



PAPER

Perceived AI literacy and learning-related outcomes among higher education students using generative AI

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ABSTRACT

This study examined how perceived AI literacy and GenAI-use frequency relate to learning confidence, learning behaviours, academic integrity perceptions, and perceived fairness in assessment among higher education students. A cross-sectional survey of 131 students assessed GenAI use, perceived AI literacy, and related learning variables. Descriptive statistics, Pearson correlations, MANOVA, and multiple regression analyses were conducted. GenAI use was common, with most students reporting moderate to frequent use. Perceived AI literacy significantly predicted confidence when using GenAI tools, learning behaviours, academic integrity concerns, and perceived fairness of assessment. GenAI-use frequency also predicted learning behaviours. Findings suggest that perceived AI literacy plays an important role in how students engage with GenAI tools and highlight the need for clear institutional guidance and curriculum-based AI literacy development

KEYWORDS: higher education, generative artificial intelligence, AI literacy, learning behaviours, academic integrity, educational technology.

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Introduction

The rapid development of artificial intelligence (AI) technologies, particularly generative artificial intelligence (GenAI), is reshaping many aspects of higher education. Recent bibliometric analyses further demonstrate the rapid expansion of GenAI-focused research in

higher education since 2022 (Dai et al., 2026). GenAI systems, such as large language models capable of producing human-like text, explanations, and summaries, are now widely accessible and increasingly incorporated into many students' academic practices. Students frequently use GenAI tools to generate ideas, summarise readings, clarify difficult concepts, and assist with writing or coding tasks (Kasneci et al., 2023). Recent large-scale surveys further confirm the widespread and rapidly increasing adoption of GenAI tools among university students, highlighting their growing role in everyday academic workflows (see Stephenson & Armstrong, 2026). As these technologies become embedded within academic environments, educators and institutions are increasingly examining how GenAI use may influence learning experiences and academic practices in higher education. In this study, GenAI tools are defined as AI systems capable of generating content, including text, summaries, explanations, and code, in response to user prompts. This definition includes ChatGPT and similar large language model-based applications, as well as AI-enabled features integrated into wider digital platforms.

GenAI technologies have the potential to support learning by providing immediate feedback, explanations, and additional learning resources that can help students engage with complex material. Contemporary research suggests that GenAI tools may facilitate personalised learning experiences, enhance access to information, and provide cognitive support that complements traditional teaching methods (Dong, 2026; Mollick & Mollick, 2023). For example, GenAI systems may assist students in exploring ideas, practicing problem-solving strategies, and receiving tailored explanations, functioning as adaptive educational resources that support learning, engagement, and knowledge construction.

At the same time, the increasing availability of GenAI has raised significant concerns regarding academic integrity and the authenticity of student work. Because these systems can produce essays, summaries, and written responses that resemble human-generated text, educators have expressed concern that students may submit AI-generated content as their own work (Cotton et al., 2024). These concerns have prompted many universities to reconsider academic integrity policies and develop new guidelines regarding the appropriate use of GenAI in coursework and assessment. In addition, questions have emerged regarding whether access to GenAI tools may create inequities among students or affect the fairness of academic assessment (Dwivedi et al., 2023).



Beyond concerns about academic integrity, the increasing use of GenAI tools in education has also sparked debate about their potential impact on students' learning behaviours and academic confidence. Some scholars have suggested that over-reliance on GenAI tools may reduce cognitive engagement, critical thinking, and independent problem-solving (Mollick & Mollick, 2023). Others suggest that, when used appropriately, GenAI tools may support learning by helping students organise ideas, clarify complex concepts, and develop academic skills (Kasneci et al., 2023). Emerging evidence indicates that the effects of GenAI on learning are highly dependent on how students engage with these tools, highlighting the importance of responsible and informed use.

An important factor shaping students' interactions with GenAI technologies is AI literacy. AI literacy refers to the knowledge, skills, and critical understanding required to use AI systems effectively and responsibly, including the ability to evaluate outputs, recognise limitations, and identify potential biases (Long & Magerko, 2020; Miao et al., 2021). Recent scholarship argues that GenAI literacy also involves critically engaging with AI-generated knowledge and navigating questions of authorship, learning, and academic integrity (Han, 2026). Reflecting the rapid development of GenAI technologies, more recent frameworks conceptualise AI literacy as a multidimensional competency encompassing technical understanding, ethical awareness, and critical evaluation skills (UNESCO, 2024).

In this context, responsible AI/GenAI use refers to the transparent and ethically aligned use of these tools to support learning. This includes using GenAI systems to generate ideas, clarify complex concepts, or receive feedback while maintaining active cognitive engagement and critically evaluating outputs. In contrast, submitting AI-generated content as one's own or relying on outputs without verification may constitute academic dishonesty. However, it is important to acknowledge that there is currently no universally accepted definition of responsible GenAI use, and the boundaries between appropriate and inappropriate use remain context dependent and continue to evolve alongside technological and institutional developments. Students with higher perceived AI literacy may be better equipped to use GenAI tools strategically, verify AI-generated information, and navigate these emerging boundaries of responsible use. However, despite growing recognition of its importance, empirical research examining how perceived AI literacy relates to students' learning behaviours, perceptions of academic integrity, and perceptions of fairness remains limited.



Although prior research has documented the increasing prevalence of GenAI use among higher education students, less is known about how perceived AI literacy relates simultaneously to learning behaviours, confidence, academic integrity perceptions, and perceived fairness of assessment within a single analytical framework. Examining relationships among GenAI-use frequency, perceived AI literacy, learning behaviours, academic confidence, and perceptions of fairness may provide important insights into how GenAI tools are shaping students' academic experiences.

This study employed a cross-sectional correlational research design to examine relationships among perceived AI literacy, GenAI-use frequency, and learning-related outcomes among higher-education students. Guided by prior theoretical and empirical work on GenAI in education, perceived AI literacy, and academic integrity, the study addressed the following research questions: (RQ1) Are there significant differences in learning confidence, learning behaviours, academic integrity concerns, and perceived fairness in academic assessment across different levels of GenAI tool use? (RQ2) What relationships exist among GenAI use, perceived AI literacy, learning behaviours, confidence in learning, academic integrity concerns, and perceptions of fairness? Moreover, (RQ3) To what extent do GenAI use and perceived AI literacy predict learning behaviours, confidence in learning, academic integrity concerns, and perceived fairness in academic assessment when considered simultaneously?

Methodology

Study design

This study was approved by the Institutional Review Board of the European International University, Paris (IRB #EIU/ECC/2025/1476). This study employed a quantitative, cross-sectional, correlational survey design to examine how students in higher education use GenAI tools for academic purposes and how GenAI use is associated with students' perception of their learning experiences, including learning confidence, learning behaviours, perceptions of academic integrity, and perceived fairness in academic assessment. The study followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines for reporting cross-sectional research (von Elm et al., 2007).



Participants and recruitment

Participants were students currently enrolled in higher education programmes, including undergraduate, graduate, and doctoral programmes. Eligibility criteria required participants to be at least 18 years of age and currently enrolled in a higher education institution. Participants were recruited using convenience sampling methods. The survey link was distributed through academic networks, student forums, and online platforms targeting higher education students. Although the sample included students from a range of academic backgrounds, it was not designed to be fully representative of the broader higher education population. The use of convenience sampling limits the generalisability of the findings, and the results should therefore be interpreted as exploratory. Future research should aim to include larger, more diverse, and systematically sampled populations to enhance external validity. Recruitment materials included a brief description of the study's purpose and eligibility criteria, and an invitation to participate voluntarily. Participation was entirely voluntary, and no financial or academic incentives were offered.

An a priori power analysis was conducted using G*Power version 3.1 (Faul et al., 2009) to determine the minimum sample size required for the planned statistical analyses. Based on a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$, and statistical power of 0.80, the analysis indicated that a minimum of 127 participants would be required to detect significant effects in the planned regression analyses.

Data collection

Data were collected using Google Forms from November 2025 to February 2026. Prior to full data collection, the questionnaire was piloted with a small group of eight participants to assess the clarity, relevance, and comprehensibility of the items. Feedback from the pilot phase resulted in minor revisions to item wording to improve clarity and ensure consistent interpretation. While the pilot sample was limited in size, it provided an important initial check of the instrument's face validity and usability. Before accessing the survey questions, participants were presented with an electronic informed consent form describing the purpose of the study, the voluntary nature of participation, confidentiality measures, and contact information for the researcher. Participants provided consent by selecting an 'I consent to participate' option before proceeding to the survey. No personally identifying information,



such as names, student identification numbers, or Internet Protocol addresses, was collected. Survey responses were stored securely and analysed in aggregate.

Measures

The questionnaire was developed specifically for this study to assess GenAI engagement, perceived AI literacy, and related learning outcomes in higher education, for which fully validated instruments remain limited. However, item development was informed by existing literature on AI literacy, digital competence, and technology use in educational contexts (see Long & Magerko, 2020; UNESCO, 2024), ensuring conceptual alignment with established frameworks. Although the instrument was not formally validated as a standalone psychometric scale, internal consistency analyses demonstrated acceptable reliability across the multi-item measures. Specific GenAI tools, prior experience, duration of use, and expertise were not assessed. Consequently, it was not possible to determine whether the observed relationships differed according to familiarity or proficiency with specific AI technologies. Participants may have used both standalone applications and AI functionalities embedded within other software (such as writing assistants or productivity tools).

Demographic and educational characteristics

Participants reported demographic and educational background information, including age group, gender, ethnicity, country of residence, international student status, level of study, mode of study (online, on-campus, or hybrid), year of study, study load (full-time or part-time), employment status, and primary study device.

GenAI tool use

GenAI tool use was assessed using two measures. Participants first reported their overall frequency of GenAI use for academic purposes during the current academic term, using a seven-point scale ranging from 0 (never) to 6 (multiple times per day). The frequency categories were designed to capture general patterns of use rather than precise counts. Participants also reported the average amount of time spent using GenAI tools per week, measured on a six-point scale ranging from 0 (none) to 5 (more than 10 hours). The use of categorical time ranges to assess technology use is consistent with prior research on digital behaviour and emerging technologies, where self-reported measures are commonly used to capture general patterns of engagement (see Dwivedi et al., 2023; Kasneci et al., 2023). Given



the exploratory nature of this study and the absence of standardised measures for GenAI use, this approach was selected to provide a practical estimate of weekly usage without requiring participants to recall precise usage data. Participants were instructed to consider GenAI tools broadly, including systems capable of generating content (such as text, summaries, explanations, or code) and AI functionalities embedded across multiple platforms. However, this broad definition may have introduced variability in how participants interpreted and reported GenAI use.

Task-specific GenAI use was assessed using multiple items measuring how often students used GenAI tools for activities such as generating ideas, explaining academic concepts, summarising readings, generating study materials, assisting with coding or data analysis, improving writing, paraphrasing text, generating coursework text, creating citations, checking originality, and organising study schedules. The items were developed specifically for this study based on recent literature on GenAI use in education (see Dwivedi et al., 2023; Kasneci et al., 2023; Mollick & Mollick, 2023) and included both learning-oriented uses (for example, concept explanation, study support) and performance-oriented uses (such as generating coursework text, paraphrasing). These items were measured using a five-point frequency scale ranging from 0 (never) to 4 (very often). The frequency categories were intended to capture general patterns of use rather than precise behavioural counts.

GenAI policy awareness

Participants' awareness of institutional policies regarding GenAI use in academic work was measured using four items assessing clarity of GenAI policies, understanding of institutional rules, confidence in knowing when GenAI use must be disclosed, and whether students disclose GenAI use when required. Responses were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Confidence in learning with and without GenAI

Two scales measured students' confidence in learning. The confidence when using GenAI tools scale included four items assessing whether GenAI tools help students understand course material, complete assignments, perform academically, and learn more efficiently. The confidence-without-GenAI tools scale included three items assessing students' perceived ability to complete academic work, learn complex material, and meet course expectations without GenAI assistance.



Learning behaviours

Learning behaviours were assessed using eight items measuring aspects of self-regulated learning, including goal setting, planning academic tasks, monitoring understanding, adjusting learning strategies, seeking academic help, reflecting on feedback, managing study time, and minimising distractions. Responses were measured using a five-point Likert scale.

Academic integrity perceptions

Academic integrity perceptions were measured using seven items that assessed students' views on whether GenAI-generated coursework constitutes academic dishonesty, the clarity of academic integrity rules regarding GenAI use, perceptions of student behaviour, concerns about unintentionally violating policies, perceptions of the likelihood of detection, and perceived consequences of improper GenAI use.

Perceived fairness of academic assessment

Perceived fairness was measured using four items assessing whether GenAI tools advantage some students more than others, whether unclear GenAI rules affect fairness in grading, whether access to GenAI creates advantages, and whether academic assessment remains fair when AI tools are used appropriately.

Perceived AI literacy

Perceived AI literacy was assessed using five items measuring students' perceived ability to evaluate AI-generated information, identify potential bias in GenAI outputs, write effective prompts, verify AI-generated information using reliable sources, and understand the limitations of AI tools in academic contexts. This measure focused on self-reported competencies most directly related to academic engagement with GenAI rather than objectively demonstrated competence. Although self-reported abilities may not fully correspond to actual performance, perceived competence remains educationally relevant because students' beliefs about their abilities may influence how they evaluate AI-generated information, engage with learning tasks, and navigate academic integrity decisions. Because these items reflected generally desirable academic behaviours, responses may have been influenced by social desirability bias. The specific perceived AI literacy items are provided in the Appendix.



Data analysis

All statistical analyses were conducted using Stata version 18. Descriptive statistics were calculated for all demographic variables and study measures. Means, standard deviations, frequencies, and percentages were reported where appropriate. Internal consistency of the multi-item scales was assessed using Cronbach's alpha, with values ≥ 0.70 interpreted as acceptable, ≥ 0.80 as good, and ≥ 0.90 as excellent (Cronbach, 1951). Pearson correlation analyses were conducted to examine relationships among the primary study variables. The correlations were interpreted as trivial effect size ($r < 0.10$), small effect size ($0.10 \leq r < 0.30$), medium effect size ($0.30 \leq r < 0.50$), large effect size ($0.50 \leq r < 0.70$), and very large effect size ($r \geq 0.70$) (Maher et al., 2013). To examine differences across AI-use levels, participants were categorised into three GenAI-use groups (low, moderate, and high) based on the original GenAI-use frequency scale. A multivariate analysis of variance (MANOVA) was conducted to assess whether GenAI-use groups differed across multiple learning-related outcomes simultaneously. When the multivariate test was significant, follow-up univariate analyses of variance (ANOVAs) and Bonferroni-adjusted post-hoc comparisons were conducted to identify specific group differences. Effect sizes for group differences were interpreted as small effect size ($\eta^2 < 0.06$), medium effect size ($0.06 \leq \eta^2 < 0.14$), and large effect size ($\eta^2 \geq 0.14$) (Cohen, 1988).

Multiple linear regression analyses were conducted to examine whether GenAI-use frequency, perceived AI literacy, and their interaction predicted learning-related outcomes, including confidence in learning when using GenAI tools, learning behaviours, academic integrity concerns, and perceived fairness of academic assessment. Demographic and academic covariates were included to account for potential confounding influences. These covariates included level of study, mode of study, study load, employment status, and international student status. The reference factor variable for level of study was undergraduate (Bachelor's); for mode of study, online programmes; for study load, full-time enrolment; for employment status, not working; and for international student status, domestic student (no). Model fit was evaluated using the coefficient of determination (R^2). Effect sizes were interpreted according to Cohen (1988), where $R^2 < 0.09$ indicates a small effect size, $0.09 \leq R^2 < 0.25$ indicates a medium effect size, and $R^2 \geq 0.25$ indicates a large effect size. Statistical significance was set at $p < 0.05$. Multicollinearity among predictors was evaluated



using variance inflation factors (VIF). Assumptions of normality, linearity, and homoscedasticity were assessed through inspection of residual plots and tests of normality.

Results

Participant characteristics

A total of 132 participants started the survey, and one did not meet the inclusion criteria. Thus, 131 students completed the survey between November 2025 and February 2026 and were included in the analysis. Participant demographic and educational characteristics are presented in Table 1. The sample included students from different age groups, levels and modes of study, and employment statuses, with a large proportion identifying as international students. Information regarding participants' academic disciplines or fields of study was not collected; therefore, differences in GenAI use patterns and learning-related outcomes across disciplinary contexts could not be examined.

Although the sample represented a range of student characteristics, it may not be fully representative of the broader higher education population. In particular, the relatively high proportion of international students and the limited representation of older students and doctoral-level participants suggest possible over- and under-representation of certain groups, likely reflecting the use of convenience sampling. Consequently, the findings should be interpreted with caution, and their generalisability may be limited.

Table 1. Participant characteristics (N = 131).

Variable	Category	n	%
Age	18-24	73	55.7
	25-34	54	41.2
	35-44	4	3.1
Gender	Female	59	45.0
	Male	69	52.7
	Prefer not to say	3	2.3
Ethnicity	White/Caucasian	88	67.2
	Black/African American	28	21.4
	Asian/Pacific Islander	15	11.5



International student	Yes	96	73.3
	No	35	26.7
Level of study	Undergraduate	68	51.9
	Master's	58	44.3
	Doctoral	5	3.8
Mode of study	On-campus	72	55.0
	Hybrid	34	26.0
	Online	25	19.1
Year of study	1st year	36	27.5
	2nd year	52	39.7
	3rd year	30	22.9
	4th year or above	13	9.9
Study load	Full-time	98	74.8
	Part-time	33	25.2
Employment status	Not working	95	72.5
	Part-time work	22	16.8
	Full-time work	14	10.7

GenAI tool use

Overall, GenAI-use frequency during the academic term showed moderate levels among participants. The mean GenAI-use frequency score was $M = 3.86$ ($SD = 1.25$) on the 0 to 6 scale, indicating that students typically reported using GenAI tools between once per week and several times per week. Average weekly time spent using GenAI tools was $M = 2.63$ ($SD = 1.19$) on the 0 to 5 scale, corresponding approximately to 1 to 5 hours per week. For multivariate analyses, GenAI-use frequency was categorised into three groups based on the original scale: low use (0 to 2), moderate use (3 to 4), and high use (5 to 6). The majority of participants fell into the moderate-use group (65.7%), followed by high-use students (22.1%), while 12.2% were classified as low AI users (Table 2).



Table 2. GenAI use among students.

Variable	Mean	SD	Minimum	Maximum
GenAI-use frequency	3.86	1.25	0	6
Weekly GenAI-use time	2.63	1.19	0	5

Reliability of multi-item scales

Internal consistency for the multi-item scales was assessed using Cronbach's alpha. All scales demonstrated acceptable to high reliability, indicating that the items within each scale were measuring consistent constructs. Cronbach's alpha values ranged from 0.77 to 0.87 across the different measures. The scale assessing confidence when using AI tools showed a reliability coefficient of $\alpha = 0.85$, while confidence without AI tools demonstrated $\alpha = 0.77$. The learning behaviours scale showed strong internal consistency ($\alpha = 0.85$), and the academic integrity concerns scale demonstrated the highest reliability ($\alpha = 0.87$). The scale measuring perceived fairness of academic assessment showed good reliability ($\alpha = 0.81$), and the perceived AI literacy scale also demonstrated strong internal consistency ($\alpha = 0.82$). These results support the use of the scale scores in subsequent statistical analyses (Table 3).

Table 3. Reliability of multi-item scales.

Scale	Number of items	Cronbach's α
GenAI policy awareness	4	0.77
Confidence using GenAI tools	4	0.85
Confidence without GenAI tools	3	0.77
Learning behaviours	8	0.85
Academic integrity concerns	7	0.87
Perceived fairness of assessment	4	0.81
Perceived AI literacy	5	0.82

Descriptive statistics

Overall, students reported relatively high levels of confidence when using AI tools, with a mean score of $M = 4.30$ ($SD = 0.76$) on the 5-point scale. This measure reflects students' overall perceived confidence when using GenAI tools rather than confidence associated with any specific tool. Confidence in learning without AI tools was also high, with a mean score of $M = 4.46$ ($SD = 0.66$). Self-reported learning behaviours showed similarly high levels, with a



mean score of $M = 4.51$ ($SD = 0.49$). These results suggest that students generally perceived themselves as engaging in effective learning strategies and study behaviours. Scores for academic integrity concerns indicated moderate levels of concern, with a mean score of $M = 3.90$ ($SD = 0.48$). In contrast, the mean score for perceived fairness of academic assessment was lower ($M = 2.39$, $SD = 0.45$), suggesting that many students perceived the availability of GenAI tools as potentially affecting fairness in academic evaluation. Participants also reported relatively high levels of perceived AI literacy, with a mean score of $M = 4.42$ ($SD = 0.55$) (Table 4).

Table 4. Descriptive statistics of primary variables.

Variable	Mean	SD
Confidence using GenAI tools	4.30	0.76
Confidence without GenAI tools	4.46	0.66
Learning behaviours	4.51	0.49
Academic integrity concerns	3.90	0.48
Perceived fairness of assessment	2.39	0.45
Perceived AI literacy	4.42	0.55

Correlations between study variables

Pearson correlation analyses were conducted to examine relationships among the primary study variables. Confidence when using GenAI tools showed a significant positive correlation with learning behaviours ($r = 0.53$, $p < 0.001$) and academic integrity concerns ($r = 0.69$, $p < 0.001$). A smaller but statistically significant correlation was observed between confidence when using GenAI tools and confidence without GenAI tools ($r = 0.20$, $p = 0.019$). Learning behaviours were positively associated with confidence without GenAI tools ($r = 0.55$, $p < 0.001$) and academic integrity concerns ($r = 0.58$, $p < 0.001$). These findings suggest that students who reported stronger learning behaviours also tended to report higher confidence in learning and greater awareness of academic integrity issues.

Perceived fairness of academic assessment showed significant negative correlations with several variables. Specifically, fairness perceptions were negatively correlated with confidence when using GenAI tools ($r = -0.60$, $p < 0.001$), learning behaviours ($r = -0.43$, $p < 0.001$), and academic integrity concerns ($r = -0.65$, $p < 0.001$), indicating that students who reported



greater confidence in GenAI use and stronger learning behaviours were more likely to perceive GenAI availability as potentially affecting fairness in academic assessment (Table 5).

Table 5. Pearson correlations among key study variables.

Variable	1	2	3	4	5
1. Confidence with GenAI	—				
2. Confidence without GenAI	0.204*	—			
3. Learning behaviours	0.531***	0.552***	—		
4. Academic integrity concerns	0.691***	0.484***	0.579***	—	
5. Perceived fairness	-0.602***	-0.183*	-0.431***	-0.654***	—

Multivariate differences across GenAI tool use groups

A MANOVA was conducted to examine whether levels of GenAI tool use were associated with differences in learning-related outcomes. The independent variable was GenAI-use group (low, moderate, high), and the dependent variables included confidence when using GenAI tools, confidence without GenAI tools, learning behaviours, academic integrity concerns, and perceived fairness of academic assessment. The multivariate test was statistically significant, Wilks' $\Lambda = 0.63$, $F(10, 248) = 6.53$, $p < 0.001$, indicating that GenAI-use levels were associated with significant differences in the combined set of outcome variables.

Univariate differences across AI tool use groups

Following the significant MANOVA result, ANOVAs were conducted to examine differences across GenAI-use groups for each outcome variable. Confidence when using GenAI tools differed significantly across GenAI-use groups, $F(2,128) = 33.86$, $p < 0.001$. Learning behaviours also differed significantly across groups, $F(2,128) = 8.77$, $p < 0.001$. Similarly, academic integrity concerns differed significantly across GenAI-use groups, $F(2,128) = 10.78$, $p < 0.001$, and perceived fairness of academic assessment also showed significant group differences, $F(2,128) = 11.54$, $p < 0.001$. In contrast, confidence in learning without GenAI tools did not differ significantly across groups, $F(2,128) = 2.06$, $p = 0.13$, indicating that GenAI-use frequency was not associated with differences in students' perceived ability to learn independently without GenAI support (Table 6).



Table 6. ANOVA results for AI-use group differences.

Outcome variable	F	df	p
Confidence using GenAI tools	33.86	(2,128)	<0.001
Confidence without GenAI tools	2.06	(2,128)	0.132
Learning behaviours	8.77	(2,128)	<0.001
Integrity concerns	10.78	(2,128)	<0.001
Perceived fairness	11.54	(2,128)	<0.001

Post-hoc comparisons

Bonferroni-adjusted post-hoc comparisons were conducted to identify specific group differences for the variables that showed significant ANOVA results. For confidence when using GenAI tools, both the moderate-use group and the high-use group reported significantly higher confidence compared with the low-use group. However, no statistically significant difference was observed between the moderate and high GenAI-use groups. A similar pattern emerged for learning behaviours, where students in both the moderate-use and high-use groups reported significantly stronger learning behaviours compared with the low-use group. Again, the difference between moderate and high GenAI-use groups was not statistically significant. For academic integrity concerns, both moderate and high GenAI-use groups reported significantly higher scores compared with the low-use group, indicating greater awareness or concern regarding academic integrity issues among students who used GenAI tools more frequently.

In contrast, perceived fairness of academic assessment showed the opposite pattern. Moderate and high GenAI-use groups reported significantly lower fairness scores compared with the low-use group, suggesting that students who used GenAI tools more frequently were more likely to perceive GenAI availability as introducing potential inequities in academic assessment (Table 7).

Table 7. Bonferroni post-hoc comparisons between GenAI-use groups.

Outcome	Comparison	Mean difference	95% CI
Confidence using GenAI	Moderate vs Low	1.39	0.98 to 1.80
	High vs Low	1.18	0.71 to 1.64
	High vs Moderate	ns	



Learning behaviours	Moderate vs Low	0.52	0.22 to 0.83
	High vs Low	0.37	0.02 to 0.72
	High vs Moderate	ns	
Integrity concerns	Moderate vs Low	0.57	0.27 to 0.87
	High vs Low	0.46	0.12 to 0.80
	High vs Moderate	ns	
Fairness perception	Moderate vs Low	-0.55	-0.82 to -0.27
	High vs Low	-0.44	-0.76 to -0.12
	High vs Moderate	ns	

Regression analyses

Multiple linear regression analyses were conducted to examine predictors of confidence when using GenAI tools, academic integrity concerns, perceived fairness of academic assessment, and learning behaviours. The predictors included GenAI-use frequency, perceived AI literacy, the interaction between GenAI use and AI literacy, and demographic covariates (level of study, mode of study, study load, work status, and international student status). For confidence when using GenAI tools, the regression model was statistically significant, $F(11,119) = 7.01$, $p < 0.001$, explaining approximately 39% of the variance ($R^2 = 0.39$). Perceived AI literacy emerged as a significant positive predictor ($\beta = 0.46$, $p = 0.025$), indicating that students with higher perceived AI literacy reported greater confidence when using GenAI tools. In contrast, GenAI-use frequency itself was not a statistically significant independent predictor in several models after accounting for perceived AI literacy and covariates. For academic integrity concerns, the regression model was also significant, $F(11,119) = 13.46$, $p < 0.001$, explaining approximately 55% of the variance ($R^2 = 0.55$). Perceived AI literacy was a significant positive predictor ($\beta = 0.43$, $p < 0.001$), suggesting that students with greater perceived AI literacy reported higher levels of concern regarding academic integrity.

For perceived fairness of academic assessment, the regression model was statistically significant, $F(11,119) = 6.38$, $p < 0.001$, explaining approximately 37% of the variance ($R^2 = 0.37$). Perceived AI literacy was a significant negative predictor ($\beta = -0.43$, $p = 0.001$), indicating that students with higher perceived AI literacy were more likely to perceive GenAI use as potentially introducing unfair advantages in academic assessment. The regression model



predicting learning behaviours was statistically significant, $F(11,119) = 19.99$, $p < 0.001$, explaining approximately 65% of the variance ($R^2 = 0.65$). Both GenAI-use frequency ($\beta = 0.44$, $p < 0.001$) and perceived AI literacy ($\beta = 0.90$, $p < 0.001$) were significant positive predictors of learning behaviours. In addition, the interaction between GenAI use and perceived AI literacy was statistically significant ($\beta = -0.086$, $p = 0.001$), indicating that the relationship between GenAI use and learning behaviours varied depending on students' level of perceived AI literacy (Table 8).

Table 8. Multiple regression models predicting learning outcomes.

Outcome variables	Significant predictors	β	p	R^2
Confidence using GenAI	Perceived AI literacy	0.46	.025	0.39
Integrity concerns	Perceived AI literacy	0.43	<.001	0.55
Perceived fairness	Perceived AI literacy	-0.43	.001	0.37
Learning behaviours	AI use frequency	0.44	<.001	0.65
	Perceived AI literacy	0.90	<.001	
	GenAI x perceived AI literacy interaction	-0.09	.001	

Note: Only statistically significant predictors are presented for brevity; full regression models are available from the corresponding author upon request.

Discussion

The primary purpose of this study was to examine how perceived AI literacy and GenAI-use frequency relate to learning behaviours, learning confidence, academic integrity perceptions, and perceived fairness of academic assessment among higher education students. The contribution of this study lies not in documenting GenAI use alone, but in examining how perceived AI literacy relates to several learning-related outcomes, including learning behaviours, confidence, academic integrity perceptions, and perceived fairness.

Consistent with recent literature, the findings indicate that GenAI tools are frequently used by students for academic tasks, with most participants reporting use several times per week. While the study did not collect data on specific tools used, the findings likely reflect engagement with widely accessible GenAI systems such as ChatGPT and similar applications. As such, this finding should be interpreted as evidence of general GenAI engagement rather than tool-specific usage patterns. Despite this limitation, the observed frequency of use is



broadly consistent with recent research indicating that students are increasingly integrating GenAI tools into their academic workflows for tasks such as idea generation, summarisation, and concept clarification (Dwivedi et al., 2023; Kasneci et al., 2023; Stephenson & Armstrong, 2026). These findings suggest that GenAI tools are increasingly incorporated into students' academic practices, although usage patterns likely vary across educational contexts and individual students.

Multivariate analyses demonstrated that GenAI use was significantly associated with several learning-related outcomes, indicating that GenAI engagement is linked to broader patterns of student learning rather than isolated effects. Students who reported higher levels of GenAI use also reported greater confidence in completing academic work when using AI tools and demonstrated stronger self-regulated learning behaviours. However, given the cross-sectional design of the study, it is not possible to determine the direction of these relationships. It remains unclear whether increased GenAI use leads to higher confidence and improved learning behaviours, or whether students who are already more confident and self-regulated are more likely to engage with GenAI tools.

In this study, self-regulated learning behaviours refer to students' active engagement in planning, monitoring, and evaluating their own learning processes. The association between GenAI use and these behaviours suggests that, for some students, GenAI tools may function as cognitive support systems that help organise tasks, clarify complex concepts, and structure learning activities. However, this interpretation should be approached with caution. While GenAI tools may support learning when used actively and critically, there is also a risk that reliance on AI-generated outputs could reduce cognitive engagement if students do not meaningfully interact with the material. Recent literature emphasises that the educational value of GenAI depends heavily on how it is used, highlighting the importance of active engagement and critical evaluation (Kasneci et al., 2023; Mollick & Mollick, 2023).

At the same time, the findings indicate that greater GenAI use was associated with stronger concerns related to academic integrity. Students who used GenAI tools more frequently reported greater concern about the appropriate use of AI-generated content in coursework. This reflects the current state of uncertainty in higher education, where norms and policies surrounding GenAI use are still evolving. Recent studies suggest that both students and educators often lack clear guidance on what constitutes acceptable use of GenAI in academic



contexts (Cotton et al., 2024; Rudolph et al., 2023). Rather than suggesting that institutions may need to provide guidance, the findings suggest that institutions may benefit from developing clearer, more consistent, and actionable policies to support ethical and transparent use of GenAI tools.

The findings also revealed that greater GenAI use was associated with lower perceived fairness of academic assessment. Students who reported higher levels of GenAI use were more likely to perceive that GenAI tools may create advantages for some students over others. This finding aligns with broader concerns regarding the potential for a widening digital divide in higher education. Access to GenAI tools, as well as the skills required to use them effectively, may not be evenly distributed across student populations. Recent literature suggests that disparities in digital competence and access to emerging technologies may contribute to new forms of educational inequality (Dwivedi et al., 2023; Han, 2026). These findings highlight the importance of ensuring equitable access to both GenAI tools and the knowledge required to use them effectively.

The role of perceived AI literacy

One of the most notable findings of this study was the significant role of perceived AI literacy across multiple learning outcomes. In this study, perceived AI literacy was defined and operationalised as a multidimensional, self-reported construct encompassing the ability to evaluate AI-generated information, identify bias, construct effective prompts, verify outputs using reliable sources, and understand the limitations of GenAI tools. This operationalisation was informed by established and updated frameworks, including Long and Magerko (2020) and the UNESCO (2024) AI competency framework, which conceptualises perceived AI literacy as a combination of technical, critical, and ethical competencies.

Perceived AI literacy emerged as a significant predictor of confidence in learning with GenAI tools, perceptions of academic integrity, perceived fairness of academic assessment, and learning behaviours. Students with higher levels of perceived AI literacy demonstrated greater confidence when using GenAI tools and reported stronger engagement in learning-related activities. Importantly, these findings should be interpreted in light of the self-reported nature of the perceived AI literacy measure. The results reflect perceived rather than objectively verified competencies, and some students may have overestimated their abilities.



The regression analyses also revealed a significant interaction between GenAI-use frequency and perceived AI literacy for learning behaviours. This suggests that the impact of GenAI use on learning may depend partly on students' ability to engage with these tools critically. Students with higher perceived AI literacy may be more likely to use GenAI as part of an active learning process that involves verification, reflection, and the integration of AI-generated information. In contrast, students with lower perceived AI literacy may be more susceptible to passive or uncritical use of AI. Recent frameworks and empirical work emphasise the importance of developing AI literacy to support meaningful and responsible engagement with GenAI tools (Mollick & Mollick, 2023; UNESCO, 2024).

Implications for higher education

The findings of this study have several implications for higher education institutions. While students increasingly use GenAI tools, their adoption remains uneven across contexts and populations. Therefore, rather than assuming full integration, it is more appropriate to consider GenAI as an emerging but rapidly expanding component of academic practice.

Given the widespread but variable use of GenAI tools, attempts to prohibit their use entirely are unlikely to be effective. Instead, institutions should focus on developing clear, practical, and context-specific guidelines for responsible use. Emerging examples include policies that emphasise transparency (such as requiring disclosure of AI use), process-based assessment (for example, drafts and reflections), and the integration of AI into learning activities rather than treating it solely as a threat.

The strong association between perceived AI literacy and learning outcomes suggests that AI literacy should be treated as a core component of modern digital literacy. Universities should consider incorporating AI literacy training into curricula, focusing on skills such as critical evaluation of AI outputs, prompt construction, bias recognition, and ethical use. Recent higher education policy frameworks increasingly recommend embedding AI literacy across curricula as a core graduate competency (Higher Education Authority, 2025).

The findings related to perceived fairness further highlight the need for consistent and transparent institutional policies. Students may perceive assessment as less fair when expectations regarding GenAI use are unclear or inconsistently applied. Clear communication, standardised guidelines, and equitable access to resources may help mitigate these concerns.



Finally, the association between GenAI use and learning confidence suggests that these tools may offer educational benefits when used appropriately. GenAI systems can support learning by providing explanations, feedback, and scaffolding for complex tasks. However, their effectiveness depends on how they are integrated into teaching and learning processes. Recent research emphasises that the pedagogical value of GenAI lies not in the tool itself, but in how it is used to support active and reflective learning (Kasneci et al., 2023; Mollick & Mollick, 2023).

Implications for Learning Development practice

The findings of this study are also relevant to Learning Development practice in higher education. Learning developers increasingly play an important role in supporting students' academic skills, critical thinking, digital literacy, and responsible engagement with emerging technologies. This is particularly relevant for learning developers working directly with students on academic writing, critical evaluation of sources, and responsible technology-supported learning practices. The strong association between perceived AI literacy and learning-related outcomes suggests that AI literacy may represent an increasingly important component of contemporary Learning Development support.

Rather than focusing solely on preventing inappropriate GenAI use, Learning Development initiatives may benefit from supporting students in critically evaluating AI-generated outputs, recognising potential bias, verifying information, and using GenAI tools transparently and ethically within academic work. Scaffolded guidance on prompt construction, reflective AI use, and responsible integration of GenAI into academic workflows may help students engage with these technologies more critically and effectively.

The findings also highlight the importance of equitable access to AI literacy development. Students with lower perceived AI literacy may be more vulnerable to passive or uncritical engagement with GenAI systems, reinforcing the need for inclusive educational support strategies.

Limitations

Several limitations should be considered when interpreting the findings of this study. The cross-sectional design limits the ability to establish causal relationships between GenAI use and learning outcomes. While associations were observed, the direction of these relationships



cannot be determined. Longitudinal studies, including emerging large-scale datasets such as those reported by Stephenson & Armstrong (2026), may provide valuable insights into how GenAI use evolves and influences learning trajectories.

The study relied on self-reported data, which may be subject to response bias, including social desirability bias, inaccurate self-assessment, and differences in participants' interpretations of AI-related concepts. This limitation is particularly relevant for the perceived AI literacy measure, which reflects students' self-assessments rather than objectively verified competencies. It is possible that some participants overestimated or underestimated their AI-related abilities or adjusted their responses according to perceived academic expectations regarding GenAI use. Although participants were provided with a definition and examples of GenAI tools, individual interpretations may still have varied. This is particularly important because GenAI technologies are increasingly embedded within broader digital platforms, including search engines, writing tools, productivity software, and multimodal applications. As a result, participants may not have shared a completely uniform understanding of what counted as GenAI use.

The study adopted a broad operationalisation of GenAI tools and did not assess participants' prior expertise, duration of use, or familiarity with specific AI systems. Because GenAI technologies evolve rapidly and increasingly include multimodal and embedded functionalities, participants may have interpreted GenAI use differently when responding to the questionnaire. In addition, given the rapid pace of development in GenAI technologies, students' experiences and usage patterns may change significantly over time. The findings of this study should therefore be understood within the specific technological and educational context in which the data were collected.

The use of convenience sampling and the sample's composition may limit generalisability. Certain groups may be over- or under-represented, and the findings should therefore be interpreted as exploratory. In addition, the study did not examine how factors such as disability status, prior digital competence, socioeconomic background, or learning support needs may influence students' engagement with GenAI technologies.

The perceived AI literacy measure captured a focused set of self-reported competencies rather than objectively demonstrated AI literacy. It did not assess all dimensions of AI literacy described in broader frameworks, such as technical understanding, societal implications, or



discipline-specific AI use. Future research should therefore include validated AI literacy instruments, performance-based measures, and qualitative approaches to examine how students actually use specific GenAI applications in learning tasks.

Future research

Future research should further explore how AI tools influence critical thinking, independent learning, and long-term knowledge retention in higher education. While AI tools may provide immediate assistance for academic tasks, it remains unclear how extensive reliance on AI may affect deeper learning processes. Qualitative studies exploring students' experiences with AI tools may provide valuable insights into how students integrate AI technologies into their learning strategies. Understanding how students perceive the benefits and limitations of AI tools may help educators design more effective AI-supported learning environments. Further research should also examine how institutional policies regarding AI use influence student behaviour and perceptions of fairness. Investigating how different policy approaches affect students' understanding of academic integrity may help universities develop clearer and more effective governance frameworks for AI use in education.

Conclusion

GenAI technologies are rapidly transforming higher education environments, and students are increasingly incorporating GenAI tools into their academic practices. The findings of this study suggest that perceived AI literacy was significantly associated with how students engaged with GenAI technologies and with several learning-related outcomes. These results highlight the importance of developing clear institutional policies and educational strategies that promote responsible GenAI use.

Rather than viewing GenAI technologies solely as threats to academic integrity, higher education institutions may benefit from focusing on AI literacy development and integrating GenAI tools into teaching and learning practices in transparent and ethical ways. As GenAI technologies continue to evolve, universities must balance the opportunities presented by GenAI-supported learning with the need to maintain academic integrity, fairness, and meaningful learning experiences. Understanding how students use GenAI tools and how these technologies influence learning processes will be essential for guiding future educational policy and practice.



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Appendix: Key questionnaire measures

AI literacy measure

Participants rated the following statements using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

1. I can evaluate whether AI-generated information is accurate.
2. I can identify potential bias in AI-generated content.
3. I know how to write effective prompts to obtain useful AI outputs.
4. I verify AI-generated information using reliable sources.
5. I understand the limitations of AI tools in academic contexts.

Overall GenAI-use frequency

Participants reported their overall frequency of GenAI tool use for academic purposes during the current academic term using the following response categories:

- 1 = Never
- 2 = Less than once per month
- 3 = About once per month
- 4 = About once per week
- 5 = Several times per week
- 6 = Daily
- 7 = Multiple times per day

Task-specific GenAI use

Participants indicated how often they used GenAI tools for the following academic activities using a five-point scale ranging from 0 (never) to 4 (very often):

- Generate ideas or brainstorm topics
- Create outlines for assignments
- Explain academic concepts
- Summarize academic readings
- Generate practice questions or study aids
- Assist with coding, data analysis, or statistics
- Improve grammar, spelling, or writing style



- Paraphrase text later submitted as coursework
- Generate coursework text
- Create citations or reference lists
- Check originality or potential plagiarism
- Plan or organize study schedules

