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The Effects of Generative AI Tools on Student Learning and Assessment: A Mixed-Methods Analysis of Performance, Self-Efficacy, and Satisfaction

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Abstract

This study used a convergent parallel mixed-methods design to examine at how generative Artificial Intelligence (AI) is reshaping educational practices, however there is limited evidence regarding its impact on students' learning outcomes, especially in developing countries. This study further examined the relationships among AI-related skills, perceived usefulness, self-efficacy, motivation, and academic performance, as well as students' experiences with generative AI in learning environments. Applying a survey design, this research collected survey data from two hundred ninety-nine (N = 299) students in Nepal, Indonesia, and Brazil. This study also conducted semi-structured interviews with fourteen (N = 14) interviewees. Quantitative results indicated low levels of AI literacy, self-efficacy, perceived usefulness, and motivation, all averaging means below midpoint scores of five point Likert scale of survey variables. Regression analyses revealed weak correlations between those independent variables and reported academic enhancement, suggesting that students often lack the confidence and skills required to integrate AI tools effectively into their learning activities.

Conversely, qualitative results highlighted significant advantages of generative AI, such as improved learning efficiency, enhanced communication, and greater problem-solving capabilities. Interviewees noted that AI tools simplified complex concepts and saved time, despite receiving limited formal training. The integration of quantitative and qualitative results exposed a perception practice gap: while students benefited from generative AI, they generally underestimated their abilities and lacked structured guidance. The study concludes that successful AI integration in education required more than mere access to technology; it requires fostering AI literacy, self-efficacy, motivation, and ethical awareness through dedicated pedagogical support.

Keywords: *generative artificial intelligence (AI), learning outcomes, learning satisfaction, self-efficacy*

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Introduction

Generative AI, particularly through deep learning, has rapidly evolved to produce human-like content and is becoming integral to educational environments by storing and organising vast amounts of information (Lim et al., 2023; Budhwar et al., 2023). It is effectively used to create stories, films, and graphics, thereby enhancing student engagement in classrooms (Jaboob et al., 2025; Kasneci et al., 2023). However, its impact on learning activities depends significantly on students' perceptions and the effectiveness of its applications (Al-Huneini, Walker & Badger, 2020).

Research indicates that positive feedback on AI tools such as ChatGPT correlates with increased acceptance and use among students, often leading to improved academic performance (Qi, Tang & Lei, 2024; Zhang et al., 2024; Boubker, 2024). Notably, studies suggest benefits such as enhanced productivity but also highlight potential downsides, including diminished communication skills and negative work habits due to over-reliance on above mentioned technologies (ElSayary, 2024; Glaser, 2023; Abbas et al., 2024).

ChatGPT's role as a virtual educator shows promise, especially in fields such as pharmaceutical education, but its reliability warrants further investigation (Cain & Rajan, 2024). Students' confidence in using technology critically influences their continued engagement in their learning activities with it, impacting self-efficacy and perceived effective learning outcomes (Ulfert-Blank & Schmidt, 2022; Bouteraa et al., 2024; Debby et al., 2026s; Tlili et al., 2023). However, there remains a gap in research concerning how ChatGPT usage directly affects students' confidence levels (Bin-Nashwan et al., 2025, 20%).

The study in question applied a within-subjects design to examine how generative AI affects learning outcomes, student satisfaction, and beliefs about individual capabilities during AI-assisted learning. It particularly focuses on perceptions of fairness, effectiveness, and ethical considerations regarding AI in educational contexts. Furthermore, the discourse around AI tools in education includes exploring their integration into vocational training, their role in accelerating learning, and the ethical implications of AI-based assessment outcomes. Concerns surrounding privacy and fairness in learning environments, especially regarding the validity of AI-generated results, are also central to the ongoing debates about the digital transformation in education (Adhikari et al., 2026).

Theoretical Foundation

The Technology Acceptance Model (TAM), first proposed by Fred Davis, offers a crucial theoretical foundation for research on how generative AI technologies affect student learning outcomes, satisfaction, and self-efficacy. According to TAM, users' attitudes, behavioural intentions, and actual usage are influenced by two basic beliefs: perceived usefulness (the degree to which a student believes that using a technology will improve learning performance) and perceived ease of use (the degree to which the technology is effortless) (Davis, 1989).

Later replications sources, such as Thong et al. (2011) TAM_2 and TAM_3, include additional elements, such as computer self-efficacy and social impact. These are particularly crucial in schools, where adoption can be influenced by peer interactions and self-assurance when utilising digital technologies (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008). While perceived ease of use influences engagement and pleasure, perceived usefulness in the context of generative AI is associated with improved learning outcomes. Additionally, self-efficacy, grounded in a comprehensive motivational theory, is an important external variable that influences usage behaviour and perceptions.

Students' acceptance of emerging technologies is a significant predictor of their satisfaction and continued usage, which ultimately affects learning effectiveness, according to empirical research using the Technology Acceptance Model (TAM) in educational contexts (Venkatesh et al., 2003). As a result, TAM and its extensions offer a comprehensive framework for studying how generative AI tools are adopted and how they

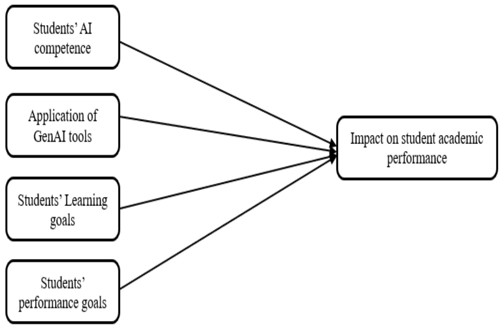

Figure 1. Association between Independent and Dependent Variables

Literature Review

Table 1. Summary of the Previous Studies

Authors and year	Methods	Results
Adhikari et al. (2026)	Utilising a systematic literature review methodology and a qualitative framework through interviews for data collection.	Responses were favourable, with AI perceived as a reliable, useful, and current source of information.
Méndez-Alarcón (2024).	Examining the exploratory and confirmatory standards for reliability and content validity.	Embedding a competency framework within AI-assisted EFL instruction is crucial for sound and effective pedagogy.
Ahmad et al. (2025).	The interview was conducted in English, but participants could also speak their native language if they wished.	Student's express enthusiasm for AI, while faculty members require further guidance to ensure smooth implementation.
May, Rosly and Azmi (2024)	A convergent mixed methods approach that uses both qualitative and quantitative research methods, such as interviews and analysis of perceptions	Student perspectives reflect a nuanced mix of optimism and apprehension regarding AI's role in developing technological skills.
Alisoy (2025).	The research employed a quantitative sampling technique to examine a targeted sample of 285 students.	Learners tend to be more comfortable adopting AI tools, whereas instructors require focused pedagogical support to integrate them.
Sutrisno et al. (2025)	A convergent mixed-methods design encompassed a survey of 250 teacher candidates, 20 interviews with experts, and case studies of three organisations employing AI in teacher education.	The findings highlight the importance of culturally sensitive curricula, cross-disciplinary instruction, and specialised training to strengthen both technological competence and cultural understanding.
Pokhrel (2025)	As part of a descriptive research study, we used face-to-face questionnaires to get information from 429 pre-service teachers at Don Mariano Marcos Memorial State University. We used exploratory factor analysis and partial least squares structural equation modeling.	Although awareness of AI in education is high (82%), only 38% feel confident applying it in classroom settings. Participants strongly advocate for structured training and raise ethical concerns, including those related to data privacy and bias.
Bautista et al. (2024)	The study used a mixed-methods approach with 377 people from Colleges of Education in North Central Nigeria, including students and teachers. We used correlation and regression analyses, along with descriptive statistics, to analyse the data.	Results suggest that pre-service teachers possess the technological, pedagogical, and content knowledge needed to use AI, with ethical understanding closely tied to their readiness.
Samson (2025)	We simultaneously surveyed 391 medical students from more than 30 countries. We used ANOVA, t-tests, and chi-square tests to identify differences across institutional types, training phases, and economic classes.	AI tools are only lightly integrated into business education curricula, yet their use is a strong indicator of students' entrepreneurial thinking and readiness, highlighting their importance in entrepreneurship education.
Hack et al. (2025).	A mixed-methods study used surveys and interviews with 300 students and 100 faculty members from different colleges and universities, using stratified random sampling.	While awareness of AI is widespread, access to AI-enabled tools remains limited, confidence in institutional readiness is low, and students show strong interest in formal AI training despite concerns about gaps in preparation, cost, and tool reliability.

Hamdan (2024)	The study employed a mixed-methods approach, using stratified random sampling to collect survey and interview data from 300 students and 100 faculty members across diverse colleges and universities.	Generative AI supports greater engagement and personalised learning, yet insufficient faculty readiness and ethical issues especially privacy and algorithmic bias pose substantial barriers to effective adoption.
Angadi and Karan (2026).	The study is grounded in established theories, including the Diffusion of Innovations, the Theory of Reasoned Action, the Technology Acceptance Model, and the Technology–Organisation–Environment framework, to develop a model for AI integration. It also proposes an approach that can be empirically examined in future research.	The study introduces a conceptual model that identifies key readiness factors for school-level AI implementation, providing a foundation for hypothesis development and future empirical research.
Al-Mutairi, Albahiri, and Alhaj (2026).	We administered a structured questionnaire to high school students and analysed the results using descriptive statistics based on a three-point Likert scale. We used a descriptive-analytic empirical design.	Students demonstrate moderate readiness for AI-supported learning, with peer collaboration positively influencing this readiness. However, family obligations and personal challenges, such as time management, attention, and self-regulation, hinder preparedness.
van der Linde, Rodríguez-Montoya and Garrido (2025)	A narrative review synthesises and interprets research on AI literacy across K–12 schooling, higher education, and professional learning contexts.	The review underscores the value of experiential learning, ethical literacy, and interdisciplinary strategies in building AI competence, while also noting diverse challenges across educational stages.
Avci, Lunn and Hazari (2025)	The study employed a qualitative approach, including a cross-sectional survey with open-ended questions administered to 27 secondary STEM teachers in the United States. Next, we employed reflexive thematic analysis to analyse the data.	Educators perceive AI as both a cognitive aid and a socio-emotional support tool that enriches teaching and interaction. However, they also report obstacles, including weak institutional support, excessive reliance on tools, financial constraints, and students' dependence on AI.
Aldawsari and Almohish (2024)	The study employed theoretical sampling to select 20 participants from four different colleges. We obtained the data via comprehensive interviews and analysed it thematically.	Ten primary challenges such as infrastructure limitations, pedagogical adjustments, and training deficits were identified, along with eight risks related to data protection and privacy, underscoring the need for strategic action to leverage AI in online higher education fully.
Hendarman et al. (2025).	The study used thematic analysis to identify patterns in how teachers taught creatively, what they chose to teach, and how they interacted with students in the classroom.	The success of gamified learning settings relies heavily on teachers' innovative and reflective instructional approaches, particularly when enhanced through AI-based personalisation.
Dewi et al. (2025).	Three undergraduate science education classes at University Negeri Semarang employed a validated rubric to assess seven AI-TPACK dimensions through a quantitative pre-experimental one-group pretest–posttest design. We used paired-comparison tests, obtained scores, and used descriptive statistics to conduct the analysis.	Substantial gains were observed across all AI-TPACK domains, particularly in integrating AI knowledge with pedagogical content knowledge, indicating that AI-TPACK-oriented instruction effectively advances technological skills and meaningful pedagogical integration.
Harahap et al. (2025)	A study employed a pre-experimental design with 46 pre-service teachers intentionally selected from an instructional design course at a private university in Indonesia. It employed a 25-question critical-thinking test and a 10-question self-efficacy test.	Substantial gains were observed across all AI-TPACK domains, particularly in integrating AI knowledge with pedagogical content knowledge, indicating that AI-TPACK-oriented instruction effectively advances technological skills and meaningful pedagogical integration.

Núñez et al. (2025)	A survey of 685 pre-service teachers from a variety of majors and academic levels was analyzed using cross-tabulation to examine variations in AI adoption, familiarity, and ethical issues.	Statistical assumptions of normality were satisfied, and both variables showed large effect sizes. These findings indicate that integrating AI into project-based learning significantly enhances preservice teachers' cognitive and emotional readiness for their future professional roles.

Research Gaps

The studies by Harahap et al. (2025) and Nunez et al. (2025) highlight the need for longitudinal research to evaluate the impact of AI on educational skills over a teacher's career, as previous research employed pre-experimental and cross-sectional designs with small sample sizes, hindering reliability. The lack of large-scale experimental studies with control groups makes it difficult to compare AI tools to traditional learning methods. While students express their satisfaction and enthusiasm when using AI, faculty require more focused pedagogical support. Future research should investigate instructors' discomfort with AI and the practical manifestation of "readiness" in teaching roles. Additionally, ethical considerations in AI education warrant further examination, and existing studies often lack methodological specificity in teaching AI across various domains (see Table 1).

Quantitative Research Design, Reliability, and Validity

We applied positivist worldviews to examine the opinions and experiences of undergraduate and graduate students from Nepal, Indonesia, and Brazil (Adhikari, 2022, 2025; 2025; Adhikari et al., 2026). The survey method was used to collect numerical data on GenAI because it is suitable for identifying associations, cost-effective and time-consuming, unbiased, and offers the strength of generalisable results across a larger population (Adhikari et al., 2026; Cohen Manion and Morrison, 2011).

The self-administered survey instrument was developed based on a review of the literature on the impact of GenAI on students' learning and support (see Table 1). A cross-sectional online survey was used to collect data from two hundred and ninety-nine (N = 299) respondents from three different countries (Adhikari et al., 2026).

We applied descriptive statistical analysis: we initially applied the factor reduction method, then calculated the means, SDs, and variances for each Principal Component (PC) (Cohen et al., 2011). The next is Binary Logistic Regression Analysis, which was applied to examine the associations among AI capability factors, technology perception factors, learning motivation and achievement motivation factors, and the impact of AI adoption on students' learning and assessment across three countries.

We addressed all ethical issues throughout the research processes by safeguarding respondent privacy through anonymity and confidentiality. Anonymity prevents the collection of identifying information, while confidentiality measures, such as encryption and secure storage, are needed if anonymity is not possible. Care was also required in wording questions to avoid disclosing a respondent's identity, especially in small or unique populations (Lichtman, 2013; Cohen et al., 2011).

Qualitative Research Design, Reliability, and Validity

This study employed a qualitative, inductive research approach rooted in constructivist philosophy to examine higher-education students' perspectives on generative AI (GAI), particularly their experiences with tools like ChatGPT (Cohen, Manion & Morrison, 2017; Lichtman, 2013). Semi-structured interviews were conducted with 14 participants from Nepal, Brazil, and Indonesia, who responded to an open email invitation. Data collection included detailed consent forms, with interviews taking place from January 11 to 14, 2026 (Adhikari, 2022; Adhikari et al., 2026; Wilson, 2014). The analysis followed Lichtman's five-cycle method to condense content and categorise information effectively. According to Lichtman (2013), the five-cycle method condenses content by creating more abstract categories and associating information, whereas the first cycle condenses the original transcribed text of each interviewee (see Figure 2).

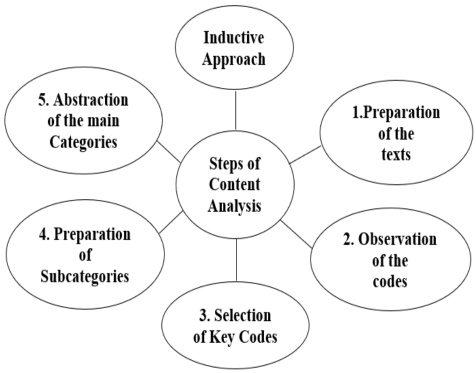

Figure 2. Processes of Content Analysis (Adhikari et al., 2026, p. 135)

Results

Students' AI Competency Skills

The knowledge, abilities, and attitudes that enable students to effectively, responsibly, and critically use artificial intelligence tools and technologies for learning, problem-solving, and decision-making.

Table 2. Factor Loadings of the First Independent Variable

Students' AI competency skills	Factors loading	Scales
I am aware of the legal and ethical implications of using AI in my academic work.	.796	AI Literacy
I understand the potential risks associated with data security and privacy when using AI tools.	.742	
I can critically evaluate the output generated by AI tools.	.631	
I believe it is my responsibility to use AI ethically in my studies.	.848	AI Self-Efficacy
I feel confident in my ability to use AI tools for learning and teaching purposes.	.741	
I can utilize AI tools effectively to enhance my learning process.	.620	
I am open to learning about new AI tools as they become available.	.536	
I can identify when an application uses artificial intelligence.	.764	AI Competence
I have a good understanding of how generative AI tools, such as ChatGPT or DeepL, function.	.752	
I can critically evaluate the output generated by AI tools.	.668	

The results show that the highest loading factor for the first Principal Component (PC) is 0.796, whereas the lowest is 0.631. The second PC has the highest factor loading of .848, followed by the lowest of .536. Similarly, the third PC has the highest factor loading of .764, followed by the lowest of .668 (see Table 2).

Table 3. Mean, SD, Alpha, Variances, and KMO Values

Scales	Mean	SD	Alpha	Variances	KMO
AI Literacy	2.18	.71	.71	21.01%	
AI Self-Efficacy	2.09	.66	.73	20.87%	.833
AI Competence	2.38	.70	.70	20.40%	

The results indicate that the variances of the first three principal components (PCs) were 21.01%, 20.87%, and 20.40% respectively. Respondents expressed disagreement with several statements regarding their awareness of the legal and ethical implications of AI in academia, their understanding of data security risks, and their evaluation of AI-generated outputs. Additionally, they disagreed with notions of ethical responsibility in AI use, confidence in using AI for education, the effective application of AI tools, and willingness to learn about new AI technologies. The means for the first, second, and third PCs were all below the mid-value of 3, reflecting respondents' general lack of confidence in these areas (see Table 3).

Table 4. Summary of the Table of Independent T-test Results

Variable	Male mean	M. SD	Females mean	F. SD	Significance
AI Literacy	2.20	.81	2.17	.67	P= .71> 0.05
AI Self-Efficacy	2.06	.79	2.09	.62	P = .68> 0.05
AI Competence	2.26	.77	2.42	.67	P = .07>0.05

Results from an independent t-test revealed no significant differences in AI literacy, self-efficacy, and competence between male (N = 84) and female students (N = 205). For AI literacy, male students had a mean score of 2.20 (SD = .81) compared to females' 2.17 (SD = .67), with t (299) = .366, p = .71. In AI self-efficacy, males scored 2.06 (SD = .79) and females 2.09 (SD = .62), yielding t (299) = -.401, p = .71. For AI competence, male students had a mean of 2.26 (SD = .77), while females scored 2.42 (SD = .67), with t (299) = -1.784, p = .71 (see Table 4).

Qualitative Results

"Can you share a situation where AI helped you solve a problem or complete a group task more effectively?"

The first main category of the interview data: AI Support in the Project and Assignment tasks

The analysis of interview data focused on how AI tools assist in solving problems and enhancing productivity in academic contexts. One of the interviewees stated: *"During a web development group project, we used AI to generate design ideas and optimise our code. It saved us considerable time, allowing us to focus more on testing and presentation"*. (Interviewee-5) Among the fourteen interviewees, three reported that Generative AI tools significantly saved time and improved their academic output, particularly highlighting a web development project in which AI assisted with generating design ideas and optimising code. One of the interviewees stated: *"Yes, AI helped me quickly summaries large volumes of research data, saving time and allowing my team to focus on analysis and decision-making rather than spending hours organising information"*. Interviewee-11).

Four interviewees noted AI's role in research and information management, emphasising its ability to quickly summaries large datasets, thereby allowing teams to focus on analysis and decision-making. One of the interviewees stated: *"Yes, during group tasks, AI facilitated brainstorming and problem-solving, thereby enhancing teamwork"*. (Interviewee-7) Very few interviewees reported that AI facilitated brainstorming and problem-solving in group tasks, there by improving teamwork. One of the interviewees stated, *"Yes, I have experience that during the data analysis, I struggled to understand many of the terms, so I used some AI tools that provided accurate examples to clarify their definitions"*. (Interviewee-11)

Conversely, only a few participants reported using AI for writing or authenticity assessment tasks. While the everyday use of Generative AI was less frequently mentioned, one interviewee acknowledged its value in providing guidelines for different activities. One of the interviewees stated: *"Generative AI tools provide guidelines for every activity"*. (Interviewee-9) Overall, the findings validate that AI's primary applications lie in research and information management, showcasing its efficiency in handling complex tasks, fostering collaboration, and addressing practical information needs in both academic and everyday scenarios.

Binary Logistic Regression Model

Table 4. Regression Analysis of Model 1

Statistical tools	Model summary	Hosmer and Lemeshow Test	Omnibus Tests of Model Coefficient
Chi-Square		15.55	13.81
df		8	3
Significance		.051	.003
Cox & Snell R Square	.045		
Nagelkerke R Square	.069		
-2 Log likelihood	306.28		
Block zero overall %	77 %		
Block one overall %	78 %		

Omnibus tests indicated that the computed model is a better fit compared to the basic model, $\chi 2 = 13.81$, df = 3, p = .003, with an associated significance level of less than 0.05. The Hosmer-Lemeshow test showed that p = .051> 0.05, indicating that the regression model is better fitted. The results further showed an overall prediction accuracy of 78.2% (see Table 5).

Table 6. Binary Logistic Regression Model to Predict

Variables of the equation	B	S.E.	Wald	df	Sin	Exp (B)	Exp (B)	
							Lower	Upper
AI Literacy	.21	.13	2.48	1	.11	1.23	.94	1.61
AI Self-Efficacy	-.30	.13	4.87	1	.02	.73	.56	.96
AI Competence	-.33	.13	5.96	1	.01	.71	.54	.93
Constant	-1.28	.14	77.96	1	<.001	.27		

The results show no association between AI literacy and AI adoption on student learning outcomes ($p > 0.05$). The results show a negative association between AI self-efficacy and AI adoption on student learning outcomes (Odds = 1.23; $p = 0.02 < 0.05$; $B = -.30 < 1$). Similarly, the results show a negative association between AI competence and impact on students' academic performance (odds = .71; $p = .01 < 0.05$; $B = -.33 < 1$ (see Table 6).

Despite achieving acceptable classification accuracy, the model demonstrates limited explanatory power, suggesting that key determinants of academic improvement may not have been fully captured. This may be due to the omission of important behavioural and contextual variables such as frequency of AI usage, type of tools utilized, and students' digital literacy levels. Future models could be strengthened by incorporating these variables, along with interaction effects between key predictors, to better reflect the complexity of AI-supported learning outcomes.

Perceived Usefulness of Generative AI tools

What is the association between perceived benefits of AI tools and AI's impact on their academic improvement?

Table 7. Factor Loadings of the First Independent Variable

Perceived Benefits of AI tools	Factors loading	Scale
A summarization tool like PaperDigest helps me save time by providing a concise overview of research articles.	.849	Perceived useful
I believe using Quillbot could help me optimize my writing process.	.811	
Using a tool like Tome would help me create better presentations more efficiently.	.783	
Using a tool like DeepL would help me better understand my learning content by translating complex texts into more accessible language.	.675	
I would use DeepL to help me achieve my learning goals.	.645	
An explanatory paper would help me better understand complex scientific concepts.	.634	
I would use a tool like Paper Digest to analyze my learning results.	.566	
Using ChatGPT would help me get better grades.	.822	Performance expectancy
Using GenAI tools supports my personal learning goals.	.769	
I believe tools like ChatGPT and Quillbot can help me achieve greater academic success.	.743	

The results show that the highest loading factor for the first Principal Component (PC) is 0.849, whereas the lowest is 0.566. Similarly, the second PC has the highest factor loading of .822, followed by the lowest of .743 (see Table 7).

Table 8. Mean, SD, Alpha, Variances, and KMO Values

Scales	Mean	SD	Alpha	Variances	KMO
Perceived useful	2.69	.74	.89	34.70%	
Performance expectancy	2.69	.83	.77	24.24%	.903

The analysis reveals that the variances of the first and second principal components (PCs) were 34.70% and 24.24%, respectively. The mean for the first PC is below the midpoint (2.69 < 3), suggesting that respondents disagree with the efficacy of tools such as PaperDigest, QuillBot, Tome, DeepL, and ExplainPaper in enhancing their academic capabilities.

Similarly, the mean for the second PC also falls below the midpoint, indicating skepticism about the usefulness of ChatGPT and GenAI tools in improving grades and supporting personal learning goals, despite some belief in their potential for academic success (see Table 8).

Table 9. Summary of the Table of Independent T-test Results

Variable	Male mean	M. SD	Females mean	F. SD	Significance
Perceived useful	2.56	.62	2.74	.76	P= .040<0.05
Performance expectancy	2.60	.80	2.71	.82	P = .280> 0.05

Results of the students' independent t-test indicate that the mean score for males (N = 84) on the first subscale, perceived usefulness (M = 2.56, SD = .62), significantly differs [t (299) =-1.848, p = .04] from that of females (N = 205) for the same variable (M = 2.74, SD = .76).

The mean of the first PC (M = 1.90) is below the midpoint, reflecting respondents' disagreement with wishing to apply their course learning to new situations, gaining satisfaction from new understandings, comprehending learning content rather than just memorising, and seeking opportunities to learn beyond required coursework. The mean of the second PC (M = 2.20) is also below the midpoint, suggesting respondents disagreed with enjoying challenging tasks for learning, focusing on personal improvement over grades, and finding the learning process more rewarding than the final grade (see Table 9).

Qualitative Results

Have you experienced faster or more effective learning when using AI-powered tools or systems?

The second main category of the interview data: AI increases learning efficiency and communication skills.

The interview data reveal that the second primary category centers on AI's role in enhancing learning efficiency and communication skills. One of the interviewees stated: *"Yes, for example, I use AI to complete my assignments because it summaries. PDFs that help me understand papers more quickly and create compelling presentations"* (Interviewee-13).

Notably, one-fifth of participants found AI valuable for learning assessments, while one-third highlighted its utility in information retrieval. The feedback regarding categories such as coding and technical support, exam and study assistance, and overall efficiency was uniformly represented, with each mentioned by four of the fourteen interviewees. However, only a few noted the application of AI for data analysis and visualisation. Three interviewees jointly addressed this statement: Interviewees noted that using *"AI significantly accelerates their learning process, particularly in generating SQL examples, preparing for exams, and quickly responding to prompts, thus enhancing their overall educational experience"*. (Interviewees: 1,4 and 5).

Additionally, very few participants used AI tools for language and grammar support. However, one of the interviewees that AI-powered language applications facilitated faster learning by providing real-time corrections to pronunciation and grammar, thereby enriching their learning experience beyond traditional methods. One of the interviewees stated: *"Yes, I learned faster using AI-powered language apps that provided real-time corrections on pronunciation and grammar, helping me progress more quickly than with traditional methods."*

Binary Logistic Regression Model

Table 10. Regression Analysis of Model 1

Statistical tools	Model summary	Hosmer and Lemeshow Test	Omnibus Tests of Model Coefficient
Chi-Square		13.47	33.61
df		8	2
Significance		.096	.001
Cox & Snell R Square	.107		
Nagelkerke R Square	.162		
-2 Log likelihood	285.96		
Block zero overall %	77.1 %		
Block one overall %	80.5%		

Omnibus tests indicated that the computed model is a better fit compared to the basic model, $\chi2$ = 33.47, df = 2, p = .001, with an associated significance level of less than 0.05. The Hosmer-Lemeshow test showed that p = .096> 0.05, indicating that the regression model is better fitted. The results further showed an overall prediction accuracy of 80.5% (see Table 10).

Table 11. Binary Logistic Regression Model to Predict

Variables of the equation	B	S.E.	Wald	df	Sin	Exp (B)	Exp (B)	
							Lower	Upper
Perceived useful	-.461	.14	10.00	1	.002	.631	.47	.83
Performance expectancy	-.698	.15	20.83	1	.001	.498	.36	.67
Constant	-1.36	.15	77.87	1	.001	.255		

The result shows a negative association between perceived usefulness and impact on student academic performance (odds = .631; p = .002 < 0.05; B = -.461). Similarly, the results show a negative association between performance expectancy and impact on student academic performance (odds = .498; p = .001 < .005; B = -.698) (see Table 11).

Although the model shows a slight improvement in predictive performance, its explanatory capacity remains modest. This limitation may be attributed to potential multicollinearity among predictors and the use of aggregated cross-country data, which can obscure context-specific effects. Enhancing the model by refining measurement scales, testing for multicollinearity, and conducting subgroup analyses by country or academic discipline may provide more precise and context-sensitive insights.

Students' Learning Goals

What is the association between students' learning goals and AI's impact on their academic improvement?

The results show that the highest loading factor for the first Principal Component (PC) is 0.861, whereas the lowest is 0.582. Similarly, the second PC has the highest factor loading of .868, followed by the lowest of .633 (see Table 12).

Table 12. Factor Loadings of the First Independent Variable

Survey Variables	Factors loading	Scale
I want to be able to apply what I learn in this course to new situations.	.861	Mastery orientation
I feel a sense of satisfaction when I gain a new understanding of a topic.	.810	
I want to understand the learning content, not just memorise it thoroughly.	.799	
I am interested in learning new things, even if they are not directly graded.	.781	
I seek out opportunities to learn beyond the required coursework.	.664	
My main goal in this course is to deepen my understanding of the subject.	.631	
I am motivated by the opportunity to master new skills and concepts.	.582	
I enjoy challenging myself with difficult tasks to learn more.	.868	Intrinsic motivation
I am more focused on improving my own abilities than on my grades.	.693	
I believe the learning process itself is more rewarding than the final grade.	.633	

Table 13. Mean, SD, Alpha, Variances, and KMO Values

Scales	Mean	SD	Alpha	Variances	KMO
Mastery orientation	1.90	.65	.89	40.92%	.907
Intrinsic motivation	2.20	.73	.70	21.51%	

The results indicate that the variances of the first and second principal components (PCs) are 40.92% and 21.51%, respectively. The mean of the first PC (M = 1.90) is below the midpoint, reflecting respondents' disagreement with wanting to apply their course learning to new situations, gaining satisfaction from new understandings, comprehending learning content rather than just memorizing, and seeking opportunities to learn beyond required coursework. The mean of the second PC (2.20) is also below the midpoint, suggesting respondents disagreed with enjoying challenging tasks for learning, focusing on personal improvement over grades, and finding the learning process more rewarding than the final grade (see Table 13).

Table 14. Summary of the Table of Independent T-test Results

Variable	Male mean	M. SD	Females mean	F. SD	Significance
Mastery orientation	2.00	.74	1.85	.60	P= .087> 0.05
Intrinsic motivation	2.23	.81	2.19	.70	P = .727> 0.05

Results of the students' independent t-test indicated that the mean score for males (N = 84) on the first subscale, mastery orientation, (M = 2.00, SD = .74), did not significantly differ [t (299) = 1.715, p = .04] from that of females (N=205) for the same variable (M = 1.85, SD = .60). The results show that the mean score for male students (N = 84) on the second subscale, intrinsic motivation (M = 2.23, SD = .81), did not significantly differ [t(299) = . 350, p = .81] from that of female (N=205) for the same variable (M = 2.19, SD = .70) (see Table 14).

Qualitative Results

Are AI-related topics or tools included in your vocational curriculum? If yes, how are they presented?

The third main category of the interview data: AI assists with productivity and research.

The results indicate that the primary focus of the interview data centers on AI's influence on curriculum and skills. One of the interviewees stated: *"Yes, AI-related topics are included in my vocational curriculum. They are taught through lectures, practical projects, and the use of AI tools for hands-on experience"* (Interviewee- 2). Among the fourteen interviewees, four noted that AI tools are beneficial for limited integration. Categories such as learning and academic support, industry and career readiness, AI exposure level, and cognitive and skill development were each noted by three interviewees.

"Three interviewees highlighted different experiences with AI in their applications: one developed "a customer support chatbot to automate routine tasks"; another noted that *"AI topics are mostly taught conceptually through lectures"; and a third mentioned "Practical*

integration of AI into robotics and automated systems training". (Interviewees: 3,8 and 12).

Only a small number of interviewees noted AI tools related to instructor-led adoption and integration strategies, as mentioned by two interviewees. One expressed uncertainty regarding the balance between technology use and self-reliance in an educational setting. Very few discussed AI's role in emerging recognition or curriculum and pedagogical constraints, with only one mention for each category. One of the interviewees stated, *"AI concepts are introduced through online resources and videos recommended by instructors, in addition to the formal curriculum"* (Interviewee-11).

Binary Logistic Regression Model

Table 15. Regression Analysis of Model 1

Statistical tools	Model summary	Hosmer and Lemeshow Test	Omnibus Tests of Model Coefficient
Chi-Square		3.81	3.75
df		8	2
Significance		.874	.153
Cox & Snell R Square	.013		
Nagelkerke R Square	.019		
-2 Log likelihood	316.34		
Block zero overall %	77.2 %		
Block one overall %	77.2%		

Omnibus tests indicated that the computed model did not fit better than the basic model, $\chi 2 = 3.75$, df = 2, p = .153, indicating that the regression model fit is insignificant. The Hosmer-Lemeshow test showed that p = .874> 0.05, indicating that the regression model is better fitted. The results further showed an overall prediction accuracy of 77.2% (see Table 15).

Table 16. Binary Logistic Regression Model to Predict

Variables of the equation	B	S.E.	Wald	df	Sin	Exp (B)	Exp (B)	
							Lower	Upper
Mastery orientation	-.49	.26	3.47	1	.062	.609	.36	1.02
Intrinsic motivation	.15	.22	.44	1	.503	1.165	.74	1.81
Constant	-.631	.48	1.67	1	.195	.532		

The logistic regression analysis indicates that students' learning goal variables, specifically mastery orientation and intrinsic motivation, do not significantly predict the impact of AI on academic performance. Mastery orientation has a negative coefficient (B = −0.49) and an odds ratio of 0.609, suggesting that greater mastery orientation correlates with a lower probability of improved academic performance via AI. However, this is not statistically significant (p = .062). In contrast, intrinsic motivation shows a positive coefficient (B = 0.15) and an odds ratio of 1.165, indicating a small increase in the likelihood of enhanced performance, yet this too is not statistically significant (p = .503). Overall, the model lacks strong predictive power as the constant term is also insignificant.

The lack of statistical significance in this model indicates that motivational factors alone may not directly explain variations in AI-assisted academic performance. This suggests the need for a more nuanced model structure that incorporates mediating variables, such as actual AI usage behaviour or student engagement. Future research should consider modeling indirect relationships, where motivation influences performance through intermediate behavioural factors, to improve explanatory power (see Table 16).

What is the association between students' performance goals and the impact of AI adoption on improving their academic performance?

Table 17. Factor Loadings of the First Independent Variable

Survey Variables	Factors loading	Scale
My primary goal is to achieve a better grade than most of my peers.	.870	Performance orientation
I need to perform better than my classmates.	.866	
My primary motivation is to get a high grade in this course.	.771	
High grades are not the principal factor influencing my motivation in this course.	.731	
I care more about outperforming others than learning something new.	.659	
I only try hard when I know others will notice my performance.	.558	
I want to be recognized for my academic achievements.	.509	
I am concerned with how others judge my performance.	.776	External validation
Getting a good grade is the most important measure of my success.	.761	
I feel successful when I get a good grade.	.696	
I am motivated to show others that I am intelligent.	.589	
I am driven by the desire to avoid looking incompetent.	.793	Avoidance motivation
I do not believe that good grades are the best indicator of my learning success.	.770	

The results show that the highest loading factor for the first Principal Component (PC) is 0.870, whereas the lowest is 0.509. The second PC has the highest factor loading of .776, followed by the lowest of .589. Similarly, the third PC has the highest factor loading of .793, followed by the lowest of .770 (see Table 17).

Table 18. Mean, SD, Alpha, Variances, and KMO Values

Scales	Mean	SD	Alpha	Variances	KMO
Performance orientation	3.13	.86	.89	30.62%	.828
External validation	2.54	.76	.70	18.28%	
Avoidance motivation	2.76	.82	.72	11.22%	

The analysis of the principal components (PCs) reveals that the first PC accounts for 30.62% of the variance, indicating that respondents prioritize outperforming peers and achieving high grades. The mean for this PC exceeds the midpoint, suggesting agreement with statements about competitive academic motivations. Conversely, the second PC, representing 18.28% of the variance, shows a mean below the midpoint, reflecting disagreement with concerns about external judgment and equating grades with success. Lastly, the third PC, at 11.22%, similarly indicates disagreement with motivations tied to avoiding incompetence and viewing grades as definitive measures of learning success (see Table 18).

Table 19. Summary of the Table of Independent T-test Results

Variable	Male mean	M. SD	Females mean	F. SD	Significance
Performance orientation	3.15	.85	3.12	.87	P= .794> 0.05
External validation	2.75	.86	2.45	.70	P = .003<0.05
Avoidance motivation	2.69	.75	2.77	83	P = .447> 0.05

Results from an independent t-test revealed that male students (N = 84) had a mean performance orientation score of 3.15 (SD = 0.85), which did not differ significantly from female students (N = 205) with a mean score of 3.12 (SD = 0.87) [t (299) = 0.262, p = 0.79]. However, there was a significant difference in external validation, with males scoring a mean of 2.75 (SD = 0.86) compared to females at 2.45 (SD = 0.70) [t(299) = 3.01, p = 0.003]. For avoidance motivation, male students had a mean score of 2.69 (SD = 0.75), which did not differ significantly from the female mean of 2.77 (SD = 0.83) [t (299) = -0.762, p = 0.44]. (see Table 19).

Qualitative Results

Do you think your study program gives enough attention to integrating AI into your learning path?

The fourth main category of the interview data: AI's impact on the curriculum and skills.

The study's findings reveal that a significant issue from the interviews is the limited integration of AI into the curriculum. Four out of fourteen interviewees indicated that their programs do not adequately focus on AI, emphasising the need for more practical applications to better prepare students for industry demands. One of the interviewees stated: *"No, my study program has a limited focus on integrating AI into the learning path. More emphasis and practical AI applications are needed to prepare better students for future industry demands"* (Interviewee-2). Categories such as academic support, industry readiness, AI exposure, and skill development were consistently mentioned by three interviewees, suggesting a need for AI content in earlier semesters and the introduction of dedicated AI courses. One of the interviewees stated: *"While I have used AI tools in projects, a dedicated AI course or workshop would help me better understand the underlying algorithms and expand my career opportunities"* (Interviewee-3). A few interviewees expressed uncertainty about the program's AI strategy, suggesting it requires clearer direction for effective integration into learning. One of the interviewees stated: *"I think the program recognises the importance of AI, but it needs a clearer strategy to fully integrate it into the learning path"* (Interview-14). Overall, the results highlight a consensus on the necessity for enhanced AI integration in educational programs.

Binary Logistic Regression Model

Table 20. Regression Analysis of Model 1

Statistical tools	Model summary	Hosmer and Lemeshow Test	Omnibus Tests of Model Coefficient
Chi-Square		10.65	18.94
Df		8	3
Significance		.222	<.001
Cox & Snell R Square	.062		
Nagelkerke R Square	.094		
-2 Log likelihood	301.150		
Block zero overall %		77.2 %	
Block one overall %		77.9%	

Omnibus tests indicated that the computed model is a better fit compared to the basic model, $\chi2$ = 18.94, df = 3, p = .001, with an associated significance level of less than 0.05. The Hosmer-Lemeshow test showed that p = .222> 0.05, indicating that the regression model is better fitted. The results further showed an overall prediction accuracy of 77.9% (see Table 20).

Table 21. Binary Logistic Regression Model to Predict

Variables of the equation	B	S.E.	Wald	df	Sin	Exp (B)	Exp (B)	
							Lower	Upper
Performance orientation	.53	.17	9.61	1	.002	1.704	.1.2	2.38
External validation	-.24	.18	.1.77	1	.183	.781	.54	1.12
Avoidance motivation	.33	.17	3.71	1	.054	1.39	.99	1.94
Constant	-.631	.48	17.94	1	<.001	.038		

The result shows a positive association between performance orientation and impact on student academic performance (odds = 1.70; p = .002 < 0.05; B = .53 < 1). The result shows no association between external validation, avoidance motivation, and students' learning outcomes (p > 0.05).

While the model achieves statistical significance, its overall explanatory strength remains limited, indicating that additional factors beyond individual perceptions can influence academic outcomes. The inclusion of contextual variables such as institutional support, access to AI tools, and instructional guidance could enhance model robustness. Furthermore, exploring non-linear relationships and composite indices can help capture more complex patterns within the data (see Table 21).

Summary of the Quantitative and Qualitative Results

This study's results show a pattern that is both differ and similar across quantitative and qualitative findings regarding the effects of generative AI on students' academic performance. The results further show that students generally have low levels of AI literacy, self-efficacy, competence, perceived usefulness, and motivation, with mean scores below the midpoint. Regression analyses reveal negative correlations between those factors and academic performance, suggesting that students can lack confidence, a structured understanding, and effective integration of AI tools into their learning processes.

The qualitative results, on the other hand, show a more positive and useful view. Students said that AI tools make learning more efficient, help with research and assignments, improve communication, and make it easier to work together and solve problems. People really liked AI because it saved them time, helped them generate new ideas, and supported their technical and academic tasks.

In general, the results show a difference between what students think and what they actually experience. For example, quantitative data shows low confidence and little perceived value, while qualitative data shows that AI tools are actually used and helpful in real learning situations.

Convergent Results

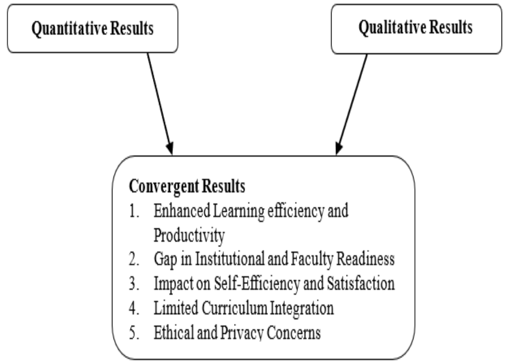

Figure 3. Summary of Convergent Results

Enhancing Learning Efficiency and Productivity: Qualitative interviews indicate that students use AI to solve technical problems, summarise complex research, and complete assignments more quickly, which associates with quantitative studies showing that students are comfortable adopting AI to enhance their learning when they perceive it as a reliable and useful source.

Gap in Institutional and Faculty Readiness: Multiple sources converge on the fact that while student interest is high, faculty and instructors require significantly more "focused pedagogical support". Research indicates that teachers often possess the necessary technical knowledge but lack the structured training to integrate AI effectively into teaching.

Impact on Self-Efficacy and Satisfaction: The findings consistently show that a student's confidence in their own abilities (self-efficacy) is closely linked to their satisfaction with AI tools. Students who believe in their skills are more likely to find ChatGPT helpful for learning. Qualitative statements and quantitative summaries indicate that AI topics are often only briefly covered through seminars and guest lectures rather than being an essential, regular part of the curriculum.

Ethical and Privacy Concerns: Despite the enthusiasm for AI, there is a consistent call across both research methods for structured training to address ethical issues, including data privacy and algorithmic bias (see Figure 3).

Discussion, Conclusion, and Recommendations

Discussion

The results confirm and build on what is already known, which make important theoretical and practical contributions. The qualitative results support what previous studies have found: generative AI makes learning more efficient, productive, and supportive of academic work, which supports what other studies have found: AI tools make people more engaged, better at research, and better at developing skills (e.g., May et al., 2024; Hamdan, 2024).

Based on Fred Davis's Technology Acceptance Model (TAM), this study reveals that although students perceive generative AI tools as neither particularly useful nor easy to use, they still use them to improve efficiency and support assignments. Quantitative results indicate weak correlations between perceived usefulness, self-efficacy, and motivation, negatively impacting academic performance and behavioral intention toward those tools. However, qualitative insights suggest a practical use that contradicts the above mentioned perceptions. The findings indicate a need to amend TAM by including contextual factors such as accessibility and task requirements, positing that generative AI can enhance education when supported by institutional infrastructure and training. Without those frameworks, students can fail to leverage AI tools effectively to improve their academic outcomes.

In the same way, AI's role in helping with assignments, communication, and problem-solving is supported by the studies showing that AI is a useful educational and cognitive support tool. However, the quantitative findings contrast with much of the existing literature by revealing low levels of AI self-efficacy, competence, perceived usefulness, and motivation among students, along with negative or negligible correlations with academic performance, which differs from studies such as Qi et al. (2023) and Boubker (2024), which find that using AI positively affects academic outcomes, that shows a big gap between how students actually use AI, which has qualitative benefits, and how confident, aware, and well-structured they are about using it in learning environments.

This study helps fill the important research gaps identified in the literature. First, this study addresses the lack of mixed-methods empirical evidence by combining both quantitative and qualitative data. The analysis shows unvisible contradictions between what people think and what they do. Second, this study goes beyond small-scale or single-method studies by providing data from multiple countries and offering a more thorough look at how AI affects learning outcomes, self-efficacy, and satisfaction.

Third, this study fills the gap in students' confidence and readiness by showing that, even though they use AI a lot, they still lack the skills, motivation, or ethical awareness they need. Lastly, the study adds to the ongoing conversation about ethical and teaching issues by highlighting concerns about responsible AI use, limited curriculum integration, and the need for structured training. This research contributes to the field by demonstrating that effective AI integration in education relies not only on the availability of tools but also on the congruence of users' capabilities, perceptions, motivations, and ethical understanding an aspect that prior studies have inadequately explored.

Finally, the relatively low explanatory power across models highlights the multifaceted nature of AI adoption in education, suggesting that future models should integrate behavioural, contextual, and institutional dimensions to achieve a more comprehensive understanding.

Conclusion

Based on Fred Davis's Technology Acceptance Model (TAM), this study examined the relationship between students' perceptions and their actual use of generative AI tools in education. While TAM emphasises that perceived usefulness and ease of use are vital for technology adoption, the results reveal a disparity between perceptions and real experiences. Quantitative data indicate low perceived usefulness, self-efficacy, and motivation, which correlate negatively with academic performance, suggesting weakened behavioral intentions and limited adoption of AI tools. Conversely, qualitative findings indicate that students use generative AI for efficiency in completing tasks and solving problems, despite lacking strong positive feelings toward the technology.

The above mentioned inconsistency prompts an enhancement of TAM for emerging technologies, highlighting that adoption is shaped not just by perceived usefulness, but also by contextual factors such as accessibility, informal learning methods, and specific task requirements. The study concludes that while generative AI can aid education with institutional support, structured training, and ethical understanding, a disconnect in use may limit students' potential for academic improvement.

The "readiness gap" is significant: students acknowledge the practical benefits of AI tools however report low AI literacy and perceived usefulness, indicating weak correlations with academic performance in formal contexts. The research emphasis`es that the success of AI in education relies not solely on availability, but rather on the congruence of student skills, perceived tool value, personal motivation, and ethical awareness. Students tend to use AI in a fragmented manner without formal guidance, limiting effective integration into their academic lives. Moreover, there is a noted "Gap in Institutional and Faculty Readiness," in which high student interest is not matched by faculty pedagogical support for teaching AI effectively. This study advocates for a holistic approach to AI in education that transcends sporadic seminars, urging a curriculum that addresses issues such as data privacy, algorithmic bias, and responsible use. It emphasises that aligning users' capabilities and ethical understanding with technology is crucial for AI to enhance academic outcomes meaningfully.

Recommendations

The recommendations in this study are directed toward multiple stakeholders within the educational ecosystem to address the "readiness gap" identified in the research.

The primary groups for whom these recommendations are intended include:

Educational Institutions and Policymakers:

They are called upon to move beyond occasional seminars and integrate generative AI into the regular curriculum. This includes creating an integrated approach that addresses data privacy, algorithmic bias, and responsible use.

Faculty and Instructors:

The study highlights a "Gap in Institutional and Faculty Readiness," noting that instructors require structured pedagogical support to teach and integrate AI effectively.

Students:

While not receiving direct instructions, the recommendations aim to benefit students by syncing their skills, motivation, and ethical awareness with the technology to improve academic outcomes.

Academic Researchers:

The study identifies specific research gaps, recommending that future studies focus on longitudinal impacts of AI on teaching careers, large-scale experimental designs with control groups, and deeper investigations into instructor discomfort with AI.

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