.14
Less analysis when using AI-generated responses	3.87	1.09
Preference for AI explanations over own research	3.67	1.20
Reduced independent problem-solving effort	3.76	1.11
Greater reliance on AI-generated ideas	3.72	1.17
Overall reduced critical-thinking score	3.75	0.68

Cronbach's α = .556.

3.4 Human Agency and Cognitive Dependence

The responses also showed cognitive dependence on AI with an overall dependence score of 3.55 ± 0.87. Participants also noted the significance of AI in their academic work (M = 3.72) and the inclination to rely on AI before engaging in critical thinking (M = 3.68). To exemplify agency in the same way, some dependence/trust items were reverse-coded to reflect greater independent agency. These indicators aligned generally below the neutral midpoint and were agency-oriented. Figure 2 displays relatively low levels of scores for the following: "independent thinking before using AI" (M = 2.32); "confidence with answers produced by AI" (M = 2.49); "verification of AI-generated answers" (M = 2.49); and "preference for own judgment" (M = 2.45). Although these measures are not a directly validated human-agency scale, they suggest that the more participants relied on AI, the less they engaged in self-directed and verification-oriented behaviors.

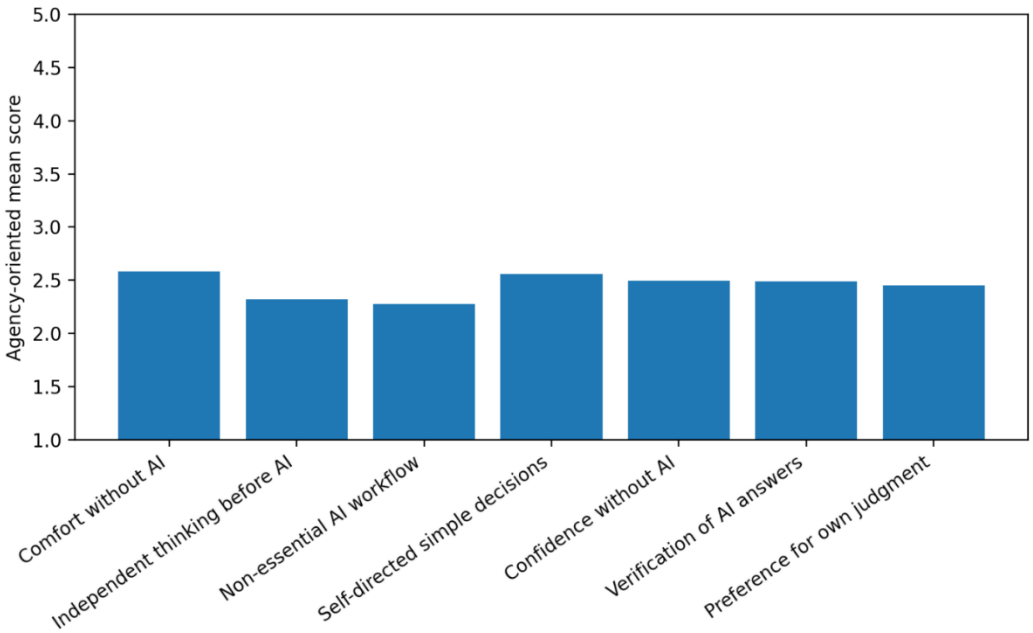

Figure 2. Agency-Oriented Indicators Derived from Cognitive Dependence and Trust Measures

3.5 AI-Assisted Academic Decision-Making

The mean score of academic decision-making was 3.75 with a standard deviation of 0.68 which highlights the wide use of AI in academic decisions. The best-rated one was the use of AI to select research topics or project ideas (M = 3.93). Also, AI recommendations on study-related choices scored quite highly (M = 3.76), whereas the general impact on academic choices scored lowest (M = 3.66). Table 3 suggests that AI has been integrated into various types of academic decision-making, with the most intensive integration in the choices of research topics and project ideas. Similar to the critical-thinking scale, the modest internal consistency of the composite measure implies that individual item patterns need to be taken into account as well.

Table 3. Descriptive Statistics for AI-Assisted Academic Decision-Making

Decision-making indicator	**Mean**	**SD**
AI influences academic decisions	3.66	1.16
AI suggestions are used for study-related decisions	3.76	1.06
AI helps select research topics or project ideas	3.93	1.13
AI recommendations are used to improve academic performance	3.71	1.16
AI positively affects academic decision-making	3.67	1.16
Overall academic decision-making score	3.75	0.68

Cronbach's α = .553.

3.6 Relationships Among Major Study Constructs

A Pearson correlation analysis showed that there were statistically significant relationships between the major constructs. Academic decision-making was moderately positively correlated with cognitive dependence ($r = .534$, $p < .001$), trust in AI ($r = .526$, $p < .001$), and AI usage ($r = .488$, $p < .001$). Weaker positive bivariate correlations with academic decision-making were observed with reduced critical thinking ($r = .106$, $p < .001$). The most positive interconstruct relationship was found between cognitive dependence and trust in AI ($r = .707$, $p < .001$). Figure 3 shows that students who said they used AI more were more cognitively dependent and trusted it were more likely to say that they used AI in academic decision-making. The correlation between cognitive dependence and trust was particularly high, which means that trust in AI and behavioral reliance were rather closely tied to each other.

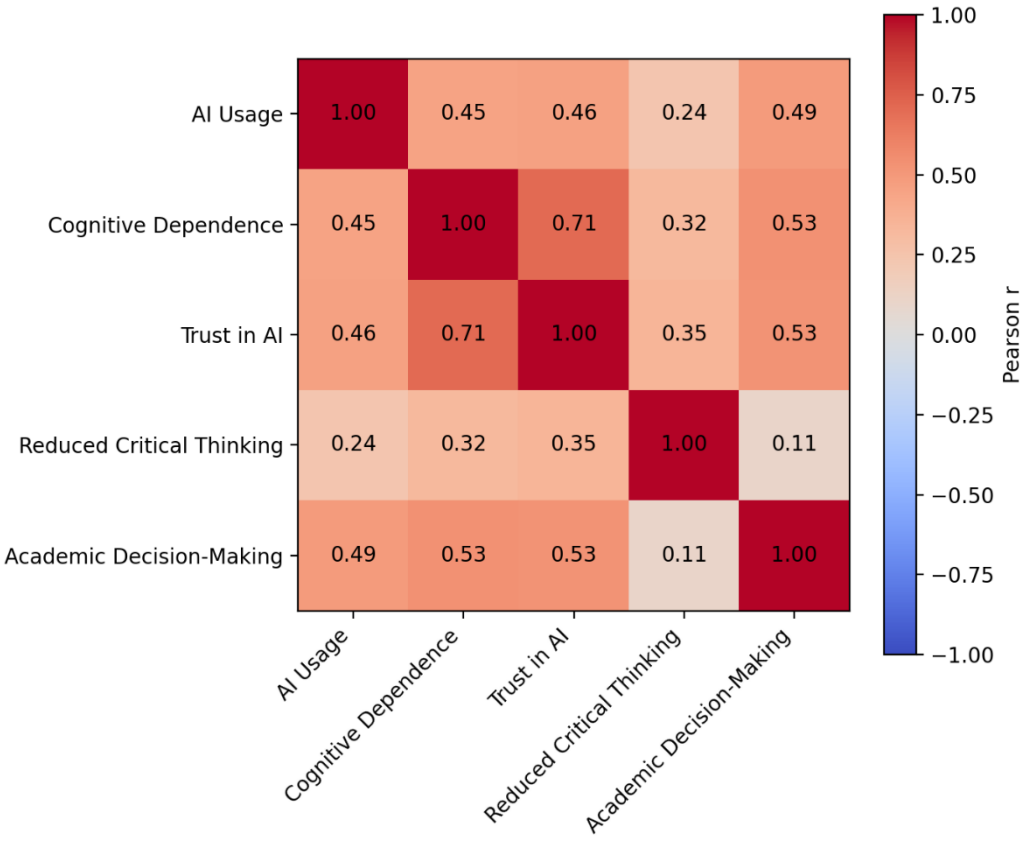

Figure 3. Correlation Matrix of Generative AI Usage, Cognitive Dependence, Trust, Critical Thinking, and Academic Decision-Making

3.7 Predictors of AI-Assisted Academic Decision-Making

The independent contribution of the major constructs to academic decision-making was examined using multiple linear regression, controlling for gender, university type and academic level. This overall model was statistically significant, $F(8, 2604) = 224.50$, $p < .001$, accounting for about 40.8% of the variance in academic decision-making ($R^2 = .408$; adjusted $R^2 = .406$). Cognitive dependence ($\beta = .292$), AI usage ($\beta = .273$) and trust in AI ($\beta = .254$) were the strongest standardized predictors. Interestingly, reduction of critical thinking had a negative coefficient when the correlated AI-use, trust and dependence variables were controlled at the same time. This coefficient is understood as a conditional multivariable association, and not proof that a decrease in critical thinking leads to a decrease in AI-related decision-making as shown in Table 4.

Table 4. Multiple Regression Predicting AI-Assisted Academic Decision-Making

Predictor	B	SE	Standardized β	t	p
AI usage	0.292	0.019	0.273	15.47	<.001
Cognitive dependence	0.228	0.018	0.292	12.97	<.001
Trust in AI	0.231	0.020	0.254	11.43	<.001
Reduced critical thinking	-0.130	0.016	-0.130	-7.99	<.001
Male gender	0.072	0.022	—	3.28	.001
Private university	0.084	0.264	—	0.32	.751
Public university	0.122	0.264	—	0.46	.643
Undergraduate level	0.082	0.022	—	3.75	<.001

3.8 Computational Model Performance

The academic decision-making score was then split at the median (3.80) to create 1,142 higher

dependence and 1,471 lower or equal dependence cases for use in the predictive analysis. Four classifiers: logistic regression, decision tree, random forest and XGBoost were then compared using the stratified training-test procedure. The ROC-AUC obtained from XGBoost is the highest (0.748) followed by random forest (0.731), decision tree (0.721), and logistic regression (0.692). The accuracy of classification varied from 63.3% with logistic regression to 68.6% with the decision tree. As indicated in Figure 4, all four classifiers were above chance level. The decision tree had the highest observed accuracy and XGBoost had the best overall discrimination.

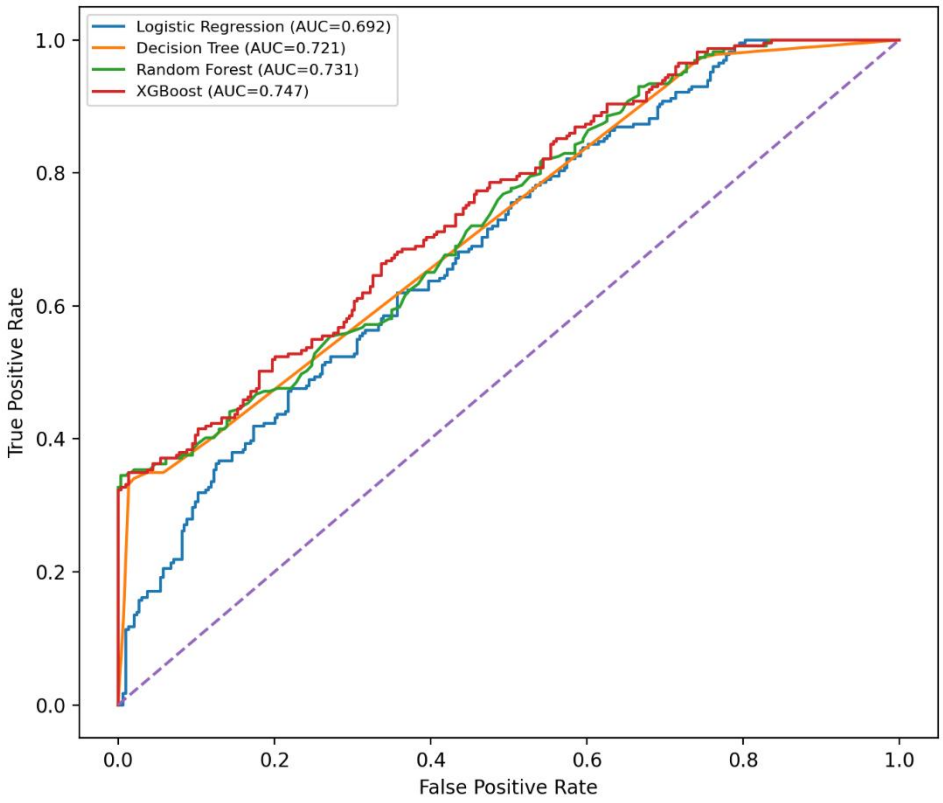

Figure 4. ROC Curves for Prediction of Higher AI-Dependent Academic Decision-Making

These results indicate that patterns of AI usage, cognitive dependence, trust, reduced critical thinking, and demographic characteristics contain meaningful, although moderate, information for identifying students with greater AI-dependent academic decision-making.

4. Discussion

The results show that generative AI is now a significant part of students' learning experiences and considerations. AI usage throughout the assignment preparation, study planning, research, and even overall academic support was noted. There were particularly strong relationships between cognitive dependence and trust in AI and AI-assisted academic decision-making, and between reduced critical thinking and a comparatively weaker association. The results suggest that generative AI impacts not only task completion, but also students' judgment, autonomy and decision-making processes. The same concerns have been raised as students increasingly offload thinking activities to AI systems (Si et al., 2026).

There is a positive correlation between using generative AI and academic decision-making, indicating that students are increasingly using AI-generated recommendations for academic decisions. AI systems give instant access to alternatives, explanations, and recommendations, thus minimizing the cognitive load involved in reaching some decisions. This is similar to findings that people can show algorithm appreciation and at times even favor algorithmic recommendations over human judgment (Logg et al., 2019). The acceptance of AI, however, depends on the context, since a lack of AI acceptance can happen when decisions are perceived as being very personal or when a human understanding is

needed (Longoni et al., 2019). Thus, it is important to have a proper balance between human and intelligent systems in the process of human-AI decision-making (Puranam, 2021).

The results showed that students perceived a decrease in deep thinking, analytical involvement, independent academic research, and problem-solving skills when using generative AI. This lends credence to worries that reliance leads to mental offloading instead of thinking (Si et al., 2026). However, the use of generative AI doesn't always diminish critical thinking. Some studies have found that well-crafted ChatGPT tasks can promote critical thinking through evaluation, questioning, and reflection (Liang & Wu, 2024). Likewise, complex critical thinking skills have been found when students interact with ChatGPT in a structured manner, and AI-enabled analysis of peer feedback offers a chance to assess reasoning processes (Suriano et al., 2025; Tang et al., 2024).

Human agency in this study was manifested in independent thinking, confidence without AI, verification behavior, and reluctance to become too dependent. Having lower ratings on some agency indicators indicates that some students might be using AI increasingly without making their own decisions. Trust is especially relevant, as reliance on AI decision aids relies on perceived credibility and risk associated with automated recommendations (Tang et al., 2024). Student perceptions also influence how ChatGPT is perceived as an assistive tool for learning or a replacement for the students' own work (Shoufan, 2023).

Cognitive dependence was the top predictor for AI-assisted academic decision making, followed by AI usage and trust. This means that reliance on a decision is not just a result of the availability of AI tools but also a function of their frequent use and trust in their results. Cognitive models of AI decision-support also highlight that reliance varies between users and depends on the way users incorporate AI advice and their own judgment (Tejeda et al., 2022).

The results underscore that universities should instead foster responsible AI literacy, rather than banning the use of AI. Pupils need to be taught to validate AI-generated answers, to make comparisons, to explain choices, and to ensure independent thinking. Studies on Generative AI in Higher Education also highlight how AI can be used to enhance learning when it is structured and responsible for the student (McGrath et al., 2025; Mohebi, 2024).

There are several caveats to be recognized. The cross-sectional design does not allow causal interpretation, and self-reported responses may lead to perception and response bias. The sample was limited to university students, and human agency was measured indirectly using dependence, verification, confidence, and independent-thinking indicators, rather than a separate validated human agency scale.

Longitudinal and experimental designs are recommended for future studies to investigate the long-term impact of regular use of generative AI on critical thinking and agency. This should be expanded to encompass broader populations and direct measures of agency. Behavioral decision-making tasks also help differentiate reported dependence from real dependence, providing a clearer understanding of how generative AI influences independent judgment.

5. Conclusion

In this study, the relationships between the use of generative AI, thinking skills, human agency, cognitive dependence and academic decision-making in digital learning environments were explored. The findings highlight the high level of use of generative AI in the academic work of students, whether in preparing assignments, planning their work, supporting research or making decisions. More use of AI, cognitive dependence, and trust in AI were correlated with increased reliance on academic decisions made with the aid of AI, with cognitive dependence being the strongest predictor. Meanwhile, students indicated that using AI frequently impacts their independent judgment skills, as they also reported decreased deep thinking, analytical engagement, independent problem solving and verification behavior. The results, however, cannot be used as causal conclusions because of the cross-sectional survey data. Human agency was also indirectly measured by confidence, verification, independence and dependence scale items not through a specific scale. The study shows that

generative AI can contribute to the efficiency of academic work and decision making, but in order to be educational, it must be accompanied by meaningful human engagement. To this end, universities have a role to play in ensuring responsible AI literacy, in encouraging verification of AI-generated content and in constructing learning activities that maintain critical thinking and autonomous decision-making. Longitudinal, experimental, and behavioral analyses are suggested as future research methods to deepen the understanding of the impact of long-term use of AI on cognition and human agency.

References

1. Albadarin, Y., Saqr, M., Pope, N., & Tukiainen, M. (2024). A systematic literature review of empirical research on ChatGPT in education. Discover Education, 3(1), 60. https://doi.org/10.1007/s44217-024-00138-2
2. Araujo, T., Helberger, N., Kruikemeier, S., & De Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. AI & SOCIETY, 35(3), 611–623. https://doi.org/10.1007/s00146-019-00931-w
3. Arifen, R., Rahman, M. K. M., & Khandakar, S. (2026). Dataset on Cognitive Dependence on Generative AI Tools among Bangladeshi University Students. 2. https://doi.org/10.17632/7m94b7yr8w.2
4. Baig, M. I., & Yadegaridehkordi, E. (2024). ChatGPT in the higher education: A systematic literature review and research challenges. International Journal of Educational Research, 127, 102411.
5. Bhullar, P. S., Joshi, M., & Chugh, R. (2024). ChatGPT in higher education—A synthesis of the literature and a future research agenda. Education and Information Technologies, 29(16), 21501–21522. https://doi.org/10.1007/s10639-024-12723-x
6. Cao, S., & Huang, C.-M. (2022). Understanding User Reliance on AI in Assisted Decision-Making. Proceedings of the ACM on Human-Computer Interaction, 6(CSCW2), 1–23. https://doi.org/10.1145/3555572
7. Castillo-Martínez, I. M., Flores-Bueno, D., Gómez-Puente, S. M., & Vite-León, V. O. (2024). AI in higher education: A systematic literature review. Frontiers in Education, 9, 1391485. https://www.frontiersin.org/journals/education/articles/10.3389/feduc.2024.1391485/full
8. 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(1), 43. https://doi.org/10.1186/s41239-023-00411-8
9. Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, 61(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148
10. Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., & Ahuja, M. (2023). Opinion Paper:"So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International Journal of Information Management, 71, 102642.
11. Essel, H. B., Vlachopoulos, D., Essuman, A. B., & Amankwa, J. O. (2024). ChatGPT effects on cognitive skills of undergraduate students: Receiving instant responses from AI-based conversational large language models (LLMs). Computers and Education: Artificial Intelligence, 6, 100198.
12. Essien, A., Bukoye, O. T., O'Dea, X., & Kremantzis, M. (2024). The influence of AI text generators on critical thinking skills in UK business schools. Studies in Higher Education, 49(5), 865–882. https://doi.org/10.1080/03075079.2024.2316881
13. Farrokhnia, M., Banihashem, S. K., Noroozi, O., & Wals, A. (2024). A SWOT analysis of ChatGPT: Implications for educational practice and research. Innovations in Education and Teaching International, 61(3), 460–474. https://doi.org/10.1080/14703297.2023.2195846
14. Grassini, S. (2023). Shaping the future of education: Exploring the potential and consequences of AI and ChatGPT in educational settings. Education Sciences, 13(7), 692.
15. Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., & Hüllermeier, E. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274.
16. Labadze, L., Grigolia, M., & Machaidze, L. (2023). Role of AI chatbots in education: Systematic literature review. International Journal of Educational Technology in Higher Education, 20(1), 56. https://doi.org/10.1186/s41239-023-00426-1
17. Liang, W., & Wu, Y. (2024). Exploring the use of ChatGPT to foster EFL learners' critical thinking skills from a post-humanist perspective. Thinking Skills and Creativity, 54, 101645.
18. Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. Organizational Behavior and Human Decision Processes, 151, 90–103.
19. Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. Journal of Consumer Research, 46(4), 629–650.
20. McGrath, C., Farazouli, A., & Cerratto-Pargman, T. (2025). Generative AI chatbots in higher education: A review

of an emerging research area. Higher Education, 89(6), 1533–1549. https://doi.org/10.1007/s10734-024-01288-w

21. Mohebi, L. (2024). Empowering learners with ChatGPT: Insights from a systematic literature exploration. Discover Education, 3(1), 36. https://doi.org/10.1007/s44217-024-00120-y
22. Puranam, P. (2021). Human–AI collaborative decision-making as an organization design problem. Journal of Organization Design, 10(2), 75–80. https://doi.org/10.1007/s41469-021-00095-2
23. Shoufan, A. (2023). Exploring students' perceptions of ChatGPT: Thematic analysis and follow-up survey. IEEE Access, 11, 38805–38818.
24. Si, S., Qi, Y., Xu, J., & Qi, X. (2026). When Thinking Is Outsourced: Cognitive Offloading and the Heterogeneity of Critical Thinking Among Chinese University Students Using Generative Artificial Intelligence. Journal of Intelligence, 14(7), 116. https://doi.org/10.3390/jintelligence14070116
25. Suriano, R., Plebe, A., Acciai, A., & Fabio, R. A. (2025). Student interaction with ChatGPT can promote complex critical thinking skills. Learning and Instruction, 95, 102011. https://doi.org/10.1016/j.learninstruc.2024.102011
26. Tang, T., Sha, J., Zhao, Y., Wang, S., Wang, Z., & Shen, S. (2024). Unveiling the efficacy of ChatGPT in evaluating critical thinking skills through peer feedback analysis: Leveraging existing classification criteria. Thinking Skills and Creativity, 53, 101607.
27. Tejeda, H., Kumar, A., Smyth, P., & Steyvers, M. (2022). AI-Assisted Decision-making: A Cognitive Modeling Approach to Infer Latent Reliance Strategies. Computational Brain & Behavior, 5(4), 491–508. https://doi.org/10.1007/s42113-022-00157-y