



Research article

Engineering students' engagement with generative AI: Perceptions, practices, and implications for learning and teaching

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Academic Editor: Feng-Kuang Chiang

Abstract: Generative artificial intelligence (GenAI) is rapidly transforming the way students learn, create, and demonstrate knowledge in higher education. While universities are developing policies and guidelines, less is known about how students in specific disciplines perceive and use these tools. Here, we provide an explorative case comparison study and investigate engineering students' engagement with GenAI across two Australian universities. A survey of 131 students examined reported GenAI use, perceived benefits and challenges, and awareness of institutional policy and training across two cohorts with different demographic and curricular contexts. Our results showed broad awareness and adoption of GenAI, with differences between cohorts in reported frequency and purposes of use, as well as in perceptions of policy training. Students reported benefits in idea generation and efficiency while identifying challenges related to accuracy, content relevance, and ethical use. Our findings suggest that GenAI literacy development should be gradual, discipline-specific, integrated into coursework, and guided by clear communication about the ethical use of GenAI. The study highlights the importance of aligning institutional strategies with students lived experiences of GenAI in learning.

Keywords: GenAI, student perceptions, educational technology, engineering education, policy awareness

1. Introduction

Generative artificial intelligence (GenAI) has moved quickly from a novelty to a common study tool at universities. Students use it to brainstorm, draft their work, check their understanding, and plan work across subjects [1]. This brings real potential for more timely help and feedback, but it also challenges long-standing approaches to teaching and assessment. Early studies in higher education revealed that students utilize GenAI for generating ideas, providing language support, and streamlining tasks while expressing concerns about accuracy and ethical use [2,3]. Teaching and assessment need to account for work that is co-produced by students and GenAI [4,5].

Universities have responded quickly with policies, guidance, and training on the proper and ethical use of GenAI, often framed in terms of academic integrity. National and international bodies have issued principles and toolkits that urge alignment of policy with assessment purpose and program outcomes (Tertiary Education Quality and Standards Agency [TEQSA] [6]). Many institutions specify which uses are acceptable, what must be acknowledged, and what counts as misconduct, building on broader academic integrity guidance. This policy momentum is necessary in a fast-changing space; however, there is a risk that responses become generic and not well-matched to what students are actually asked to do in their courses and across stages of study [7]. Research suggests that compliance-first approaches often overlook how students utilize GenAI in their day-to-day studies [8]. There are calls for a shift from policing toward possibilities, with support grounded in disciplinary needs, authentic tasks, and student agency. Furthermore, some challenges appear common across groups, especially verifying the accuracy of GenAI outputs, which suggests a need for capability building that develops over time rather than through one-off training [9,10].

Engineering students face different demands as they progress through the curriculum. Early years focus on academic literacy, core concepts, and learning how to frame problems. Later years focus on integrating knowledge, meeting professional standards, and working efficiently on complex, real-world tasks [11]. In engineering, studies suggest that GenAI can help build transferable skills, such as information literacy and critical thinking, when integrated into authentic tasks with clear scaffolds. However, support needs to match students' stage and the assessment design to be effective [4,12]. The core takeaway is that GenAI policy and training should be discipline-embedded, staged across the degree, and linked to assessment, rather than uniform across all learners and levels.

2. Literature review

GenAI tools offer students immediate feedback, language support, and enhanced efficiency, but also introduce challenges around accuracy, overreliance, and ethics [13]. Their growing presence requires a rethinking of assessment and the knowledge and judgement that higher education seeks to develop. Early institutional and scholarly responses were characterized by urgency and risk aversion. Universities initially adopted prohibition and detection strategies to protect assessment integrity [14,15]. Detection tools, however, proved unreliable and inequitable, disproportionately misclassifying non-native English speakers [16,17]. Such measures reassured stakeholders but reinforced a compliance culture that treated GenAI as a threat rather than a catalyst for pedagogical innovation [18].

More evidence suggests that GenAI use is becoming normalized across higher education, meaning that research needs to move beyond documenting whether students use these tools to explaining how, why, and under what conditions they do so. Chung et al. [19], in a multi-institutional

Australian study of more than 8000 students, found that GenAI is widely used for study-related purposes, particularly editing, summarizing, and idea generation. Importantly, their findings suggest that student engagement is often pragmatic rather than uncritical, with students using GenAI because it is useful, even while recognizing limitations in trust, accuracy, and institutional guidance. This supports earlier student-centered research showing that students see GenAI as valuable for personalized learning, writing support, brainstorming, research, and analysis, while raising concerns about accuracy, privacy, ethics, and future employability [1].

Authentic assessment provides the most pedagogically sound response to GenAI's disruptive potential [20]. By engaging students in context-rich, creative, and evaluative tasks, authentic assessments reduce the risk of unthinking AI use while cultivating judgement and transferability [21]. The literature also highlights that authentic assessment should include ethical reflection on the social and environmental dimensions of GenAI use [3]. The principle of evaluative judgement, students' capacity to critically assess the quality of their own and others' work, has been identified as a vital, non-automatable skill [9]. When students engage in activities that evaluate GenAI outputs for accuracy, tone, and appropriateness, they engage precisely this higher-order capability. In this sense, GenAI intensifies rather than diminishes the importance of evaluative judgement. Students are not only required to judge the quality of their own work, but also to assess the reliability, relevance, and appropriateness of AI-generated outputs and the processes through which those outputs are produced. Bearman et al. [22] argued that assessment in the GenAI era should support students to develop evaluative judgement of GenAI outputs, evaluative judgement of AI-supported processes, and the capacity to demonstrate their own judgement in relation to GenAI use. This provides a useful conceptual lens for this study because students' reported use and perceived challenges can identify contexts in which evaluative judgement may be required without providing direct evidence of students' evaluative capability.

As higher education's understanding of GenAI develops, the literature response shifts from reactive containment toward purposeful integration. National and international bodies such as the Australasian Academic Integrity Network (AAIN) [23] and TEQSA [6] advocate for capability building, transparency, and ethical literacy. GenAI has now been reframed as a "wicked problem", which is complex, iterative, and inseparable from broader shifts in higher education [24]. This framing positions GenAI integration not as a single policy fix, but as an ongoing process of adapting pedagogy, assessment, and support to a rapidly changing technological landscape.

Frameworks demonstrate how institutions are operationalizing these principles. The Project-work Artificial Intelligence Integration Framework (PAIIF) [12] offers a CDIO-based model that aligns policy with authentic STEM assessment practices. Similarly, the Assessment Adaptation Model – GenAI (AAM-GenAI) [25] provides educators with tools to evaluate the vulnerability of existing assessments and redesign them to require genuine disciplinary reasoning. These initiatives reflect a sectoral turn toward educative integrity which is helping students understand, apply, and critique GenAI responsibly [26].

Disciplinary variation also plays a key role: Technology-oriented fields often adopt GenAI more readily, while others face ethical tensions and slower adoption [27]. This issue is particularly important in engineering education, where GenAI use intersects with technical accuracy, design reasoning, professional responsibility, safety, sustainability, and the development of engineering judgement. While broad higher education research has established that students are using GenAI, engineering education requires closer attention to how these tools are used within disciplinary tasks and professional preparation. Dai [28], for example, found that engineering students did not adopt

GenAI uniformly in design tasks, with use shaped by task characteristics, student confidence, perceived usefulness, and contextual factors. Similarly, Fan et al. [29] found that engineering students reported benefits for learning efficiency, initiative, and creativity, but also raised concerns about accuracy and domain-specific reliability. These findings suggest that engineering students' GenAI engagement should not be treated as generic higher education behavior, but as a situated practice shaped by curriculum, assessment, institutional guidance, and emerging professional identity. Even within the same university, students may receive conflicting messages depending on the subject or teacher. This variation can lead to confusion about what constitutes acceptable use, what should be acknowledged, and where boundaries lie [30]. These inconsistencies underscore the importance of exploring student awareness of institutional GenAI policies and their expectations of university support.

Findings on performance impact remain contradictory, with some studies reporting benefits for formative learning and others raising concerns about reduced engagement, overreliance, and weaker summative outcomes [31,32]. These inconsistencies highlight an empirical gap, particularly as most evidence relies on self-report data and lacks direct measures of learning or performance. Work by Quince and Faulconer [33] revealed how students used GenAI in an engineering unit in response to policy changes. Students tended to use GenAI tools only when it was a substitution for another technology. Thus, understanding how students at different stages use and interpret GenAI, and how they perceive their university's role in preparing them for AI-integrated learning is essential.

This study was designed as an exploratory comparison of students' reported awareness, use and perceptions of GenAI rather than as a test of evaluative judgement, educative integrity, or technology-adoption theory. These concepts are therefore used to connect the descriptive findings to their educational significance. As summarized in Table 1, reported patterns of GenAI use are interpreted in relation to the students' immediate learning contexts, reported verification challenges identify situations in which evaluative judgement may be needed, and perceptions of policy and training indicate areas in which an educative approach to responsible GenAI use may be strengthened. We do not directly assess students' behavior, competence, judgement, or academic-integrity practices.

Table 1. Role of the interpretive concepts in this exploratory study.

Exploratory element	Evidence provided by the survey	Interpretive relevance
Engineering learning context	The cohorts differ in institution, year of study, subject context and demographic profile.	Provides the context within which reported GenAI engagement is considered.
Reported GenAI engagement	Students reported their awareness, frequency of use, tools used and purposes of use.	Helps identify how GenAI use may be associated with immediate learning needs and disciplinary tasks. This is described as situated adoption.
Perceived verification challenges	Students reported difficulties relating to the accuracy and relevance of GenAI-generated information.	Identifies situations in which students may need to exercise evaluative judgement when deciding whether an output is credible, relevant or appropriate.
Perceived institutional support	Students reported their awareness of policy, experiences of training and beliefs about the university's responsibility.	Informs discussion of an educative approach to integrity, in which policy expectations are translated into learning support and task-level guidance.

To respond to this need, we report on the contextualized patterns from a first-year sustainable and humanitarian engineering subject at a regional Australian university, and a second-year mechanical design studio subject at a metropolitan university, recognizing that the datasets differ in structure and are not directly comparable. This will be achieved by answering the following two research questions:

RQ1: How do the adoption, use, and perceptions of GenAI tools in higher education differ across two student cohorts?

To address this, we aim to investigate the patterns in the two cases by: (i) examining the frequency of use; (ii) identifying the purposes for which students use GenAI and investigating patterns across the two cohorts; and (iii) exploring students' perceptions of the benefits, challenges, and accuracy of using generative AI in academic work.

RQ2: How do awareness of AI-related policies, ethical principles, and training provisions and these differences shape their beliefs about the university's role in preparing students for AI-integrated learning differ across cohorts at a regional university and a metropolitan university?

To address this, we aim to: (i) investigate students' awareness of institutional policies and training related to GenAI use; and (ii) investigate students' expectations of their university's role in preparing them for AI-integrated learning.

Regarding these questions, we aim to provide a structured approach to understanding how context, curriculum demands, and institutional support shape student engagement with emerging GenAI technologies.

3. Methodology

In this exploratory study, we employed a quantitative, cross-sectional survey design to investigate and report on patterns of the perceptions, use, and experiences of GenAI. A contextualized comparison of patterns was made between a first-year engineering sustainable and humanitarian subject cohort at a regional Australian university, referred to as Cohort 1 (C1), and a second-year mechanical design studio subject cohort at a metropolitan university, referred to as Cohort 2 (C2).

3.1. Participants

A total of 131 undergraduate engineering students participated, drawn from two purposely selected cohorts to represent different learning contexts and stages of academic development. The first cohort consisted of 28 first-year engineering students from a regional university, while the second cohort comprised 103 second-year mechanical engineering students from a metropolitan university. These sample sizes represent approximately 30% of the full cohort. This sampling strategy enabled the comparison of patterns across university context and year of study. The metropolitan second-year cohort was almost 18–25 years, with only 1.92% above 25. The regional first-year cohort showed a wider spread, with 28.57% aged 18–20, 35.71% aged 21–25, and 35.71% above 25.

Table 2. Age profile of students.

Age	C1	C2
18-20	28.57%	71.15%
21-25	35.71%	26.92%
26-30	3.57%	0.00%
31-35	14.29%	1.92%
36-40	10.71%	0.00%
50-55	7.14%	0.00%

3.2. Survey instrument

Data was collected via an online survey consisting of 11 questions designed to capture a range of data points related to student engagement with GenAI, as per Table 3. The instrument was structured around three thematic areas. The first section captured demographics, frequency of GenAI use, and the specific purposes, tools, benefits, and challenges of use through categorical questions. For the second section, we used a set of 5-point Likert scale questions to measure student perceptions of GenAI's accuracy and their beliefs about the university's role in GenAI education. The final section contained five additional Likert scale questions that measured students' awareness and perceptions of the institutional environment, including university policies and training related to GenAI ethics and use. The survey was validated by students and academics through cross-institutional deployment, including eight institutions.

Table 3. Survey questions.

Question	Response Options
Q1. Have you ever used generative AI tools (e.g., AI writing assistants, AI art generators) for academic purposes?	Yes, frequently Yes, occasionally No, but I am aware of them No, and I am not aware of them GPT (e.g., OpenAI's ChatGPT, GPT-3) Google's AI (any) Bing AI
Q2. Which of the following generative AI tools have you used for any purpose, including academic, personal, or entertainment? (select all that apply) - Selected Choice	DALL-E Grammarly AI Brainly DeepAI Codex I don't use AI Studying or tutoring Research and writing
Q3. For what purposes do you use generative AI tools in your academic work? (Select all that apply)	Creating presentations or visuals Help with numerical questions Generating code or working on programming assignments I do not use generative AI for academic purposes

Q4. Generally, what do you see as the benefits of using GenAI for studying? (Select all that apply) - Selected Choice	Improved efficiency and speed in completing assignments Enhanced creativity and idea generation Personalized learning and tutoring Access to a wide range of information and perspectives Assistance with language translation and understanding complex texts Development of technical skills and understanding of AI technology Support in research by quickly generating relevant data and insights Challenges in verifying the accuracy of generated information
Q5. What challenges have you faced while using generative AI tools for academic purposes? (Select all that apply) - Selected Choice	Ethical concerns about using AI in academic work Difficulty in generating relevant content Technical issues with the AI tool Cost of AI tools None, I have not experienced any challenges
Q6. The university has a role in preparing students in the use of AI	
Q7. I am aware of my universities policies in using AI	5 Strongly Agree
Q8. I am aware of the ethical use of AI	4 Somewhat Agree
Q9. My university provided me with training about the use of AI	3 Neither Agree nor Disagree
Q10. My university provided me with training on the universities policies on AI	2 Somewhat Disagree
Q11. My university provided me with training on the ethical use of AI	1 Strongly Disagree

3.3. Data analysis

All quantitative data was analyzed using SPSS (Version 28). For nominal data where participants could select all that applied, a series of Chi-Square tests of independence were performed for each option, with significance adjusted using a Bonferroni correction ($\alpha = .05 / \text{number of comparisons within each question}$). This test was used to determine if a statistically significant association existed between a student's cohort and their likelihood of selecting a specific option. To indicate precision of estimates, 95% confidence intervals for proportions are reported. For the ordinal data collected from the Likert scale questions, a series of Independent-Samples Mann-Whitney U tests were conducted using a standard significance level of $\alpha = .05$. This non-parametric test was chosen as it was appropriate for comparing the distributions of ordinal responses between two independent groups without assuming a normal distribution.

3.4. Ethics approval and data availability

This study was approved by the UNSW Human Research Ethics Committee under approved code iRECS5789. Data are not publicly available due to ethical restrictions.

3.5. Limitations

Our findings of this study should be interpreted in the context of several limitations. Primarily, the two cohorts differed not only by geographical context but also by year of study, making it impossible to definitively isolate whether observed differences resulted from the institutional environment or from student maturation and academic progression. Furthermore, the unequal sample sizes, while accommodated by the statistical tests, meant that the smaller regional cohort reduced overall statistical power, as reflected in the wider confidence intervals. The cross-sectional design provided a snapshot in time; a longitudinal study tracking a single cohort would be required to draw more definitive conclusions about how student perceptions and use of GenAI evolve. The study was also conducted with engineering students at two Australian universities, which may have limited the generalizability of findings to other disciplines or contexts. Finally, the survey relied on self-reported data, which may be subject to recall or social desirability biases. These results should therefore be interpreted as students' reported current practices and perceived awareness. To investigate behavior or competence, researchers should consider triangulating findings with additional data such as learning analytics, assignment analysis, or qualitative focus groups/interviews. Moreover, evaluative judgement, responsible GenAI practice, and educative integrity were not directly operationalized or measured; these concepts were used only to interpret the educational significance of the reported perceptions and to identify directions for future research.

4. Results

In this section, we present the survey findings, organized into two parts to address the corresponding research questions. The first includes the adoption, use, and perception of working with GenAI. We cover the adoption rates, tool preferences, purpose of use, perceived benefits, challenges, and accuracy. In the second part, we address the Institutional environments, detailing students' awareness and training experiences related to university GenAI policies.

4.1. Adoption, use, and perceptions of GenAI tools

The adoption profiles between C1 and C2 differed. In the C1 cohort, no students reported frequent use; usage was split evenly between occasional users (50.00%) and aware non-users (50.00%), with no unaware students. In the metropolitan cohort, 8.74% reported frequent use, 62.14% occasional use, 28.16% were aware but not using, and 0.97% were unaware. This indicates stronger integration in the metropolitan cohort and a larger 'on the sidelines' group in the regional cohort.

4.1.1. Tool preference & Purpose of use

Valid Q2 responses were available for 130 students (C1 = 28; C2 = 102). GPT-based tools dominated in both settings, showing strong uptake in C1 (82.14%) and C2 (98.04%). The C2 students more often reported using Google's AI (23.53% vs 7.14%), whereas C1 students more often reported Bing AI (21.43% vs 1.96%). Similar usage was observed for Grammarly AI (C1 = 17.86% vs C2 = 20.59%).

To investigate patterns of use across the cohorts (Q3), a series of Chi-square tests of independence was performed on the most frequently selected options, with significance set at $\alpha = 0.0083$. Based on the whole-of-cohort data in Table 4, a larger segment of C1 reported that they "do

not use generative AI for academic purposes" at all (C1 = 35.71% vs C2 = 9.71%; $p < .001$). Therefore, the complete cohort population was included, as well as the removal of non-users from the population, to investigate if those that use GenAI engage in a similar manner; significance was set at $\alpha = 0.01$. Percentages are reported along with 95% confidence intervals (CIs) to indicate the precision of cohort estimates. Moreover, a large portion of C2 students reported the use of GenAI for core academic tasks. While most C2 students using it for the purpose of "Research and writing" and "Studying or tutoring" ($> 57\%$), compared to just over a third of the first-year regional students (respectively 35.7%), there was no significant difference.

Almost half of C2 reported using GenAI for generating code (46.60%), compared with 7.14% of C1, representing a statistically significant difference in the whole-sample analysis ($p < .001$). This difference remained statistically significant after respondents who reported no academic GenAI use were excluded (C1 = 11.11%; C2 = 50.54%; $p = .002$), meeting the Bonferroni-adjusted threshold of $\alpha = .01$. No other purpose-of-use comparison met the relevant adjusted threshold. Although presentation use was descriptively higher among active users in C1 than C2 (38.89% vs 13.98%), this difference did not meet the Bonferroni-adjusted threshold ($p = .012$).

Table 4. Overview of GenAI student purpose of use (Q3).

Item	C1 (%) [95% CI]	C2 (%) [95% CI]	χ^2	p-value	Cramér's V	C1 (%) [95% CI]	C2 (%) [95% CI]	χ^2	p-value	Cramér's V
All Participants (N=131)						Non-GenAI users removed (N=111)				
I do not use generative AI	35.71 [17.97, 53.46]	9.71 [3.99, 15.43]	11.509	<.001*	0.296	-	-	-	-	-
Research and writing	35.71 [17.97, 53.46]	58.25 [48.73, 67.78]	4.494	0.034	0.185	55.56 [32.60, 78.51]	62.37 [52.52, 72.21]	0.295	0.587	0.052
Studying or tutoring	35.71 [17.97, 53.46]	57.28 [47.73, 66.83]	4.108	0.043	0.177	55.56 [32.60, 78.51]	61.29 [51.39, 71.19]	0.207	0.649	0.043
Generating code	7.14 [0.00, 16.68]	46.60 [36.97, 56.24]	14.525	<.001*	0.333	11.11 [0.00, 25.63]	50.54 [40.38, 60.70]	9.508	0.002*	0.293
Help with numerical questions	28.57 [11.84, 45.30]	35.92 [26.66, 45.19]	0.528	0.468	0.063	44.44 [21.49, 67.40]	38.71 [28.81, 48.61]	0.207	0.649	0.043
Creating presentations	25.00 [8.96, 41.04]	13.59 [6.97, 20.21]	2.128	0.145	0.127	38.89 [16.37, 61.41]	13.98 [6.93, 21.03]	6.335	0.012	0.239

Note: Values are presented as percentages and 95% confidence intervals in square brackets. Percentages are calculated within each group. Adjusted sample excludes participants who reported not using AI ($N = 111$). All tests are Chi-square tests of independence ($df = 1$). Cramér's V is reported as effect size. * indicates significance after Bonferroni correction for all participants ($\alpha = 0.0083$) and without non-AI users ($\alpha = 0.01$).

4.1.2. Perceived benefits, challenges, and accuracy

To investigate benefits (Q4) and challenges (Q5) of GenAI, a series of Chi-square tests of independence were performed on the most frequently selected options by GenAI users ($N = 111$); significance was set at $\alpha = 0.00714$ for Q4 and $\alpha = 0.0083$ for Q5.

Table 5 summarizes the benefits of GenAI reported by respondents who used GenAI for

academic purposes. Enhanced creativity and idea generation was reported more frequently by C1 than C2 (88.89% vs 41.94%; $p < .001$). Development of technical skills was also reported more frequently by C1 (66.67% vs 27.96%; $p = .002$). Both differences met the Bonferroni-adjusted significance threshold of $\alpha = .00714$.

No statistically significant differences were identified for improved efficiency and speed (72.22% vs 61.29%; $p = .379$), personalized learning or tutoring (50.00% vs 51.61%; $p = .900$), access to information (55.56% vs 52.69%; $p = .823$), assistance with language (66.67% vs 36.56%; $p = .018$), or support in research (55.56% vs 38.71%; $p = .184$). Although some descriptive differences were observed, they did not meet the adjusted significance threshold.

Table 5. Students' perception of the benefits of using GenAI (Q4).

Item	C1 (%) [95% CI]	C2 (%) [95% CI]	χ^2	p-value	Cramér's V
Improved efficiency and speed	72.22 [51.53, 92.91]	61.29 [51.39, 71.19]	0.774	0.3791	0.084
Enhanced creativity	88.8 [74.37, 100.00]	41.94 [31.91, 51.96]	13.300	<.001*	0.346
Personalised learning/tutoring	50.00 [26.90, 73.10]	51.61 [41.46, 61.77]	0.016	0.9003	0.012
Access to information	55.56 [32.60, 78.51]	52.69 [42.54, 62.84]	0.050	0.8234	0.021
Assistance with language	66.67 [44.89, 88.44]	36.56 [26.77, 46.35]	5.633	0.0176	0.225
Development of technical skills	66.67 [44.89, 88.44]	27.96 [18.84, 37.08]	10.037	.002*	0.301
Support in research	55.56 [32.60, 78.51]	38.71 [28.81, 48.61]	1.764	0.1842	0.126

Note: Values are presented as percentages with 95% confidence intervals in square brackets. Participants are GenAI users only ($N = 111$: C1 = 18, C2 = 93). All tests are Chi-square tests of independence ($df = 1$). *indicates significance after Bonferroni correction ($\alpha = 0.00714$).

Table 6 summarizes the challenges reported by GenAI users. Verifying the accuracy of generated information was the most frequently reported challenge in both cohorts (C1 = 66.67%; C2 = 77.42%). Difficulty generating relevant content was reported by 61.11% of C1 and 51.61% of C2, while ethical concerns about using GenAI in academic work were reported by 66.67% of C1 and 32.26% of C2. Ethical concerns about using GenAI in academic work were reported more frequently by C1 than C2 (66.67% vs 32.26%; $p = .006$), meeting the Bonferroni-adjusted significance threshold of $\alpha = .0083$. No statistically significant differences were identified for the other five challenge options.

Table 6. Students' perception of the difficulties of using GenAI.

Item	C1 (%) [95% CI]	C2 (%) [95% CI]	χ^2	p-value	Cram é's V
Verifying accuracy	66.67% [44.89%, 88.44%]	77.42% [68.92%, 85.92%]	0.947	0.330	0.092
Difficulty in generating content	61.11% [38.59%, 83.63%]	51.61% [41.46%, 61.77%]	0.546	0.460	0.070
Ethical concerns	66.67% [44.89%, 88.44%]	32.26% [22.76%, 41.76%]	7.591	0.006*	0.262
Technical issues	38.89% [16.37%, 61.41%]	18.28% [10.42%, 26.13%]	3.780	0.052	0.185
Cost of AI tools	27.78% [7.09%, 48.47%]	21.51% [13.15%, 29.86%]	0.340	0.560	0.055
None, I have no challenges	5.56% [0.00%, 16.14%]	2.15% [0.00%, 5.10%]	0.665	0.415	0.077

Note: Values are presented as percentages with 95% confidence intervals in square brackets. Participants are GenAI users only (N = 111: C1 = 18, C2 = 93). All tests are Chi-square tests of independence (df = 1). Cram é's V is reported as effect size and Bonferroni correction ($\alpha = 0.0083$).

4.2. Institutional environment: Policy awareness and training

To investigate patterns of all students (users and non-users) across the two cohorts on their perceived institutional environment, a series of six Mann-Whitney U tests were conducted on the ordinal data from questions 6 through 11. Using a standard significance level of $p < .05$, the analysis revealed a specific difference between the two groups. One incomplete entry was identified and removed from the full analysis, considering $N = 130$.

In exploring whether students believe the university has a role in preparing them for the use of AI (Q6), no statistically significant difference was found between the two groups ($U = 1332.5$, $z = -0.54$, $p = .589$, $r = .05$). Both cohorts reported high levels of agreement (Mdn = 5 for both groups), with the regional cohort ($M = 4.61$) and metropolitan cohort ($M = 4.57$) showing nearly identical mean scores. An examination of the responses showed strong consensus within both groups, where 96.4% of the regional cohort and 95.1% of the metropolitan cohort either 'Somewhat' or 'Strongly' agreed that the university has a role in preparing them for the use of AI.

The tests revealed no statistically significant differences between the cohorts on their awareness of university policies (Q7, $U = 1394.5$, $z = -0.27$, $p = .790$, $r = .02$) or awareness of ethical use of AI (Q8, $U = 1105.5$, $z = -1.89$, $p = .059$, $r = .17$). Similarly, there was no significant difference reported for training on the general use of AI (Q9, $U = 1230$, $z = -1.19$, $p = .234$, $r = .10$) or training on the ethical use of AI (Q11, $U = 1332.5$, $z = -0.54$, $p = .589$, $r = .05$).

However, a statistically significant difference was found for Q10, which asked if the university had provided training on its policies regarding AI ($U = 1033.5$, $z = -2.29$, $p = .022$). A review of the descriptive data showed that the regional cohort reported higher levels of agreement with this statement (Mdn = 4, $M = 4.25$) compared to the metropolitan cohort (C2; Mdn = 4, $M = 3.78$). This represents a small effect size ($r = .20$), suggesting a modest but meaningful practical difference in perceived AI training provision between the two institutions.

5. Discussion

In this exploratory study, we compare the reported GenAI awareness, use, and perceptions of two engineering cohorts in different learning contexts. The reported adoption and purposes of GenAI use are considered in relation to the immediate curricular and cohort contexts. Students' reported

difficulties in verifying GenAI outputs indicate situations in which evaluative judgement may be required, while their perceptions of university policy and training inform discussion of how responsible GenAI use may be supported educationally. These concepts connect the descriptive findings to implications for engineering education; they are not treated as constructs directly measured or tested by the survey.

5.1. The adoption, use, and perceptions of generative AI tools

The adoption profiles differed between cohorts. The second-year metropolitan cohort (C2) showed stronger integration of GenAI, including a large group of frequent users, whereas C1 had a larger number of students who are aware but not using it. It is worth noting that the C1 cohort consisted of 35.71% students above 25 years of age, and that before the use of GenAI in academia, it was found that mature-age students use technology less frequently [34]. The age differences, as well as stage of study, may therefore contribute to the observed differences in adoption and use, although their independent effects cannot be isolated in this study.

There were also descriptive differences between general GenAI awareness and reported academic use. Although half of C1 reported being aware but not using GenAI in general, a smaller, but still substantial proportion reported not using it for academic purposes (35.71%). This suggests that a portion of C1 users may be experimenting with GenAI outside academic contexts but have not fully translated that into their studies. This may be owing to the different attitude toward technology by different age groups, or perhaps that the more mature students are further dedicated to learning, which is a well-established consideration in higher education [35,36].

It is important to consider that the characteristics of a cohort may appear skewed when compared to one with less demographic variation. This was particularly observed when investigating the use of AI in academic contexts. When considering the complete population, C2 students reported higher use of AI for the core academic tasks “Research and writing” (58.25% vs 35.71%; $p = .034$) and “Studying or tutoring” (57.28% vs 35.71%; $p = .043$) compared with C1; however, neither difference met the Bonferroni-adjusted significance threshold of $\alpha = .0083$. Once non-users were removed from the data set, these differences remained non-significant, indicating that C1’s larger segment of non-users may contribute to the descriptive differences observed between the cohorts.

There was, however, one significant difference after removing the non-users: generating code. The C2 cohort reported much higher use for generating code prior to the removal of non-users compared with C1 (46.60% vs 7.14%; $p < .001$), and the difference remained significant after the removal of non-users (50.54% vs 11.11%; $p = .002$). This suggests a divergence in reported practice that may be tied to disciplinary focus and coursework where C2 students had already been exposed to coding tasks. For generating presentations, there was no significant difference at the whole-of-cohort level, and although C1 reported greater use than C2 after removing non-users (38.89% vs 13.98%; $p = .012$), this did not meet the Bonferroni-adjusted threshold of $\alpha = .01$. This descriptive pattern may reflect differences in curricular exposure to presentation tasks. At the time of surveying, students in C1 had had opportunities to present their work as part of coursework, whereas C2 students had completed a mechatronics subject related to coding. These patterns suggest that GenAI adoption in engineering education may be better understood as situated and task-dependent rather than as a generalized student disposition toward technology. The higher use of GenAI for coding in C2 appears to be connected to the curricular demands of a more advanced mechanical/mechatronics

context, while the descriptively higher use of GenAI for presentations among active C1 users may reflect a different form of support related to communication and transition into university study. This extends Dai's [28] finding that engineering students' GenAI use and non-use are shaped by task characteristics, learner characteristics, and context rather than by tool availability alone. It also resonates with Luo et al.'s [37] finding that engineering students often prioritize the functional and outcome-oriented affordances of GenAI, whereas instructors tend to emphasize process, oversight, and responsible integration. The findings, therefore, suggest that cohort differences should not be interpreted only through demographic variables such as age or year level, but through the alignment between GenAI affordances and the immediate demands of engineering learning tasks.

Improved efficiency and speed was commonly reported by both cohorts (C1 = 72.22%; C2 = 61.29%), with no statistically significant difference between them ($p = .379$). C1 students were significantly more likely than C2 students to report enhanced creativity and idea generation as a benefit (88.89% vs 41.94%; $p < .001$) and the development of technical skills and understanding of AI technology (66.67% vs 27.96%; $p = .002$). Both results met the Bonferroni-adjusted threshold of $\alpha = .00714$.

Although C1 also reported higher percentages for assistance with language and support in research, these differences did not meet the adjusted significance threshold. The findings therefore suggest that creativity and technical-skill development were particularly prominent perceived benefits within C1, while efficiency was a commonly reported benefit across both cohorts.

These patterns may reflect differences in learning needs and in the contexts in which students adopt GenAI. Mirriahi et al. [38] found that students' acceptance of GenAI was associated with self-regulated learning factors, including self-efficacy, social support, intrinsic motivation, and effort regulation. Fan et al. [29] similarly found that engineering students reported perceived benefits relating to learning efficiency, initiative, and creativity while recognizing concerns about performance and reliability. The findings should therefore be interpreted as students' perceptions of the benefits they associate with GenAI, rather than as evidence of measured improvements in creativity, technical capability, or learning outcomes.

None of the six perceived challenge options differed significantly between the cohorts after Bonferroni correction. Verifying the accuracy of generated information was the most frequently reported challenge in both cohorts (C1 = 66.67%; C2 = 77.42%), although the difference was not statistically significant ($p = .069$). Difficulty generating relevant content and ethical concerns were also reported across both cohorts, without statistically significant between-cohort differences. These findings indicate that concerns relating to output verification, relevance, and ethical use are present in both learning contexts, but they do not establish that the cohorts experienced these challenges to the same extent.

Because we rely on self-reported perceptions, we do not assess students' actual ability to verify GenAI outputs. Nevertheless, the frequency with which verification was reported as a challenge identifies an educational need for explicit support in evaluating the credibility, assumptions, relevance, and limitations of generated material. Bearman et al. [22] argued that GenAI-era assessment should support students in judging AI outputs, AI-supported processes, and their own decisions when using GenAI. This is particularly important in engineering, where plausible but incorrect outputs may affect calculations, design reasoning, coding decisions, or professional communication.

Similarly, Quince et al. [39] found that engineering students analyzing GenAI-related failure cases prioritize control and oversight, decision-making under risk and uncertainty, output quality and accuracy, and transparency and accountability. Walton et al. [40] further demonstrated that students' work with GenAI involves decisions about when to accept, reject, revise, or contextualize generated material. The implication is therefore not simply that students should be instructed to "check" GenAI outputs, but that verification processes and the reasoning behind final decisions should become visible components of engineering learning.

5.2. Institutional environment: Policy training signal and role expectations

Policy awareness and ethical training were comparable across cohorts (Q's 6-9, and 11) with no significant differences. Students' level of agreement that the university has a role in preparing them to use AI (Q6) was high in both cohorts and did not differ ($p = .589$; $Mdn = 5$ for both), indicating shared expectations of institutional responsibility despite the difference observed in perceived policy-training provision. However, one institutional difference emerged for university policy-specific training (Q10). The regional cohort (C1) reported higher agreement that the university had provided training on its AI policies ($U = 1033.5$, $p = .022$, $r = .20$), with both cohorts having a median response of 4 but a higher mean in C1 ($M = 4.25$) than C2 ($M = 3.78$). These findings suggest that institutional support should be understood as an educative integrity issue rather than a policy-awareness issue alone. Students may know that policies exist but still be uncertain about how those policies apply to specific tasks, tools, and disciplinary expectations. Gonsalves [41] found that 74% of students failed to declare GenAI use despite declaration being required, with non-compliance shaped by fear of consequences, ambiguous guidance, inconsistent enforcement, and peer influence. Luo et al. [37] similarly showed that students and instructors in engineering education may hold different assumptions about GenAI, with students placing greater emphasis on utility and outcomes, while instructors focus more on risks, process, and oversight. In this study, students' expectation that universities should prepare them to use AI suggests a need for guidance that is embedded in assessment practice, not only communicated as institutional policy. Educative integrity therefore requires students to practice making and explaining responsible decisions about GenAI use within particular engineering tasks. This may reflect either recent, targeted onboarding or local communication practices.

It is important to consider how broader demographic factors within specific cohorts, such as mature-age students, may influence perspectives on the use of GenAI, particularly in academic contexts. While most studies and recommendations aim to be inclusive, they may not fully account for variations in digital literacy or cultural attitudes, which could affect equitable access to opportunities [39,42].

6. Synthesis and implications for engineering education: A pathway forward

Considered together, the findings provide a more nuanced account than a simple comparison of whether engineering students use GenAI. First, the purposes for which students reported using GenAI varied in ways that appear consistent with their immediate curricular experiences. The greater reported use of GenAI for coding in the second-year mechanical engineering cohort and for presentations among active users in the first-year cohort suggests that engagement may be shaped by

the alignment between GenAI functions and the tasks students encounter. These findings should not be interpreted as evidence that curriculum or stage of study caused the observed differences, but they indicate that GenAI engagement is situated within particular learning contexts rather than occurring uniformly across engineering students.

Second, the differences in reported adoption did not correspond with substantial differences in the challenges students perceived. Both cohorts commonly reported difficulties related to verifying the accuracy and relevance of GenAI-generated information. This shared concern is educationally important because it suggests that support for evaluating GenAI outputs should not be limited to first-year students, new adopters, or students who use GenAI less frequently. Verification and critical evaluation may instead represent continuing needs across stages of engineering education [43].

Third, students in both cohorts strongly supported a university role in preparing them to use GenAI, while their reported experiences of policy communication and training did not necessarily indicate how institutional expectations were understood within specific learning tasks. This distinction suggests that institutional policy is necessary but insufficient on its own. Responsible GenAI use must also be supported through subject-level guidance, assessment design, and opportunities for students to explain how they evaluate and use AI-generated material.

Table 7 draws these findings together and shows how they inform the engineering-education implications developed in this section.

Table 7. Synthesis of exploratory findings and implications for engineering education.

Key exploratory finding	Interpretation	Implication for engineering education
Reported purposes of GenAI use differed across the two cohorts, particularly for coding and presentations.	GenAI engagement may be shaped by the alignment between available AI functions and immediate curricular tasks.	Guidance should be situated within particular engineering subjects, assessments and learning outcomes rather than relying only on generic institution-wide information.
Both cohorts commonly reported difficulties verifying the accuracy and relevance of GenAI outputs.	Evaluating output quality appears to be a shared educational need across different reported adoption profiles.	Verification and evaluative practices should be developed progressively across engineering programs, not treated only as introductory AI literacy.
Students expected universities to prepare them to use GenAI, but perceived policy and training provision varied.	Awareness of policy may not automatically translate into confident task-level decisions about acceptable and responsible use.	Institutional policy should be translated into explicit assessment expectations, disclosure guidance, instructional scaffolding and opportunities to demonstrate responsible decision-making.

The findings point to a pathway forward that is less about increasing or restricting GenAI use in general, and more about making student judgement visible within engineering learning tasks. Research on student work with GenAI in assessments suggests that the key issue is not simply whether students use GenAI, but how they make decisions while using it, including when they reject, revise, verify, or contextualize AI-generated material. The implication is that responsible GenAI integration should focus on the quality of student–AI interaction rather than tool use alone.

This also means that institutional guidance needs to be translated into subject-level learning practices. Awareness of GenAI policy does not necessarily produce confident or critically informed use, particularly when students encounter different expectations across tasks or teaching teams. A more educative response is therefore to design assessment activities that require students to explain

what they used GenAI for, how they evaluated its outputs, and how they made final decisions. This shifts the emphasis from detecting or discouraging GenAI use toward developing students' capacity to use it critically, transparently, and in ways aligned with engineering learning outcomes.

Our findings support a “dual strategy” for GenAI in engineering education: (i) an institutional baseline (clear policy, consistent messaging, and accessible training), and (ii) subject-level scaffolds that align GenAI use with disciplinary aims and assessment design. While institutional policy and central training are often beyond the control of individual educators, our results indicate several practical actions that subject convenors and teaching teams can implement immediately to support responsible GenAI use and reduce overreliance or uncritical adoption.

Within this dual strategy, human-in-the-loop learning provides the connection between institutional guidance and students' responsible use of GenAI within engineering tasks. Human involvement should not be understood simply as an educator approving an AI-generated answer after it has been produced. Instead, educators establish the task purpose, acceptable-use boundaries, and disciplinary quality criteria; model how GenAI outputs should be questioned; and provide feedback that helps students calibrate their judgements. Students remain responsible for examining assumptions, checking calculations and sources, comparing alternatives, identifying limitations, and deciding whether generated material should be accepted, revised, or rejected. GenAI is therefore positioned as a provisional source of explanation, feedback, or alternatives rather than as the final authority.

Instructional support can be progressively reduced as students develop greater responsibility. Early activities may involve educators modelling the evaluation of flawed or incomplete GenAI responses. Students can then undertake guided evaluation using disciplinary criteria, worked examples, reference data, or independent calculations, followed by educator or peer feedback. Later tasks can require students to apply and document these checks independently. Although the level of instructional support may decrease, human accountability remains necessary, particularly where engineering decisions involve technical accuracy, safety, sustainability, or professional responsibility. Based on our results, we suggest the following:

1. Make expectations concrete in the assessment documents. Even when institutional policy exists, students may not translate it into subject-specific decisions. Teaching teams can therefore include a short, explicit “GenAI in this assessment” box in each task description:
 - Permitted uses (e.g., idea generation, explanation, translation, drafting, and code debugging).
 - Not permitted uses (e.g., submitting AI-generated final answers/derivations/design rationales as the student's own).
 - Disclosure requirement (one sentence minimum: tool + purpose + what was changed).
 This reduces inconsistent interpretation across courses and directly addresses the confusion seen in both cohorts around training and expectations. This approach has been effective in engineering units at other Australian universities [33].
2. Scaffold evaluative judgement: Teach students how to check GenAI outputs (and why). Given that concerns about accuracy and overreliance were common across cohorts, subject teams can explicitly develop students' evaluative judgement, their capability to appraise the quality, credibility and suitability of GenAI outputs, rather than assuming that students will verify outputs independently. This can be scaffolded progressively across a teaching period through

structured activities that: (i) Involve educators modeling and checking practices using flawed or incomplete GenAI outputs; (ii) provide students with guided practice using disciplinary criteria and educator or peer feedback; and (iii) require students to apply and document these checking practices independently. This human-in-the-loop approach retains educators' responsibility for establishing quality criteria, modeling disciplinary judgement, and providing feedback, while students remain accountable for checking assumptions, calculations, and sources and for deciding whether GenAI-generated material should be accepted, revised, or rejected. The level of instructional support may decrease as students develop greater capability, but responsibility for the final engineering decision remains human. Evaluative judgement is an important capability that students will need to develop throughout their studies [22].

3. Build “understanding checks” into learning tasks: If it is unclear, pause and investigate. To reduce uncritical reliance, teaching teams can embed lightweight checks that require students to demonstrate that they understand what GenAI produced, how it produced it (at least at the level of assumptions/inputs), and where it may be unreliable. The intent is not to police use, but to normalize a professional rule: If you cannot explain the output, you should not use it until you have investigated.
4. Teach “prompting for engineering thinking”, not prompting for answers. To shift GenAI use from answer-generation to learning support, teaching teams can give students a small set of discipline-aligned prompt stems that deliberately ask for assumptions, alternatives, and checks. For example, students can be encouraged to prompt: “List the assumptions and constraints you’re using,” “Give two possible approaches and the trade-offs,” and “Suggest quick sanity checks or benchmarks I should run—don’t give the final answer.”

7. Conclusions

This study highlights differences in the reported GenAI adoption patterns of two engineering cohorts that also differed in stage of study, age profile, curriculum, and institutional context. The metropolitan second-year students reported more extensive integration of GenAI into academic workflows, while regional first-year students showed broad awareness but lower reported academic use. Among active users, most purposes of use were similar, with generating code representing the principal statistically significant difference between the cohorts. Perceived benefits aligned with developmental priorities, as support for first years versus productivity for advanced students; however, the challenges and accuracy concerns remained similar. These findings underscore the need for a dual strategy: a common institutional framework for AI literacy and ethics, complemented by stage-specific scaffolds and discipline-tailored practices. In future studies, researchers should examine the impact on various demographic backgrounds, such as age, gender, and whether these are local or international students, to study the longitudinal impacts on equitable learning outcomes.

Author contributions

Anna Lidfors Lindqvist: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Validation, Resources, Project administration, Writing – original draft, Writing – review & editing; Zachery Quince: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Validation, Resources, Project administration, Writing – original draft, Writing – review & editing.

Use of Generative-AI tools declaration

The authors declare the use of generative artificial intelligence (GenAI) tools to assist in the development of this paper. Specifically, ChatGPT and Microsoft Copilot were used to provide feedback, assist with literature searches, and review the data analysis. All GenAI-generated outputs were critically reviewed and verified by the authors prior to inclusion in the manuscript.

Conflict of interest

The authors declare no conflicts of interest

Ethics declaration

This study was approved by the UNSW Human Research Ethics Committee under approved code iRECS5789. Data are not publicly available due to ethical restrictions.

References

1. Chan, C.K.Y. and Hu, W., Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *Int. J. Educ. Technol. High. Educ.*, 2023, 20: 43. <https://doi.org/10.1186/s41239-023-00411-8>
2. Johnston, H., Wells, R.F., Shanks, E.M., Boey, T. and Parsons, B.N., Student perspectives on the use of generative artificial intelligence technologies in higher education. *Int. J. Educ. Integr.*, 2024, 20: 2. <https://doi.org/10.1007/s40979-024-00149-4>
3. Quince, Z. and Nikolic, S., Student identification of the social, economic and environmental implications of using generative artificial intelligence (GenAI): Identifying student ethical awareness of ChatGPT from a scaffolded multi-stage assessment. *Eur. J. Eng. Educ.*, 2026, 51(1): 43–62. <https://doi.org/10.1080/03043797.2025.2482830>
4. Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., et al., ChatGPT for good? On opportunities and challenges of large language models for education. *Learn. Individ. Differ.*, 2023, 103: 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
5. Stroud, R. and Du, J., Student acceptance of ChatGPT in higher education: A mixed-method study of attitudes, intentions, and concerns. *J. Appl. Learn. Teach.*, 2025, 8(2): 35–48. <https://doi.org/10.37074/jalt.2025.8.2.7>
6. Lodge, J.M., The evolving risk to academic integrity posed by generative artificial intelligence: Options for immediate action. Tertiary Education Quality and Standards Agency, 2024. Available from: <https://www.teqsa.gov.au/guides-resources/resources/corporate-publications/evolving-risk-academic-integrity-posed-generative-artificial-intelligence-options-immediate-action>
7. Henderson, M., Selwyn, N. and Aston, R., What works and why? Student perceptions of “useful” digital technology in university teaching and learning. *Stud. High. Educ.*, 2017, 42(8): 1567–1579. <https://doi.org/10.1080/03075079.2015.1007946>
8. Luo, J., A critical review of GenAI policies in higher education assessment: A call to reconsider the “originality” of students' work. *Assess. Eval. High. Educ.*, 2024, 49(5): 651–664. <https://doi.org/10.1080/02602938.2024.2309963>

9. Boud, D. and Falchikov, N., Aligning assessment with long-term learning. *Assess. Eval. High. Educ.*, 2006, 31(4): 399–413. <https://doi.org/10.1080/02602930600679050>
10. Carless, D. and Boud, D., The development of student feedback literacy: Enabling uptake of feedback. *Assess. Eval. High. Educ.*, 2018, 43(8): 1315–1325. <https://doi.org/10.1080/02602938.2018.1463354>
11. Felder, R.M. and Brent, R., The intellectual development of science and engineering students: Part 2—Teaching to promote growth. *J. Eng. Educ.*, 2013, 93(4): 279–291. <https://doi.org/10.1002/j.2168-9830.2004.tb00817.x>
12. Nikolic, S., Quince, Z., Lindqvist, A.L., Neal, P., Grundy, S., Lim, M., et al., Project-work artificial intelligence integration framework (PAIIF): Developing a CDIO-based framework for educational integration. *STEM Educ.*, 2025, 5(2): 310–332. <https://doi.org/10.3934/steme.2025016>
13. Kim, J., Yu, S., Detrick, R. and Li, N., Exploring students’ perspectives on generative AI-assisted academic writing. *Educ. Inf. Technol.*, 2025, 30: 1265–1300. <https://doi.org/10.1007/s10639-024-12878-7>
14. Curtis, G.J., The two-lane road to hell is paved with good intentions: Why an all-or-none approach to generative AI, integrity, and assessment is insupportable. *High. Educ. Res. Dev.*, 2025, 44(8): 2151–2158. <https://doi.org/10.1080/07294360.2025.2476516>
15. Liu, D., Fawns, T., Cowling, M. and Bridgeman, A., *Responding to generative AI in Australian higher education [Preprint]*, OSF, 2023. https://osf.io/9wa8p_v1
16. Kim, J. and Danilina, E., Towards inclusive and equitable assessment practices in the age of GenAI: Revisiting academic literacies for multilingual students in academic writing. *Innov. Educ. Teach. Int.*, 2025, 62(5): 1593–1597. <https://doi.org/10.1080/14703297.2025.2456223>
17. Pratama, A.R., The accuracy-bias trade-offs in AI text detection tools and their impact on fairness in scholarly publication. *PeerJ Comput. Sci.*, 2025, 11: e2953. <https://doi.org/10.7717/peerj-cs.2953>
18. Lee, D., Arnold, M., Srivastava, A., Plastow, K., Strelan, P., Ploeckl, F., et al., The impact of generative AI on higher education learning and teaching: A study of educators’ perspectives. *Comput. Educ. Artif. Intell.*, 2024, 6: 100221. <https://doi.org/10.1016/j.caeai.2024.100221>
19. Chung, J., Henderson, M., Slade, C., Liang, Y., Pepperell, N., Corbin, T., et al., The use and usefulness of GenAI in higher education: Student experience and perspectives. *Comput. Educ. Open*, 2026, 10: 100347. <https://doi.org/10.1016/j.caeo.2026.100347>
20. Vlachopoulos, D. and Makri, A., A systematic literature review on authentic assessment in higher education: Best practices for the development of 21st-century skills, and policy considerations. *Stud. Educ. Eval.*, 2024, 83: 101425. <https://doi.org/10.1016/j.stueduc.2024.101425>
21. Wiggins, G., *Educative assessment: Designing assessments to inform and improve student performance*, Jossey-Bass, 1998.
22. Bearman, M., Tai, J., Dawson, P., Boud, D. and Ajjawi, R., Developing evaluative judgement for a time of generative artificial intelligence. *Assess. Eval. High. Educ.*, 2024, 49(6): 893–905. <https://doi.org/10.1080/02602938.2024.2335321>
23. Australasian Academic Integrity Network, *Generative artificial intelligence guidelines [PDF]*, 2023. Available from: <https://www.teqsa.gov.au/sites/default/files/2023-04/aain-generative-ai-guidelines.pdf>
24. Corbin, T., Bearman, M., Boud, D. and Dawson, P., The wicked problem of AI and assessment.

-
- Assess. Eval. High. Educ.*, 2026, 51(4): 736–752. <https://doi.org/10.1080/02602938.2025.2553340>
25. Quince, Z., Munn, J. and Greenaway, R., Adapting assessment in the age of generative AI: The AAM-GenAI framework (Practice report). *Southern Cross University Scholarship of Learning and Teaching Paper Series*, 2025, Paper No. 28. SSRN. <https://doi.org/10.2139/ssrn.5371850>
 26. Quince, Z. and Greenaway, R., *GenAI policy evolution at Southern Cross University (Practice report)*, *Southern Cross University Scholarship of Learning and Teaching Paper*, 2025, No. 26, SSRN. <https://doi.org/10.2139/ssrn.5330009>
 27. Qu, Y., Tan, M.X.Y. and Wang, J., Disciplinary differences in undergraduate students' engagement with generative artificial intelligence. *Smart Learn. Environ.*, 2024, 11: 51. <https://doi.org/10.1186/s40561-024-00341-6>
 28. Dai, Y., Why students use or not use generative AI: Student conceptions, concerns, and implications for engineering education. *Digit. Eng.*, 2025, 4: 100019. <https://doi.org/10.1016/j.dte.2024.100019>
 29. Fan, L., Deng, K. and Liu, F., Educational impacts of generative artificial intelligence on learning and performance of engineering students in China. *Sci. Rep.*, 2025, 15: 26521. <https://doi.org/10.1038/s41598-025-06930-w>
 30. Hughes, L., Malik, T., Dettmer, S., Al-Busaidi, A.S. and Dwivedi, Y.K., Reimagining higher education: Navigating the challenges of generative AI adoption. *Inf. Syst. Front.*, 2025. <https://doi.org/10.1007/s10796-025-10582-6>
 31. Qadeer, A., The mediating impact of student engagement on the association between generative AI-based feedback and academic performance in higher education. *J. Res. Innov. Strateg. Educ. (RISE)*, 2025, 2(1): 29–44. <https://doi.org/10.70148/rise.18>
 32. Weeks, J.O., Voshaar, J., Plate, B.J. and Zimmermann, J., Generative AI usage and exam performance. In *Proceedings of the European Conference on Information Systems (ECIS 2025)*, 2025, Paper 8. <https://aisel.aisnet.org/ecis2025/education/education/8>
 33. Quince, Z. and Faulconer, E., Adapting Assessment in the GenAI Era: AN Undergraduate Physics Case Study. In *Proceedings of The Australian Conference on Science and Mathematics Education*, 2025: 87–92.
 34. Staddon, R.V., Bringing technology to the mature classroom: Age differences in use and attitudes. *Int. J. Educ. Technol. High. Educ.*, 2020, 17: 11. <https://doi.org/10.1186/s41239-020-00184-4>
 35. Bellare, Y., Smith, A., Cochran, K. and Lopez, S., Motivations and barriers for adult learner achievement: Recommendations for institutions of higher education. *Adult Learn.*, 2023, 34(2): 30–39. <https://doi.org/10.1177/10451595211059574>
 36. Zhang, M., Older people's attitudes towards emerging technologies: A systematic literature review. *Public Underst. Sci.*, 2023, 32(8): 948–968. <https://doi.org/10.1177/09636625231171677>
 37. Luo, Y., Chen, E., Liu, H., Riener, K. and Yang, S.-H., Generative AI in engineering education: A survey of student and instructor usage and attitudes. In *Proc. Hum. Factors Ergon. Soc. Annu. Meet.*, 2025, 69(1): 272–277. <https://doi.org/10.1177/10711813251358792>
 38. Mirriahi, N., Marrone, R., Barthakur, A., Gabriel, F., Colton, J., Yeung, T.N., et al., The relationship between students' self-regulated learning skills and technology acceptance of GenAI. *Australas. J. Educ. Technol.*, 2025, 41(2): 16–33. <https://doi.org/10.14742/ajet.10006>
 39. Quince, Z., Nikolic, S. and Goh, S., Student perceptions of GenAI integration into engineering practice: How students interpret liability, safety, professional conduct and ethics across disciplines.
-

- Int. J. Mech. Eng. Educ.*, 2025, 1–22. <https://doi.org/10.1177/03064190251407621>
40. Walton, J., Bearman, M., Crawford, N., Tai, J.H.-M. and Boud, D., How university students work on assessment tasks with generative artificial intelligence: Matters of judgement. *Assess. Eval. High. Educ.*, 2026, 51(6): 1066–1082. <https://doi.org/10.1080/02602938.2025.2570328>
41. Gonsalves, C., Addressing student non-compliance in AI use declarations: Implications for academic integrity and assessment in higher education. *Assess. Eval. High. Educ.*, 2025, 50(6): 1066–1082. <https://doi.org/10.1080/02602938.2024.2415654>
42. Getenet, S., Cantle, R., Redmond, P. and Albion, P., Students' digital technology attitude, literacy and self-efficacy and their effect on online learning engagement. *Int. J. Educ. Technol. High. Educ.*, 2024, 50(4): 592-606. <https://doi.org/10.1186/s41239-023-00437-y>
43. Quince, Z., Chen, P. and Lidfors Lindqvist, A., Engineering students' perspectives on how generative AI is reshaping engineering skills and education: A multi-institution qualitative study. *Eur. J. Eng. Educ.*, 2026. <https://doi.org/10.1080/03043797.2026.2705883>

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