JOURNAL OF MULTIDISCIPLINARY SCIENTIFIC KNOWLEDGE

Vol. 01, Issue. 02, June, 2026

Digital Learning Readiness, Artificial Intelligence Adoption, and Academic Performance among University Students: A Multidisciplinary Empirical Study

Bijoy Mitra

Received:- 03/05/2026, Revised:- 07/06/2026, Accepted:- 15/06/2026, Published:- 22/06/2026

Abstract

The study adopts quantitative, cross-sectional and explanatory research design with harmonized analytical sample of 3999 students from first, second and third year academic levels. The students' level of preparation for digital learning, their level of use of Artificial Intelligence(AI) and their learning outcomes were assessed using composite indicators based on the technological, behavioural and academic indicators. Descriptive statistics, group comparison tests, Pearson correlation analysis and hierarchical multiple regression were used. The results indicated that digital learning readiness and AI adoption were generally at a moderate to high level for most students, and academic performance was mostly at a moderate level. Demographic and behavioural factors explained 32% of the variance in EJSS scores, with digital learning readiness accounting for the remaining variance and contributing positively.Demographic and behavioural factors accounted for 32% of the variance in EJSS scores and digital learning readiness was a significant positive independent predictor, when controlling for the demographic and behavioural factors. Students' academic achievement was much higher for those with high readiness compared to moderate and low readiness. However, there was no significant relationship between academic performance and AI adoption, nor was the interaction between digital learning readiness and AI adoption significant. There were positive associations between concept understanding and academic performance, as well as between attendance and academic performance. The research findings indicate that being technologically prepared is more directly linked to students' learning outcomes than the level of AI use. Higher education institutions, therefore, have the responsibility for enhancing digital competence, self-directed learning, responsible AI literacy, and pedagogically guided technology integration to boost academic resu006Cts.

Keywords: Digital learning readiness; Artificial intelligence adoption; Academic performance; University students; Higher education

Department of Geography and the Environment, College of Natural Sciences and Mathematics, University of Denver, Denver, CO, USA

Corresponding Author: Bijoy Mitra

1. Introduction

Digital transformation has transformed the education sector, providing greater access to online platforms, digital resources, virtual classrooms, and intelligent learning systems in the domain of higher education. The use of technology in teaching is gaining ground in universities to provide flexibility, engagement and continuity in learning. The use of e-learning services has been linked with sustainable learning practices and enhanced academic outcomes when the students have the capability and willingness to learn using these services (Alam et al., 2021). Active mixed learning can also be used as a tool to enrich students' learning experiences, by fostering students' participation, interaction and responsibility for learning (Armellini et al., 2021).

Digital learning readiness is defined as students' readiness to engage successfully in learning through technology. It involves access to devices and internet services, digital competence, self-directed learning, communication skills, motivation and confidence in the use of online platforms. Readiness is crucial because students with a lack of technological skills and a weak self-regulation ability will find it difficult even if they have access to digital learning systems. Joosten and Cusatis (2020) highlighted that online learning readiness has several behavioural and technological aspects which affect students success. There is also cross-national evidence showing that the readiness of university students to utilize digital media and online learning tools varies significantly among different groups (Küsel et al., 2020). Other factors that have been associated with online readiness include satisfaction, self-regulation, and academic success (Yavuzalp & Bahcivan, 2021). Artificial Intelligence(AI) has added another layer of significant importance in the field of education. AI tools can be used to enhance personalized learning, provide automated feedback, create content, evaluate learning, and facilitate academic decision-making. While not without challenges, AI is poised to revolutionize higher education, as discussed by Bates et al. (2020). Hwang et al. (2020) also recognized personalization, intelligent tutoring and adaptive learning as some of the biggest opportunities that come with the application of AI in education. Generative AI is helping to drive students closer to intelligent technologies. Students are more and more relying on applications like ChatGPT to explain concepts, generate summaries, create assignment content, solve problems, and get instant feedback. Overall, university students view generative AI as a helpful, accessible, and learning-enabling tool, but with some reservations about accuracy, dependence, privacy and academic honesty issues (Chan & Hu, 2023).

The factors that affect the acceptance of ChatGPT include perceived usefulness, ease of use, social influence and facilitating conditions (Strzelecki, 2024). The intention to use ChatGPT was also reported in studies by Habibi et al. (2023) to be depending on both the technical acceptance and educational expectation of students. Studies have yielded conflicting results on the impact of AI on education. When AI tools are used as a support mechanism instead of a replacement for critical thinking, they can enhance the learning process and encourage self-education, potentially boosting learning outcomes (Boubker, 2024). The use of generative AI can boost achievement by increasing feelings of self-efficacy and cognitive engagement (Liang et al., 2023). Based on current experimental evidence, ChatGPT has the potential to enhance learning in a controlled educational environment (Deng et al., 2025). But over-reliance on the quick AI response can reduce critical thinking, originality, and mental work (Essel et al., 2024). A SWOT analysis of ChatGPT also revealed educational possibilities and threats such as misinformation, dependence, and assessment integrity (Farrokhnia et al., 2024). Digital learning conditions continue to be relevant to academic outcomes as well. The use of pre-recorded and live online lectures could be helpful to achievement in different ways contingent on students' learning preferences and engagement (Le, 2022). Digital devices can enhance academic performance or detract from it when they are used for academic tasks or for other purposes (Limniou, 2021). The factors affecting academic achievement in online courses include participation, motivation, course structure, and readiness of the students (Choi, 2021). In addition, graduate students report that access to and interaction with and personal learning management influence achievement in online settings (Omar et al., 2021).

Digital competence can thus be considered as a basis for effective involvement in technology-rich education (López Aguilar et al., 2022). The educational technology of digital learning and learning outcomes are also significant factors in determining whether they can be transferred to meaningful learning outcomes (Nikou & Aavakare, 2021). According to recent reviews, ChatGPT can be used to aid teaching and learning, but this depends on the discipline, the design of the task, and the way in which it is used (Lo, 2023). Additionally, there is some evidence suggesting that generative AI can enhance learning outcomes for university students as well, but the amount of improvement relies on the context of the learning and how it is used responsibly (Chen & Cheung, 2025). Even though the adoption of technology is important, it is not enough to ensure the achievement of learning outcomes, it is still necessary to prepare students for online learning (Sukmawati, 2022). Therefore, this study is designed to explore the relationships between digital learning readiness, AI adoption, and academic performance of university students. It is applicable to students with varying academic levels and profiles of learning in a multidisciplinary environment in higher education.

The aims are to Gauge the current digital learning readiness level and AI adoption level of students. Compare academic performance across the categories of digital learning readiness and AI adoption. Explore the correlation between the major constructs. Examine the relationship between digital learning readiness and AI adoption as they relate to academic performance. Test the independent and independent-interactive relationship between digital learning readiness and AI adoption as they relate to academic performance. Identify differences in academic performance across various categories of digital learning readiness and AI adoption. Identify differences in academic performance based on students' AI adoption level. Identify differences in academic performance based on students' digital learning readiness level.

2. Methodology

2.1 Research Design and Study Population

The research design in this study was quantitative, cross sectional, and explanatory in nature to see the relationships between digital learning readiness and the use of artificial intelligence with academic performance of university students. A multidisciplinary approach was adopted by having students from various levels and learning profiles. This analytical sample comprised 3999 students from first-, second-, and third-year university students (Abdullah Rashid, 2025). Demographic, behavioural, technological, and academic information were provided for each observation to assess the proposed relationships (Shamim, 2024). The records have been assembled from two structured student level data sources, neither of which included a common identification variable. Thus, it was not feasible to link individual-level records. A profile-matching process was conducted to achieve the integration of similar observations with regard to age, gender, study intensity, attendance, examination performance and assignment performance. Data were used as a harmonized analytical sample instead of as data collected from the same respondents at one time. Before analysis, duplicate entries were identified, incomplete records were checked, categories were checked for consistency, and values were compared to see if they were outside of reasonable bounds.

2.2 Variables and Measurement

The initial explanatory construct was digital learning readiness. It was evaluated with indicators that involve with Internet access, availability of digital resources, participation in online courses, online discussion involvement, use of educational technology in the process of study, completion of assignments, motivation to learn, attendance, and study behaviour. These were standardized and then aggregated together to create a Digital Learning Readiness Index (DLRI) on a scale of 0-100. The higher the scores, the more prepared they were to be effectively involved in technology-mediated learning. AI adoption was included in the study based on the following indicators AI-use status, duration of use of AI daily, number of prompts used per week, types of AI tools used, purpose of using AI, level of dependence on AI, percentage of content generated by AI, and scores for responsible use of AI or AI-ethics. The indicators were then harmonised across the different measurement scales and then aggregated into an AI Adoption Index (0-100). Higher scores indicated a higher level of engagement with academic activities with the help of AI. Academic performance was used as the primary outcome variable. It was assessed with the help of examination scores, average score on assignments, final score, attendance, concept-understanding scores, consistency of study, improvement rate, assignment completion, and pass status. The measures were standardized and consolidated into an Academic Performance Index. To make a descriptive comparison, the three indices were also divided into low, moderate, and high. Control variables included were age, gender, academic year, study hours, sleep hours, social-media usage, tutoring hours, class participation, stress level, and learning style.

2.3 Data Preparation and Quality Assessment

All variables were restructured for standardization of names, category recoding, numerical conversion, missing value check, outlier detection, and scale harmonization as part of the data-preparation process. The composite indices were created by aggregating continuous indicators measured on different scales which were standardized to 0-100. Wherever conceptually feasible, items that measured negative aspects of the variables were reverse coded.

The internal reliability of the composite measures was assessed by internal reliability analysis. The item–total relationships and correlation patterns were analysed to ensure the selected indicators had good coverage of the constructs they represented. Tolerance statistics and variance inflation factors were used to check for multicollinearity. Skewness, Kurtosis, Histograms and normality tests were used to assess the distributional assumptions.

2.4 Statistical Analysis

Descriptive statistics such as frequencies, percentages, means, standard deviations, minimums and maximums were computed to summarize the student characteristics and the three main indices. Independent-samples t-tests and one-way analysis of variance were conducted to compare differences between gender, academic year, AI-use status and readiness categories. For situations in which the distributional assumptions were not met, non-parametric alternatives were used. Pearson correlation analysis was used to determine the direction and strength of associations among digital learning readiness, AI adoption, and academic performance.

A hierarchical multiple regression analysis was then performed to account for the individual effects of digital learning readiness and AI adoption while accounting for the effects of the demographic and behavioural characteristics. An interaction effect between digital learning readiness and AI use was added to measure whether readiness further enhanced the academic gains from using AI. A 5% level of significance was used for the statistical significance, and standardized coefficients, confidence interval, model fit and effect sizes were reported for the interpretation.

2.5 Ethical Considerations

The study was based on anonymized student-level data, which did not contain names, contact details, institutional identifiers or other information that could be used to identify the student. Only academic research was permitted to use the data and it was kept securely to ensure that no unauthorised use was made of it. Results were presented in summary form to prevent names from being given of any student or institution. All principles of confidentiality, responsible data use and research integrity were taken into account in performing the analysis.

3. Results

3.1 Participant Profile and Descriptive Statistics

Three thousand, nine hundred and ninety-nine university students were analyzed. Male students made up 49.6% of the sample, female 46.8% and 3.6% selected other gender category. The distribution of students by academic year was fairly even (33.9% in the first year, 32.7% in the second year and 33.4% in the third year). About 63.8% of the students said that they used AI tools for academic or learning activities. The average Digital Learning Readiness Index was found to be at 60.70 ± 13.42 (moderate). The mean AI Adoption Index was 58.28 ± 16.23 and the Academic Performance Index averaged 60.17 ± 12.00. The three indices were found to be reasonably symmetrically distributed as the median values did not differ much from the mean values and the skewness coefficients were small. Table 1 presents the demographic and academic profile of the 3,999 university students, such as gender, academic year, AI-use, and descriptive statistics of digital learning readiness, AI adoption and academic performance. From this, it is clear that the three main indices are generally distributed in bell shapes with AI adoption manifesting more variation than digital learning readiness and academic performance (as shown in Figure 1).

Table 1. Participant characteristics and descriptive statistics

Variable	Category/measure	n (%) or Mean ± SD	Minimum–Maximum
Gender	Female	1,872 (46.8%)	—
	Male	1,985 (49.6%)	—
	Other	142 (3.6%)	—
Academic year	First year	1,356 (33.9%)	—
	Second year	1,309 (32.7%)	—
	Third year	1,334 (33.4%)	—
AI-use status	Uses AI	2,551 (63.8%)	—
	Does not use AI	1,448 (36.2%)	—
Digital learning readiness	Continuous index	60.70 ± 13.42	8.80–99.20
AI adoption	Continuous index	58.28 ± 16.23	7.25–97.99
Academic performance	Continuous index	60.17 ± 12.00	24.06–92.86

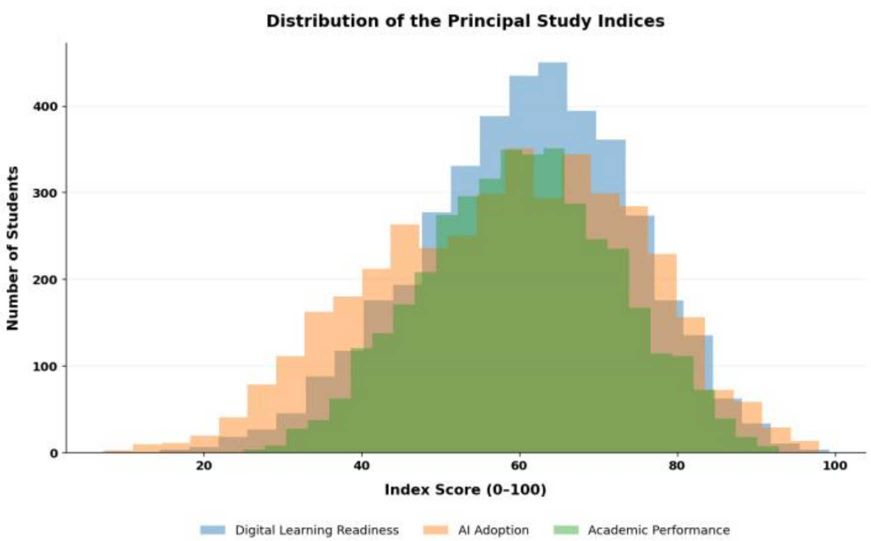

Figure 1. Distribution of digital learning readiness, artificial intelligence adoption, and academic performance index scores among university students

3.2 Levels of Digital Readiness, AI Adoption, and Academic Performance

The majority of students were in the “moderate digital learning readiness” category. Specifically, 62.5% of the students (2498) were moderately ready, while 1,398 students were high ready. There were 103 students identified as "low digital learning readiness. Likewise, a moderate uptake of AI was noted among 2350 students representing 58.8% of the sample. 1,357 students were identified as high adopters of AI, and 292 students were identified as low adopters of AI. The majority of students' academic performance was moderate, 2308 students, or majority of the students was in moderate category. 868 students were reported as high achievers while 823 were reported as low achievers. Table 2 reveals that the majority of students were in the moderate range of digital learning readiness, AI adoption, and academic performance with relatively fewer students being in the low-readiness range. As can be seen in Figure 2, academic performance has shown a steady improvement with the progressive increase in the degree of readiness of the students in the low-readiness group, moderate-readiness group, and high-readiness group, respectively.

Table 2. Distribution of the principal study constructs by category

Construct	Category	Frequency	Percentage
Digital learning readiness	Low	103	2.6%
	Moderate	2,498	62.5%
	High	1,398	35.0%
AI adoption	Low	292	7.3%
	Moderate	2,350	58.8%
	High	1,357	33.9%
Academic performance	Low	823	20.6%
	Moderate	2,308	57.7%
	High	868	21.7%

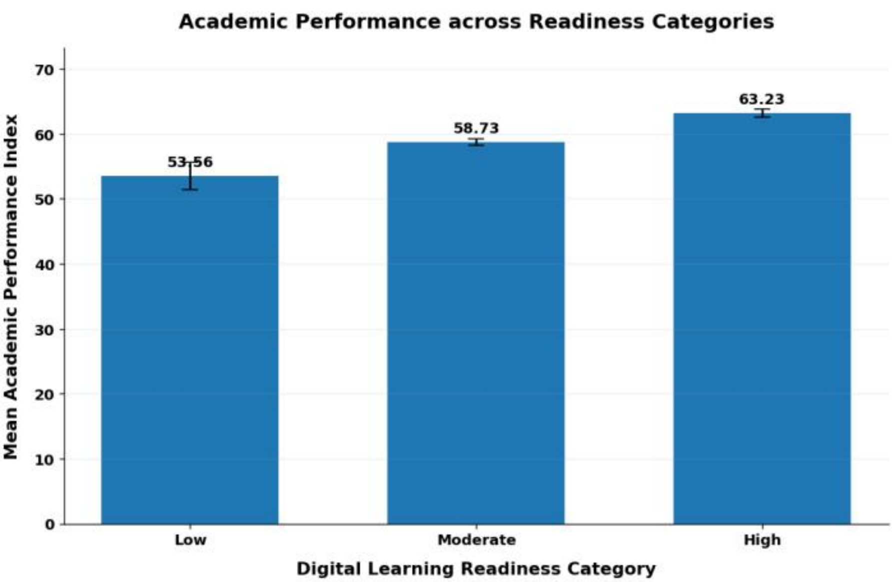

Figure 2. Mean academic performance index across low, moderate, and high digital learning readiness categories error bars represent 95% confidence intervals

3.3 Group Differences in Academic Performance

Significant differences in academic performance was found between the digital learning readiness groups ($F = 82.19$) ($p < 0.001$). The average scores of the students were highest for the high readiness level and lowest for the low readiness level. However, there was no significant difference between the three categories of AI in academic performance ($F = 1.38$, $p = 0.252$).

The average performance scores were not significantly different between low, moderate and high AI adopters. Gender and academic year, as well as general AI-use status, did not show any statistically significant differences. As indicated in Table 3, there were significant differences between the academic performance of the various digital learning readiness categories, but no significant differences in academic performance between the various categories of AI adoption, gender, academic year, and AI-use status.

Table 3. Comparison of academic performance across student groups

Grouping variable	Category	n	Academic performance Mean ± SD	Test statistic	p-value
Digital learning readiness	Low	103	53.56 ± 10.86	F = 82.19	<0.001
	Moderate	2,498	58.73 ± 11.94		
	High	1,398	63.23 ± 11.50		
AI adoption	Low	292	59.08 ± 12.15	F = 1.38	0.252
	Moderate	2,350	60.19 ± 12.03		
	High	1,357	60.36 ± 11.90		
Gender	Female	1,872	60.12 ± 12.00	F = 0.09	0.917
	Male	1,985	60.19 ± 11.98		
	Other	142	60.54 ± 12.34		
Academic year	First year	1,356	59.98 ± 12.06	F = 1.12	0.328
	Second year	1,309	59.96 ± 11.72		
	Third year	1,334	60.57 ± 12.19		
AI-use status	Non-user	1,448	60.02 ± 12.06	t = −0.61	0.545
	User	2,551	60.26 ± 11.96		

3.4 Correlation Analysis

The result of Pearson correlation analysis for academic performance and digital learning readiness was $r = 0.220$, $p< 0.001$, which indicates that there was a positive correlation between the two variables. This suggests that learning outcomes were more positive overall for students who were more ready to learn in digital learning environments.

There was no significant correlation between using AI and academic performance ($r = 0.009$, $p = 0.589$). There was also no association between digital learning readiness and the use of AI, ($r = 0.005$), ($p = 0.756$). The concept understanding was the most highly correlated with academic performance ($r = 0.427$), ($p < 0.001$), followed by attendance ($r = 0.145$), ($p < 0.001$), among the academic variables that were supporting. As seen in Table 4, there was a positive correlation between digital learning readiness and academic performance, attendance and concept understanding, with no significant relationship between AI adoption and academic performance. The academic performance was the highest positively correlated with concept understanding, followed by digital learning readiness and attendance, while AI adoption did not have a significant correlation. (See Figure 3)

Table 4. Pearson correlations among the principal study variables

Variable	1	2	3	4	5	6
1. Digital learning readiness	1.000					
2. AI adoption	0.005	1.000				
3. Academic performance	0.220***	0.009	1.000			
4. Study hours	0.015	−0.012	0.028	1.000		
5. Attendance	−0.056***	0.044**	0.145***	0.007	1.000	
6. Concept understanding	−0.013	−0.004	0.427***	0.020	0.008	1.000

*Note: **p < 0.01; **p < 0.001.

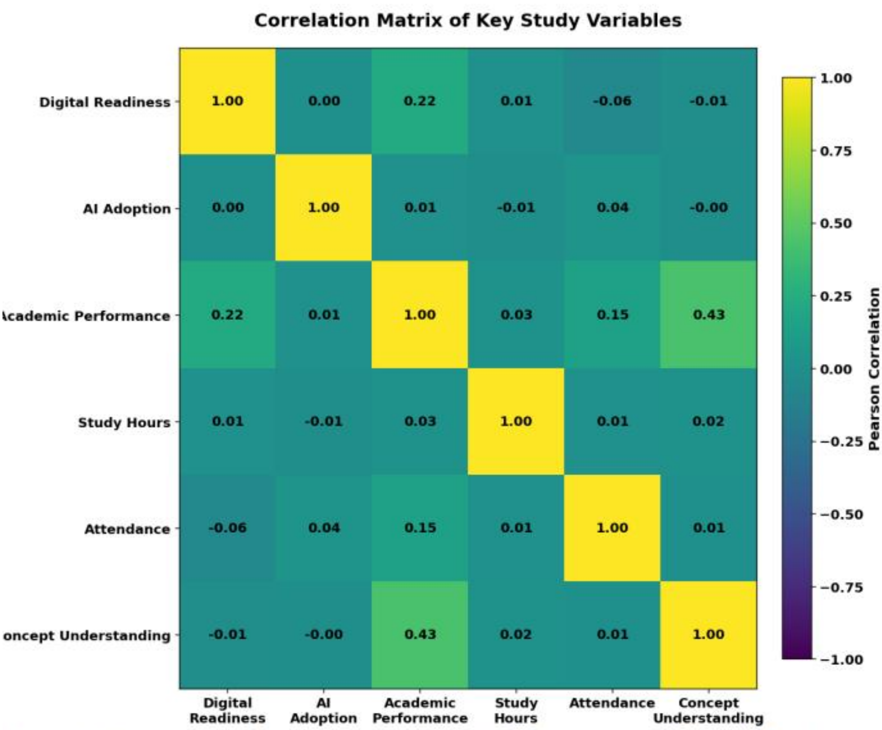

Figure 3. Pearson correlation matrix for digital learning readiness, AI adoption, academic performance, study hours, attendance, and concept understanding

3.5 Predictors of Academic Performance

To answer the question of whether digital learning readiness and AI adoption independently predicted academic performance, hierarchical multiple regression was used. There was no significant difference in academic performance found in the control-only model (R^2 = 0.001), and adjusted (R^2 = -0.001) (p = 0.950).

The inclusion of digital learning readiness and the adoption of AI brought this explained variance to 4.9% with a change in (R^2) of 4.8%. Digital learning readiness emerged as a statistically significant positive predictor of academic performance, (\beta = 0.220), (t = 14.24), (p < 0.001), 95% CI [0.190, 0.250]. This finding indicates that a one-standard-deviation increase in readiness was associated with an approximately 0.22-standard-deviation increase in academic performance after accounting for demographic and behavioural characteristics.

AI adoption did not independently predict academic performance, (\beta = 0.008), (t = 0.54), (p = 0.590), 95% CI [−0.022, 0.039]. The interaction between digital learning readiness and AI adoption was also non-significant, (\beta = -0.013), (p = 0.415). The relationship between digital learning readiness and the use of AI was non-significant as well, (\beta = -0.013), (p = 0.415). Thus, there was no significant difference between the relationships of the use of AI and performance among students with different levels of digital learning readiness.

The final regression model explained 4.9% of the variance in academic performance, (R^2 = 0.049), adjusted (R^2 = 0.046), (F = 17.23), (p < 0.001). Figure 4 highlights that only digital learning readiness was a significant positive predictor of academic performance, with the confidence intervals for AI adoption and interaction with readiness crossing zero.

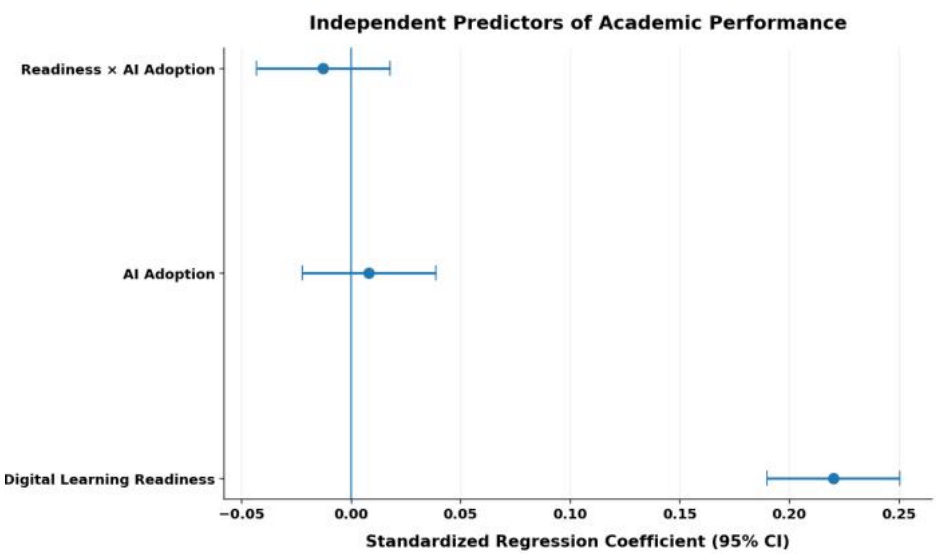

Figure 4. Standardized regression coefficients and 95% confidence intervals for digital learning readiness, AI adoption, and their interaction in predicting academic performance

4. Discussion

The results show that the general digital learning readiness, AI adoption, and academic performance of most university students were moderate to high. The overall mean Digital Learning Readiness Index was that generally students were prepared to engage in technology-supported education ,however, readiness was not even distributed. The findings align with the idea of online learning readiness being multidimensional and influenced by access to technology, motivation, self-management and communication competence (Joosten & Cusatis, 2020). It also aligns with findings that students' readiness for digital learning differs, depending on their previous experience and confidence of educational technologies (Küsel et al., 2020). Academic performance was found to be related positively with digital learning readiness to a significant extent. There were significant differences between the academic performance scores of students in the high-readiness group compared to the moderate- and low-readiness groups. This discovery implies that preparedness helps students to utilize online sources, work on assignments, engage in online activities and handle learning more effectively. Yavuzalp and Bahcivan (2021) reported similar relationships between e-learning readiness, SRL, satisfaction and academic achievement.

This also reinforces the finding that when students are ready to learn through e-learning, their performance in learning is enhanced by providing effective e-learning services (Alam et al., 2021). The regression analysis results showed that digital learning readiness is the most significant independent factor affecting academic achievement among the constructs. While the overall explained variance was not large, evidence suggests that readiness is a factor that influences achievement in addition to demographic and behavioural factors. Faster and more proficient student digital skills learners might be more likely to navigate learning platforms, assess online information, engage with teachers and utilize technology for learning. In research carried out during periods of learning with the use of technology, emphasis is given to the importance of digital competence for university achievement (López Aguilar et al., 2022). Likewise, Nikou and Aavakare (2021) suggested that digital literacy has an impact on how students can make use of the technologies in higher education. By contrast, there were no significant direct relationships between academic performance and the use of AI. Students' performance scores were relatively the same across different levels of AI adoption (Low, Moderate and High).

The study reveals that regular use of AI doesn't necessarily lead to better academic performance. The impact of AI on education might be more about how and why it is used than how strident. While students appreciate the convenience and personalized support of generative AI, they are also concerned about reliability and overreliance (Chan & Hu, 2023). The same results were found by Strzelecki (2024), who determined that perceived usefulness and ease of use are associated with acceptance of ChatGPT, potentially leading to increased adoption without increased achievement. The non-significant AI effect stands out from studies that find positive learning outcomes when using structured AI. Boubker (2024) discovered that when students use AI to reinforce their understanding and for personal learning, it can assist with self-education. According to Liang et al.

(2023), generative AI interaction could have a positive impact on achievement via self-efficacy and cognitive engagement. This distinction could be attributed to the present study looking at the adoption of AI as a broader term and examining how often, for how long, with which prompts, with which tools, for which purpose, and to what extent, AI has been used.

High adoption can thus be viewed as productive learning and as an unconsciously sustained dependence on created content. The findings align with the apprehension that students might be tempted to use AI-generated responses without thorough evaluation and self-critique, which can diminish their cognitive effort in the process. Essel et al. (2024) highlighted that AI-based conversational systems have the potential to have both positive and negative impacts on the cognitive capabilities of undergraduate students. Farrokhnia et al. (2024) also found dependency, misinformation, and originality issues to be significant vulnerabilities. Thus, AI adoption must go hand-in-hand with AI literacy, ethical advice, source checking, and task design that calls for critical engagement. Digital learning readiness and the use of AI was also non-significant. Thus, readiness has no significant impact on the relationship between the use of AI and academic achievement.

One possible reason is that readiness is linked to wider academic practices, while AI use is an aspect of a specific technological practice that requires context for its usefulness. Assessment of educational impacts for ChatGPT has also resulted in mixed findings across disciplines, assessment types, pedagogical designs, and so on (Lo, 2023). Recent meta-analytic evidence shows that generative AI can yield better results when used in a structured and guided manner aligned with learning goals (Chen & Cheung, 2025). The correlation between concept understanding and academic performance was the highest and attendance also had positive correlation. This suggests that good achievement continues to link closely with understanding and active engagement. Choi (2021) also found that engagement and course-related behaviours are associated with success in online courses in a university setting. Le (2022), found that the effectiveness of online lecture formats depend on the interaction and management of the lecture activities performed by the participants, which are the students.

In conclusion, the results indicate that universities should first become ‘digital ready’ and then look to drive academic excellence with the use of AI technologies. Institutions should offer digital-skills training, structured AI guidance, ethical-use policies, and learning activities to encourage independent thinking. AI should be seen as an academic assistant and not as an automatic solution to raising achievement.

5. Conclusion

This empirical study of a multi-disciplinary nature explored the relationships between digital learning readiness, adoption of AI and academic performance of 3,999 university students. The results indicated that the level of digital learning readiness and AI adoption for the majority of students was in the medium to high range and that the level of academic performance was mostly medium. The most prominent factor was digital learning readiness, which was related to academic success. Students in the high readiness group performed significantly better academically than students in the moderate and low readiness groups and readiness was significantly and positively related to students' academic performance even after controlling for the effects of demographic and behavioural characteristics. However, direct links with academic performance were not statistically significant for AI adoption. Performance scores were found to be similar across students with low, moderate and high levels of AI adoption. The relationship between digital learning readiness and AI adoption was also non-significant, suggesting that there was no independent positive impact on the academic impact of AI adoption when one considers digital learning readiness. The results indicate that there is a need to use AI more often and with greater intensity to enhance learning outcomes. The educational impact of AI might hinge on the responsible, critical, and purposeful use of these tools in the context of education. There were also positive correlations between student performance and comprehension and between student performance and attendance, which further emphasize that comprehension and attendance are important factors in student success. In general, it is recommended that universities focus more on the four areas of digital competence, self-directed learning skills, access to learning technologies, and responsible AI literacy. AI tools are not meant to replace independent thought, engagement, and knowledge of a topic but should be used as an aid. Therefore, institutional training, moral guidelines, and pedagogically suitable practices with AI are crucial to making technological use fruitful for academic purposes.

References

1. Abdullah Rashid. (2025). Academic outcomes & AI dependency analysis dataset [Data set]. Kaggle. https://www.kaggle.com/datasets/abdullahmeo/academic-outcomes-and-ai-dependency-analysis-dataset
2. Alam, M. M., Ahmad, N., Naveed, Q. N., Patel, A., Abohashrh, M., & Khaleel, M. A. (2021). E-learning services to achieve sustainable learning and academic performance: An empirical study. Sustainability, 13(5), 2653.
3. Armellini, A., Teixeira Antunes, V., & Howe, R. (2021). Student perspectives on learning experiences in a higher education active blended learning context. TechTrends, 65(4), 433-443.
4. Bates, T., Cobo, C., Mariño, O., & Wheeler, S. (2020). Can artificial intelligence transform higher education?. International Journal of Educational Technology in Higher Education, 17(1), 42.
5. Boubker, O. (2024). From chatting to self-educating: Can AI tools boost student learning outcomes?. Expert Systems with Applications, 238, 121820.
6. 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.
7. Chen, S., & Cheung, A. C. (2025). Effect of generative artificial intelligence on university students learning outcomes: A systematic review and meta-analysis. Educational Research Review, 100737.
8. Choi, H. J. (2021). Factors affecting learners' academic success in online liberal arts courses offered by a traditional Korean university. Sustainability, 13(16), 9175.
9. Deng, R., Jiang, M., Yu, X., Lu, Y., & Liu, S. (2025). Does ChatGPT enhance student learning? A systematic review and meta-analysis of experimental studies. Computers & Education, 227, 105224.
10. 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.

11. 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.
12. Habibi, A., Muhaimin, M., Danibao, B. K., Wibowo, Y. G., Wahyuni, S., & Octavia, A. (2023). ChatGPT in higher education learning: Acceptance and use. Computers and Education: Artificial Intelligence, 5, 100190.
13. Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of Artificial Intelligence in Education. Computers and Education: Artificial Intelligence, 1, 100001.
14. Joosten, T., & Cusatis, R. (2020). Online learning readiness. American Journal of Distance Education, 34(3), 180-193.
15. Küsel, J., Martin, F., & Markic, S. (2020). University students' readiness for using digital media and online learning—Comparison between Germany and the USA. Education sciences, 10(11), 313.
16. Le, K. (2022). Pre-recorded lectures, live online lectures, and student academic achievement. Sustainability, 14(5), 2910.
17. Liang, J., Wang, L., Luo, J., Yan, Y., & Fan, C. (2023). The relationship between student interaction with generative artificial intelligence and learning achievement: serial mediating roles of self-efficacy and cognitive engagement. Frontiers in psychology, 14, 1285392.
18. Limniou, M. (2021). The effect of digital device usage on student academic performance: A case study. Education Sciences, 11(3), 121.
19. Lo, C. K. (2023). What is the impact of ChatGPT on education? A rapid review of the literature. Education sciences, 13(4), 410.
20. López Aguilar, D., García Prieto, FJ, & Delgado García, M. (2022). Digital competence of university students and academic performance in times of COVID-19.
21. Nikou, S., & Aavakare, M. (2021). An assessment of the interplay between literacy and digital Technology in Higher Education. Education and Information Technologies, 26(4), 3893-3915.
22. Omar, H. A., Ali, E. M., & Belbase, S. (2021). Graduate students' experience and academic achievements with online learning during COVID-19 pandemic. Sustainability, 13(23), 13055.
23. Shamim, A. (2024). Student performance and learning behavior dataset [Data set]. Kaggle. https://www.kaggle.com/datasets/adilshamim8/student-performance-and-learning-style
24. Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. Innovative higher education, 49(2), 223-245.
25. Sukmawati, A. (2022). Scrutinizing University Students' Online Learning Readiness and Learning Achievement. Pegem Journal of Education and Instruction, 12(3), 275-282.
26. Yavuzalp, N., & Bahcivan, E. (2021). A structural equation modeling analysis of relationships among university students' readiness for e-learning, self-regulation skills, satisfaction, and academic achievement. Research and Practice in Technology Enhanced Learning, 16(1), 15.