



## Determinants of Generative Artificial Intelligence Adoption among College Students in Kathmandu Nepal

**Renisha Regmi**

Department of Information Technology, Texas College of Management and IT, Texas, United States of America

\* Corresponding Author: **Renisha Regmi**

---

### Article Info

**ISSN (online):** 2583-6641

**Volume:** 05

**Issue:** 05

**Received:** 24-07-2026

**Accepted:** 22-08-2026

**Published:** 21-09-2026

**Page No:** 185-191

### Abstract

Generative artificial intelligence has quickly become part of students' academic practice, yet adoption depends on more than awareness or access to a chatbot. This study examined the factors associated with behavioural intention and actual academic use primarily among bachelor-level students among different colleges in Kathmandu, Nepal. A cross-sectional online survey produced 74 consenting submissions. Six uniform response patterns across all 20 scale items were excluded through a pre-specified data-quality rule, leaving 68 records for analysis. Perceived usefulness, perceived ease of use, facilitating conditions, behavioural intention, and actual use were measured with four-item scales; institutional guidance was measured with one teacher-clarity item. Cronbach's alpha ranged from .792 to .939. The HC3-robust regression predicting behavioural intention was significant,  $F(4, 63) = 43.79$ ,  $p < .001$ , and explained 73.5% of the variance. Facilitating conditions were the strongest independent predictor ( $Beta = .379$ ,  $p < .001$ ), followed by perceived ease of use ( $Beta = .334$ ,  $p = .004$ ) and perceived usefulness ( $Beta = .278$ ,  $p = .020$ ). Institutional guidance was not significant after the other predictors were controlled ( $Beta = -.026$ ,  $p = .776$ ). Behavioural intention strongly predicted actual use ( $Beta = .629$ ,  $p < .001$ ), explaining 39.5% of its variance. Four of the five hypotheses were supported. The findings indicate that adoption is most likely when students perceive academic value, can use the tools without excessive effort, and have adequate devices, access, help, and institutional support. The single guidance item should not be interpreted as evidence that policy is unimportant; a broader multi-item measure is required. The results are specific and are not representative of all students in Kathmandu Valley or Nepal.

**Keywords:** Generative artificial intelligence, higher education, technology adoption, bachelor students, perceived usefulness, facilitating conditions, behavioural intention, Nepal

---

### 1. Introduction

Generative artificial intelligence (GenAI) has moved rapidly into higher education through conversational systems that can explain concepts, summarize material, generate text and code, translate content, and provide immediate feedback. Recent reviews show that higher-education research has concentrated heavily on acceptance and use, while also warning that adoption does not by itself demonstrate improved learning <sup>[1]</sup>. Students and teachers recognize potential academic value but remain concerned about accuracy, ethics, privacy, and the effect of automated assistance on learning <sup>[2, 3]</sup>.

Technology-acceptance research is therefore useful for explaining why students intend to use GenAI and why those intentions may become routine behaviour. The Technology Acceptance Model (TAM) emphasizes perceived usefulness and perceived ease of use <sup>[4]</sup>, while the Unified Theory of Acceptance and Use of Technology (UTAUT) adds social and environmental conditions such as access, support, and facilitating resources <sup>[5]</sup>. Recent GenAI studies generally support the importance of performance expectancy, effort expectancy, competence, and trust, but the strength of each factor varies by educational context <sup>[6, 8]</sup>.

Bachelor students require particular attention because they are developing academic writing, research, self-regulation, and source-evaluation habits while adapting to a new institutional environment. Early reliance on GenAI may support access and confidence, but it can also encourage dependence before students have enough disciplinary knowledge to recognize inaccurate or fabricated output. Evidence from first-year cohorts indicates that AI competence and attitudes are related to both intended and reported use <sup>[7]</sup>.

Nepalese colleges are adopting GenAI within a setting where device access, connectivity, paid features, teacher guidance, and institutional policy may be uneven. The present article is derived from a broader thesis on GenAI adoption. It focuses specifically on the explanatory model: perceived usefulness, perceived ease of use, facilitating conditions, and institutional guidance as predictors of behavioural intention, and behavioural intention as a predictor of actual use. Descriptive barriers and institutional priorities are reserved for a separate companion article.

The study addresses two research questions: (1) which measured factors independently predict behavioural intention to use GenAI for academic purposes; and (2) to what extent does behavioural intention predict actual academic use? Five hypotheses were tested: H1, perceived usefulness positively predicts behavioural intention; H2, perceived ease of use positively predicts behavioural intention; H3, facilitating conditions positively predict behavioural intention; H4, institutional guidance positively predicts behavioural intention; and H5, behavioural intention positively predicts actual use.

### 1.1. Contributions

This paper makes four main contributions:

- It provides exploratory evidence on GenAI adoption within a bachelor cohort in Kathmandu, a setting that remains underrepresented in published acceptance research.
- It tests a compact model combining TAM constructs with facilitating conditions and a limited institutional-guidance measure.
- It distinguishes behavioural intention from reported academic use and quantifies the relationship between them.
- It reports transparent data screening, reliability, robust standard errors, confidence intervals, and limitations without creating values for constructs that were absent from the administered dataset.

## 2. Literature Review

### 2.1. Generative AI in Higher Education

GenAI differs from earlier educational technologies because one interface can support explanation, drafting, coding, translation, brainstorming, and feedback. This flexibility helps students begin difficult tasks and obtain assistance outside normal class hours. It also makes governance difficult because the same tool can scaffold learning or replace work that a student is expected to perform independently. Reviews of the emerging field show rapid growth in acceptance studies, but comparatively less evidence connecting adoption to learning theory or objectively measured outcomes <sup>[1]</sup>.

Student perspectives are not uniformly positive. Large surveys show that students may accept limited assistance

while opposing the generation of complete assignments, and they frequently request clear institutional rules and equal access <sup>[3]</sup>. Faculty and students also identify policy, ethical use, disciplinary differences, and AI-related competence as important conditions for effective integration <sup>[2]</sup>. Adoption should therefore be interpreted as an interaction among the learner, the tool, the academic task, and the institutional environment.

### 2.2. Bachelor Students and AI Competence

Newly enrolled students are learning both course content and the norms of higher education. GenAI can reduce the effort required to obtain explanations or examples, but easy access does not guarantee the ability to verify a claim, recognize a fabricated reference, or decide when assistance is inappropriate. Delcker *et al.* found that first-year students' AI-related knowledge, skills, and attitudes were associated with intended and actual use of AI tools for learning <sup>[7]</sup>. This supports the inclusion of usefulness, ease, access, and competence-related conditions in studies of early-stage students.

Decisions not to use GenAI may also be purposeful. Dai reported that students' use and non-use reflected concerns about learning value, teamwork, reliability, and the benefit of solving problems without automated assistance <sup>[9]</sup>. Consequently, high usage should not be equated automatically with competence, and lower usage should not be treated automatically as resistance.

### 2.3. Technology Acceptance Model and UTAUT

TAM proposes that perceived usefulness and perceived ease of use are central beliefs shaping technology acceptance <sup>[4]</sup>. In an academic GenAI context, usefulness includes efficiency, clearer understanding, improved work quality, and support for learning goals. Ease of use includes learning the interface, writing effective prompts, understanding responses, and using the tool without extensive technical help.

UTAUT broadens the explanation by including performance expectancy, effort expectancy, social influence, and facilitating conditions <sup>[5]</sup>. UTAUT2 later added consumer-oriented factors such as habit, hedonic motivation, and price value <sup>[13]</sup>. In this study, usefulness corresponds to performance expectancy, ease of use corresponds to effort expectancy, and facilitating conditions represent internet and device access, availability of suitable tool features, access to help, and institutional support. Institutional guidance is represented separately by one item asking how often teachers clearly explain when GenAI is allowed.

### 2.4. Evidence from Recent Adoption Studies

Recent studies provide consistent but context-dependent support for the proposed relationships. Strzelecki found that performance expectancy influenced behavioural intention and that intention contributed to use behaviour among university students <sup>[6]</sup>. Shahzad, Xu, and Javed reported that perceived usefulness and ease of use contributed to adoption intention, while trust shaped the acceptance process <sup>[8]</sup>. Delcker *et al.* linked AI competence and attitudes to intended and reported use among first-year students <sup>[7]</sup>. Together, this evidence supports H1, H2, and H5.

Facilitating conditions are especially relevant when adoption depends on reliable connectivity, a suitable device, access to sufficiently capable tools, and available help. Their role may

be direct or may operate through intention, depending on the research model and context. Institutional guidance can reduce uncertainty about acceptable use, disclosure, and assessment rules. However, one teacher-clarity item cannot capture policy quality, consistency, trust, enforcement, or practical support, so H4 is necessarily a limited test.

### 2.5. Responsible and Institutionally Supported Adoption

The educational value of GenAI depends on more than frequency of use. UNESCO's AI Competency Framework for Students emphasizes a human-centred mindset, ethics, knowledge of AI techniques and applications, and responsible design <sup>[10]</sup>. In higher education, these priorities include verification, privacy protection, disclosure, retention of human judgement, and recognition of tasks for which AI assistance is inappropriate.

Academic-integrity research recommends clear policy and assessment design instead of dependence on automated

detection alone <sup>[11]</sup>. A SWOT analysis of ChatGPT similarly identifies opportunities for personalized support alongside misinformation, bias, privacy concerns, and overdependence <sup>[12]</sup>. These risks reinforce the importance of facilitating conditions that include guidance and support, not only technical access.

### 2.6. Research Gap and Conceptual Model

Published evidence on GenAI acceptance has grown quickly, but studies of Nepalese college students remain limited. Broad university samples can also obscure the transition into the first year, when students are establishing study practices. The present study addresses this gap through a delimited single-cohort analysis. It does not claim national representativeness; instead, it tests whether the relationships predicted by TAM and UTAUT are visible within the accessible Kathmandu cohort.

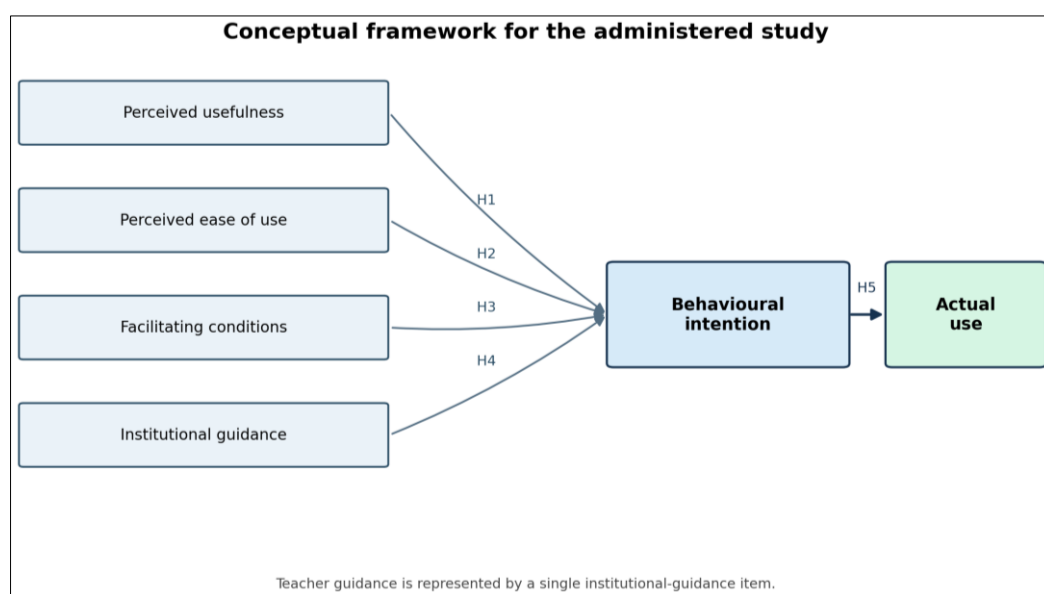


**Fig 1:** Conceptual Framework for the Study

## 3. Methodology

### 3.1. Study Design and Setting

A post-positivist, cross-sectional survey design was used to describe current GenAI adoption and test associations among measured constructs at one point in time. The questionnaire was administered through Google Forms to newly enrolled bachelor-level students at one college in Kathmandu. The college is not named to preserve institutional privacy. Because the accessible cohort was homogeneous, age and institutional comparisons were not used in the explanatory analysis.

### 3.2. Participants and Data Screening

All students who received the survey link could participate voluntarily. The export contained 74 consenting submissions, all with complete responses to the 20 scale items. No exact duplicate response vectors were found. Six records assigned the same numeric rating to all 20 scale statements and were excluded as uniform low-information patterns. The final analytical sample was  $N = 68$ . The exclusion rule was based on response quality rather than demographic characteristics or hypothesis outcomes.

### 3.3. Measures

Perceived usefulness (PU), perceived ease of use (PEOU), facilitating conditions (FC), behavioural intention (BI), and actual use (AU) were each measured with four items. PU, PEOU, FC, and BI used five-point agreement scales from 1 = strongly disagree to 5 = strongly agree. AU used a five-point frequency scale from 1 = never to 5 = very often. Composite scores were calculated as the arithmetic mean of the four items, preserving the original one-to-five metric. Institutional guidance (IG) was measured with one frequency item asking how often teachers clearly explain when GenAI is allowed, coded from 1 = never to 5 = always. The response export did not contain the planned social-influence items; consequently, no social-influence score was created or tested. The questionnaire also measured awareness, frequency, tools, purposes, responsible use, concerns, institutional priorities, and optional comments, although the present article concentrates on the acceptance model.

### 3.4. Statistical Analysis and Ethics

Cronbach's alpha assessed the internal consistency of the five multi-item scales. Means, standard deviations, ranges, and Pearson correlations summarized the constructs. H1-H4 were

tested with ordinary least-squares regression predicting BI from PU, PEOU, FC, and IG. H5 was tested with a separate regression predicting AU from BI. HC3 heteroskedasticity-consistent standard errors and 95% confidence intervals were used. Standardized coefficients were reported for comparison, variance inflation factors assessed multicollinearity, and alpha was set at .05. The cross-sectional design supports association, not causal inference.

Participation was anonymous and voluntary. The opening information described the academic purpose, estimated completion time, use of aggregate reporting, and the right to close the form before submission. No names, student identifiers, email addresses, or phone numbers were requested. All retained records included the required consent response.

## 4. Results and Analysis

**Table 1:** Reliability and Descriptive Statistics of Study Measures

| Measure                 | Items | Cronbach's alpha | Mean | SD   |
|-------------------------|-------|------------------|------|------|
| Perceived usefulness    | 4     | .939             | 3.72 | 0.99 |
| Perceived ease of use   | 4     | .792             | 3.40 | 0.69 |
| Facilitating conditions | 4     | .848             | 3.50 | 0.75 |
| Behavioural intention   | 4     | .867             | 3.58 | 0.77 |
| Actual use              | 4     | .851             | 3.42 | 0.86 |
| Institutional guidance  | 1     | -                | 3.72 | 1.02 |

**Note.** N = 68. Institutional guidance was a single item and therefore has no internal-consistency coefficient.

### 4.3. Correlation Analysis

Behavioural intention was strongly correlated with facilitating conditions ( $r = .762$ ), perceived usefulness ( $r = .755$ ), and perceived ease of use ( $r = .724$ ), all  $p < .001$ . BI was also strongly correlated with actual use ( $r = .629$ ,  $p$

### 4.1. Awareness and Frequency of Academic Use

Awareness and exposure were high. Sixty-three respondents (92.6%) had heard of GenAI before the survey. Sixty-two respondents (91.2%) reported using GenAI for academic purposes either daily or several times per week. The descriptive pattern shows that the model explains adoption within a cohort where GenAI was already familiar and frequently used rather than among complete non-users.

### 4.2. Reliability and Descriptive Statistics

All five multi-item scales demonstrated acceptable or stronger internal consistency. Perceived usefulness had the highest mean ( $M = 3.72$ ,  $SD = 0.99$ ), followed by behavioural intention ( $M = 3.58$ ,  $SD = 0.77$ ). All composite means were above the neutral midpoint of 3, indicating generally favourable, although not uniformly strong, acceptance.

$< .001$ ). Institutional guidance had a smaller and non-significant correlation with BI ( $r = .223$ ,  $p = .068$ ). The correlations among the multi-item predictors were substantial but remained below levels normally treated as evidence of severe redundancy.

**Table 2:** Pearson Correlation Matrix

| Measure | PU      | PEOU    | FC      | IG    | BI      | AU    |
|---------|---------|---------|---------|-------|---------|-------|
| PU      | 1.000   |         |         |       |         |       |
| PEOU    | .638*** | 1.000   |         |       |         |       |
| FC      | .707*** | .577*** | 1.000   |       |         |       |
| IG      | .210    | .274*   | .258*   | 1.000 |         |       |
| BI      | .755*** | .724*** | .762*** | .223  | 1.000   |       |
| AU      | .663*** | .562*** | .514*** | .228  | .629*** | 1.000 |

**Note.** \*  $p < .05$ ; \*\*  $p < .01$ ; \*\*\*  $p < .001$ . PU = perceived usefulness; PEOU = perceived ease of use; FC = facilitating conditions; IG = institutional guidance; BI = behavioural intention; AU = actual use.

### 4.4. Predictors of Behavioural Intention

The multiple regression model was statistically significant,  $F(4, 63) = 43.79$ ,  $p < .001$ . It explained 73.5% of the variance in BI ( $R^2 = .735$ ; adjusted  $R^2 = .719$ ). Variance inflation

factors ranged from 1.10 to 2.38, indicating that multicollinearity was not severe. Residual normality was acceptable (Shapiro-Wilk  $W = .982$ ,  $p = .436$ ).

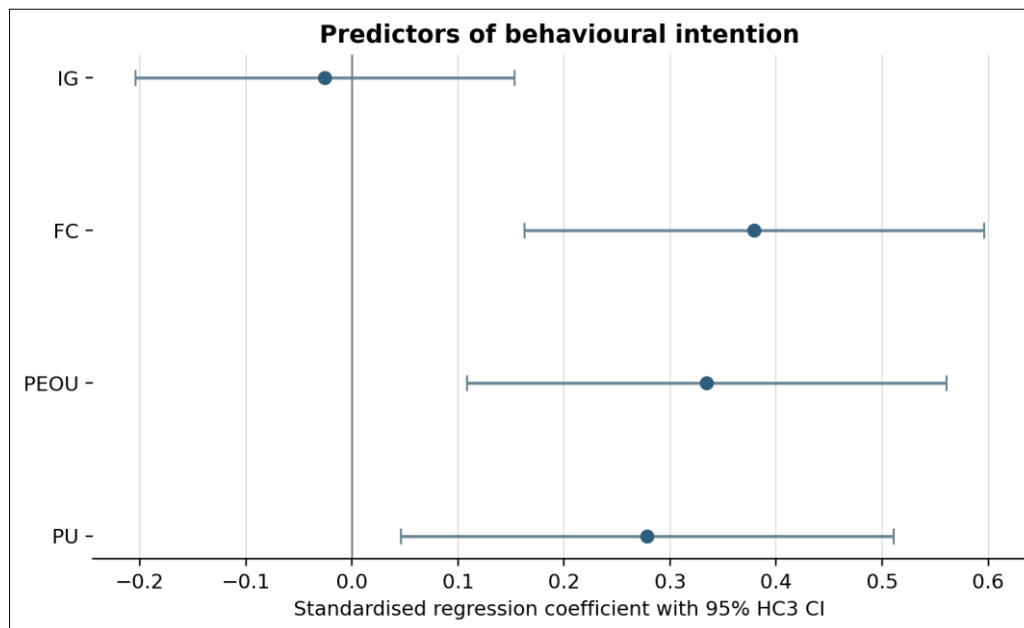
**Table 3:** HC3 Regression Predicting Behavioural Intention

| Predictor               | B (HC3 SE)     | Beta  | p     | 95% CI for B                  |
|-------------------------|----------------|-------|-------|-------------------------------|
| Constant                | 0.193 (0.487)  | -     | .693  | [-0.780, 1.16 <sup>71</sup> ] |
| Perceived usefulness    | 0.218 (0.091)  | .278  | .020  | [0.036, 0.40 <sup>11</sup> ]  |
| Perceived ease of use   | 0.375 (0.127)  | .334  | .004  | [0.122, 0.62 <sup>91</sup> ]  |
| Facilitating conditions | 0.391 (0.112)  | .379  | <.001 | [0.168, 0.61 <sup>51</sup> ]  |
| Institutional guidance  | -0.019 (0.068) | -.026 | .776  | [-0.155, 0.11 <sup>61</sup> ] |

**Note.** N = 68.  $R^2 = .735$ ; adjusted  $R^2 = .719$ . Beta denotes the standardized coefficient; CI = confidence interval.

Facilitating conditions were the strongest independent predictor of BI (Beta = .379,  $p < .001$ ), supporting H3. PEOU (Beta = .334,  $p = .004$ ) and PU (Beta = .278,  $p = .020$ ) were also

significant, supporting H2 and H1. IG was not significant after the other predictors were controlled (Beta = -.026,  $p = .776$ ), so H4 was not supported.



**Note.** Points are standardized regression coefficients. Horizontal lines show 95% HC3 confidence intervals. IG = institutional guidance; FC = facilitating conditions; PEOU = perceived ease of use; PU = perceived usefulness.

**Fig 2:** Standardized Predictors of Behavioural Intention

#### 4.5. Behavioural Intention and Actual Use

The regression predicting AU from BI was significant,  $F(1, 66) = 43.11$ ,  $p < .001$ . BI explained 39.5% of the variance in

AU ( $R^2 = .395$ ; adjusted  $R^2 = .386$ ), and residual normality was acceptable ( $W = .982$ ,  $p = .437$ ).

**Table 4:** HC3 Regression Predicting Actual Use

| Predictor             | B (HC3 SE)    | Beta | p     | 95% CI for B               |
|-----------------------|---------------|------|-------|----------------------------|
| Constant              | 0.912 (0.366) | -    | .015  | [0.181, 1.64 <sup>3]</sup> |
| Behavioural intention | 0.699 (0.104) | .629 | <.001 | [0.491, 0.90 <sup>7]</sup> |

**Note.**  $N = 68$ .  $R^2 = .395$ ; adjusted  $R^2 = .386$ .

BI had a strong positive association with AU ( $Beta = .629$ ,  $p < .001$ ), supporting H5. A one-point increase in the BI composite was associated with an estimated 0.699-point increase in AU. Overall, H1, H2, H3, and H5 were supported; H4 was not supported.

## 5. Discussion

### 5.1. Overall Adoption Pattern

The results show that GenAI was already a routine academic technology in the surveyed student cohort. More than nine in ten respondents reported daily or several-times-per-week academic use. Within this high-use context, the compact model explained nearly three-quarters of the variance in behavioural intention. This strong model fit suggests that perceived value, usability, and enabling conditions captured important parts of students' willingness to continue using GenAI.

The findings are consistent with recent acceptance research, particularly studies showing that performance expectancy, effort expectancy, competence, and trust contribute to intention<sup>[6, 8]</sup>. They also reinforce the distinction between acceptance and educational effectiveness. The study explains students' reported adoption; it does not demonstrate that GenAI improved grades, understanding, or long-term learning.

### 5.2. Facilitating Conditions Were the Strongest Predictor

Facilitating conditions produced the largest standardized coefficient. This result is important because the scale included reliable connectivity and a suitable device, access to a tool with needed features, knowledge of where to obtain help, and sufficient institutional guidance. The result therefore reflects a usable support ecosystem rather than internet access alone.

For colleges, the practical implication is that adoption policy cannot be separated from provision. Students need clear access arrangements, reliable campus connectivity, basic technical help, and guidance that is available when they encounter difficulty. A policy document without implementation support is unlikely to create the same conditions as a coordinated academic and technical system.

### 5.3. Usefulness and Ease of Use Remained Important

PU and PEOU both retained significant independent effects after FC and IG were controlled. The PU result indicates that students' intentions are stronger when they believe GenAI saves time, improves understanding, enhances work quality when used appropriately, and supports learning goals. This is consistent with TAM<sup>[4]</sup> and recent GenAI evidence<sup>[6, 8]</sup>. The PEOU result suggests that adoption also depends on whether students can learn the interface, write effective instructions, understand responses, and operate the tool without extensive assistance. Ease should not be interpreted only as convenience. AI-literacy training can improve the quality of prompting, interpretation, verification, and revision, allowing students to use simple interfaces more critically.

### 5.4. Institutional Guidance Requires Better Measurement

H4 was not supported. IG had a small positive bivariate relationship with BI but became slightly negative and clearly non-significant in the multivariable model. This does not

show that institutional guidance is unimportant. The measure asked only how often teachers clearly explain when GenAI is allowed. It did not assess whether the guidance was consistent, trusted, assessment-specific, supportive, restrictive, or connected to practical help.

There is also conceptual overlap because the FC scale included an item on sufficient institutional guidance. Once the broader support construct was controlled, the single teacher item contributed little unique variance. Future research should use a multi-item measure covering policy clarity, teacher consistency, disclosure requirements, assessment-specific instructions, enforcement, and access to advice.

### 5.5. Behavioural Intention Predicted Actual Use

BI strongly predicted AU and explained 39.5% of its variance, supporting the central logic of TAM and UTAUT<sup>[4, 5]</sup>. The result is also consistent with Strzelecki's finding that intention contributes to use behaviour<sup>[6]</sup>. Students who planned to use GenAI for appropriate purposes, expected to use it regularly, recommended responsible use, and intended to improve their skills also reported more frequent academic use, checking, and revision.

More than half of the variance in AU remained unexplained. Actual use may also depend on assignment requirements, teacher permission, peer practices, subject area, habit, tool cost, language, and access to advanced features. Longitudinal studies and task or platform logs would provide a stronger test of use than one cross-sectional self-report survey.

### 5.6. Implications for Higher Education

The combined findings favour a supportive governance model. Colleges should introduce first-year AI literacy that covers prompting, verification, fabricated references, privacy, disclosure, and the difference between assistance and substitution. Assessment briefs should specify whether GenAI is prohibited, restricted, permitted with disclosure, or intentionally integrated. Teachers should model verification and require evidence of reasoning, process, or reflection where appropriate.

Access and support also require attention. Where institutions recommend or integrate GenAI, they should consider device availability, connectivity, the limitations of free versions, data retention, accessibility, and a clear route for help. This aligns with competency and integrity frameworks that combine technical knowledge with ethics and human responsibility<sup>[10, 11]</sup>.

### 5.7. Study Limitations

Several limitations should guide interpretation. First, the analytical sample contained 68 students from one newly enrolled bachelor cohort at one Kathmandu college, so the findings are exploratory and cannot be generalized to all students in Kathmandu Valley or Nepal. Second, the design was cross-sectional and cannot establish causation. Third, all central variables were self-reported in one questionnaire, creating possible common-method bias. Fourth, six uniform response patterns were excluded through a transparent screening rule, but other low-effort responses may remain. Fifth, IG was measured with one item and overlapped conceptually with FC. Sixth, the planned social-influence scale was absent from the response export and was not backfilled. Finally, actual use combined task support with checking and revision practices; future studies could separate

frequency, task type, dependence, and responsible-use quality. Larger multi-institutional samples and longitudinal designs are needed.

### 6. Conclusion

This study examined five hypotheses concerning GenAI adoption among 68 bachelor students from one college in Kathmandu. PU, PEOU, and FC significantly predicted BI, while the single IG item did not. BI strongly predicted AU. Four of five hypotheses were supported, and the results align with the central expectations of TAM and UTAUT.

The strongest practical message is that adoption depends on an enabling environment as well as favourable beliefs. Students are more willing to continue using GenAI when it has clear academic value, is manageable to operate, and is supported by adequate access, features, help, and institutional resources. Institutions should therefore connect policy with training, technical provision, privacy protection, and assessment-specific guidance.

Within the limits of a small single-cohort study, the evidence indicates that GenAI adoption in early higher education is already substantial but not self-governing. The next research and policy challenge is to ensure that responsible use, verification, and human judgement develop at the same pace as access and intention.

### References

- 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.
- 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.
- 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.
- Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.* 1989;13(3):319-40. doi:10.2307/249008.
- Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: toward a unified view. *MIS Q.* 2003;27(3):425-78. doi:10.2307/30036540.
- 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.
- 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.
- 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.
- 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.

10. UNESCO. AI competency framework for students. Paris: UNESCO; 2024. Available from: <https://unesdoc.unesco.org/ark:/48223/pf0000391105>
11. 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.
12. 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.
13. Venkatesh V, Thong JYL, Xu X. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Q.* 2012;36(1):157-78. doi:10.2307/41410412.
14. Hair JF, Black WC, Babin BJ, Anderson RE. *Multivariate data analysis.* 8th ed. Boston (MA): Cengage; 2019.

**How to Cite This Article**

Regmi R. Determinants of generative artificial intelligence adoption among college students in Kathmandu, Nepal. *International Journal of Management and Organizational Research.* 2026;5(5):185-191.

**Creative Commons (CC) License**

This is an open access journal, and articles are distributed under the terms of the Creative Commons Attribution NonCommercial-ShareAlike 4.0 International (CC BY-NC-SA 4.0) License, which allows others to remix, tweak, and build upon the work non-commercially, as long as appropriate credit is given and the new creations are licensed under the identical terms.