



Responsible Use Barriers and Institutional Priorities for Generative AI among College Students in Kathmandu Nepal

Renisha Regmi

Department of Information Technology, Texas College of Management and IT, Kathmandu, Nepal

* Corresponding Author: **Renisha Regmi**

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Abstract

Generative artificial intelligence is already used frequently by many students, but frequent use does not ensure verification, disclosure, privacy awareness, or protection against dependence. This study examined responsible-use practices, student-reported barriers, and institutional priorities among a newly enrolled bachelor-level cohort in Kathmandu, Nepal. A cross-sectional online survey received 74 consenting submissions; six uniform response patterns across 20 scale items were excluded, leaving 68 records for descriptive analysis. Although 62 respondents (91.2%) used generative AI daily or several times per week, only 27 (39.7%) always or often verified important generated information and 21 (30.9%) always or often disclosed AI use when disclosure was required. Privacy or data-security concerns were the most frequently selected barrier (39; 57.4%), followed by overdependence (35; 51.5%), inaccurate information (32; 47.1%), and the cost of paid tools (29; 42.6%). Students most often prioritized AI training for students and teachers (41; 60.3%), privacy and data-security guidance (38; 55.9%), clear generative AI policies (37; 54.4%), and improved internet and technical support (35; 51.5%). Of 33 substantive open comments, 18 requested practical AI-literacy training and 12 requested clearer rules or responsible-use guidance. The findings show a gap between high adoption and consistent critical practice. Institutions should combine first-year AI literacy, assessment-specific rules, standard disclosure processes, privacy safeguards, verification routines, technical support, and assessment design that preserves student reasoning. The evidence is descriptive and specific to one college cohort; it should not be generalized to all students in Kathmandu Valley or Nepal.

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1. Introduction

Generative artificial intelligence (GenAI) can explain concepts, summarise readings, produce text and code, translate material, generate practice questions, and assist with presentations. These functions make GenAI attractive to students because support is immediate and available outside normal teaching hours. In the surveyed cohort, 62 of 68 respondents used GenAI for academic purposes daily or several times per week. Understanding difficult concepts was the most common purpose. Adoption had therefore progressed beyond experimentation and into routine academic activity.

Routine use creates a second question that adoption statistics cannot answer: whether students use the technology critically and responsibly. A fluent response may contain inaccurate claims, fabricated references, biased explanations, insecure code, or inappropriate reuse of copyrighted or personal material. Students may also submit generated content without sufficient revision or disclosure, or become dependent on assistance in tasks designed to develop independent judgement. Recent higher-education research consequently distinguishes acceptance of GenAI from the quality of learning that occurs through its use ^[1, 2].

Institutional responses have often developed more slowly than student practice. Students may receive different instructions from different teachers, and rules may vary by assignment without an agreed method for disclosure. Uncertainty can encourage hidden use, while blanket prohibition may be difficult to enforce and may prevent teachers from modelling appropriate practice. International evidence indicates that students generally favour clear guidance and equitable access rather than a total ban ^[3]. Competency frameworks similarly emphasize human responsibility, ethics, critical evaluation, and knowledge of AI limitations alongside technical skill ^[6].

These issues are particularly important for first-year students. Newly enrolled learners are still developing academic writing, research, citation, self-regulation, and disciplinary judgement. GenAI can provide scaffolding, but premature dependence may reduce the productive struggle through which these skills develop. First-year evidence shows that AI knowledge, skills, and attitudes are associated with intended and reported use, which means unequal competence may translate into unequal or unsafe practice ^[4].

This companion article is derived from a broader thesis on GenAI adoption. Article 1 examined perceived usefulness, perceived ease of use, facilitating conditions, behavioural intention, and actual use. The present article focuses on responsible-use behaviour and institutional action. It asks four questions: (1) How consistently do students receive guidance, verify output, and disclose AI use? (2) Which concerns and barriers are most common? (3) Which institutional responses do students prioritise? and (4) How can the findings be translated into a practical barrier-to-action framework?

1.1. Contributions

This paper makes four contributions:

- It provides a descriptive profile of verification, disclosure, and teacher guidance within a high-use first-year cohort.
- It ranks privacy, dependence, accuracy, cost, fabricated references, and academic-integrity concerns using student-level survey evidence.
- It identifies the institutional responses students most often request, including training, privacy guidance, clear policy, technical support, assessment rules, and redesign.
- It converts the measured findings into a practical barrier-to-action framework while clearly identifying the framework as an interpretation rather than an additional survey result.

2. Literature Review

2.1 From Adoption to Responsible Use

Research on GenAI in higher education has expanded rapidly, but acceptance models remain more common than explicit theories of learning ^[1]. Acceptance research explains why a student intends to use a tool; it does not establish whether the student verifies claims, protects data, discloses assistance, or learns the intended skills. This distinction is central because the same interface can support explanation and practice in one task while replacing student reasoning in another.

Kim *et al.* found that faculty and students recognised possible educational benefits while remaining concerned about ethical use, learning competencies, and policy ^[2]. Dai likewise

showed that students' decisions to use or avoid GenAI reflect concerns about learning, teamwork, reliability, and the value of solving problems without automated assistance ^[5]. Responsible adoption therefore involves task judgement, not simply frequency of use.

2.2 Accuracy Verification and Fabricated Sources

Large language models generate plausible sequences rather than retrieving only verified facts. Their answers can combine accurate information with errors that are difficult for novice learners to detect. Fabricated citations are especially risky in higher education because a response may present a realistic author, title, journal, or link that does not exist. Farrokhnia *et al.* identify misinformation, bias, and dependence among the threats accompanying the educational opportunities of ChatGPT ^[8].

Verification is therefore a core academic skill. It includes locating the original source, checking whether a citation exists, comparing important claims with credible evidence, testing code or calculations, and revising output through disciplinary knowledge. Verification cannot be reduced to asking the same system whether its answer is correct. The UNESCO student competency framework places ethics, critical judgement, human agency, and understanding of AI techniques within the same capability model ^[6].

2.3 Privacy Security Cost and Equity

GenAI systems may retain prompts, use interactions to improve services, or process data through external infrastructure. Students can unknowingly enter personal information, unpublished work, research data, institutional documents, or details about other people. Responsible institutional practice therefore requires guidance on data classification, approved tools, account settings, and information that must never be uploaded. Privacy is not an abstract policy concern; it is a prompt-level decision made each time a user supplies context.

Cost also shapes responsible access. Free versions may have lower limits, older models, fewer privacy controls, or restricted features, while paid subscriptions can produce unequal capability across students. Shahzad *et al.* show that trust interacts with awareness and technology-acceptance beliefs ^[10], and Strzelecki's acceptance study reinforces the relevance of facilitating conditions and behavioural intention ^[9]. Institutions that encourage GenAI without addressing access may create a new form of digital inequality.

2.4 Academic Integrity Disclosure and Assessment

Academic integrity depends on whether assistance is permitted, how much of the intellectual work remains with the student, and whether the use is represented honestly. Cotton, Cotton, and Shipway argue that institutions need clear policy and assessment practice rather than reliance on detection alone ^[7]. Detection systems can misclassify human and AI writing, and a detector score does not show which learning decisions the student made.

Johnston *et al.* found that students differentiated between limited assistance and the generation of a complete essay, while also supporting clearer institutional policy ^[3]. This supports assessment-specific guidance: proofreading may be acceptable in one task, brainstorming may require disclosure in another, and generation may be prohibited where independent performance is the learning outcome. A standard

disclosure statement can make permitted use visible without treating every form of assistance as misconduct.

2.5 AI Literacy and Institutional Capacity

AI literacy combines operational skill with critical and ethical judgement. Students need to define a task, write useful prompts, evaluate evidence, recognise uncertainty, revise outputs, protect data, and decide when not to use AI. Teachers need parallel competence to design assignments, explain boundaries, model verification, and evaluate process as well as product. Delcker *et al.* demonstrate that competence matters even among first-year students who may otherwise be assumed to be uniformly comfortable with digital tools ^[4]. Training must be connected to institutional capacity. A short demonstration of a chatbot does not solve inconsistent rules, inaccessible paid features, weak connectivity, or the absence of technical help. Sustainable implementation requires coordination among academic leadership, teachers, librarians, information-technology staff, and students. The emerging literature therefore supports a socio-technical approach in which policy, pedagogy, access, privacy, and support are treated as one system ^[1, 2, 6].

2.6 Research Gap

Recent studies describe GenAI adoption, competence, integrity, and student attitudes, but fewer provide locally grounded evidence on responsible-use routines and institutional priorities in Nepalese higher education. Evidence is particularly limited for newly enrolled bachelor students. The present study addresses this gap descriptively by examining guidance, verification, disclosure, concerns, priorities, and open recommendations within Kathmandu colleges. It does not claim national representation or causal effects.

3. Methodology

3.1 Study Design and Setting

A descriptive cross-sectional survey design was used. The questionnaire was administered online through Google Forms to newly enrolled bachelor-level students at one college in Kathmandu in 2026. The institution is not named because the analysis concerns the cohort rather than an institutional evaluation. The design was appropriate for estimating the prevalence of reported practices, concerns, and preferred responses at one point in time.

3.2 Sample and Data Screening

The accessible first-year cohort was approached through a census-style convenience process. Seventy-four students submitted the required consent statement. All scale fields were complete, and no exact duplicate response vectors were identified when timestamps were excluded. Six records assigned the same numeric rating to all 20 scale statements across five constructs and were excluded as uniform low-information response patterns. The final analytical sample

was 68.

The screening rule was based on response pattern rather than demographics or whether a response supported an expected result. Nine retained respondents selected the tool-list option indicating no prior use together with one or more named tools. For the descriptive tool summary, the contradictory no-use option was ignored and the named selections were retained. This rule did not alter responsible-use, barrier, priority, or scale responses.

3.3 Measures

Teacher guidance asked how often teachers clearly explain when GenAI is allowed. Verification asked how often respondents check important information generated by AI. Disclosure asked how often respondents disclose GenAI use when disclosure is required. Five-point response categories were collapsed into three descriptive groups: always or usually/often, sometimes, and rarely or never. The wording of the positive category differs because the teacher item used 'usually' and the two practice items used 'often.'

Concerns and institutional priorities were checkbox questions, so respondents could select more than one option. Percentages therefore represent the proportion of the 68 respondents selecting each item and do not sum to 100%. The optional open question asked for the most important institutional action. Thirty-nine comments were submitted, of which 33 contained a substantive recommendation. Comments were manually assigned to one or more descriptive themes.

3.4 Data Analysis

Frequencies and percentages were calculated for all responsible-use, concern, priority, and comment variables. The analysis is descriptive; it does not test whether the reported barriers cause particular patterns of use. Figures present the same values as the tables. The barrier-to-action framework is an interpretive synthesis of survey findings and recent literature, not a separate questionnaire measure. Percentages are reported to one decimal place using $N = 68$, except comment-theme percentages, which use the 33 substantive comments as the denominator.

4. Results and Analysis

4.1 Context of Use

GenAI use was already intensive in this cohort. Forty respondents (58.8%) reported daily academic use and 22 (32.4%) used it several times per week. Five used it weekly and one reported never using it. ChatGPT was selected by 63 respondents, Google Gemini by 58, and Claude by 48. Understanding difficult concepts was selected by 64 respondents. This high-use setting makes responsible practice an immediate institutional issue rather than a future concern.

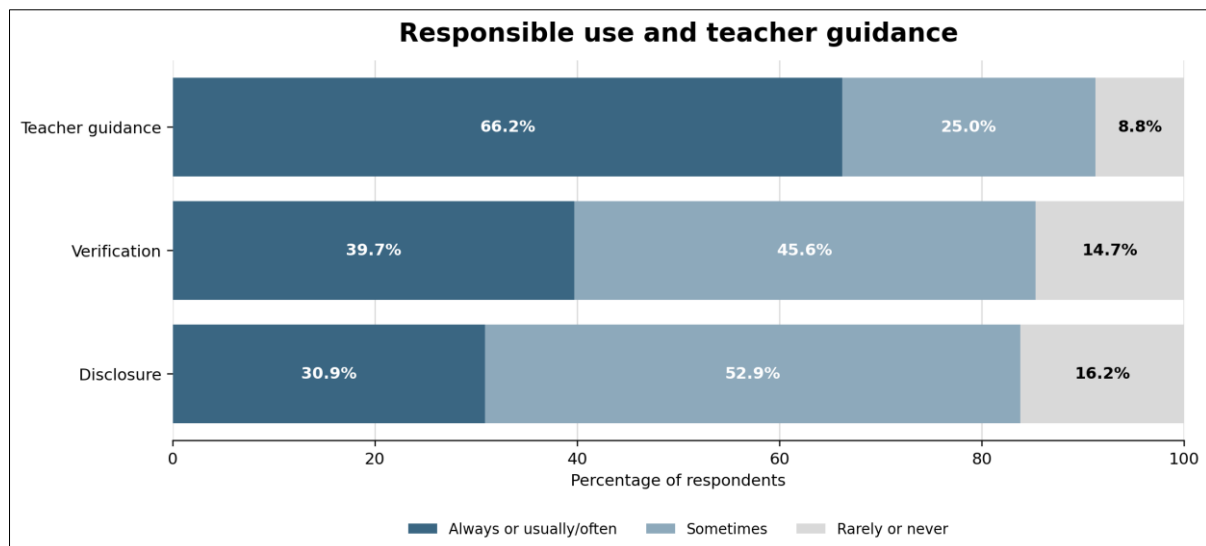
4.2 Responsible Use and Teacher Guidance

Table 1: Responsible-use practices and teacher guidance (N = 68)

Indicator	Category	n	%
Teacher guidance	Always or usually	45	66.2
Teacher guidance	Sometimes	17	25.0
Teacher guidance	Rarely or never	6	8.8
Verification	Always or often	27	39.7
Verification	Sometimes	31	45.6
Verification	Rarely or never	10	14.7
Disclosure	Always or often	21	30.9
Disclosure	Sometimes	36	52.9
Disclosure	Rarely or never	11	16.2

Two-thirds of respondents reported that teachers always or usually explain when GenAI is allowed. Guidance was therefore more frequent than either verification or disclosure. Only 27 students always or often checked important AI-generated information, while 31 did so only sometimes. Ten rarely or never verified important output. The result indicates that access to guidance had not yet become a consistent checking routine for all students.

Disclosure was less consistent. Twenty-one respondents always or often disclosed AI use when required, 36 disclosed sometimes, and 11 rarely or never did so. Because the item was conditional on disclosure being required, these responses may reflect both student behaviour and uncertainty about when a requirement applies. The finding supports clearer assignment-level instructions and a standard disclosure format.



Note. The first category is always or usually for teacher guidance and always or often for verification and disclosure. Percentages are based on N = 68.

Fig 1: Responsible-use practices and teacher guidance

4.3 Concerns and Barriers

Table 2: Concerns and barriers affecting generative AI use (N = 68)

Concern or barrier	n	% of respondents
Privacy or data-security concerns	39	57.4
Risk of overdependence	35	51.5
Inaccurate information	32	47.1
Cost of paid tools	29	42.6
Fabricated references or links	18	26.5
Plagiarism or academic-integrity concerns	14	20.6

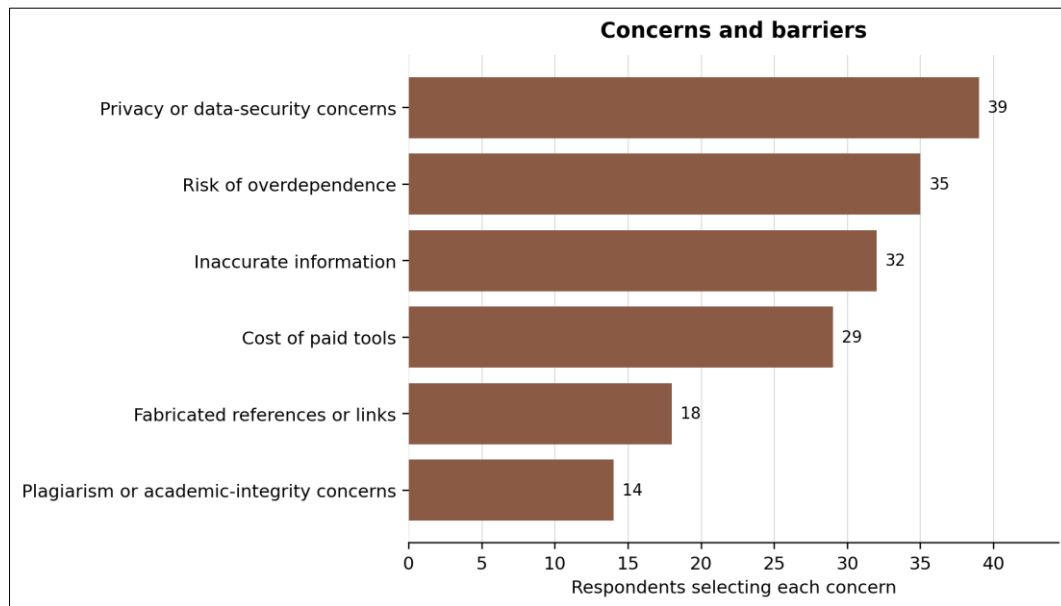
Note. Multiple selections were permitted; percentages do not sum to 100%.

Privacy or data-security concerns ranked first, selected by 39 respondents. This indicates that students were aware that prompts can expose information even though the survey did not test detailed knowledge of platform data practices. Overdependence ranked second, suggesting that learners also recognised the risk of substituting generated output for independent thinking. These two leading concerns extend beyond simple technical performance.

Accuracy remained prominent: 32 respondents selected inaccurate information and 18 selected fabricated references or links. The lower frequency for fabricated references may mean that this specific failure is encountered less often, is less well recognised, or is understood as part of the broader accuracy category. Cost was selected by 29 students, showing that unequal access to advanced features can remain relevant even in an urban college cohort. Academic-integrity concerns

were selected by 14 respondents; this relatively lower selection should not be interpreted as absence of risk,

particularly because disclosure was often inconsistent.



Note. Counts exceed 68 because respondents could select more than one concern.

Fig 2: Student-reported concerns and barriers

4.4 Institutional Priorities

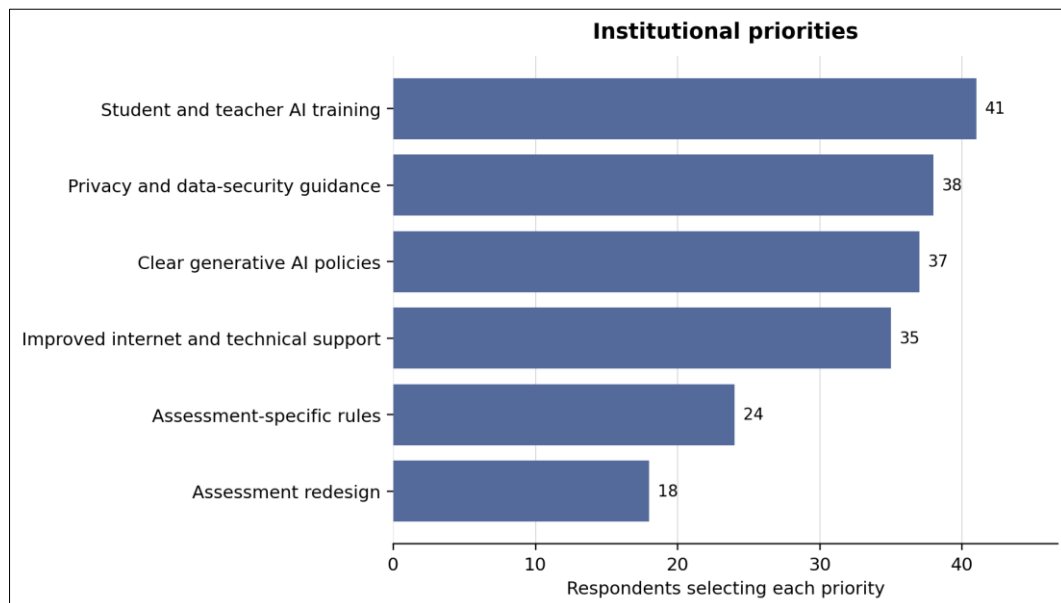
Table 3: Institutional priorities selected by respondents (N = 68)

Priority	n	% of respondents
Student and teacher AI training	41	60.3
Privacy and data-security guidance	38	55.9
Clear generative AI policies	37	54.4
Improved internet and technical support	35	51.5
Assessment-specific rules	24	35.3
Assessment redesign	18	26.5

Note. Multiple selections were permitted; percentages do not sum to 100%.

Training for both students and teachers was the most frequently selected institutional priority. Privacy guidance and clear policy followed closely, and more than half of respondents also selected improved internet and technical support. The ranking shows that students did not frame responsible GenAI use as a matter of rules alone. They requested capability, governance, and enabling infrastructure together.

Assessment-specific rules were selected by 24 respondents and assessment redesign by 18. These options ranked below general training and policy, but they address a distinct problem: students need to know what is permitted in each task, and teachers need assessment designs that make learning visible. The priorities therefore support staged implementation, beginning with foundational literacy and clear rules while developing more substantial assessment changes.



Note. Counts exceed 68 because respondents could select more than one priority.

Fig 3: Institutional priorities for generative AI

4.5 Open-Ended Recommendations

Thirty-nine respondents submitted an open comment and 33 provided a substantive institutional recommendation. Eighteen of the 33 substantive comments (54.5%) called for AI literacy or practical training. Twelve (36.4%) requested clear rules or responsible-use guidance. Five (15.2%) mentioned internet, laboratory, or technical support, and three (9.1%) warned against overdependence. One comment requested access to approved or premium tools and one requested assessment redesign. Because a comment could

receive more than one code, theme percentages do not sum to 100%.

The comments reinforce the checkbox results. Students primarily asked institutions to teach appropriate use and clarify expectations rather than prohibit the technology. The overlap between training, responsible-use guidance, and technical support also suggests that implementation should be integrated into first-year orientation, course teaching, library support, and assessment communication rather than delegated to a single office.

4.6 Barrier-to-Action Synthesis

Table 4: Practical barrier-to-action framework derived from the findings

Observed finding	Institutional risk	Priority response
Verification is often intermittent	Errors or fabricated material enter academic work	Teach source tracing, cross-checking, citation verification, and testing of claims, code, and calculations
Disclosure is often intermittent	Permitted assistance remains hidden or expectations are misunderstood	Use assessment-specific rules and a short standard disclosure statement
Privacy is the leading concern	Students upload personal, research, or institutional data	Define prohibited data, review tool settings, provide privacy training, and identify approved tools
Overdependence concerns more than half	AI substitutes for reasoning and practice	Require process evidence, reflection, oral explanation, drafts, and human revision
Accuracy and fabricated references are common concerns	Fluent output is mistaken for credible evidence	Model disciplinary verification and require original-source checking
Cost affects 42.6%	Paid features create unequal capability	Provide equitable campus access or recommend transparent, accessible alternatives
Training is the leading priority	Students and teachers develop uneven skills	Embed practical AI literacy in first-year orientation and continuing staff development

Note. This framework is an interpretive synthesis of the survey findings and literature; it is not an additional questionnaire item.

5. Discussion

5.1 High Use Coexists with Incomplete Critical Practice

The central finding is a practice gap. More than nine in ten respondents used GenAI daily or several times per week, but fewer than four in ten always or often verified important output and fewer than one-third consistently disclosed use when required. The cohort had adopted GenAI more quickly than it had developed stable routines for checking and transparent reporting. This supports the literature's distinction between technology acceptance and educationally

responsible use ^[1, 2].

The guidance result adds nuance. Most students reported frequent teacher explanation, yet verification and disclosure remained less consistent. Information about whether AI is allowed may be necessary but insufficient. Students also need demonstrations, repeated practice, accessible tools, clear consequences, and assessment designs that make critical use worthwhile. Guidance quality and consistency were not measured, so the study cannot determine which forms of teacher communication are most effective.

5.2 Privacy Dependence and Accuracy Form a Connected Risk Pattern

The three leading substantive concerns were privacy, overdependence, and inaccurate information. These risks are connected. A student seeking a more tailored answer may provide more personal or contextual data; a student who trusts the response may then rely on inaccurate material; repeated reliance can weaken independent checking. Responsible-use education should therefore avoid teaching privacy, verification, and dependence as isolated topics.

The prominence of privacy is consistent with a human-centred competency approach^[6]. Institutions should provide concrete examples of data that must not be entered into public tools, including personal identifiers, student records, confidential placement material, unpublished research data, examination content, and information about third parties. Guidance should also explain that removing a name does not always make a detailed prompt anonymous.

Accuracy training should be discipline-specific. A fabricated reference, an incorrect legal interpretation, unsafe clinical advice, and insecure code require different checking strategies. Students need original-source verification and should understand that asking a model for reassurance is not independent confirmation. Teachers and librarians can collaborate on exercises that compare generated responses with scholarly databases, primary sources, calculations, or executable tests.

5.3 Students Prefer Capacity Building and Practical Governance

The institutional-priority results show that students favour a supportive governance model. Training ranked first, but privacy guidance, clear policy, and technical support were nearly as common. Open comments produced the same order: practical literacy was the leading theme, followed by clear rules and responsible-use guidance. These results align with research showing that students and faculty see value in GenAI while seeking institutional clarity^[2, 3].

Training should be role-specific. Students require task definition, prompting, verification, citation, disclosure, privacy, and reflection. Teachers require assessment design, communication of permitted use, evaluation of process, and ways to respond consistently to suspected misuse. Librarians can support source verification and citation; technical staff can support approved access and data settings; academic leaders can maintain a policy framework that allows course-level decisions without contradiction.

5.4 Policy Must Reach the Assignment Level

A general policy cannot answer every academic-use question. The same activity may be acceptable in a formative brainstorming exercise and prohibited in an examination or an assignment measuring independent writing. Johnston *et al.* found that students distinguish limited assistance from complete generation^[3], while Cotton *et al.* emphasise policy and assessment responses rather than dependence on detection^[7]. The present findings support a simple task-level classification such as prohibited, restricted, permitted with disclosure, or intentionally integrated.

Disclosure should be proportionate. A brief statement can identify the tool, purpose, and extent of use, followed where necessary by representative prompts or a process appendix. The objective is not to burden permitted use but to preserve transparency and authorship. Consistent disclosure also

provides teachers with better information for evaluating whether the student met the learning outcome.

5.5 Assessment and Support Implications

Assessment redesign was selected less often than training or policy, but it becomes important once GenAI is routinely available. Authentic tasks, local data, staged drafts, annotated decisions, oral explanation, supervised components, and reflection can make learning processes more visible. These approaches can reduce the incentive for undisclosed substitution while allowing appropriate assistance. They also avoid placing excessive confidence in automated AI-detection scores.

Cost and technical support require parallel attention. If an institution expects students to use GenAI, it should consider the limitations of free accounts, device and connectivity constraints, accessibility, and availability of help. Approved-tool guidance should include data practices and educational suitability, not only popularity. Where equal access cannot be provided, assessments should not depend on premium functions.

5.6 Recommended Institutional Sequence

The findings support a practical sequence. First, establish a concise institutional policy with definitions, privacy boundaries, and a common disclosure method. Second, issue assignment-level instructions that state whether and how GenAI may be used. Third, provide first-year student training and continuing teacher development using authentic disciplinary examples. Fourth, provide a clear route for technical and academic help and review access to approved tools. Fifth, redesign selected assessments and monitor how students verify, disclose, and revise AI-supported work.

Evaluation should measure more than tool uptake. Institutions can track student understanding of policy, ability to identify fabricated sources, quality of disclosure, confidence in protecting data, and capacity to explain or defend submitted work. This keeps the objective focused on learning and accountability rather than maximum technology use.

5.7 Study Limitations

Several limitations constrain interpretation. The final sample only contained 68 students from newly enrolled bachelor cohort at colleges in Kathmandu only. The results are therefore descriptive evidence from this setting, not estimates for all higher-education students in Kathmandu Valley or Nepal. The convenience setting and small sample limit external validity, and the cross-sectional design cannot establish causal relationships.

All measures were self-reported. The study did not independently observe prompts, submitted assignments, verification behaviour, disclosure statements, privacy knowledge, or learning outcomes. The teacher-guidance, verification, and disclosure measures were single questions rather than validated multi-item scales. Collapsing response categories improves readability but reduces detail. Checkbox selections indicate recognised concerns, not their severity or actual incidence. Open-theme coding was descriptive and based on 33 substantive comments. Future research should use larger multi-institutional samples, validated responsible-use scales, interviews or task observation, and longitudinal designs.

6. Conclusion

This study examined responsible GenAI use, barriers, and institutional priorities among 68 first-year bachelor students at colleges in Kathmandu. The cohort used GenAI frequently, but verification and disclosure were not yet consistent. Privacy, overdependence, inaccurate information, and cost were the leading concerns. Students most often requested training, privacy guidance, clear policy, and improved technical support.

The results show that responsible adoption is a socio-technical task. Policy without training leaves students uncertain; training without assessment guidance leaves rules abstract; access without privacy safeguards creates exposure; and convenient output without verification can weaken academic quality. Institutions should connect AI literacy, assignment-level rules, disclosure, privacy, technical support, and assessment design in a single implementation strategy.

Within the limits of a small single-cohort study, the evidence favours guided and transparent use rather than blanket prohibition or unmanaged adoption. The practical objective is not simply to increase or reduce GenAI use, but to ensure that students retain human judgement, protect information, verify evidence, and demonstrate the learning for which they receive academic credit.

References

1. McGrath C, Farazouli A, Cerratto-Pargman T. Generative AI chatbots in higher education: a review of an emerging research area. *High Educ.* 2025;89:1533-49. doi:10.1007/s10734-024-01288-w.
2. Kim J, Klopfer M, Grohs JR, Eldardiry H, Weichert J, Cox LA II, *et al.* Examining faculty and student perceptions of generative AI in university courses. *Innov High Educ.* 2025;50:1281-1313. doi:10.1007/s10755-024-09774-w.
3. Johnston H, Wells RF, Shanks EM, Boey T, Parsons BN. Student perspectives on the use of generative artificial intelligence technologies in higher education. *Int J Educ Integr.* 2024;20:2. doi:10.1007/s40979-024-00149-4.
4. Delcker J, Heil J, Ifenthaler D, Seufert S, Spirgi L. First-year students AI-competence as a predictor for intended and de facto use of AI-tools for supporting learning processes in higher education. *Int J Educ Technol High Educ.* 2024;21:18. doi:10.1186/s41239-024-00452-7.
5. Dai Y. Why students use or not use generative AI: student conceptions, concerns, and implications for engineering education. *Digit Eng.* 2025;4:100019. doi:10.1016/j.dte.2024.100019.
6. UNESCO. AI competency framework for students. Paris: UNESCO; 2024. Available from: <https://unesdoc.unesco.org/ark:/48223/pf0000391105>
7. Cotton DRE, Cotton PA, Shipway JR. Chatting and cheating: ensuring academic integrity in the era of ChatGPT. *Innov Educ Teach Int.* 2024;61(2):228-39. doi:10.1080/14703297.2023.2190148.
8. Farrokhnia M, Banihashem SK, Noroozi O, Wals A. A SWOT analysis of ChatGPT: implications for educational practice and research. *Innov Educ Teach Int.* 2024;61(3):460-74. doi:10.1080/14703297.2023.2195846.
9. Strzelecki A. Students' acceptance of ChatGPT in higher education: an extended unified theory of acceptance and use of technology. *Innov High Educ.* 2024;49:223-45. doi:10.1007/s10755-023-09686-1.
10. Shahzad MF, Xu S, Javed I. ChatGPT awareness, acceptance, and adoption in higher education: the role of trust as a cornerstone. *Int J Educ Technol High Educ.* 2024;21:46. doi:10.1186/s41239-024-00478-x.

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