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Academic Integrity in the Age of Generative AI: Perceptions, Practices and Policy Awareness among Pakistani EFL University Students

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ABSTRACT

Students who write in English as a foreign language (EFL) use generative AI (GenAI) heavily, often where institutional guidance is limited. We know little about how they decide what is acceptable help and what is misconduct. This convergent mixed-methods study asked Pakistani EFL university students about academic integrity, their AI-assisted writing practices, their awareness of guidance, and the benefits and concerns they see. Sixty-seven students (48 female; 64.2% MPhil) were recruited by convenience sampling and completed an online questionnaire between May and September 2026. Likert responses were analyzed (N = 67) with descriptive statistics, Wilson confidence intervals, paired Wilcoxon tests and Spearman correlations (Holm-adjusted). Open-ended responses analyzed (n = 54 analyzed) thematically. Most respondents accepted GenAI for grammar correction (85.1%) and brainstorming (73.1%), and most rejected submitting AI-generated content without revision (68.7% disagreed). However, 85.1% said they always revise AI output, but only 41.8% said they clearly mention using it. At the same time, 70.1% saw unacknowledged use as similar to plagiarism (paired difference $p < .001$). Just over half (52.2%) agreed that their university gives clear guidelines. In contrast, 71.6% said they understand ethical use and 68.7% wanted regulation. Concern about incorrect information (79.1%) and harm to learning (76.1%) was common, but few admitted dependence (29.9%). Seven themes described supportive but limited use, gains in efficiency and understanding, heavier delegation by a minority, the burden of checking output, fear of losing skills, practical barriers, and calls for rules and AI-literacy teaching. Five of 53 respondents wanted restriction. The results suggest a gap in disclosure and guidance more than a problem of compliance. The sample was self-selected and the data are self-reported, so the findings are exploratory.

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1. Introduction

ChatGPT was released to the public in late 2022, and it quickly changed every day academic work. Students now use GenAI to find ideas, improve language and summarize sources. They also worry about accuracy, dependence and integrity (Chan & Hu, 2023; Kim et al., 2025). Systematic reviews show the same two sides. GenAI can support engagement and learning, but it also challenges assumptions about authorship, assessment and misconduct (Bittle & El-Gayar, 2025; Memarian & Doleck, 2026).

Part of the problem is conceptual. Plagiarism, cheating and collusion do not fit easily with text that has no identifiable human author and is not copied from another source (Perkins, 2023; Sullivan et al., 2023). Attribution and disclosure are still unsettled, and detection software is not an easy solution. Cotton et al. (2024) argued that institutions should rethink assessment and policy and should not depend only on policing. Liang et al. (2023) found that widely used GPT detectors labelled the writing of non-native English speakers as AI-generated. This finding is very important for EFL students.

EFL learners feel these problems more strongly. Academic English needs vocabulary, grammatical control and discourse knowledge that many learners are still developing. This makes the immediate language support of GenAI very attractive (Hossain et al., 2025). Studies of EFL students in Turkey, Saudi Arabia, Indonesia and Ecuador report positive views of AI-assisted writing. The same studies report moderate ethical awareness, uncertainty about what is acceptable, and worry about plagiarism and skill development (Almusharraf et al., 2025; Çiftci, 2025; Hossain et al., 2025; Nelson et al., 2025; Sipayung et al., 2025).

Pakistan is a useful setting that has received little study. Pakistani students already use ChatGPT widely, and they report benefits as well as concerns about accuracy, integrity and dependence (Alghazo et al., 2025). ChatGPT use has also been linked to perceived gains in academic performance (Ashraf et al., 2025). Rafiq-uz-Zaman (2025) argues that regulation has not kept pace with adoption, and that the Higher Education Commission and major universities still use plagiarism policies from before AI. English is the language of instruction in postgraduate study, so questions of integrity cannot be separated from questions of language support. To the best of our knowledge, no published study has examined perceptions, self-reported practices, policy awareness, and perceived benefits and concerns together among Pakistani EFL students using mixed methods.

We address this gap with an exploratory convergent mixed-methods study. It has four research questions:

- **RQ1.** How do Pakistani EFL students perceive academic integrity in relation to GenAI-assisted writing?
- **RQ2.** What AI-related writing practices do they report, including revision and disclosure?
- **RQ3.** How aware are they of institutional guidance on GenAI use, and how do they view regulation?
- **RQ4.** What benefits and concerns do they identify?

This paper gives descriptive evidence from a setting where guidance is limited. It tests whether students' stated integrity beliefs match what they say they do. It links the numbers to students' own reasoning in a joint display. It also reads the results through the six values of the International Center for Academic Integrity (ICAI, 2021) in order to suggest educational and policy options.

2. Literature review and conceptual framework

2.1. Academic integrity values and generative AI

ICAI (2021) describes academic integrity as a commitment to six values: honesty, trust, fairness, respect, responsibility and courage. GenAI puts pressure on each value. Honesty is tested when the AI contribution is not acknowledged. Trust and fairness are tested when students differ in their access to AI and their skill with it. Responsibility is tested when users do not check what the tool produces. Evidence on what shapes conduct is useful here. In a survey of 401 U.S. students, Lund et al. (2025) found that personal ethical beliefs, and not awareness of institutional policy, were the strongest predictors of perceived misconduct and of actual AI use. Policy awareness had no significant effect on ethical judgment. Gonsalves (2025) found that unclear guidance and perceived risk reduced compliance with required AI-use declarations in a business school. Both studies suggest that publishing a rule is not the same as creating understanding.

2.2. Students' perceptions and practices

In many contexts, students accept AI for supportive, lower-order tasks such as brainstorming and language correction. They are more divided about generating drafts or whole assignments (Chan & Hu, 2023; Kim et al., 2025). Views also differ within groups. Lo and Chan (2025) found that Hong Kong students were divided by grade-point average, and that higher-GPA students were more worried about dependency, plagiarism and critical thinking. Maxwell et al. (2025) reported demographic differences

in readiness, perceived benefits and challenges among U.S. students. Almost all of this evidence is self-reported. Alsadoon (2026) is a rare exception. That study observed EFL students using ChatGPT in real time while writing, compared drafts with final essays, and combined these data with surveys, teacher ratings and short interviews. It shows the value of going beyond self-report, and also its cost.

2.2.1. EFL learners

EFL writers have different gains and risks. Hossain et al. (2025) surveyed 427 Turkish EFL students. They found limited technical understanding of AI in spite of concern about plagiarism and integrity. Çiftci (2025) studied 162 Turkish EFL learners and reported moderate ethical awareness, more non-disclosure and over-reliance among frequent users, uncertainty about acceptable use, and feelings of guilt. Almusharraf et al. (2025) found high satisfaction and self-efficacy but only moderate use of AI writing strategies among 399 Saudi EFL students. Nelson et al. (2025) reported that Ecuadorian EFL students were more worried about harming their own writing development than about being caught. Neff et al. (2024) compared EFL students' and teachers' views on the ethical use of AI tools. Yeo (2023) discussed how revision tools and content-generating tools raise different questions of authorship in TESOL. In Indonesia, Sipayung et al. (2025) used open-ended questionnaires. They found that students valued AI but worried about plagiarism and over-reliance, and that they asked for institutional guidelines.

2.3. Institutional responses and the Pakistani context

Institutional responses range from prohibition to guided integration. Azevedo et al. (2025) describe the tension between innovation, integrity and fair access, and they propose faculty-focused policies that encourage transparency. Kangwa et al. (2025) reviewed studies from 2021 to 2024 and concluded that academic support, self-regulation and institutional guidelines work together. Temper et al. (2025) propose a risk-based framework adapted from the EU AI Act, and Francis et al. (2025) ask for ethical frameworks, GenAI literacy and revised assessment. Wu and Carroll (2026) followed one university for two years. Students reported continuing concerns about integrity and ethical AI use. In the second year, they said that instructors' policies were clear, but they still wanted clearer university-level policy. Evidence from Pakistan is limited. Alghazo et al. (2025) surveyed 400 students across Pakistani universities, and Ashraf et al. (2025) modelled ChatGPT use and performance. Neither study examined integrity perceptions, practices and policy awareness together. Rafiq-uz-Zaman (2025) offers a critical analysis centered on one university. It argues that policy has not kept pace with adoption and proposes national guidance, university AI-policy units, faculty training and compulsory disclosure. This is an argument and not an empirical finding, so it supports our question but does not answer it.

2.4. Conceptual framework

The ICAI values provide the normative lens. For analysis, we separate three dimensions that earlier studies often examined separately. These are what students believe is acceptable (perceptions), what they do (practices), and what they know about institutional rules (policy awareness). Related studies have used the Theory of Planned Behaviour for similar questions (Gonsalves, 2025; Sipayung et al., 2025), but we do not fit a causal model. This study describes each dimension, test a few paired contrasts and associations that match the research questions, adjust for multiple testing, and use the qualitative strand to explain where the dimensions differ. Perceived benefits and concerns (RQ4) cut across all three dimensions.

3. Methodology

3.1. Research design

We used a convergent mixed-methods design (Creswell & Plano Clark, 2018). The Likert items and the open-ended questions were collected together in one online questionnaire. They were analyzed separately and then brought together at interpretation through a joint display (Table 6; Figure 1). This design suits the questions. RQ1–RQ3 need a descriptive account of how common particular views and practices are, and all four questions invite students' own reasoning. The qualitative strand consists of short written answers and not interviews, which limits depth (Section 6).

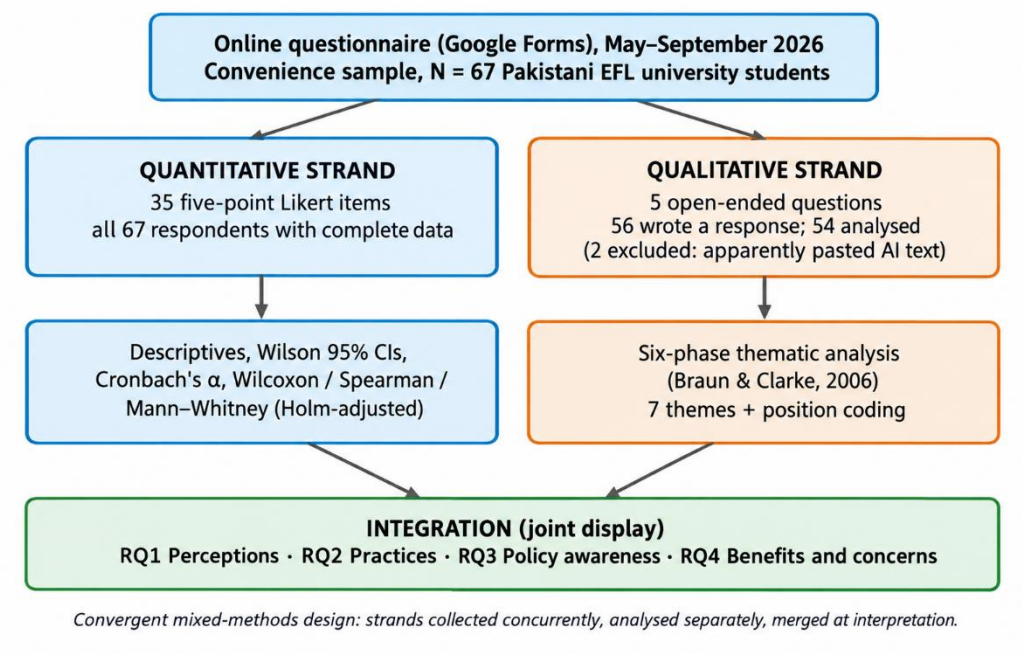


Figure 1. Convergent mixed-methods design and participant flow. N = 67 respondents; all provided complete Likert data; 56 wrote at least one open-ended response, of which 54 were analyzed.

3.2. Participants and sampling

Sixty-seven Pakistani EFL university students completed the questionnaire, recruited by convenience sampling and responding online between 31 May and 6 September 2026 (46 responses in May–June, 21 in September). The sample comprised 48 female students (71.6%) and 19 male students (28.4%). Forty-three participants (64.2%) were MPhil students, 12 (17.9%) BS students, five (7.5%) MA/MSc students and seven (10.4%) in other programmes. Nearly half (47.8%) were aged 27 or above. Thirty (44.8%) had graduated, and 37 (55.2%) were between the first and eighth semester. Thirty-seven participants (55.2%) reported using GenAI daily and 11 (16.4%) weekly (Table 1).

Table 1. Participant characteristics (N = 67)

Characteristic	n	%
Gender: female	48	71.6
Gender: male	19	28.4
Age: 18–20	6	9.0
Age: 21–23	11	16.4
Age: 24–26	18	26.9
Age: 27 and above	32	47.8
Programme: MPhil	43	64.2
Programme: BS	12	17.9
Programme: MA/MSc	5	7.5
Programme: other	7	10.4
Stage: graduated	30	44.8
Stage: semesters 1–2	21	31.3
Stage: semesters 3–4	8	11.9
Stage: semesters 5–6	6	9.0
Stage: semesters 7–8	2	3.0

Characteristic	n	%
GenAI use: daily	37	55.2
GenAI use: weekly	11	16.4
GenAI use: occasionally	15	22.4
GenAI use: rarely	3	4.5
GenAI use: never	1	1.5

Note. Percentages may not sum to 100 because of rounding.

3.3. Instrument

The questionnaire (Appendix A) comprised demographic questions, a question on frequency of GenAI use, 35 five-point Likert items (strongly disagree to strongly agree), and five open-ended questions. The Likert items covered AI-assisted writing practices (items 1–8), perceived benefits (9–15), perceived concerns (16–22), integrity perceptions and ethical practice (23–28), and policy awareness and attitudes (29–35). The open-ended questions asked how students use GenAI, what benefits and what challenges they had experienced, what they think about GenAI in assignments and exams, and whether universities should allow or restrict it and why. Items were developed from the integrity literature (ICAI, 2021; Lund et al., 2025; Perkins, 2023) and reviewed for content validity by experts in applied linguistics and educational technology.

Internal consistency was good for the practices scale (α = .87, eight items) and the benefits scale (α = .85, seven items), acceptable for the policy and attitudes items (α = .70, seven items), and weak for the concerns items (α = .56, seven items) and the ethical-practice items (α = .62, five items; the reverse-keyed item on submitting AI content without revision was excluded) (Table 2). Because the last three groups mix distinct constructs, we analyze them at item level and use composite scores only for practices and benefits.

Table 2. Reliability and descriptive statistics for Likert item groups (N = 67)

Item group	Items	Cronbach's α	M	SD	Use in analysis
AI-assisted writing practices	8	.87	3.37	0.79	Composite
Perceived benefits	7	.85	3.77	0.63	Composite
Policy awareness and attitudes	7	.70	3.75	0.56	Item level
Ethical practice and integrity perceptions	5	.62	3.77	0.58	Item level
Perceived concerns	7	.56	3.46	0.55	Item level

Note. Scale scores are means of item ratings (1 = strongly disagree, 5 = strongly agree).

3.4. Procedure and ethics

The questionnaire was administered online using Google Forms in English. Participation was voluntary. Informed consent was obtained from all respondents before they completed the questionnaire, and participants were informed of the study's purpose, their right to withdraw, and the anonymity of their responses.

3.5. Data screening

There were no missing Likert responses and no duplicate submissions. Four respondents gave the same rating to all 35 items which were retained and checked sensitivity by excluding them (Section 4.7). Two open-ended responses (P10 and P35; respondents are identified by their row number in the export, P1–P67) were excluded from the qualitative analysis as their content indicated pasted AI output: one opened by stating that it had no personal opinions, and the other was a bulleted, second-person list in the style of a chatbot answer. The decision rested on content and not on detector scores, which are unreliable for non-native writers (Liang et al., 2023). Fifty-six respondents wrote at least one open-ended response, and 54 were analyzed.

3.6. Data analysis

Quantitative. Responses were summarized as frequencies, percentages (agree/strongly agree, neutral, disagree/strongly disagree), means and standard deviations, with Wilson 95% confidence intervals for the proportion agreeing. Paired contrasts between conceptually linked items were tested with Wilcoxon signed-rank tests, with discordant pairs reported from the dichotomized items. Associations were examined with Spearman's rank correlations. Exploratory group comparisons (gender;

undergraduate versus postgraduate or other) used Mann–Whitney tests with rank-biserial effect sizes. Because several tests were run, we report Holm-adjusted p values within each family (six paired contrasts, eight correlations, ten group comparisons). We also compared the two collection waves and repeated key estimates without the four straight-lining respondents. All tests are exploratory.

Qualitative. Responses (n = 54) were analyzed inductively using Braun and Clarke's (2006) six phases: familiarization, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. Each respondent was coded to every theme expressed anywhere in their answers, so theme counts overlap. Responses to the allow-or-restrict question were also classified by position (allow without stated conditions, allow with conditions, restrict, unclear). Coding was carried out by a single coder, and the respondent-level coding matrix is provided as supplementary material so that assignments can be checked. Integration. Findings were merged by comparing patterns for each research question in a joint display (Table 6).

4. Results

4.1. Integrity perceptions (RQ1)

Respondents were most accepting of supportive uses (Figure 2). Fifty-seven (85.1%) agreed that GenAI is acceptable for grammar correction and 49 (73.1%) for brainstorming. Submitting AI-generated content without revision was widely rejected: 46 (68.7%) disagreed and 14 (20.9%) agreed that it is acceptable. Forty-seven respondents (70.1%) agreed that using GenAI without acknowledgement is similar to plagiarism, while 13 (19.4%) were neutral and seven (10.4%) disagreed. Item-level frequencies, means and confidence intervals are in the Supplementary Materials (Table S1).

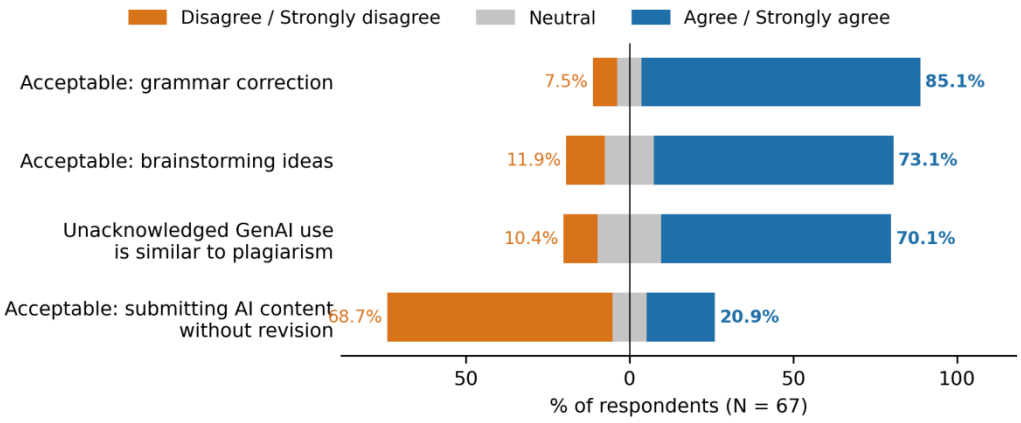


Figure 2. Perceptions of acceptable AI use and of unacknowledged use (N = 67).

Theme 1: Support, not substitution (39 of 54 respondents, 72.2%). Open-ended responses mirrored the Likert pattern. Students described GenAI as a helper for ideas, outlines, language and understanding, and drew the line at replacing their own work: "I use it for refining my work, not for creating it" (P15); "I mostly use it as an assistant rather than someone who does the entire work for me" (P59); "It should be used responsibly as a helper, not a replacement" (P17). Several described retaining authorship through their own wording: "By only getting the idea and points of the relevant topic and then writing in your own words" (P47). This is in line with EFL studies that report favorable views of supportive AI use alongside integrity concerns (Almusharraf et al., 2025; Sipayung et al., 2025).

4.2. Self-reported practices (RQ2)

Reported use was widespread and mostly supportive (Figure 3). Fifty respondents (74.6%) used GenAI to summarize readings, 46 (68.7%) to generate ideas and to enhance vocabulary, 43 (64.2%) to improve grammar and 41 (61.2%) to paraphrase. Delegated writing was less common but not rare: 33 (49.3%) said they use GenAI mainly during drafting, 27 (40.3%) to write full paragraphs, and 19 (28.4%) said they rely on it throughout the writing process, while 37 (55.2%) disagreed with the last statement. Revision was widely claimed (57, 85.1%, always revise AI-generated content), whereas disclosure was not: 28 respondents (41.8%) agreed that they clearly mention their GenAI use, 23 (34.3%) were neutral and 16 (23.9%) disagreed.

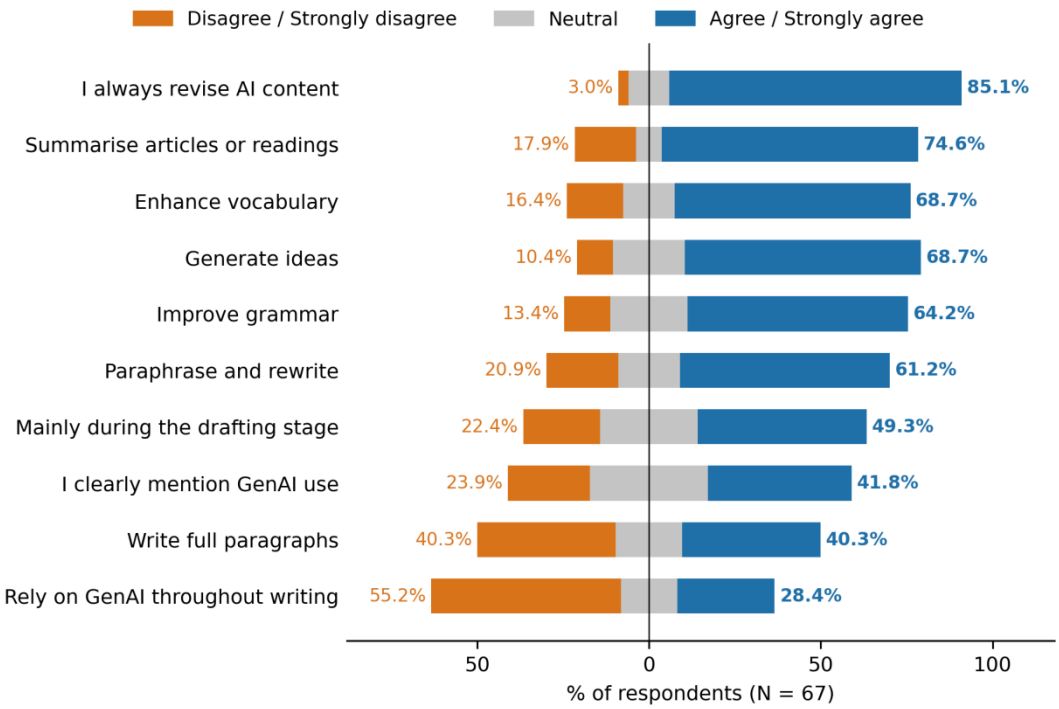


Figure 3. Self-reported AI-assisted writing practices, revision and disclosure (N = 67), ordered by agreement.

Theme 3: Heavier delegation among a minority (7 respondents, 13.0%). A few described using GenAI to produce text and did not mention revising it: “Copy and re write as per required” (P1), “i use generative AI tools for drafting my answers and assignments” (P64), and “From brain storming, to drafting and all the way to writing” (P65). These accounts were brief and did not discuss disclosure, which matches the Likert result that about four in ten respondents write full paragraphs with GenAI.

4.3. Do stated beliefs match reported practice? Paired contrasts

Four of five paired contrasts showed a significant difference after Holm adjustment (Table 3; Figure 4). The clearest was between belief and disclosure. Seventy per cent regarded unacknowledged use as similar to plagiarism, but only 41.8% said they mention their use ($W = 88$, adjusted $p < .001$, $r = .46$); 20 respondents held the belief without reporting disclosure, and only one did the reverse. Belief and disclosure were nevertheless positively related ($\rho = .54$, adjusted $p < .001$; Table 4), so the gap is one of degree and not of direction. Respondents also saw more risk in general than in themselves: 76.1% agreed that overuse may harm learning, but 29.9% agreed that they themselves become dependent (adjusted $p < .001$, $r = .56$). Acceptance of grammar correction (85.1%) exceeded reported grammar use (64.2%; adjusted $p = .019$, $r = .32$), whereas acceptance of brainstorming (73.1%) and its reported use (68.7%) did not differ (adjusted $p = .70$).

Table 3. Paired contrasts between linked items (N = 67)

Contrast (first vs second item)	% agree first	% agree second	Discordant (first only / second only)	W	Holm p	r
Unacknowledged use is plagiarism vs I clearly mention my GenAI use	70.1	41.8	20 / 1	88	< .001	.46
Overuse may harm learning vs I become dependent	76.1	29.9	37 / 6	213	< .001	.56
Grammar correction acceptable vs I use GenAI for grammar	85.1	64.2	15 / 1	56	.019	.32
University guidelines are clear vs I understand ethical use	52.2	71.6	5 / 18	52	< .001	.45
Brainstorming acceptable vs I use GenAI for ideas	73.1	68.7	8 / 5	229	.70	.05

Note. Wilcoxon signed-rank tests on five-point ratings; discordant pairs counted from agree versus not agree. Holm adjustment across six paired contrasts (the sixth, acceptance of unrevised submission versus always revising, is oppositely keyed and omitted here; adjusted p < .001). r = Z/√N, with Z obtained from the p value.

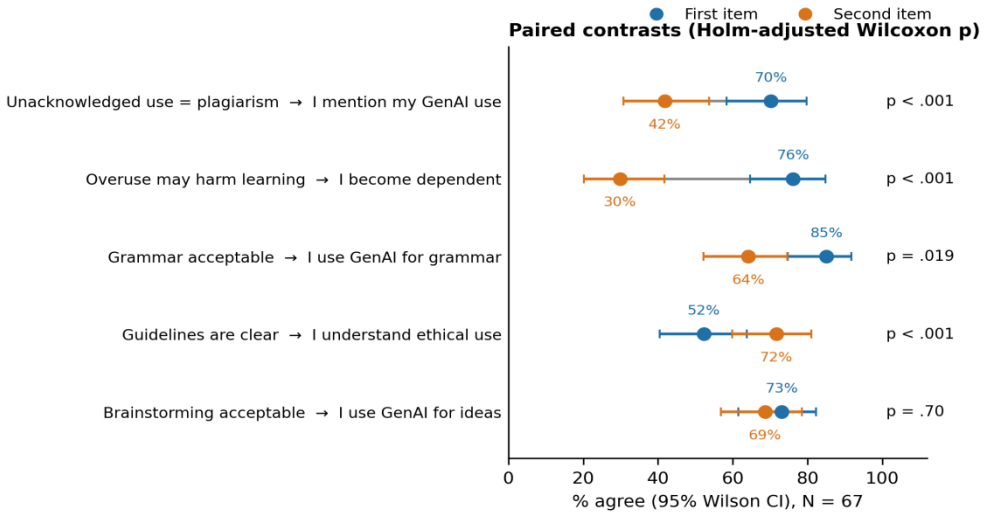


Figure 4. Paired contrasts between linked items, with 95% Wilson confidence intervals (N = 67). Adjusted p values are from Wilcoxon signed-rank tests.

Theme 2: Efficiency, comprehension and confidence (27 respondents, 50.0%). Qualitative accounts of benefits explain why use is so common. Students wrote of time saved ("It saves time and speeds up the writing process", P17), of understanding difficult material, and of confidence: "i am not anxious about spellings or grammar. I feel confident" (P65). For one student the main benefit was multilingual: GenAI "generate[s] the definitions in my native language Baloch, and Urdu which is the biggest benefit" (P15). Such accounts may help explain why concern about learning is not accompanied by high reported dependence.

4.4. Policy awareness and regulation (RQ3)

Perceived clarity of guidance was the weakest policy indicator (Figure 5). Thirty-five respondents (52.2%) agreed that their university provides clear guidelines on AI use, 19 (28.4%) were neutral and 13 (19.4%) disagreed. By contrast, 48 (71.6%) agreed that they understand what constitutes ethical GenAI use, a significant difference, with understanding exceeding perceived clarity (adjusted p < .001, r = .45; Table 3). Almost seven in ten (68.7%) agreed that universities should regulate GenAI use in assignments, while 55 (82.1%) saw GenAI as a useful learning tool, 49 (73.1%) supported integrating it into university learning, and 53 (79.1%) agreed that traditional writing skills remain important.

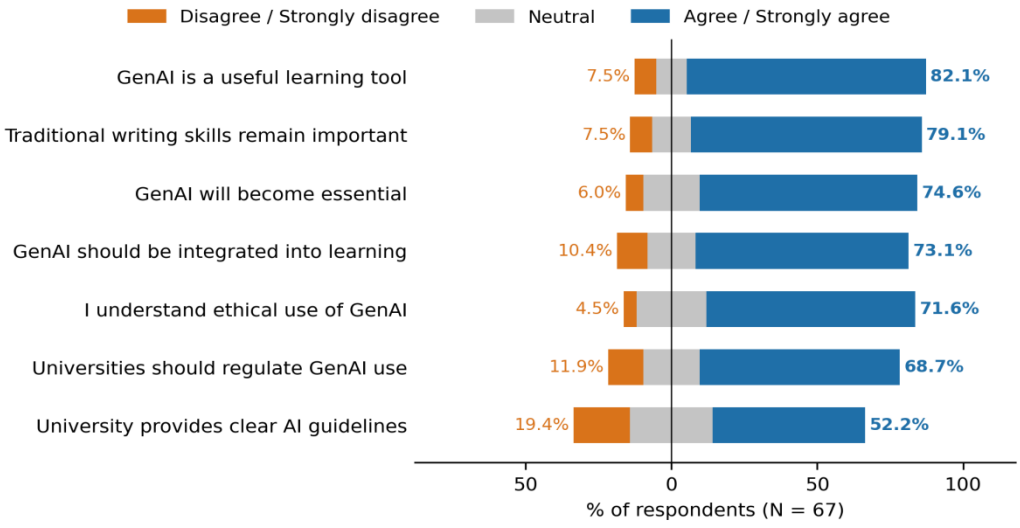


Figure 5. Policy awareness and attitudes towards GenAI in academic writing (N = 67).

Awareness was linked to transparency (Table 4). Perceived guideline clarity (ρ = .33, adjusted p = .034) and understanding of ethical use (ρ = .42, adjusted p = .002) were each positively associated with clearly mentioning GenAI use. Understanding of ethical use and always revising were also positively associated (ρ = .29), but the association did not survive adjustment (adjusted p = .077). Frequency of use was unrelated to disclosure (ρ = −.02), to reported dependence (ρ = .16) and to perceived concerns (ρ = −.15); its association with perceived benefits (ρ = .25) was not significant after adjustment (adjusted p = .18).

Table 4. Spearman correlations between selected items (N = 67)

Association	ρ	p	Holm p
Unacknowledged use is plagiarism × I clearly mention GenAI use	.54	< .001	< .001
I understand ethical use × I clearly mention GenAI use	.42	< .001	.002
University guidelines are clear × I clearly mention GenAI use	.33	.006	.034
I understand ethical use × I always revise AI content	.29	.015	.077
Frequency of use × perceived benefits	.25	.046	.18
Frequency of use × I become dependent	.16	.18	.55
Frequency of use × perceived concerns	−.15	.22	.55
Frequency of use × I clearly mention GenAI use	−.02	.86	.86

Note. Holm adjustment across eight correlations. Frequency of use coded 1 (never) to 5 (daily). Perceived benefits is the mean of seven benefit items; perceived concerns is the mean of seven concern items (α = .56).

Theme 7: Conditional permission and demand for rules, teaching and AI literacy (30 respondents, 55.6%). Of the 53 respondents who answered the allow-or-restrict question, 29 (54.7%) favoured allowing GenAI with conditions, 13 (24.5%) favoured allowing it without stating conditions, five (9.4%) favoured restriction, and six (11.3%) gave unclear or off-topic answers. Conditions took the form of rules, limits, ethics and teaching: “there should be a policy around, the instructor can ask to submit plagiarism report” (P65); “there should be some trsinning program in uni how to use it” (P39); “universities need to explain those boundaries properly because many students are still confused about what counts as acceptable AI use” (P59). Seven respondents separated assignments, where GenAI was acceptable, from exams, where it was not (for example P17: “using it in exams can be unfair and dishonest”). Some pointed to a lack of guidance: “the teachers not guid us properly” (P31). Others asked for acknowledgement without shame: “it must be allowed but with acknowledgement and credit, without being ashamed” (P15). The minority favouring restriction cited creativity and critical thinking: “Universities must not allow the use of GPT” (P20).

4.5. Benefits and concerns (RQ4)

Perceived benefits were broad (Figure 6a). Fifty-eight respondents (86.6%) agreed that GenAI helps them understand complex topics, 55 (82.1%) that it helps develop ideas, 52 (77.6%) that it helps them write faster, 51 (76.1%) that it improves the quality of their writing, and 50 (74.6%) that it improves grammar accuracy. About two-thirds said it increases their confidence in English (65.7%) and reduces writing anxiety (67.2%). Concerns were also common (Figure 6b): 53 (79.1%) agreed that GenAI sometimes provides incorrect information, 51 (76.1%) that overuse may harm learning, 46 (68.7%) that they feel less creative, and 40 (59.7%) that it reduces their critical thinking. Nearly half (47.8%) were unsure about the accuracy of AI output, and 29 (43.3%) found it difficult to decide when not to use GenAI; only 29.9% said they become dependent. The concerns items had low internal consistency (α = .56), so they are interpreted separately.

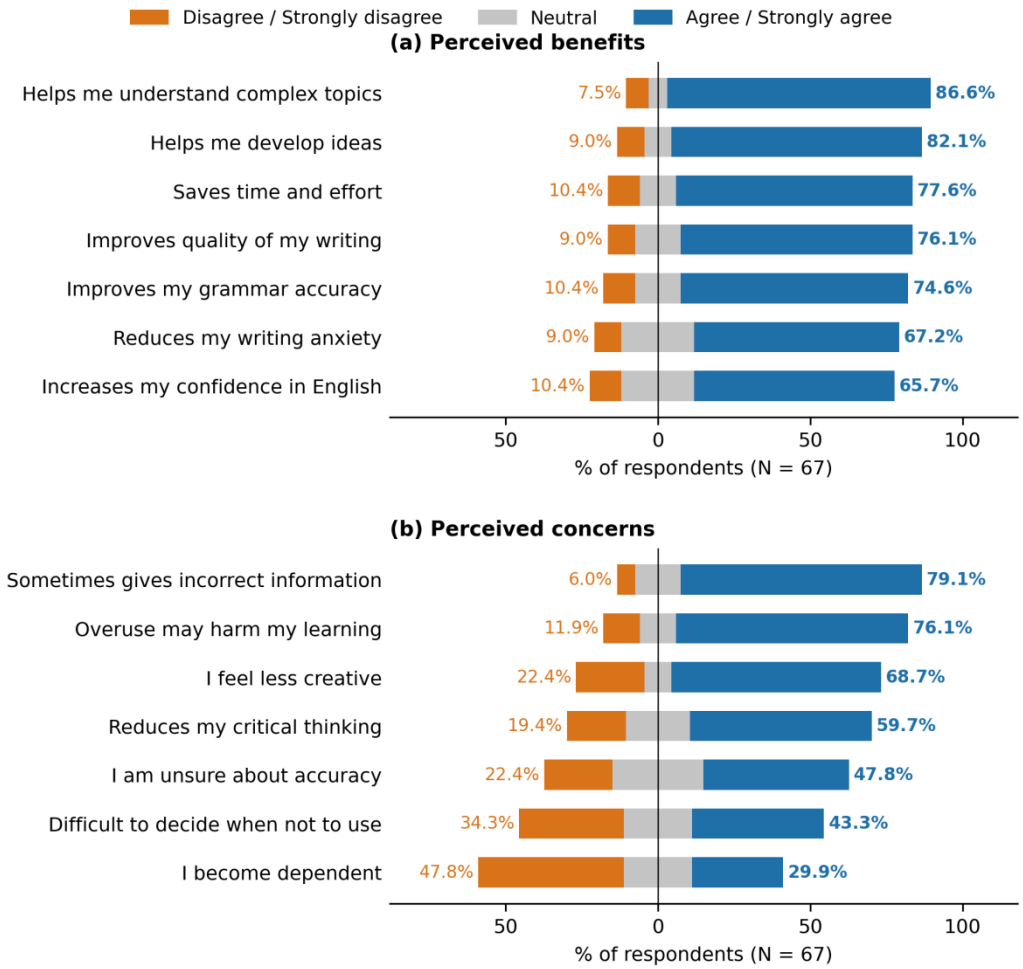


Figure 6. (a) Perceived benefits and (b) perceived concerns about GenAI in academic writing (N = 67).

Theme 4: Reliability and verification burden (31 respondents, 57.4%). Inaccuracy was the most frequently described challenge, and some students had developed verification habits: "AI can sometimes give completely wrong information but present it with so much confidence that, if you don't already know the topic, you might actually believe it" (P59). Two respondents mentioned fabricated citations ("using/making up wrong quotes and citations", P54; P59: "So now I never blindly trust references generated by AI").

Theme 5: Dependence and loss of skills, creativity and confidence (11 respondents, 20.4%). A smaller group worried about their own capacities: "I become dependent upon using genAI so my own creativity gets hindered" (P16); "I often go for perfection that AI provides in my normal writing, which makes me lose my confidence" (P48). One restrictive respondent argued that reliance "strongly hinder[s] a student's ability to use critical thinking skills" (P45).

Theme 6: Practical and access barriers (9 respondents, 16.7%). Some challenges were practical and unevenly distributed: "Internet availability is the major problem sometimes" (P15); limits on the free version ("I could only use it 3 times in a day", P34); difficulty writing prompts ("I always face problem in giving prompt", P63); and loss of control over one's text ("my work is my work; it is not to be changed even for AI's good causes", P66).

4.6. Thematic summary and integration

Table 5 lists the seven themes with the number of respondents contributing to each, and Table 6 sets them beside the quantitative findings.

Table 5. Themes generated from open-ended responses (n = 54 analysed)

Theme	Description	n (%)	RQ
1. Support, not substitution	GenAI as helper for ideas, language and understanding; own words and revision retained	39 (72.2)	1, 2
2. Efficiency, comprehension and confidence	Time saved, easier understanding, less anxiety, multilingual explanation	27 (50.0)	2, 4
3. Heavier delegation among a minority	Drafting or full-process use, rarely with revision or disclosure	7 (13.0)	2
4. Reliability and verification burden	Incorrect, outdated, irrelevant or fabricated output; need to check	31 (57.4)	4
5. Dependence and loss of skills, creativity and confidence	Worry about reliance, critical thinking, creativity and writing confidence	11 (20.4)	4
6. Practical and access barriers	Internet, paid versions, prompting difficulty, loss of control over text	9 (16.7)	4
7. Conditional permission and demand for rules, teaching and AI literacy	Allow with limits, ethics, acknowledgement, training; assignments versus exams	30 (55.6)	3

Note. Respondents could contribute to more than one theme, so counts overlap. Percentages are of 54 respondents. Respondent-level coding is provided in the supplementary coding matrix.

Table 6. Joint display: integration of quantitative and qualitative findings

RQ	Quantitative strand (N = 67)	Qualitative strand (n = 54)	Integration
1	Grammar 85.1% and brainstorming 73.1% acceptable; unrevised submission rejected (68.7% disagree); unacknowledged use akin to plagiarism 70.1%	T1: help, not replacement; own words	Convergence: clear support-versus-substitution norm; students largely share the integrity values that policies assume
2	Revision 85.1% vs mention 41.8%; full paragraphs 40.3%; throughout 28.4%	T3: minority delegates; T1: revision; disclosure rarely discussed	Expansion: revision is claimed far more than disclosure; delegation is a minority practice
3	Clear guidelines 52.2% vs understand ethics 71.6%; regulate 68.7%; both associated with disclosure	T7: 54.7% conditional, 9.4% restrict; calls for rules and training; “teachers not guid us”	Convergence: students want structure, not prohibition. Expansion: they feel more capable than guided
4	Benefits 65.7–86.6%; incorrect information 79.1%; harm to learning 76.1%; personal dependence 29.9%	T2 benefits; T4 verification; T5 dependence; T6 access barriers	Convergence on benefit and accuracy concern; expansion: access barriers raise fairness questions

4.7. Robustness checks and exploratory comparisons

Excluding the four straight-lining respondents (n = 63) changed key proportions by no more than 3.5 percentage points (for example, disclosure 41.8% to 39.7%; clear guidelines 52.2% to 50.8%). The two collection waves (46 respondents in May–June, 21 in September) did not differ significantly on the five scale scores (all $p > .10$) or on six key items on unrevised submission, revision, disclosure, plagiarism, guideline clarity and ethical understanding (all $p \geq .064$). Gender and level of study (undergraduate versus postgraduate or other) were not related to the practices or benefits scores (all $p > .70$). Across ten exploratory comparisons of the five scale scores by gender and level, none was significant after Holm adjustment (smallest unadjusted $p = .087$, for policy and attitudes by level, with lower scores among undergraduates).

5. Discussion

5.1. Principal findings

Students in this study share a clear norm about supportive use versus substitutive use. They accepted GenAI for grammar and brainstorming, strongly rejected submitting AI output without revision, and most regarded unacknowledged use as similar to plagiarism. This agrees with EFL studies that report favourable views of supportive AI use together with integrity concerns (Almusharraf et al., 2025; Sipayung et al., 2025). It suggests that students' stated values are not the main problem.

Where transparency is concerned, practice is behind belief. Although 85.1% said they revise AI output, only 41.8% said they clearly mention their use. The difference from the belief that unacknowledged use is plagiarism was large and significant. The two were positively associated, so those who held the belief disclosed more, but many who held it did not report disclosing. The open-ended answers suggest a reason. Disclosure was seldom discussed, and one student wanted to use GenAI "without being ashamed" (P15), which suggests a feeling of stigma. This agrees with evidence that unclear guidance and perceived risk reduce compliance with AI declarations (Gonsalves, 2025), and with the observation that transparency is a cornerstone of ethical AI-assisted writing (Cheng et al., 2025). Unlike Çiftci (2025), we found no association between frequency of use and disclosure. Self-report cannot show whether stated revision matches real behaviour. Observational designs such as that of Alsadoon (2026) would be needed.

Students also felt more capable than guided. Only about half agreed that their university provides clear guidelines. In contrast, nearly three-quarters said they understand ethical use, and about seven in ten wanted regulation. This is similar to the combination of clear instructor policy and requests for clearer institutional policy reported by Wu and Carroll (2026). It also agrees with the argument that policy has not kept pace with adoption in Pakistan (Rafiq-uz-Zaman, 2025). It adds to the finding of Lund et al. (2025) that policy awareness did not shape ethical judgment. In our sample, perceived guideline clarity and understanding of ethical use were both positively associated with disclosure. These are cross-sectional associations between self-reports. They do not show that guidance causes transparency, and self-rated understanding may be higher than real understanding.

Finally, concern about GenAI existed together with a low sense of personal risk. Most respondents agreed that overuse harms learning and that GenAI sometimes gives incorrect information, but fewer than one in three said they themselves become dependent. This difference is consistent with an optimism effect, in which risks are judged to apply more to other people. Our data cannot test this explanation, and using GenAI for understanding, confidence and language support may really help students. The qualitative strand adds two points that the Likert items did not capture. The first is access barriers, such as internet, paid versions and skill in writing prompts. The second is multilingual support: one student used GenAI to get definitions in Baloch and Urdu. Both points are important in EFL contexts and for fairness.

5.2. Interpretation through the ICAI values

Honesty is the value most directly affected. The gap between believing that unacknowledged use is plagiarism and saying one mentions it is the clearest integrity signal in this study. Trust depends on shared expectations. With fewer than six in ten students seeing clear guidance, instructors and students may have different views of what is expected. Fairness is raised by the access barriers, because paid versions and reliable internet may favour some students. It is also raised by evidence that detection tools can misjudge non-native writers (Liang et al., 2023). Responsibility appears in the very common claims to revise and in verification habits. However, a low sense of personal dependence does not fit well with the general worry about learning. Respect, for the work of others and for the learning community, appears in the repeated idea that GenAI should be a helper and not a replacement. Courage appears in students' requests for clearer rules and for permission to acknowledge use openly. This suggests that some students would be transparent if the environment allowed it.

5.3. Implications

The findings suggest several practical steps. Students rejected submitting AI output without revision, and most regarded unacknowledged use as similar to plagiarism, but fewer than half said they clearly mention their use. Universities and teachers could therefore make disclosure routine and safe, for example through short, non-punitive declarations with a reflective explanation (Gonsalves, 2025; Cheng et al., 2025; Almusharraf et al., 2025). Only about half of the students saw their university's guidelines as clear, and most wanted regulation. Task-level statements in course outlines, with examples of acceptable and unacceptable use, and institution-level guidance that is updated regularly would meet this need (Azevedo et al., 2025; Kangwa et al., 2025; Temper et al., 2025; Wu & Carroll, 2026).

The qualitative answers point to further steps. Students worried about incorrect information, including invented citations, so verification of AI output and of citations should be taught as part of AI literacy (Francis et al., 2025; Kangwa et al., 2025).

Students saw general risks to learning, but few saw themselves as dependent, so reflective and process-based assessment, such as drafts, learning logs and teacher-led interviews, may help students to notice their own reliance (Francis et al., 2025; Cong-Lem, 2026). Access barriers, such as the limits of free versions and unreliable internet, raise a question of fairness, and institutions could consider providing access and help with writing prompts (Azevedo et al., 2025). Rules can also be stated separately for assignments and exams, and AI-detector scores should not be the only evidence of misconduct, because detectors can mislabel the writing of non-native speakers (Cotton et al., 2024; Liang et al., 2023). These suggestions apply to similar EFL settings in postgraduate programmes and are not national prescriptions.

6. Limitations

Several limits should be stated. The sample (N = 67) is small and non-random, it was collected over three months, and it has more female students (71.6%) and postgraduate students. The findings cannot be generalized to Pakistani EFL students or to other levels, disciplines and institutions, and the confidence intervals are wide. All data are self-reported and may be affected by social desirability and recall bias. Claims to revise AI output may be too high, and students' understanding of ethical use is self-rated and not verified (Alsadoon, 2026). The design is cross-sectional, so the associations cannot show that guidance or understanding causes disclosure. The concern items (α = .56) and ethical-practice items (α = .62) have weak internal consistency and were examined at item level. The wording of the plagiarism and disclosure items is also brief. Many tests were run. We adjusted for multiple testing but treat all inferential results as exploratory. The qualitative strand consists of short written answers, which limits depth and prevents follow-up questions. Coding was done by one coder with no independent check, so no inter-coder agreement statistic is available. Two open-ended responses looked like pasted AI output and were excluded. Other responses may have been written with AI help without our knowledge, and screening by content cannot be fully reliable. Finally, we did not check students' reports of policy against institutional documents, so "clear guidelines" reflects perception and not verified fact.

7. Directions for future research

Probability-based samples from different institutions and disciplines are needed to test whether these patterns hold. This includes the gap between belief and disclosure and the difference between perceived guidance and perceived understanding. Interviews and focus groups would give more depth to the qualitative strand, and independent double coding would make it stronger. Observational and trace-data studies, as in Alsadoon (2026), could test how well reported revision and disclosure match what students really do. Studies of faculty would show how policy is communicated and enforced. Intervention studies could ask whether scenario-based AI-literacy teaching or non-punitive declarations increase disclosure and verification. Comparative studies would help to separate universal integrity problems from local ones.

8. Conclusion

In this convenience sample of Pakistani EFL university students, GenAI was used often and valued for ideas, understanding and language support. Students shared a clear norm against submitting unrevised AI output. The main integrity signal was transparency. Most students saw unacknowledged use as similar to plagiarism, but fewer than half said they clearly mention their own use. Only about half felt that their university gives clear guidance, most wanted regulation and few wanted prohibition. Both understanding and perceived clarity of guidance were associated with more disclosure. As a first and limited contribution, the study suggests that institutions serving similar groups may gain more from making disclosure safe and teachable, and from clarifying rules task by task, than from policing or prohibition. It also identifies questions that further observational studies should test.

References

Alghazo, R., Fatima, G., Malik, M., Abdelhamid, S. E., Jahanzaib, M., Nayab, D. e., & Raza, A. (2025). Exploring ChatGPT's role in higher education: Perspectives from Pakistani university students on academic integrity and ethical challenges. Education Sciences, 15(2), 158. https://doi.org/10.3390/educsci15020158

Almusharraf, A., Bailey, D., Almusharraf, N., & Alotaibi, T. (2025). Students' perceptions of generative AI in EFL writing: Strategies, self-efficacy, satisfaction and behavioural intention. Australasian Journal of Educational Technology, 41(5), 18–36. https://doi.org/10.14742/ajet.10045

Alsadoon, R. (2026). Perceptions vs. practices: Academic integrity and actual ChatGPT use among EFL students. Frontiers in Psychology, 17, Article 1796737. https://doi.org/10.3389/fpsyg.2026.1796737

Ashraf, M. A., Alam, J., & Kalim, U. (2025). Effects of ChatGPT on students' academic performance in Pakistan higher education classrooms. Scientific Reports, 15, Article 16434. https://doi.org/10.1038/s41598-025-92625-1

Azevedo, L., Robles, P., Best, E., & Mallinson, D. J. (2025). Institutional policies on artificial intelligence in higher education: Frameworks and best practices for faculty. New Directions for Adult and Continuing Education, 2025(188), 70–78. https://doi.org/10.1002/ace.70013

Bittle, K., & El-Gayar, O. (2025). Generative AI and academic integrity in higher education: A systematic review and research agenda. Information, 16(4), 296. https://doi.org/10.3390/info16040296

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101. https://doi.org/10.1191/1478088706qp0630a

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. International Journal of Educational Technology in Higher Education, 20, Article 43. https://doi.org/10.1186/s41239-023-00411-8

Cheng, A., Calhoun, A., & Reedy, G. (2025). Artificial intelligence-assisted academic writing: Recommendations for ethical use. Advances in Simulation, 10. https://doi.org/10.1186/s41077-025-00350-6

Çiftci, H. (2025). Navigating ethics: EFL learners' awareness and use of AI tools in writing classes. Focus on ELT Journal, 7(2), 22–45. https://doi.org/10.14744/felt.7.2.2

Cong-Lem, N. (2026). "Is this really your work?": A qualitative study of teacher-led interviews and student accountability in the age of generative AI. Journal of Academic Ethics, 24. https://doi.org/10.1007/s10805-025-09704-1

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, 61(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Creswell, J. W., & Plano Clark, V. L. (2018). Designing and conducting mixed methods research (3rd ed.). SAGE.

Francis, N. J., Jones, S., & Smith, D. P. (2025). Generative AI in higher education: Balancing innovation and integrity. British Journal of Biomedical Science, 81, Article 14048. https://doi.org/10.3389/bjbs.2024.14048

Gonsalves, C. (2025). Addressing student non-compliance in AI use declarations: Implications for academic integrity and assessment in higher education. Assessment & Evaluation in Higher Education, 50(4), 592–606. https://doi.org/10.1080/02602938.2024.2415654

Hossain, Z., Çelik, Ö., & Hınız, G. (2025). Exploring EFL students' AI literacy in academic writing: Insights into familiarity, knowledge and ethical perceptions. Journal of Theoretical Educational Sciences, 18(1), 157–181. https://doi.org/10.30831/akukeg.1538011

International Center for Academic Integrity. (2021). The fundamental values of academic integrity (3rd ed.). https://academicintegrity.org/aws/ICAI/pt/sp/values

Kangwa, D., Msafiri, M. M., & Fute, A. (2025). Balancing innovation and ethics: Promote academic integrity through support and effective use of GenAI tools in higher education. AI and Ethics, 5, 3497–3530. https://doi.org/10.1007/s43681-025-00689-6

Kim, J., Yu, S., Detrick, R., & Li, N. (2025). Exploring students' perspectives on generative AI-assisted academic writing. Education and Information Technologies, 30(1), 1265–1300. https://doi.org/10.1007/s10639-024-12878-7

Liang, W., Yuksekgonul, M., Mao, Y., Wu, E., & Zou, J. (2023). GPT detectors are biased against non-native English writers. Patterns, 4(7), 100779. https://doi.org/10.1016/j.patter.2023.100779

Lo, N., & Chan, S. (2025). From chat to cheat: The disruptive effects of ChatGPT and academic integrity in Hong Kong higher education. SN Computer Science, 6, Article 993. https://doi.org/10.1007/s42979-025-04532-x

Lund, B., Mannuru, N. R., Teel, Z. A., Lee, T. H., Ortega, N. J., Simmons, S., & Ward, E. (2025). Student perceptions of AI-assisted writing and academic integrity: Ethical concerns, academic misconduct, and use of generative AI in higher education. AI in Education, 1(1), 2. https://doi.org/10.3390/aieduc1010002

Maxwell, D. G., Oyarzun, B., Kim, S., & Bong, J. (2025). Generative AI in higher education: Demographic differences in student perceived readiness, benefits, and challenges. TechTrends, 69. https://doi.org/10.1007/s11528-025-01109-6

Memarian, B., & Doleck, T. (2026). A systematic review of academic integrity and misconduct with artificial intelligence in higher education. SN Computer Science, 7, Article 49. https://doi.org/10.1007/s42979-025-04569-y

Neff, J., Arciaga, K., & Burri, M. (2024). EFL students' and teachers' perceptions of the ethical uses of AI tools. Technology in Language Teaching & Learning, 6(3), 1–20. https://doi.org/10.29140/tltl.v6n3.1714

Nelson, A. S., Santamaría, P. V., Javens, J. S., & Ricaurte, M. (2025). Students' perceptions of generative artificial intelligence (GenAI) use in academic writing in English as a foreign language. Education Sciences, 15(5), 611. https://doi.org/10.3390/educsci15050611

Perkins, M. (2023). Academic integrity considerations of AI large language models in the post-pandemic era: ChatGPT and beyond. Journal of University Teaching and Learning Practice, 20(2). https://doi.org/10.53761/1.20.02.07

Rafiq-uz-Zaman, M. (2025). Between adoption and ambiguity: Navigating the AI policy vacuum in Pakistani higher education. Research Journal for Social Affairs, 3(6), 877–885. https://doi.org/10.71317/RJSA.003.06.0523

Sipayung, F. L. M., Luhtfiyyah, R., & Rozak, D. R. (2025). The academic integrity in the use of AI-assisted academic writing: University students' perspectives and practices. JELITA, 6(2), 600–611. https://doi.org/10.56185/jelita.v6i2.1095

Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. Journal of Applied Learning and Teaching, 6(1), 31–40. https://doi.org/10.37074/jalt.2023.6.1.17

Temper, M., Tjoa, S., & David, L. (2025). Higher Education Act for AI (HEAT-AI): A framework to regulate the usage of AI in higher education institutions. Frontiers in Education, 10, Article 1505370. https://doi.org/10.3389/feduc.2025.1505370

Wu, C., & Carroll, J. M. (2026). Evolving perspectives on generative AI in higher education: Insights from two years of university stakeholder analysis. TechTrends, 70(2), 346–363. https://doi.org/10.1007/s11528-025-01150-5

Yeo, M. A. (2023). Academic integrity in the age of artificial intelligence (AI) authoring apps. TESOL Journal, 14, e716. https://doi.org/10.1002/tesj.716

Appendix A. Questionnaire structure

The 35 Likert items are numbered as in the Supplementary Materials (Table S1).

Section	Content	Format
Demographics	Age band, gender, degree programme, semester or year	Closed
GenAI use frequency	Daily, weekly, occasionally, rarely, never	Closed
Practices (items 1–8)	Generate ideas; improve grammar; enhance vocabulary; paraphrase; summarise readings; write full paragraphs; use mainly during drafting; rely throughout the writing process	Five-point Likert
Perceived benefits (items 9–15)	Writing quality; speed and efficiency; grammar accuracy; developing ideas; confidence; reduced anxiety; understanding complex topics	Five-point Likert
Perceived concerns (items 16–22)	Dependence; incorrect information; critical thinking; creativity; unsure about accuracy; learning harm; difficulty deciding when not to use	Five-point Likert
Integrity perceptions and ethical practice (items 23–28)	Acceptability of brainstorming, grammar correction, and submitting AI content without revision; always revising; clearly mentioning use; unacknowledged use akin to plagiarism	Five-point Likert
Policy awareness and attitudes (items 29–35)	Clear university guidelines; understanding of ethical use; usefulness; integration into learning; future importance; traditional writing skills; regulation	Five-point Likert
Open-ended questions (5)	How GenAI is used; benefits; challenges; opinion on GenAI in assignments and exams; whether universities should allow or restrict it, and why	Free text

Appendix B: Supplementary Materials

Table S1 reports every Likert item for N = 67. Agree combines agree and strongly agree; disagree combines disagree and strongly disagree. CI = Wilson 95% confidence interval for the proportion agreeing. The respondent-level qualitative coding matrix is provided as a separate spreadsheet.

Table S1. Likert item results (N = 67)

#	Item	Agree n (%)	Neutral n (%)	Disagree n (%)	M (SD)	95% CI agree
1	I use GenAI tools to generate ideas for writing tasks.	46 (68.7)	14 (20.9)	7 (10.4)	3.72 (1.03)	56.8–78.5
2	I use GenAI to improve grammar in my assignments.	43 (64.2)	15 (22.4)	9 (13.4)	3.61 (1.04)	52.2–74.6
3	I use GenAI to enhance vocabulary in academic writing.	46 (68.7)	10 (14.9)	11 (16.4)	3.64 (1.04)	56.8–78.5
4	I use GenAI for paraphrasing and rewriting texts.	41 (61.2)	12 (17.9)	14 (20.9)	3.46 (1.12)	49.2–72.0
5	I use GenAI to summarize research articles or readings.	50 (74.6)	5 (7.5)	12 (17.9)	3.69 (1.09)	63.1–83.5
6	I use GenAI to write full paragraphs for assignments.	27 (40.3)	13 (19.4)	27 (40.3)	3.04 (1.19)	29.4–52.3
7	I use GenAI mainly during the drafting stage of writing.	33 (49.3)	19 (28.4)	15 (22.4)	3.27 (1.05)	37.7–60.9
8	I rely on GenAI throughout the entire writing process.	19 (28.4)	11 (16.4)	37 (55.2)	2.55 (1.17)	19.0–40.1
9	GenAI improves the quality of my academic writing.	51 (76.1)	10 (14.9)	6 (9.0)	3.73 (0.88)	64.7–84.7
10	GenAI helps me write faster and more efficiently.	52 (77.6)	8 (11.9)	7 (10.4)	3.69 (0.86)	66.3–85.9
11	GenAI improves my grammar accuracy.	50 (74.6)	10 (14.9)	7 (10.4)	3.75 (0.89)	63.1–83.5
12	GenAI helps me develop ideas more easily.	55 (82.1)	6 (9.0)	6 (9.0)	3.90 (0.94)	71.3–89.4
13	GenAI increases my confidence in writing in English.	44 (65.7)	16 (23.9)	7 (10.4)	3.64 (0.90)	53.7–75.9
14	GenAI reduces my writing anxiety.	45 (67.2)	16 (23.9)	6 (9.0)	3.70 (0.85)	55.3–77.2
15	GenAI helps me understand complex topics better.	58 (86.6)	4 (6.0)	5 (7.5)	4.00 (0.82)	76.4–92.8
16	I become dependent on GenAI for writing tasks.	20 (29.9)	15 (22.4)	32 (47.8)	2.73 (1.16)	20.2–41.7
17	GenAI sometimes provides incorrect information.	53 (79.1)	10 (14.9)	4 (6.0)	4.07 (0.91)	67.9–87.1
18	GenAI reduces my critical thinking skills.	40 (59.7)	14 (20.9)	13 (19.4)	3.48 (1.04)	47.7–70.6
19	I feel less creative when using GenAI.	46 (68.7)	6 (9.0)	15 (22.4)	3.61 (1.09)	56.8–78.5

#	Item	Agree n (%)	Neutral n (%)	Disagree n (%)	M (SD)	95% CI agree
20	I am unsure about the accuracy of AI-generated content.	32 (47.8)	20 (29.9)	15 (22.4)	3.34 (1.07)	36.3–59.5
21	Overuse of GenAI may harm my learning development.	51 (76.1)	8 (11.9)	8 (11.9)	3.90 (0.97)	64.7–84.7
22	I find it difficult to decide when not to use GenAI.	29 (43.3)	15 (22.4)	23 (34.3)	3.10 (1.05)	32.1–55.2
23	It is acceptable to use GenAI for brainstorming ideas.	49 (73.1)	10 (14.9)	8 (11.9)	3.76 (0.95)	61.5–82.3
24	It is acceptable to use GenAI for grammar correction.	57 (85.1)	5 (7.5)	5 (7.5)	3.90 (0.87)	74.7–91.7
25	It is acceptable to submit AI-generated content without revision.	14 (20.9)	7 (10.4)	46 (68.7)	2.28 (1.22)	12.9–32.1
26	I always revise AI-generated content before submitting it.	57 (85.1)	8 (11.9)	2 (3.0)	4.18 (0.87)	74.7–91.7
27	I clearly mention when I use GenAI in my assignments.	28 (41.8)	23 (34.3)	16 (23.9)	3.28 (1.04)	30.7–53.7
28	Using GenAI without acknowledgement is similar to plagiarism.	47 (70.1)	13 (19.4)	7 (10.4)	3.75 (0.89)	58.3–79.8
29	My university provides clear guidelines on AI use.	35 (52.2)	19 (28.4)	13 (19.4)	3.31 (1.14)	40.5–63.7
30	I understand what constitutes ethical use of GenAI in writing.	48 (71.6)	16 (23.9)	3 (4.5)	3.79 (0.77)	59.9–81.0
31	GenAI is a useful learning tool for academic writing.	55 (82.1)	7 (10.4)	5 (7.5)	3.93 (0.88)	71.3–89.4
32	GenAI should be integrated into university learning.	49 (73.1)	11 (16.4)	7 (10.4)	3.76 (0.97)	61.5–82.3
33	GenAI will become essential in future academic writing.	50 (74.6)	13 (19.4)	4 (6.0)	3.88 (0.84)	63.1–83.5
34	Traditional writing skills will still remain important.	53 (79.1)	9 (13.4)	5 (7.5)	3.96 (0.93)	67.9–87.1
35	Universities should regulate the use of GenAI in assignments.	46 (68.7)	13 (19.4)	8 (11.9)	3.64 (1.04)	56.8–78.5

Note. Groups: items 1–8 practices; 9–15 benefits; 16–22 concerns; 23–28 integrity perceptions and ethical practice; 29–35 policy awareness and attitudes.