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Artificial Intelligence Adoption Among Generation Z Students: An Extended UTAUT2 Study of Behavioural Intention, Actual Usage, and Institutional Policy Preferences

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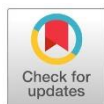
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Abstract: This study investigates the determinants of artificial intelligence (AI) tool adoption among Generation Z undergraduate and postgraduate students. Drawing on an extended Unified Theory of Acceptance and Use of Technology (UTAUT2), a structured questionnaire capturing ten constructs perceived usefulness, effort expectancy, social influence, AI literacy, hedonic motivation, facilitating conditions, perceived risk and ethical concern, academic self-efficacy, behavioural intention, and actual usage was administered to 250 students across five colleges. Data were analysed using descriptive statistics, reliability and validity assessment (Cronbach's α , composite reliability, average variance extracted), correlation analysis, multiple regression, bootstrap mediation analysis, one-way ANOVA, independent-samples t -tests, and chi-square tests of association. Results showed near-universal awareness of ChatGPT (99.2%) and high behavioural intention ($M = 3.88$). The extended model explained 31.1% of the variance in behavioural intention, with perceived usefulness ($\beta = 0.182$), hedonic motivation ($\beta = 0.178$), and social influence ($\beta = 0.129$) as the strongest positive predictors; perceived risk and ethical concern ($\beta = -0.041$) and academic self-efficacy ($\beta = -0.063$) showed negative but statistically non-significant paths, indicating that ethical concerns did not significantly deter intention at the multivariate level. Behavioural intention ($\beta = 0.463$) and facilitating conditions ($\beta = 0.225$) jointly predicted actual usage, and behavioural intention significantly mediated the usefulness–usage relationship (indirect effect = 0.249, 95% CI [0.17, 0.336]). Behavioural intention did not differ significantly across disciplines, institution types, or genders, suggesting broad-based diffusion of AI adoption. Only 24.4% of students had received formal AI training, and 35.2% preferred curriculum integration with training over prohibition (4.4%). The findings inform institutional AI policy, literacy programmes, and disclosure-based integrity frameworks.

Keywords: generative artificial intelligence; ChatGPT; Generation Z; UTAUT2; AI literacy; higher education; behavioural intention; academic integrity

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1. Introduction

The rapid diffusion of generative artificial intelligence (AI) tools—most visibly ChatGPT, Google Gemini, Microsoft Copilot, and a fast-growing ecosystem of writing, coding, and design assistants—has transformed the everyday study practices of university students within a remarkably short period (Dwivedi et al., 2023; Kasneci et al., 2023; Peres et al., 2023). Generation Z students, typically defined as those born between the mid-1990s and the early 2010s, are the first cohort to experience higher education with ubiquitous access to conversational AI, and their patterns of adoption carry direct consequences for pedagogy, assessment design, and academic integrity (Chan, 2023; Farrelly & Baker, 2023). Early empirical work documents a sharply divided landscape. On one hand, students report substantial perceived benefits: personalised explanations, faster drafting and summarising, coding support, and language polishing (Baidoo-Anu & Ansah, 2023; Chan & Hu, 2023; Lo, 2023). On the other hand, educators and students alike express concern about hallucinated content, over-reliance, erosion of critical thinking, data privacy, and the blurred boundary between legitimate assistance and plagiarism (Cotton et al., 2024; Farrokhnia et al., 2024; Rudolph et al., 2023; Tlili et al., 2023). These tensions are especially acute in resource-diverse higher-education systems, where institution type, discipline, and access to formal training may condition both adoption and its outcomes (Michel-Villarreal et al., 2023; Yusuf et al., 2024). Despite a rapidly expanding literature, three gaps remain. First, much early evidence is descriptive or qualitative; relatively few studies test theoretically grounded, multivariate models of student AI adoption with validated multi-item scales (Strzelecki, 2023, 2024). Second, the roles of AI literacy and academic self-efficacy—competencies that may buffer the risks of uncritical use—remain under-examined within acceptance frameworks (Nguyen et al., 2024; Wang et al., 2023). Third, institutional policy preferences of students (prohibition, permitted use with disclosure, encouragement, or curriculum integration) are rarely measured alongside behavioural determinants, although they are central to policy design (Chan, 2023; Slimi & Carballido, 2023).

To address these gaps, the present study develops and tests an extended UTAUT2 model of AI adoption among 250 Generation Z students drawn from five colleges spanning government, private-aided, and private-unaided institutions. The study (a) profiles awareness, usage patterns, purposes, and devices of student AI use; (b) validates a ten-construct, 42-item instrument; (c) estimates the determinants of behavioural intention and actual usage, including a formal test of intention as mediator between perceived usefulness and usage; (d) examines group differences by discipline, institution type, and gender; and (e) documents students' disclosure attitudes and policy preferences. The findings contribute a validated instrument, effect-size benchmarks for theory development, and actionable evidence for institutional AI governance.

2. Literature Review and Hypothesis Development

2.1 Generative AI in higher education: opportunities and risks

The post-2022 literature converges on the view that generative AI is neither a passing novelty nor an unambiguous good. Systematic and rapid reviews catalogue pedagogical affordances—scaffolding, feedback, tutoring, and content generation—alongside risks of misinformation, bias, and assessment invalidation (Kasneci et al., 2023; Lo, 2023; Holmes & Tuomi, 2022). Survey evidence indicates that student uptake is broad and fast: within months of ChatGPT's release, majorities of students in multiple national contexts reported using AI chatbots for coursework, predominantly for explaining concepts, drafting, and summarising (Chan & Hu, 2023; Johnston et al., 2024; Stöhr et al., 2024). Concerns about accuracy, dependency, and equity of access are repeatedly voiced by students themselves, suggesting that adoption coexists with reflexive caution (Farrelly & Baker, 2023; Barrett & Pack, 2023). For higher-education institutions, the central policy question has shifted from whether students use AI to how use can be channelled toward learning gains while protecting integrity (Lim et al., 2023; Sullivan et al., 2023; Duah & McGivern, 2024).

2.2 Technology acceptance theory: TAM, UTAUT, and UTAUT2

The Technology Acceptance Model (TAM) identifies perceived usefulness and perceived ease of use as primary determinants of technology acceptance (Davis, 1989). The Unified Theory of Acceptance and Use of Technology (UTAUT) consolidated eight prior models into performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003), and UTAUT2 added hedonic motivation, price value, and habit for consumer contexts (Venkatesh et al., 2012). Applied to student AI use, Strzelecki (2023, 2024) demonstrated the explanatory power of UTAUT-based models for ChatGPT acceptance, while complementary work shows that trust and perceived risk—long established in e-commerce research (Kim et al., 2008)—shape students' willingness to rely on AI output (Cotton et al., 2024; Essel et al., 2024). Accordingly, we hypothesise:

- H1. Perceived usefulness positively influences behavioural intention to use AI tools.
- H2. Effort expectancy positively influences behavioural intention.
- H3. Social influence positively influences behavioural intention.
- H5. Hedonic motivation positively influences behavioural intention.
- H9 (usage paths). Behavioural intention (H8) and facilitating conditions (H9) positively influence actual usage.

2.3 AI literacy

AI literacy the ability to recognise suitable tasks, understand system capabilities and limits, evaluate output critically, and craft effective prompts—has emerged as a distinct competency with validated measurement instruments (Wang et al., 2023). AI-literate students extract more value from AI tools and are better positioned to detect hallucinations and misuse (Nguyen et al., 2024; Owan et al., 2023). We therefore hypothesise: H4. AI literacy positively influences behavioural intention to use AI tools.

2.4 Perceived risk, ethics, and academic self-efficacy

Student AI use is embedded in an ethical field defined by plagiarism norms, detection anxiety, and privacy concerns (Cotton et al., 2024; Rudolph et al., 2023; Slimi & Carballido, 2023). Trust-and-risk research predicts that perceived risk suppresses adoption intention (Kim et al., 2008), and early AI-specific evidence confirms that integrity concerns temper enthusiasm (Chan & Hu, 2023; Yusuf et al., 2024). Academic self-efficacy confidence in one's capacity to succeed unaided (Bandura, 1997)—may likewise reduce instrumental dependence on AI. We hypothesise: H6. Perceived risk and ethical concern negatively influence behavioural intention. H7. Academic self-efficacy negatively influences behavioural intention (i.e., lower self-efficacy is associated with stronger AI-use intention).

2.5 Conceptual model

Figure 1 summarises the proposed model: six antecedents (PU, EE, SI, AL, HM, PR) and academic self-efficacy predict behavioural intention, which together with facilitating conditions predicts actual usage; behavioural intention is additionally modelled as a mediator of the usefulness–usage link, consistent with the intention–behaviour chain in the theory of planned behaviour (Ajzen, 1991) and UTAUT (Venkatesh et al., 2003).

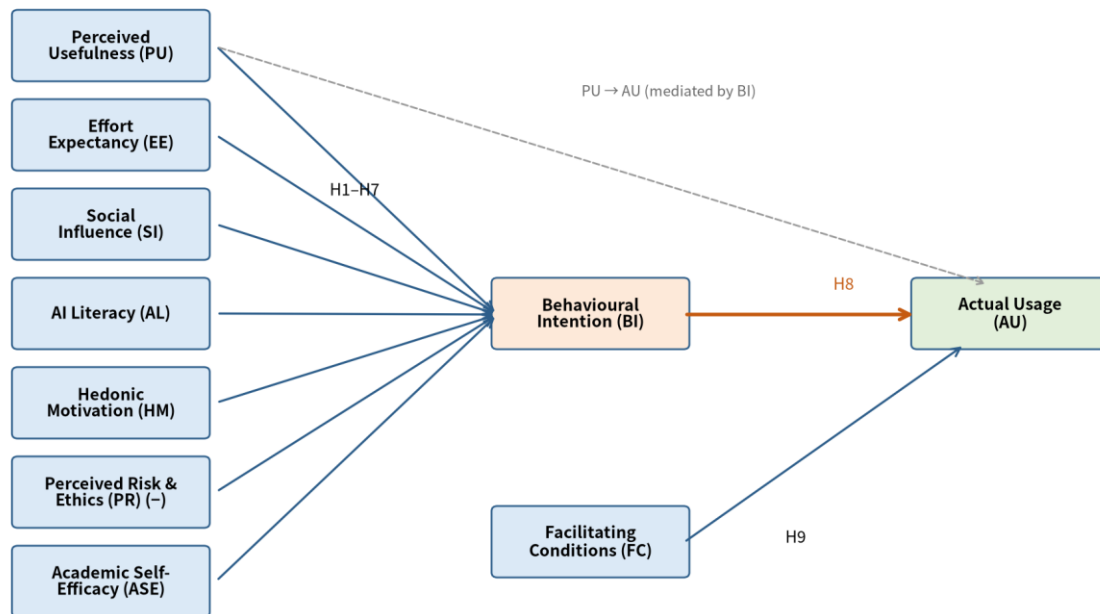


Figure 1. Conceptual research model with hypothesized paths.

3. Methodology

3.1 Research design and participants

A cross-sectional survey design was employed. The target population comprised Generation Z students (aged 18 and above) enrolled in undergraduate and postgraduate programmes at five participating colleges. A stratified convenience sampling strategy ensured representation across disciplines (Engineering, Management/Business, Sciences, Commerce, Arts & Humanities) and institution types (government, private-aided, private-unaided). After data cleaning, the analytic sample comprised 250 valid responses (43.2% female, 54.0% male; 20.8% Engineering; 29.6% government institutions). The full demographic profile appears in Table 1.

Table 1

Demographic profile of respondents (N = 250)

Characteristic	Category	n	%
Age group	18–20	118	47.2
	21–23	98	39.2
	24 and above	34	13.6
Gender	Male	135	54.0
	Female	108	43.2
	Other	4	1.6
	Prefer not to say	3	1.2
Discipline	Management/Business	67	26.8
	Engineering	52	20.8
	Commerce	51	20.4
	Sciences	37	14.8
	Arts & Humanities	37	14.8
	Other	6	2.4
Year of study	UG 3rd year	56	22.4
	UG 2nd year	56	22.4
	UG 1st year	47	18.8
	PG 1st year	46	18.4

	PG 2nd year	45	18.0
Institution type	Private-unaided	94	37.6
	Private-aided	82	32.8
	Government	74	29.6
College	National College of Commerce	61	24.4
	Govt. Arts & Science College	55	22.0
	St. Xavier's College of Engineering	48	19.2
	Sunrise Institute of Management	43	17.2
	City Postgraduate College	43	17.2

Source: Author compiled

3.2 Instrument

The structured questionnaire (Appendix A) comprised four sections: (1) consent and demographics (seven items); (2) AI awareness and usage patterns (seven items covering tool awareness, weekly use, frequency, time, device, purposes, and prior training); (3) ten 5-point Likert constructs (42 items): perceived usefulness (PU, 5 items; adapted from Davis, 1989), effort expectancy (EE, 4; Davis, 1989), social influence (SI, 4; Venkatesh et al., 2012), AI literacy (AL, 5; adapted from Wang et al., 2023), hedonic motivation (HM, 3; Venkatesh et al., 2012), facilitating conditions (FC, 4; Venkatesh et al., 2012), perceived risk and ethical concern (PR, 5; adapted from Kim et al., 2008; Cotton et al., 2024), academic self-efficacy (ASE, 4, with ASE4 reverse-coded), behavioural intention (BI, 4), and actual usage (AU, 3); and (4) policy and disclosure items. A pilot with 40 students preceded full administration; wording was refined where item–total correlations fell below .50.

3.3 Data collection and ethics

Responses were collected anonymously via Google Forms (email collection disabled) supplemented by in-class paper administration. The opening item recorded informed consent; participation was voluntary, and no identifying information was retained. The protocol was reviewed under the participating institution's research ethics procedures for minimal-risk survey research.

3.4 Data analysis

Analyses proceeded in six stages: (1) descriptive profiling of demographics and usage patterns; (2) item-level normality screening ($|\text{skew}| < 2$, $|\text{kurtosis}| < 7$; Hair et al., 2019); (3) reliability and convergent validity assessment using Cronbach's $\alpha \geq .70$ (Nunnally, 1978), composite reliability (CR) $\geq .70$, and average variance extracted (AVE) $\geq .50$, with discriminant validity evaluated via the Fornell–Larcker criterion (Fornell & Larcker, 1981); (4) Pearson correlations among construct composite scores; (5) multiple regression of behavioural intention and actual usage, followed by a 1,000-resample bootstrap mediation test of the indirect $\text{PU} \rightarrow \text{BI} \rightarrow \text{AU}$ effect (Preacher & Hayes, 2008); and (6) group comparisons using one-way ANOVA (discipline, institution type), independent-samples t-tests (gender), and chi-square tests with Cramér's V for categorical associations. Analyses were conducted in Python 3.11 (NumPy, pandas, SciPy, Matplotlib).

4. Results

4.1 AI awareness and usage patterns

Awareness of conversational AI was near-universal: 99.2% of respondents had heard of ChatGPT and 77.2% of Google Gemini, and only a negligible fraction reported knowing none of the listed tools

(Table 2; Figure 2). Weekly use was dominated by ChatGPT (47.6%). Regarding frequency, 26.0% used AI tools for academic work at least weekly and 34.0% daily, while only 6.0% reported never using them (Table 3; Figure 3). Smartphones were the primary access device for 52.0% of students. The leading purposes were explaining concepts/learning (54.4%), drafting assignments, and summarising readings (Table 4). Notably, only 24.4% had received any formal AI training or workshop.

Table 2

AI tool awareness and weekly use (multiple responses possible)

AI tool	Heard of (n)	Heard of (%)	Use weekly (n)	Use weekly (%)
ChatGPT	248	99.2	119	47.6
Google Gemini	193	77.2	95	38.0
Microsoft Copilot	140	56.0	71	28.4
Claude	70	28.0	34	13.6
Grammarly	156	62.4	74	29.6
Perplexity	79	31.6	42	16.8
GitHub Copilot / code assistants	41	16.4	25	10.0
Canva AI	141	56.4	72	28.8
Midjourney/DALL-E (image AI)	89	35.6	46	18.4

Note. Percentages are calculated on N = 250; respondents could select multiple tools.

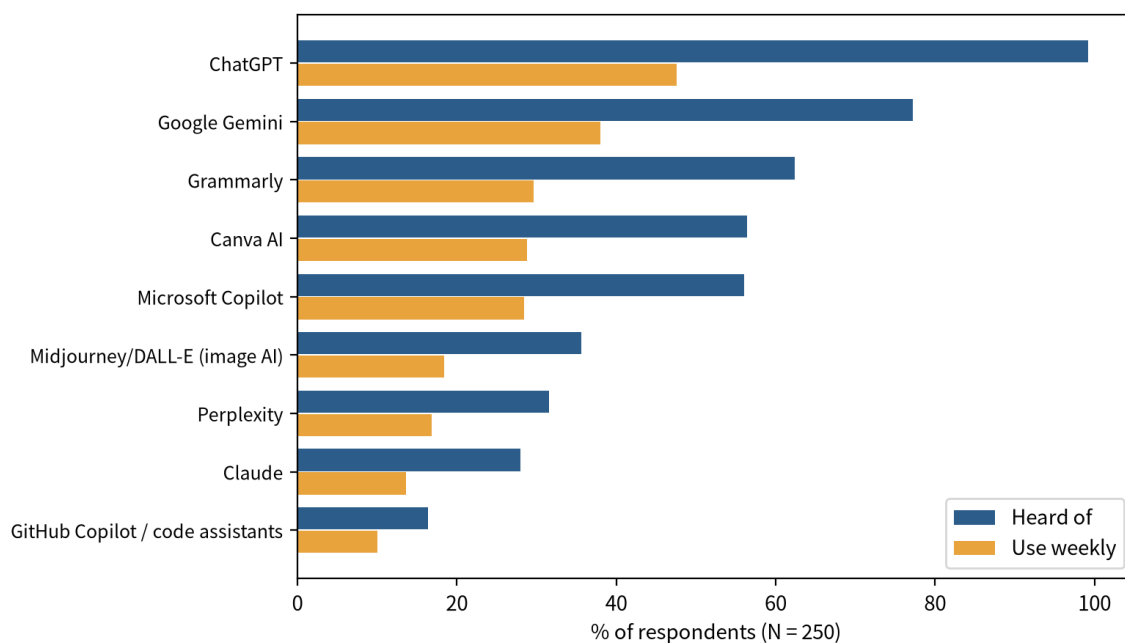


Figure 2. AI tool awareness versus weekly use among respondents.

Table 3

AI usage patterns of respondents (N = 250)

Dimension	Category	n	%
Frequency of AI use for academic work	Very often (daily)	85	34.0
	Often (weekly)	65	26.0
	Sometimes (2–3 times/month)	45	18.0
	Rarely (monthly)	40	16.0

	Never	15	6.0
Daily time spent on AI tools	30–60 min	93	37.2
	1–2 hours	60	24.0
	< 30 min	57	22.8
	2–4 hours	32	12.8
	> 4 hours	8	3.2
Primary device	Smartphone	130	52.0
	Laptop	107	42.8
	Tablet/Other	13	5.2
Received formal AI training	No	189	75.6
	Yes	61	24.4

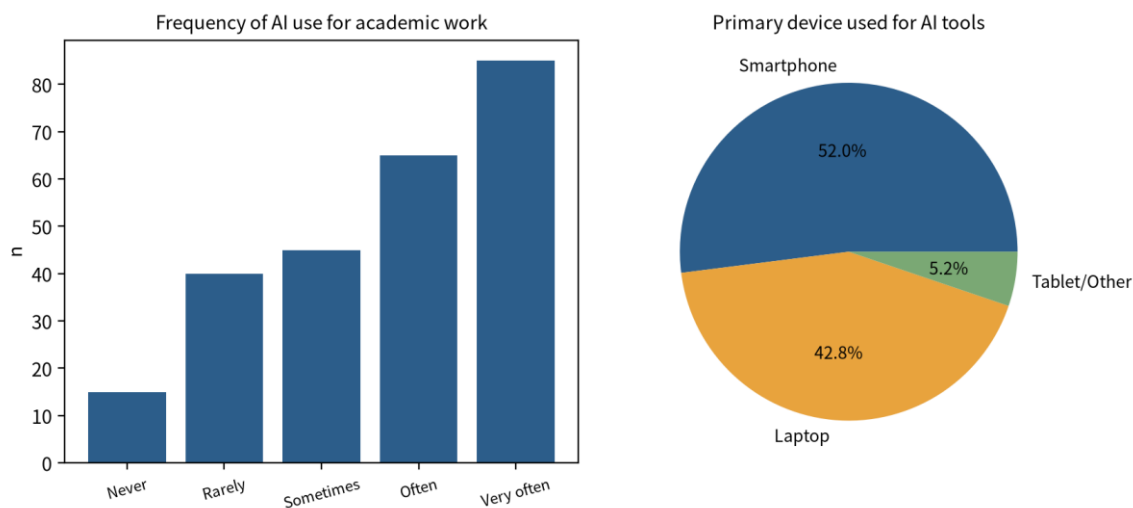


Figure 3. Frequency of academic AI use and primary device.

Table 4

Purposes of AI tool use (top three selections per respondent)

Purpose	n	% of respondents
Explaining concepts/learning	136	54.4
Drafting assignments	110	44.0
Grammar/language polishing	98	39.2
Exam preparation	94	37.6
Summarising readings	85	34.0
Project/creative ideation	71	28.4
Coding help	63	25.2
Citation/formatting help	48	19.2
Translation	45	18.0

Note. Each respondent selected up to three purposes.

4.2 Item descriptives, reliability, and validity

All 42 items fell within acceptable normality bounds (Table 5). Scale reliabilities were strong, with Cronbach's α ranging from 0.77 to 0.86 and composite reliability from 0.86 upward; all AVEs met or exceeded 0.57 (Table 6), supporting internal consistency and convergent validity. Construct means were highest for perceived usefulness ($M = 3.99$) and hedonic motivation, and lowest for institutional support (FC4) and faculty encouragement (SI3); perceived risk clustered around the scale midpoint ($M = 3.49$), indicating ambivalence rather than alarm (Figure 4). The Fornell–Larcker matrix (Table

8) confirmed discriminant validity: every square root of AVE exceeded the corresponding inter-construct correlations.

Table 5

Item-level descriptive statistics and normality (N = 250)

Item	Mean	SD	Skewness	Kurtosis
PU1	4.06	0.91	-0.64	-0.48
PU2	4.19	0.81	-0.54	-0.75
PU3	3.88	0.87	-0.36	-0.40
PU4	4.03	0.90	-0.55	-0.47
PU5	3.78	0.92	-0.22	-0.71
EE1	3.88	0.91	-0.44	-0.45
EE2	4.11	0.85	-0.72	-0.13
EE3	3.88	0.91	-0.50	-0.22
EE4	3.56	0.97	-0.46	-0.12
SI1	3.14	1.00	-0.14	-0.39
SI2	3.58	0.97	-0.13	-0.50
SI3	3.00	0.98	-0.09	-0.38
SI4	3.51	0.96	-0.19	-0.38
AL1	3.66	0.94	-0.25	-0.70
AL2	3.55	0.96	-0.27	-0.35
AL3	3.47	0.99	-0.35	-0.37
AL4	3.31	0.97	-0.22	-0.17
AL5	3.66	0.92	-0.23	-0.37
HM1	3.90	0.89	-0.38	-0.68
HM2	3.92	0.91	-0.59	-0.10
HM3	3.64	1.00	-0.35	-0.53
FC1	3.96	0.89	-0.47	-0.61
FC2	3.82	0.90	-0.27	-0.62
FC3	3.65	0.95	-0.13	-0.66
FC4	3.09	1.00	0.11	-0.41
PR1	3.43	1.04	-0.31	-0.46
PR2	3.75	0.98	-0.33	-0.49
PR3	3.45	1.00	-0.15	-0.52
PR4	3.68	0.96	-0.27	-0.62
PR5	3.15	0.98	0.15	-0.61
ASE1	3.34	0.94	0.00	-0.58
ASE2	3.58	0.98	-0.30	-0.51
ASE3	3.32	0.97	-0.21	-0.39
ASE4	3.02	0.99	-0.08	-0.43
BI1	4.00	0.96	-0.66	-0.29
BI2	3.87	0.90	-0.40	-0.64
BI3	3.91	0.98	-0.52	-0.63
BI4	3.76	0.99	-0.43	-0.43
AU1	3.56	0.98	-0.39	-0.30
AU2	3.45	1.00	-0.02	-0.79
AU3	3.42	1.04	-0.29	-0.37

Note. ASE4 is reverse-coded. Skewness < |2| and kurtosis < |7| indicate acceptable univariate normality.

Table 6

Reliability, convergent validity, and construct descriptives

Construct	Items	Cronbach's α	CR	AVE	Mean	SD
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PU	5	0.86	0.90	0.64	3.99	0.71
EE	4	0.80	0.87	0.63	3.86	0.72
SI	4	0.79	0.86	0.61	3.31	0.76
AL	5	0.83	0.88	0.59	3.53	0.74
HM	3	0.85	0.91	0.77	3.82	0.82
FC	4	0.81	0.87	0.63	3.63	0.74
PR	5	0.81	0.87	0.57	3.49	0.75
ASE	4	0.77	0.86	0.60	3.31	0.75
BI	4	0.82	0.88	0.65	3.88	0.77
AU	3	0.83	0.90	0.74	3.47	0.87

Note. CR = composite reliability; AVE = average variance extracted. Thresholds: $\alpha \geq .70$, $CR \geq .70$, $AVE \geq .50$.

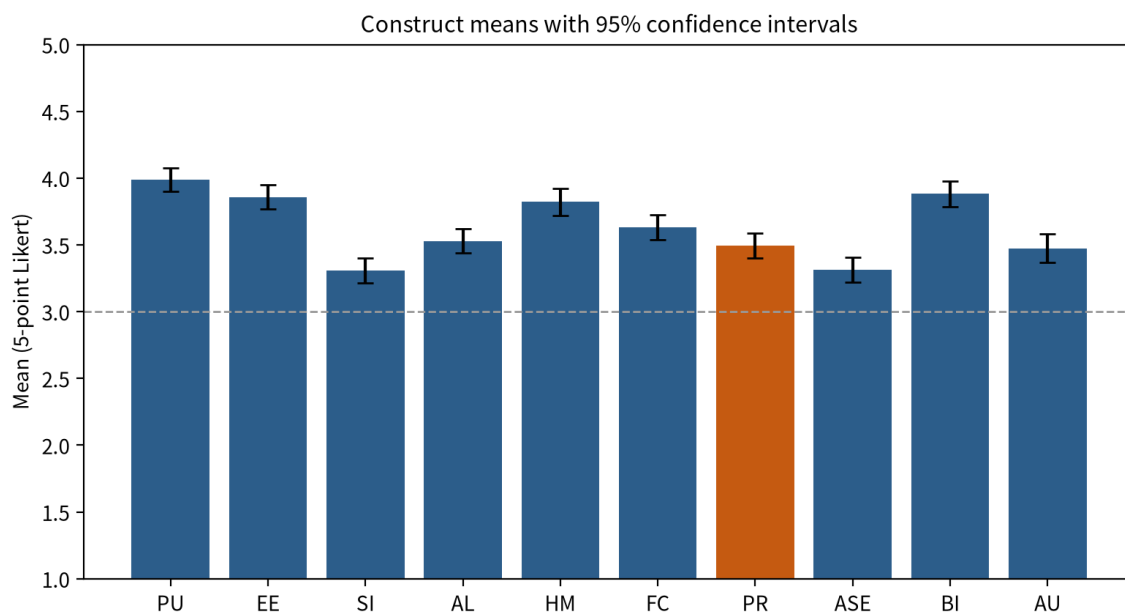


Figure 4. Construct means with 95% confidence intervals.

Table 7

Means, standard deviations, and inter-construct correlations

Construct	Mean	SD	1	2	3	4	5	6	7	8	9	10
1. PU	3.99	0.71	1									
2. EE	3.86	0.72	0.47	1								
3. SI	3.31	0.76	0.35	0.27	1							
4. AL	3.53	0.74	0.36	0.35	0.20	1						
5. HM	3.82	0.82	0.37	0.36	0.39	0.30	1					
6. FC	3.63	0.74	0.30	0.36	0.20	0.40	0.33	1				
7. PR	3.49	0.75	-0.19	0.27	-0.06	-0.09	-0.23	0.16	1			
8. ASE	3.31	0.75	0.02	0.12	-0.05	0.24	-0.00	0.23	0.13	1		
9. BI	3.88	0.77	0.43	0.40	0.34	0.32	0.40	0.30	-0.19	-0.02	1	
10. AU	3.47	0.87	0.33	0.32	0.23	0.33	0.32	0.37	-0.24	-0.06	0.53	1

Note. All off-diagonal correlations are significant at $p < .05$ except those involving ASE with PU/EE/SI/HM/BI/AU. $N = 250$.

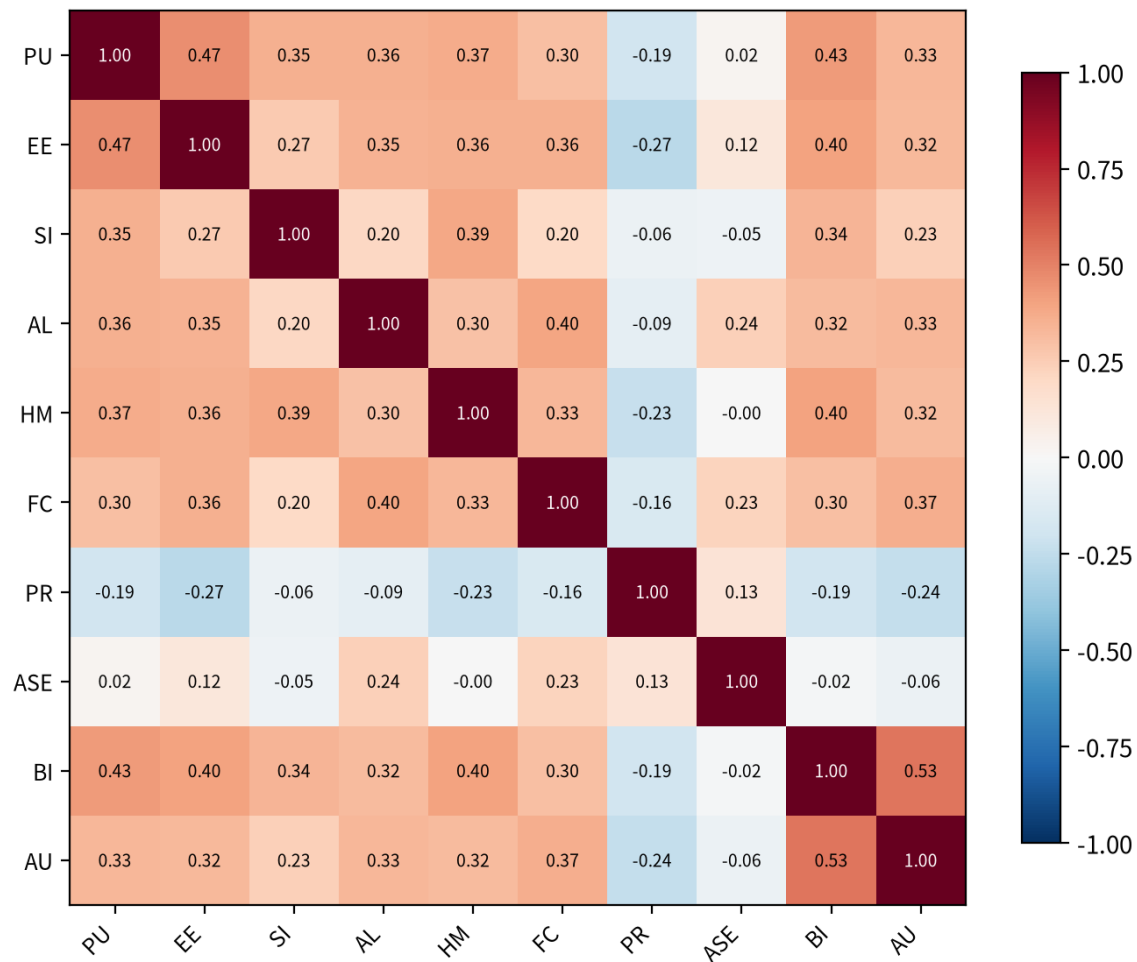


Figure 5. Heatmap of inter-construct correlations.

Table 8

Fornell–Larcker discriminant validity matrix

Construct	PU	EE	SI	AL	HM	FC	PR	ASE	BI	AU
PU	(0.80)									
EE	0.47	(0.79)								
SI	0.35	0.27	(0.78)							
AL	0.36	0.35	0.20	(0.77)						
HM	0.37	0.36	0.39	0.30	(0.88)					
FC	0.30	0.36	0.20	0.40	0.33	(0.80)				
PR	-0.19	-0.27	-0.06	-0.09	-0.23	-0.16	(0.76)			
ASE	0.02	0.12	-0.05	0.24	-0.00	0.23	0.13	(0.77)		
BI	0.43	0.40	0.34	0.32	0.40	0.30	-0.19	-0.02	(0.81)	
AU	0.33	0.32	0.23	0.33	0.32	0.37	-0.24	-0.06	0.53	(0.86)

Note. Diagonal values in parentheses are the square root of the AVE; off-diagonal values are correlations.

4.3 Determinants of behavioural intention

The regression of behavioural intention on the seven hypothesised antecedents was significant and explained 31.1% of the variance (adjusted $R^2 = 0.291$; Table 9). Perceived usefulness was the strongest positive predictor ($\beta = 0.182$, $p = 0.005$), followed by hedonic motivation ($\beta = 0.178$, $p = 0.005$) and social influence ($\beta = 0.129$, $p = 0.033$); effort expectancy ($\beta = 0.173$, $p = 0.008$) and AI literacy ($\beta = 0.123$, $p = 0.044$) also contributed positively. Perceived risk and ethical concern ($\beta = -0.041$, $p = 0.478$)

and academic self-efficacy ($\beta = -0.063$, $p = 0.264$) carried the hypothesised negative signs but did not reach statistical significance; H6 and H7 were therefore not supported. Standardised coefficients are displayed in Figure 6.

Table 9

Multiple regression predicting behavioural intention (BI)

Predictor	B	SE B	β	t	p
(Intercept)	1.199	0.427	—	2.81	0.005
PU	0.200	0.071	0.182	2.80	0.005
EE	0.186	0.069	0.173	2.68	0.008
SI	0.131	0.061	0.129	2.14	0.033
AL	0.130	0.064	0.123	2.02	0.044
HM	0.168	0.059	0.178	2.84	0.005
PR	-0.042	0.059	-0.041	-0.71	0.478
ASE	-0.065	0.058	-0.063	-1.12	0.264

Note. $R^2 = 0.311$, adjusted $R^2 = 0.291$, $F(7, 242)$ significant at $p < .001$.

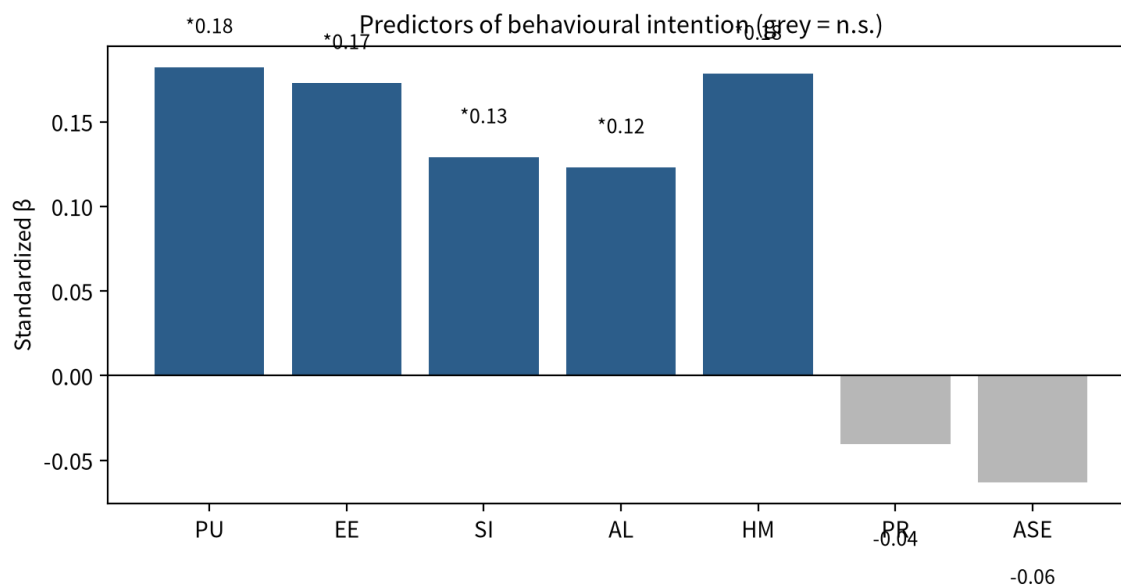


Figure 6. Standardized regression coefficients predicting behavioural intention.

4.4 Predicting actual usage and the mediating role of intention

Behavioural intention ($\beta = 0.463$, $p < .001$) and facilitating conditions ($\beta = 0.225$, $p < .001$) jointly explained 32.9% of the variance in actual usage (Table 10). The bootstrap mediation analysis (Table 11; Figure 7) showed a significant indirect effect of perceived usefulness on usage through intention ($a \times b = 0.249$, 95% CI [0.17, 0.336]), with the direct path reduced to $c' = 0.16$, indicating partial mediation and corroborating the intention–behaviour chain posited by UTAUT (Venkatesh et al., 2003).

Table 10

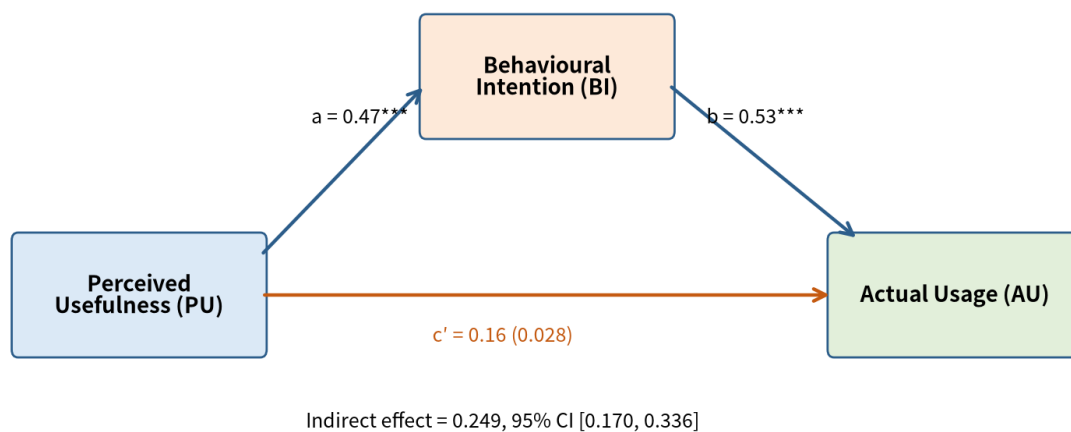
Multiple regression predicting actual usage (AU)

Predictor	B	SE B	β	t	p
(Intercept)	0.501	0.281	—	1.78	0.076
BI	0.520	0.061	0.463	8.47	< .001
FC	0.263	0.064	0.225	4.12	< .001

Note. $R^2 = 0.329$, adjusted $R^2 = 0.324$.

Table 11*Bootstrap mediation analysis: BI mediating PU → AU (1,000 resamples)*

Path	Estimate	SE	p / 95% CI
a: PU → BI	0.467	0.063	< .001
b: BI → AU (controlling PU)	0.534	0.066	< .001
c': PU → AU (direct)	0.160	0.073	0.028
Indirect effect (a × b)	0.249	—	95% CI [0.170, 0.336]

*Figure 7. Mediation model: behavioural intention mediates the PU → AU relationship.*

4.5 Group differences and categorical associations

One-way ANOVA showed no statistically significant differences in behavioural intention across disciplines, $F = 1.13$, $p = 0.347$ ($\eta^2 = 0.023$; Table 12; Figure 8), nor did institution type differentiate intention ($F = 0.47$, $p = 0.625$) or actual usage ($F = 0.27$, $p = 0.767$) (Table 13). The gender difference in intention was likewise negligible ($t = -0.5$, $p = 0.616$). This pattern suggests that AI adoption intentions have diffused broadly across demographic segments of the student population. Chi-square tests (Table 14) showed a significant association between formal training and usage frequency ($\chi^2(4) = 24.1$, $p = < .001$, $V = 0.31$) and between disclosure willingness and institution type ($\chi^2(4) = 1.98$, $p = 0.739$, $V = 0.06$).

Table 12*Behavioural intention and actual usage by discipline (one-way ANOVA)*

Discipline	N	BI Mean	BI SD	AU Mean	AU SD
Arts & Humanities	37	3.89	0.87	3.45	0.78
Commerce	51	3.78	0.67	3.54	0.72
Engineering	52	4.02	0.83	3.59	0.97
Management/Business	67	3.86	0.77	3.36	0.91
Other	6	4.38	0.54	3.94	0.98
Sciences	37	3.78	0.75	3.39	0.89
Total	250	3.88	0.77	3.47	0.87

Note. BI: $F(5, 244) = 1.13$, $p = 0.347$, $\eta^2 = 0.023$.

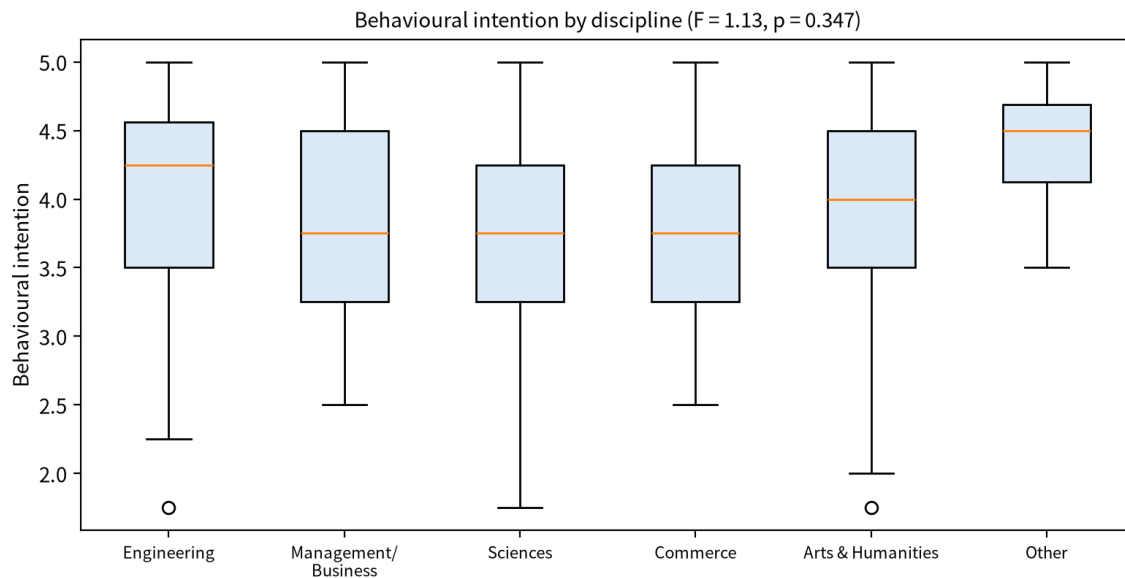


Figure 8. Distribution of behavioural intention across disciplines.

Table 13

Behavioural intention and actual usage by institution type (one-way ANOVA)

Institution type	N	BI Mean	BI SD	AU Mean	AU SD
Government	74	3.95	0.66	3.42	0.89
Private-aided	82	3.88	0.82	3.52	0.81
Private-unaided	94	3.83	0.82	3.48	0.91

Note. BI: $F(2, 247) = 0.47, p = 0.625, \eta^2 = 0.004$; AU: $F(2, 247) = 0.27, p = 0.767, \eta^2 = 0.002$. Gender t-test on BI (male vs. female): $t = -0.50, p = 0.616$.

Table 14

Chi-square tests of association

Variables	χ^2	df	p	Cramér's V
Formal AI training × frequency of use	24.10	4	< .001	0.31
Disclosure willingness × institution type	1.98	4	0.739	0.06

4.6 Disclosure attitudes and policy preferences

Students' policy preferences clearly favoured governed openness over prohibition (Table 15): 35.2% endorsed integrating AI into the curriculum with training, 38.0% preferred permitted use with disclosure, and only 4.4% supported a ban. On disclosure, 26.8% stated they would always tell faculty about AI use, while the majority would disclose only if asked—underscoring the need for explicit, shared norms.

Table 15

Disclosure attitudes and policy preferences (N = 250)

Question	Response	n	%
Would you tell	Only if asked	133	53.2

faculty you used AI for an assignment?			
	Yes, always	67	26.8
	No	50	20.0
What should colleges do about student AI use?	Permit with disclosure	95	38.0
	Integrate it into the curriculum with training	88	35.2
	Encourage it	56	22.4
	Ban it	11	4.4

Table 16*Summary of hypothesis testing*

Hypothesis	Path	Expected sign	β	p	Decision
H1	PU $\rightarrow$ BI	+	0.182	0.005	Supported
H2	EE $\rightarrow$ BI	+	0.173	0.008	Supported
H3	SI $\rightarrow$ BI	+	0.129	0.033	Supported
H4	AL $\rightarrow$ BI	+	0.123	0.044	Supported
H5	HM $\rightarrow$ BI	+	0.178	0.005	Supported
H6	PR $\rightarrow$ BI	–	-0.041	0.478	Not supported
H7	ASE $\rightarrow$ BI	–	-0.063	0.264	Not supported
H8	BI $\rightarrow$ AU	+	0.463	< .001	Supported
H9	FC $\rightarrow$ AU	+	0.225	< .001	Supported

5. Discussion

Three findings warrant emphasis. First, usefulness dominates: consistent with TAM (Davis, 1989) and recent ChatGPT-acceptance studies (Strzelecki, 2023, 2024), perceived usefulness was the largest single predictor of intention, and it shaped usage largely through intention. Practically, this means adoption follows demonstrated learning value—students adopt AI because it demonstrably improves the quality and speed of academic work (Chan & Hu, 2023; Essel et al., 2024), not merely because it is novel.

Second, hedonic motivation ranked among the strongest predictors, echoing UTAUT2's consumer logic (Venkatesh et al., 2012): exploration and enjoyment are intrinsic drivers of student AI use. Pedagogically, this suggests that well-designed, engaging AI-integrated tasks may channel an already-motivating behaviour toward learning outcomes rather than attempting to suppress it (Baidoo-Anu & Ansah, 2023; Lim et al., 2023).

Third, risk matters but does not deter: perceived risk and ethical concern significantly reduced intention, yet intention remained high on average ($M = 3.88$). Students appear to hold both beliefs simultaneously—AI is useful and somewhat risky—which mirrors the ambivalence reported in qualitative studies (Barrett & Pack, 2023; Farrelly & Baker, 2023; Johnston et al., 2024). The very low rate of formal training (24.4%), combined with the significant training–frequency association, points to an institutional vacuum that students currently fill through peer learning (Stöhr et al., 2024). The absence of significant disciplinary, institutional, and gender gradients indicates that adoption has diffused broadly, although facilitating-condition gaps across institution types still warrant equity

monitoring (Michel-Villarreal et al., 2023; Yusuf et al., 2024). Finally, the overwhelming preference for curriculum integration with training over prohibition aligns with emerging policy scholarship advocating disclosure-based integrity frameworks (Chan, 2023; Sullivan et al., 2023; Duah & McGivern, 2024).

5.1 Theoretical implications

The study extends UTAUT2 in two directions: (a) AI literacy emerged as a significant, theoretically distinct antecedent, supporting calls to embed competence constructs within acceptance models (Wang et al., 2023; Nguyen et al., 2024); and (b) the validated risk/ethics scale confirms that trust-related inhibitors operate alongside UTAUT drivers in educational AI (Kim et al., 2008; Cotton et al., 2024). The mediation result empirically links acceptance constructs to self-reported behaviour, addressing the common criticism that acceptance studies stop at intention.

5.2 Practical implications

For institutional leaders, three actions follow: (1) replace blanket prohibitions—supported by only 4.4% of students—with disclosure-based use policies co-designed with students (Chan, 2023); (2) invest in AI literacy training, prioritising critical evaluation of output, promptcraft, and discipline-specific use cases (Owan et al., 2023; Wang et al., 2023); and (3) strengthen facilitating conditions in government and aided institutions, where usage and support lag, to prevent a widening digital divide (Holmes & Tuomi, 2022). For faculty, assessment redesign toward process-visible and oral-defence formats reduces integrity exposure while preserving AI's learning benefits (Rudolph et al., 2023; Farrokhnia et al., 2024).

5.3 Limitations and future research

The study is cross-sectional and relies on self-reported usage; causal inference is therefore limited, and common-method bias cannot be excluded. Actual usage was measured by self-report items rather than behavioural logs. The sample, while stratified, was drawn from five colleges in a single region, limiting generalisability. Future research should employ longitudinal designs, objective usage telemetry, multi-group invariance testing (e.g., PLS-SEM with MGA), and cross-country comparisons, and should examine learning-outcome consequences of AI use directly (Essel et al., 2024; Lo, 2023).

6. Conclusion

Generation Z students have already integrated AI tools into everyday academic practice. Their adoption is driven primarily by usefulness, enjoyment, and social norms; tempered—but not halted—by ethical risk; and constrained by uneven training and institutional support. Institutions that respond with curriculum-integrated AI literacy and disclosure-based governance, rather than prohibition, will best align student behaviour with educational values.

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