

Determinants of Responsible Generative Artificial Intelligence Use among Higher Education Students: Integrating Technology Beliefs, Ethical Awareness and Social Norms

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Abstract - Generative artificial intelligence is increasingly used by higher education students, raising concerns regarding verification, acknowledgement, privacy and independent academic work. This study examines determinants of responsible use intention by integrating the Technology Acceptance Model and the Theory of Planned Behaviour. A quantitative cross-sectional survey of 382 students measured Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Ethical Awareness (EA), Subjective Norms (SN), Attitude towards Responsible Use (ATT) and Responsible Use Intention (RGI). Data were analysed using descriptive statistics, reliability analysis, Pearson correlation, independent-samples t-tests, one-way ANOVA, multiple regression and bootstrapped mediation. All constructs showed acceptable internal consistency ($\alpha = .852-.883$). PEOU, PU and EA significantly predicted ATT and explained 53.4 per cent of its variance, with EA emerging as the strongest predictor ($\beta = .439$). PU, ATT and SN significantly predicted RGI and explained 54.9 per cent of its variance, with ATT as the strongest predictor ($\beta = .501$). ATT partially mediated the relationship between PU and RGI (indirect $B = .136$, 95% CI [.076, .198]). Gender differences were not significant, whereas use-frequency groups differed significantly. The findings show that responsible-use intentions are shaped by technology beliefs together with ethical awareness, attitudes and social norms.

Key Words: generative artificial intelligence, responsible academic use, ethical awareness, higher education, technology acceptance, social norms.

I. INTRODUCTION

Generative Artificial Intelligence (GenAI) refers to digital systems capable of producing text, images, code and other outputs in response to user instructions. Higher education students increasingly use systems such as ChatGPT, Gemini and Copilot for explanation, outlining, language support and organisation of study material. Their growing presence in academic work has made responsible use an important issue because students must evaluate accuracy, acknowledge assistance where required, protect confidential information and preserve independent academic contribution.

Recent higher education research shows that students' use of generative artificial intelligence is influenced by perceived usefulness, ease of use, attitudes and learning-related beliefs (Duong et al., 2023; Habibi et al., 2023; Foroughi et al., 2024; Shahzad et al., 2025; Strzelecki, 2024a, 2024b). Ethical considerations are equally important. Concerns about authorship, originality, bias, transparency and the reliability of system outputs have increased the need for clear standards of responsible academic use (Das & Kundu, 2024; Fang & Cai, 2025).

Indian technology-adoption studies also demonstrate that behavioural intention is shaped by a combination of perceived utility, attitudes and contextual conditions. Aparna (2024) identifies usefulness, ease and attitude as important in digital-payment adoption, while Suvarni and Deeksha (2025) report the importance of usefulness and compatibility in technology adoption. Social and psychological influences have likewise been associated with behavioural intention in Indian settings (Diddimani, 2025; Naik & Prabhu, 2025; Raghavendra, 2024).

These findings support an integrated examination of technology beliefs, ethical awareness and social expectations.

The Technology Acceptance Model (TAM) identifies Perceived Ease of Use and Perceived Usefulness as central beliefs in technology acceptance (Davis, 1989). The Theory of Planned Behaviour (TPB) explains behavioural intention through attitude and perceived social expectations (Ajzen, 1991). Building on these perspectives, the present study incorporates Ethical Awareness, Subjective Norms, Attitude towards Responsible Use and Responsible Use Intention. The model therefore connects perceptions of the technology with academic-integrity considerations and the social environment surrounding its use.

Although earlier studies have examined willingness to adopt or continue using generative artificial intelligence, responsible-use intention has received less integrated attention. In particular, verification, acknowledgement, privacy, independent academic contribution and compliance with assessment rules need to be considered alongside usefulness and ease. This study addresses that gap using primary survey data from 382 higher education students and examines direct relationships, group differences and the mediating role of attitude.

Responsible academic use is treated in this study as a behavioural orientation rather than as simple technology acceptance. A student may perceive a system as easy to use and useful while still differing in willingness to verify information, acknowledge assistance, protect private information or comply with assessment requirements. Separating these ideas is important because technology acceptance models primarily explain willingness to engage with a system, whereas academic

integrity requires additional evaluative and social considerations. The integrated framework therefore examines whether ethical awareness, attitude and subjective norms add explanatory value beyond ease and usefulness.

The study has four objectives: to examine the influence of PEOU, PU and EA on ATT; to assess the influence of PU, ATT and SN on RGI; to test whether ATT mediates the relationship between PU and RGI; and to examine whether responsible-use constructs differ across gender and use-frequency groups. These objectives provide a coherent empirical test of the proposed framework and connect technology beliefs with academic-integrity considerations in a single model.

II. LITERATURE REVIEW

A. Technology Beliefs and Responsible Use

Perceived Ease of Use (PEOU) is the degree to which students believe that a generative artificial intelligence system can be used with relatively little effort, while Perceived Usefulness (PU) reflects the perceived value of the system for academic tasks. TAM proposes that ease of use contributes to perceived usefulness (Davis, 1989). Higher education studies similarly identify ease and usefulness as important determinants of student acceptance (Duong et al., 2023; Shahzad et al., 2025). Accordingly, H1 proposes that PEOU positively influences PU.

Ease of use may also shape attitudes towards responsible use because students who can understand and control a system may find verification and disclosure practices easier to apply. H2 therefore proposes that PEOU positively influences ATT. Perceived usefulness may strengthen both attitude and future responsible-use intention when students regard the system as relevant to their academic tasks. Consistent with TAM research (Duong et al., 2023; Foroughi et al., 2024; Shahzad et al., 2025), H3 proposes that PU positively influences ATT and H7 proposes that PU positively influences RGI.

PEOU and PU are conceptually distinct even when they are strongly related. Ease concerns the effort required to operate a system, whereas usefulness concerns the value that students believe they obtain from it. In an academic setting, this distinction is important because low effort can encourage frequent interaction without necessarily improving judgement about the quality of an output. The model therefore treats technology beliefs as antecedent perceptions and examines responsible use through separate ethical, attitudinal and normative constructs.

B. Ethical Awareness and Subjective Norms

Ethical Awareness (EA) refers to students' recognition that system outputs may contain incorrect or unverifiable

information, that unacknowledged copying may violate academic rules and that confidential information requires protection. Research on ethics and student use of generative artificial intelligence emphasises authorship, originality, transparency and responsible decision-making (Das & Kundu, 2024; Fang & Cai, 2025). H4 therefore proposes that EA positively influences ATT.

Subjective Norms (SN) represent perceived expectations from teachers, classmates and institutions. TPB identifies social expectations as an important source of behavioural intention (Ajzen, 1991). Indian behavioural studies also report significant roles for subjective norms and related social influences (Naik & Prabhu, 2025; Raghavendra, 2024). In higher education, clear expectations can reduce uncertainty about acceptable use across different assessment tasks. H5 therefore proposes that SN positively influences RGI.

Subjective norms are particularly relevant when institutional practices are still developing. Students may encounter different expectations across teachers, courses and forms of assessment, making social cues an important part of decision-making. Consistent guidance can therefore influence responsible-use intention by signalling what forms of assistance are acceptable, what forms require acknowledgement and what practices remain inconsistent with independent academic work.

C. Attitude, Responsible Use Intention and Mediation

Attitude towards Responsible Use (ATT) reflects a favourable or unfavourable evaluation of verification, appropriate acknowledgement, privacy protection and independent academic effort. TPB treats attitude as a direct antecedent of behavioural intention (Ajzen, 1991). H6 therefore proposes that ATT positively influences RGI.

Perceived usefulness may also influence responsible-use intention indirectly through attitude. When students consider the technology relevant to academic tasks, they may form stronger evaluations of how such use should be governed, which can subsequently influence intention. H8 therefore proposes that ATT mediates the relationship between PU and RGI.

The mediation proposition is theoretically important because it distinguishes a direct utility-based route from an evaluative route. A student may intend to use a useful technology within academic rules directly, but part of that intention may arise because perceived usefulness contributes to a more favourable attitude towards responsible practice. Testing both paths allows the analysis to determine whether attitude carries a meaningful portion of the usefulness-intention relationship.

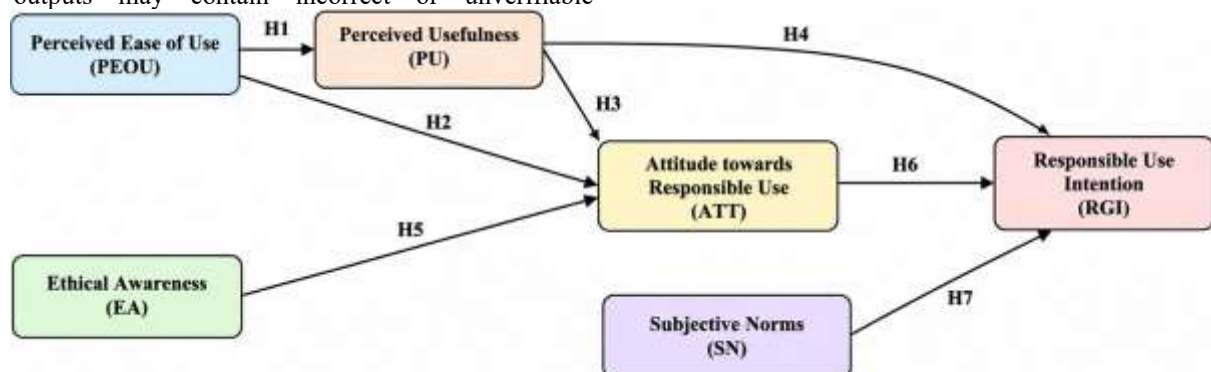


Fig. 1. Proposed analytical framework.

Note. PEOU = Perceived Ease of Use; PU = Perceived Usefulness; EA = Ethical Awareness; SN = Subjective Norms; ATT = Attitude towards Responsible Use; RGI = Responsible Use Intention. The PU → RGI path represents the retained direct relationship in the partial mediation model.

III. METHODOLOGY

A. Research Design and Respondents

A quantitative cross-sectional survey design was adopted. Primary data from 382 higher education students were analysed. Respondents represented different age groups, genders, study levels, academic disciplines and frequencies of generative artificial intelligence use. The final dataset contained one respondent-level record for each participant and was used for descriptive, comparative and explanatory analyses.

B. Measures

The structured questionnaire contained six constructs with four items each. PEOU measured perceived ease, PU measured perceived academic utility, EA measured awareness of verification and privacy risks, SN measured social expectations, ATT measured evaluation of responsible academic use and RGI measured future responsible-use intention. All items were rated on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree), and construct scores were calculated as item means. Responsible use was operationalised through verification of information, appropriate acknowledgement, protection of confidential information, preservation of independent academic contribution and compliance with institutional or assessment rules.

The use of multi-item construct scores reduced reliance on any single questionnaire statement and permitted the six concepts to be examined consistently across correlation, group-comparison, regression and mediation analyses. Demographic variables were retained separately for respondent profiling and group comparisons, while the construct means served as the principal analytical variables in the explanatory models.

C. Statistical Analysis

Frequency and percentage were used to describe categorical characteristics. Means and standard deviations summarised construct scores. Approximate normality was assessed through

skewness and kurtosis, using values within ± 2 as acceptable for the planned parametric analyses (George & Mallery, 2019). Internal consistency was evaluated using Cronbach's alpha, with .70 or above treated as acceptable (Nunnally & Bernstein, 1994). Pearson correlation assessed bivariate relationships among the constructs.

An independent-samples t-test compared female and male respondents; the nine respondents who selected 'prefer not to say' were excluded from this comparison. Levene's test assessed equality of variances and Hedges' g was reported as the effect-size measure. One-way ANOVA compared rarely, monthly, weekly and daily users. Eta squared represented the proportion of group variation explained, and Tukey's Honestly Significant Difference test identified significant pairwise differences in RGI.

Two Ordinary Least Squares regression models tested the principal relationships. Model 1 predicted ATT from PEOU, PU and EA. Model 2 predicted RGI from PU, ATT and SN. Standardised beta coefficients were used to compare predictor strength. Variance Inflation Factor values assessed multicollinearity and the Durbin-Watson statistic assessed residual independence. VIF values below 5 were treated as acceptable (Hair et al., 2022). Mediation was tested using the product of the PU-to-ATT and ATT-to-RGI coefficients. A 5,000-resample non-parametric bootstrap generated the 95 per cent confidence interval; mediation was supported when the interval excluded zero (Hayes, 2022).

IV. RESULTS

A. Respondent Profile

The respondent profile is presented in Table I. Female respondents constituted 53.4 per cent and male respondents 44.2 per cent. Undergraduate students represented 60.5 per cent of the sample. Commerce and Management was the largest disciplinary group at 27.0 per cent. Weekly use was the most common frequency category at 39.5 per cent, followed by daily use at 22.8 per cent.

TABLE I. RESPONDENT PROFILE

Variable	Category	Frequency	Percentage
Age group	18-20 years	115	30.1
	21-23 years	107	28.0
	24-26 years	82	21.5
	Above 26 years	78	20.4
Gender	Female	204	53.4
	Male	169	44.2
	Prefer not to say	9	2.4
Study level	Undergraduate	231	60.5
	Postgraduate	151	39.5
Discipline	Commerce and Management	103	27.0
	Education	74	19.4
	Other	54	14.1
	Arts and Humanities	69	18.1
	Social Sciences	82	21.5
GenAI use frequency	Daily	87	22.8
	Weekly	151	39.5
	Monthly	83	21.7
	Rarely	61	16.0

Note. N = 382. Percentages are rounded to one decimal place. Source: Primary survey data.

B. Descriptive Statistics, Reliability and Correlations

Construct means ranged from 3.699 for EA to 3.760 for SN. Standard deviations were close to .90. Skewness ranged from -.600 to -.448 and kurtosis from -.673 to -.266, indicating

acceptable distributional properties for the planned analyses. Cronbach's alpha ranged from .852 to .883, demonstrating satisfactory internal consistency across all six constructs.

TABLE II. DESCRIPTIVE STATISTICS, NORMALITY AND INTERNAL CONSISTENCY

Code	Construct	Mean	SD	Skewness	Kurtosis	Alpha
PEOU	Perceived Ease of Use	3.736	0.945	-0.600	-0.266	0.875
PU	Perceived Usefulness	3.750	0.929	-0.524	-0.598	0.862
EA	Ethical Awareness	3.699	0.946	-0.476	-0.586	0.879
SN	Subjective Norms	3.760	0.904	-0.448	-0.511	0.852
ATT	Attitude towards Responsible GenAI Use	3.740	0.937	-0.531	-0.541	0.883
RGI	Responsible GenAI Use Intention	3.755	0.936	-0.466	-0.673	0.882

Note. SD = Standard Deviation; Alpha = Cronbach's alpha. Each construct contains four five-point items. Source: Primary survey data.

TABLE III. PEARSON CORRELATION MATRIX

Construct	PEOU	PU	EA	SN	ATT	RGI
PEOU	1.000					
PU	0.720**	1.000				
EA	0.228**	0.312**	1.000			
SN	0.165**	0.209**	0.251**	1.000		
ATT	0.531**	0.577**	0.577**	0.244**	1.000	
RGI	0.481**	0.538**	0.503**	0.415**	0.676**	1.000

Note. N = 382. ** $p < .01$, two-tailed. Source: Primary survey data.

All reported correlations were positive and statistically significant. The strongest technology-belief relationship was between PEOU and PU ($r = .720$), while ATT and RGI were also strongly associated ($r = .676$). EA correlated .577 with ATT and .503 with RGI, indicating that ethical awareness was meaningfully related to both attitude and responsible-use intention.

C. Group Differences

No statistically significant gender difference was found for any construct. The largest difference was observed for RGI, where the female mean was 3.828 and the male mean was 3.672, $t = 1.612$, $p = .108$. Hedges' g values ranged from -.007 to .167, indicating small group differences.

TABLE IV. INDEPENDENT-SAMPLES T-TEST BY GENDER

Construct	Female M	Female SD	Male M	Male SD	t	p	Hedges g
PEOU	3.745	0.945	3.740	0.946	0.055	0.956	0.006
PU	3.745	0.911	3.751	0.959	-0.066	0.948	-0.007
EA	3.733	0.974	3.651	0.905	0.835	0.404	0.087
SN	3.806	0.866	3.703	0.955	1.099	0.272	0.114
ATT	3.797	0.890	3.685	0.976	1.154	0.249	0.120
RGI	3.828	0.987	3.672	0.868	1.612	0.108	0.167

Note. Female $n = 204$; male $n = 169$. Nine respondents who selected 'prefer not to say' were excluded from the two-group test. Source: Primary survey data.

TABLE V. ONE-WAY ANOVA BY USE FREQUENCY

Construct	Between-group SS	df	F	p	Eta squared
PEOU	60.781	3	27.392	< .001	0.179
PU	50.402	3	22.795	< .001	0.153
EA	25.207	3	10.053	< .001	0.074
SN	8.599	3	3.581	0.014	0.028
ATT	23.414	3	9.477	< .001	0.070
RGI	28.562	3	11.788	< .001	0.086

Note. ANOVA = Analysis of Variance; SS = sum of squares; df = degrees of freedom. Error $df = 378$. Source: Primary survey data.

TABLE VI. RESPONSIBLE USE INTENTION BY USE FREQUENCY AND TUKEY COMPARISONS

Group/comparison	n	Mean	SD	Mean difference	Adjusted p	Significant
Rarely	61	3.189	0.914			
Monthly	83	3.705	0.900			
Weekly	151	3.841	0.917			
Daily	87	4.052	0.854			
Daily vs Monthly				0.347	0.059	No
Daily vs Rarely				0.863	< .001	Yes

Group/comparison	n	Mean	SD	Mean difference	Adjusted p	Significant
Daily vs Weekly				0.211	0.304	No
Monthly vs Rarely				0.516	0.004	Yes
Monthly vs Weekly				-0.136	0.684	No
Weekly vs Rarely				0.653	< .001	Yes

Note. The first four rows show group summaries; remaining rows show Tukey Honestly Significant Difference comparisons. Mean difference is the first group minus the second group. Source: Primary survey data.

Use frequency produced statistically significant differences across all constructs. The largest effects occurred for PEOU, $F(3, 378) = 27.392$, $p < .001$, eta squared = .179, and PU, $F(3, 378) = 22.795$, $p < .001$, eta squared = .153. RGI also differed significantly by use frequency, $F(3, 378) = 11.788$, $p < .001$, eta squared = .086. Daily users recorded the highest RGI mean (4.052) and rare users the lowest (3.189). Tukey comparisons showed that rare users differed significantly from daily, monthly and weekly users.

TABLE VII. MULTIPLE REGRESSION PREDICTING ATTITUDE TOWARDS RESPONSIBLE USE

Predictor	B	SE B	Beta	t	p	95% CI LL	95% CI UL	VIF
PEOU	0.235	0.050	0.237	4.681	< .001	0.136	0.333	2.074
PU	0.272	0.052	0.269	5.198	< .001	0.169	0.374	2.178
EA	0.435	0.037	0.439	11.888	< .001	0.363	0.507	1.108

Note. Outcome = ATT. B = unstandardised coefficient; SE = standard error; Beta = standardised coefficient; CI = confidence interval; LL = lower limit; UL = upper limit; VIF = Variance Inflation Factor. $R^2 = .534$; adjusted $R^2 = .531$; $F(3, 378) = 144.600$, $p < .001$. Source: Primary survey data.

TABLE VIII. MULTIPLE REGRESSION PREDICTING RESPONSIBLE USE INTENTION

Predictor	B	SE B	Beta	t	p	95% CI LL	95% CI UL	VIF
PU	0.198	0.043	0.197	4.636	< .001	0.114	0.282	1.509
ATT	0.500	0.043	0.501	11.697	< .001	0.416	0.584	1.535
SN	0.261	0.037	0.252	7.048	< .001	0.188	0.334	1.071

Note. Outcome = RGI. $R^2 = .549$; adjusted $R^2 = .545$; $F(3, 378) = 153.200$, $p < .001$. Other abbreviations are defined in Table VII. Source: Primary survey data.

Model 2 explained 54.9 per cent of the variation in RGI (adjusted R squared = .545), $F(3, 378) = 153.200$, $p < .001$. ATT was the strongest predictor (beta = .501), followed by SN (beta = .252) and PU (beta = .197). All paths were statistically significant. VIF values were below 1.535 and the Durbin-Watson statistic was 1.934.

D. Regression Results

Model 1 explained 53.4 per cent of the variation in ATT (adjusted R squared = .531), $F(3, 378) = 144.600$, $p < .001$. All three predictors were statistically significant. EA was the strongest predictor (beta = .439), followed by PU (beta = .269) and PEOU (beta = .237). VIF values ranged from 1.108 to 2.178, indicating no serious multicollinearity, and the Durbin-Watson statistic was 2.060.

E. Mediation

PU positively predicted ATT and ATT positively predicted RGI after PU and SN were included in the model. The indirect effect of PU on RGI through ATT was .136, with a bootstrap 95 per cent confidence interval from .076 to .198. Because the interval excluded zero, the indirect effect was significant. The direct PU-to-RGI effect also remained significant, indicating partial mediation. The Sobel test produced $z = 4.750$, $p < .001$.

TABLE IX. MEDIATION OF PERCEIVED USEFULNESS THROUGH ATTITUDE

Effect	Path	B	SE	Test value	p	95% CI LL	95% CI UL
a path	PU → ATT	0.272	0.052	5.198	< .001		
b path	ATT → RGI	0.500	0.043	11.697	< .001		
Direct effect	PU → RGI	0.198	0.043	4.636	< .001		
Indirect effect	PU → ATT → RGI	0.136	0.030		< .001	0.076	0.198

Note. Bootstrap resamples = 5,000. The indirect-effect confidence interval excludes zero. Source: Primary survey data.

V. DISCUSSION

A. Technology Beliefs and Attitude

PEOU strongly predicted PU and also contributed to ATT, supporting the central TAM proposition that ease of use influences perceptions of usefulness (Davis, 1989). The findings are consistent with higher education studies in which ease and usefulness are important determinants of student acceptance of generative artificial intelligence (Duong et al., 2023; Shahzad et al., 2025). The strong PEOU-PU correlation also confirms that students who find the technology easier to operate tend to perceive greater academic utility.

PEOU, PU and EA all predicted ATT, but EA had the largest standardised coefficient. Ethical awareness therefore made the strongest contribution to students' evaluations of responsible-use practices. Awareness of inaccurate information, unverifiable references, privacy risks, acknowledgement

requirements and academic rules appears central to the development of responsible attitudes. This result is consistent with research emphasising authorship, transparency and ethical decision-making in the use of generative artificial intelligence (Das & Kundu, 2024; Fang & Cai, 2025).

B. Attitude, Social Norms and Responsible Use Intention

ATT was the strongest predictor of RGI, supporting TPB's view that behavioural evaluation is a major antecedent of intention (Ajzen, 1991). Students who valued verification, acknowledgement, privacy protection and independent academic effort reported stronger responsible-use intentions. Similar higher education research identifies attitudes as an important determinant of student use intentions (Foroughi et al., 2024; Haq et al., 2025).

SN also had a significant positive effect on RGI. Teachers, peers and institutions therefore contribute to the social

environment in which students interpret acceptable academic use. This result aligns with behavioural research showing that subjective norms and related social influences shape intention (Naik & Prabhu, 2025; Raghavendra, 2024). Consistent expectations across courses and assessment types can strengthen responsible-use norms and reduce ambiguity.

C. Mediation and Group Differences

PU had both direct and indirect relationships with RGI. The significant partial mediation through ATT indicates that perceived usefulness influences responsible-use intention partly through students' evaluations of responsible practice. This finding connects the technology-belief component of TAM with the attitudinal mechanism emphasised in TPB.

The combined model therefore offers a clearer explanation than either technology beliefs or behavioural factors considered in isolation. TAM contributes the perceptions that make a technology attractive or manageable, while TPB contributes the evaluative and social processes through which students form behavioural intentions. Ethical awareness strengthens this integration by introducing an academic-integrity dimension directly relevant to responsible use. The explanatory power of both regression models, each accounting for more than half of the variance in its outcome, supports the usefulness of this combined perspective.

Gender differences were not statistically significant and effect sizes were small. Use frequency, however, produced significant differences across the constructs, with rare users reporting the lowest RGI mean. Because the design is cross-sectional, these differences are interpreted as associations among respondent groups rather than as evidence of a directional causal process.

D. Practical Implications

Higher education institutions can strengthen responsible use by establishing clear assessment-specific expectations. Guidance should specify when generative artificial intelligence support is permitted, restricted or prohibited and should clarify standards for verification, acknowledgement, privacy and independent academic contribution. These expectations are particularly important because ethical awareness and attitude emerged as the strongest predictors in the two regression models.

The results also have implications for teaching practice. Rather than relying only on general institutional statements, instructors can communicate expectations at the level of the assignment. Students can be told whether the technology may be used for brainstorming, language editing, coding, summarisation or other forms of assistance, and what evidence of independent work is expected. Such specificity can strengthen subjective norms and reduce uncertainty before assessment work begins.

Responsible-use education should focus on critical evaluation rather than tool operation alone. Students need practical routines for checking factual claims and references, identifying limitations in system outputs, protecting confidential information and documenting permitted assistance. Clear institutional communication can reinforce these practices through consistent social expectations.

E. Limitations

The cross-sectional design limits causal inference and the findings reflect the characteristics of the 382 respondents included in the study. The measures are self-reported and the model focuses on responsible-use intention rather than direct observation of academic behaviour. Generalisability may therefore vary across institutions, disciplines and assessment

contexts. Future studies can incorporate longitudinal designs, behavioural measures and larger multi-institution samples.

VI. CONCLUSION

This study tested an integrated TAM-TPB model of responsible generative artificial intelligence use among 382 higher education students. PEOU, PU and EA significantly predicted ATT, while PU, ATT and SN significantly predicted RGI. EA was the strongest predictor of ATT and ATT was the strongest predictor of RGI. ATT also partially mediated the relationship between PU and RGI. Gender differences were not significant, whereas use-frequency groups differed across the constructs.

The findings establish that responsible academic use is shaped by more than technology-related convenience or utility. Ethical awareness, favourable attitudes towards responsible practice and clear social expectations make substantial contributions to students' intentions. The model therefore provides a focused explanation of how technology beliefs and academic-integrity conditions operate together in higher education.

Future research can extend the framework through longitudinal analysis, behavioural measures, perceived behavioural control, institutional policy clarity and comparisons across disciplines and institutions. Multi-group analysis can examine whether structural relationships differ by study level, discipline or institutional type, while qualitative research can clarify how students interpret verification, acknowledgement and independent contribution in different assessment settings. These extensions would deepen understanding of how responsible-use intentions translate into academic practice.

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