Journal of Education and Learning Reviews, 3 (6): November-December 2026. ISSN: 3057-0387
Website: https://so19.tci-thaijo.org/index.php/JELS/about
Article ID: e4077

Generative AI Misuse and Rule Compliance Among University Students in Bhutan: Implications for Assessment and Institutional AI Policy

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Received 04/10/2026	Revised 03/11/2026	Accepted 10/11/2026

Abstract

Background and Aim: Generative artificial intelligence (AI) use is expanding in Bhutanese universities while institutional policies remain under development. Guided by an extended Theory of Planned Behavior, this study examined factors associated with unauthorized AI use and intention to comply with institutional AI policies.

Materials and Methods: An anonymous, cross-sectional survey was conducted in June 2026 among a convenience sample of 713 Bhutanese university students. Seven-point Likert-type responses were analyzed using factor analyses, reliability assessments, correlations with false discovery rate correction, multiple and moderated regression, and bootstrapped indirect association tests. Robustness checks included robust standard errors and demographic controls.

Results: The models explained 24.5% of variance in AI misuse and 19.6% in compliance intention. Approximately 29% of respondents endorsed at least one misuse item. Misuse was associated with misuse acceptability, AI familiarity, academic pressure, moral rationalization, rule clarity, subjective norms, and learning impact. Compliance intention was associated with subjective norms, rule clarity, behavioral control, productive AI use, institutional enforcement, and moral rationalization. Institutional enforcement showed a small independent association with compliance intention ($\beta = .086$). Compliance intention was inversely associated with misuse ($B = -0.10$, $p = .004$). All six indirect associations were small, with bootstrap confidence intervals excluding zero. Demographic adjustment preserved findings; academic level showed no significant moderation.

Conclusion: Findings support evaluating assignment-specific AI guidance, coordinated workloads, classroom discussion of misuse rationalizations, and communicated institutional policies. Cross-sectional data preclude causal inference, and convenience sampling limits generalizability. These associations provide a basis for evaluating approaches to responsible AI governance.

Keywords: Generative Artificial Intelligence; Academic Integrity; Assessment Design; Higher Education Policy; Bhutan

Introduction

Generative artificial intelligence has become part of ordinary student life across higher education, and Bhutan is no exception. Dorji (2026) found that 88.2% of surveyed lecturers at Bhutanese higher education institutions had observed students using generative AI in academic work, in line with a global survey in which 71% of more than 23,000 students across 109 countries and territories had already used ChatGPT by early 2024 (Ravšelj et al., 2025). Adoption has outpaced institutions' capacity to define, communicate, and enforce expectations about appropriate use (Cotton et al., 2024), a gap that matters because institutional policies and climate shape students' integrity decisions (McCabe et al., 2001). Where rules are unclear, students are left to decide for themselves which uses count as legitimate assistance and which count as misconduct. The Theory of Planned Behavior (TPB; Ajzen, 1991), which holds that intention and behavior are shaped by attitudes, subjective norms, and perceived behavioral control, has been applied to student cheating for more than three decades (Beck & Ajzen, 1991; Harding et al., 2007) and, more recently, to AI-related misconduct (Baig & Paparo, 2026; Koscielniak et al., 2026; Senali, 2026).

None of these TPB studies of AI misuse examined whether a national values-education policy relates to students' decisions. Bhutan offers a setting in which that question arises. Since 2010, its schools and colleges have operated under the Educating for Gross National Happiness (EdGNH) policy, which asks teachers to infuse Gross National Happiness (GNH) values, honesty among them, into their academic subjects and extracurricular programs (Gyamtso et al., 2017). Most participants in the present study (mean age 21) have been schooled under this policy since their early school years, although the

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oldest were already in secondary school when it began. Generative AI has also not arrived in a governance vacuum. Bhutan is well connected, with internet penetration of 88.4% by early 2025 (Kemp, 2025), and the Royal University of Bhutan (RUB) has been reported to be drafting policy on generative AI in academic writing (Dendup, 2024). The country therefore combines high connectivity, a national values-education policy, and AI governance that is under construction rather than mature or absent.

This study asks whether the attitudinal, normative, and institutional factors that predict AI misuse elsewhere operate the same way in this setting. It forms part of a larger multi-country study of generative AI misuse among university students, earlier reports of which examined students in Myanmar and Iraq (Swanson, 2026a, 2026b). It applies the extended TPB model used in the Myanmar companion study to two outcomes: self-reported generative AI misuse and intention to comply with institutional AI policy. The model adds institutional enforcement, drawing on McCabe et al. (2001), and moral rationalization, drawing on Sykes and Matza's (1957) neutralization theory, alongside academic pressure. Existing Bhutanese evidence comes from a mixed-methods survey of 76 lecturers (Dorji, 2026) and a focus-group study of 180 students' perspectives at five Royal University of Bhutan colleges (Tamang et al., 2026). Neither model predicts student misuse nor uses TPB or a comparable framework, and a search of the literature found no published study of these predictors among Bhutanese university students. Beyond testing whether the model extends to Bhutan, the study describes the balance of predictors in a setting with a national values-education policy. Because EdGNH exposure was not measured, it cannot test whether that policy accounts for any differences from prior work.

These questions are practical as well as theoretical. Every course that sets written work now has to decide which uses of AI are allowed, and every institution has to decide how to communicate and enforce those decisions. Bhutanese lecturers have already begun redesigning assessments and relying on detection software while reporting that institutional guidance is lacking (Dorji, 2026), and a study of students at five RUB colleges recommended comprehensive policy frameworks for ethical AI use (Tamang et al., 2026). Knowing which conditions are associated with students' AI misuse and their willingness to follow AI rules can help teachers decide where to put their effort, whether in clearer assignment instructions, in assessment schedules, or in classroom discussion, and can help institutions such as RUB decide what their emerging policies should emphasize. In this way, the study contributes to research on AI in education, on assessment practice, and on higher education governance.

Objectives

The study aimed to (1) identify the attitudinal, normative, and institutional factors associated with self-reported generative AI misuse (AI Misuse) among Bhutanese university students; (2) identify the factors associated with their intention to comply with institutional AI policy (Compliance Intention); (3) explore whether Compliance Intention carries indirect associations between those factors and AI Misuse and whether academic level moderates the association between Misuse Acceptability and AI Misuse; and (4) translate these findings into implications for assessment design, course-level AI policy, and institutional governance in Bhutanese higher education.

Literature Review

Generative AI and academic integrity: Global context

Research on generative AI in higher education has documented both enthusiasm and unease. Hong Kong students held broadly favorable views of generative AI as a learning aid but raised concerns about accuracy, privacy, ethics, and effects on their personal development (Chan & Hu, 2023). In a 109-country survey, students called for AI regulation over concerns about cheating, plagiarism, and social isolation, and doubted ChatGPT's value for developing critical thinking (Ravšelj et al., 2025). Yusuf et al. (2024), surveying 1,217 respondents across 76 countries, found that views of generative AI's benefits and concerns, including its potential for academic dishonesty, were strongly correlated with cultural orientation. Across these studies, enthusiasm about generative AI and concern about its misuse sit side by side rather than in opposition.

Other work proposes institutional responses. Cotton et al. (2024) recommended combining clear policies, training and support, and methods to detect and prevent cheating, although AI-text

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detectors remain too unreliable to serve as the sole basis for misconduct decisions (Hadra et al., 2026). Jayasinghe et al. (2026) distilled six intervention themes from 96 articles, among them policy and governance, faculty development, and assessment adaptation, and Issa and Hall (2024) reported that a teamwork-based assessment framework reduced misconduct while building collaborative skills. Perkins et al. (2024) proposed the AI Assessment Scale, which asks educators to set the level of generative AI use permitted in each assessment according to its learning outcomes, giving students and staff a shared reference point. Teachers have also responded to AI-assisted work by adding oral questioning, in-class tasks, and performance-based assessment to make student thinking visible (Mendiola et al., 2026), and generative AI weakens the reliability of product-based assessment unless it is supported by process evidence, supervised production, and disclosure of AI use (Verri, 2026). Policy clarity recurs across these proposals, in part because students disagree about how serious different AI-assisted practices are (Lund et al., 2025).

These dynamics are not confined to well-resourced Western universities. Surveying 262 students at nine Nigerian institutions through the lens of Prospect Theory, Ogbaga et al. (2026) found that AI-related ethical decisions reflected a weighing of risk and reward in which low perceived detection risk and academic pressure often outweighed potential sanctions. Knowing the rules and following them are different things once pressure is high and detection seems unlikely. In Ghana, a mixed-methods study of 12 universities found that none had a formal, publicly accessible AI policy, which left assessment practices inconsistent and raised concerns about fairness and accountability (Adjei et al., 2026), and Malaysian university students who reported learning benefits from AI tools also called for clearer institutional guidelines on their use (Ismail & Maharani, 2026).

Higher education, connectivity, and values education in Bhutan

Bhutan's higher education system is young and centralized. The Royal University of Bhutan, established by royal decree in 2003, comprises nine constituent colleges and two affiliated private colleges (Royal University of Bhutan, n.d.-a), including Sherubtse College, the College of Natural Resources, Gyalpozhing College of Information Technology, and the Paro and Samtse Colleges of Education (Royal University of Bhutan, n.d.-b). The wider sector includes health sciences, nursing, and law institutions outside RUB (Dorji, 2026). Connectivity is comparatively high: internet penetration reached 88.4% by early 2025, and mobile connections equaled 100% of the population, although 54.7% of Bhutanese live in rural areas (Kemp, 2025), across mountainous terrain with dispersed settlements. Access to generative AI is therefore not mainly a question of infrastructure.

What distinguishes Bhutan is the formal place of values education. The EdGNH policy, introduced into schools and colleges in 2010, rests on the GNH development philosophy first articulated by the Fourth King in the early 1970s and asks teachers to infuse GNH values, honesty among them, across their teaching (Gyamtso et al., 2017). Implementation has been uneven, and that unevenness is itself informative. Earlier studies found it problematic in schools, and a study of 66 teacher educators at RUB's two colleges of education, some six years after the policy began, concluded that lecturers still needed to build EdGNH into their modules and strengthen their own knowledge of GNH values (Gyamtso et al., 2017). Values education, including honesty, is therefore official policy in Bhutan, but it has not been shown that this policy reliably shapes student attitudes or behavior.

AI-specific governance is emerging. In mid-2024, RUB was reported to be drafting generative AI regulations for academic writing that would go beyond plagiarism rules, with the draft awaiting presentation to its Academic Board (Dendup, 2024). In Dorji's (2026) survey, only 21.0% of lecturers agreed that their institution had guidelines on responsible generative AI use, and nearly 80% disagreed or were neutral. Lecturers called for institutional policy; many relied on detection tools such as Turnitin and Copyleaks, although some doubted their effectiveness, including for content in local languages such as Dzongkha. At the time of the most recent evidence, clear and consistently perceived classroom-level rules were not yet in place.

Regional perspectives: South Asia

Evidence from South Asia is emerging. In Nepal, students interviewed by Ghimire et al. (2024) viewed ChatGPT positively for learning and writing but acknowledged its misuse and reported harms to their creativity, writing habits, and independent research skills. As in the global literature, students

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treated the benefits and risks of generative AI not as contradictory but as two faces of the same tool. In Bangladesh, students interviewed by Hasib and Islam (2025) found ChatGPT useful, but some had devised ways to bypass plagiarism detection systems, while Atikuzzaman and Ahmed (2025), studying plagiarism in general rather than generative AI, examined how demographic variables relate to university students' attitudes toward plagiarism. A targeted search found no comparable peer-reviewed studies of generative AI and academic integrity in India or Sri Lanka, so the regional evidence remains concentrated in a few countries.

Research gap

Taken together, this literature shows that generative AI is reshaping academic integrity across very different higher education systems and that TPB, often augmented with institutional-enforcement and rationalization constructs, is a widely used framework for explaining how students navigate it. The Bhutanese evidence, however, stops short of modeling student misuse: the two existing studies describe lecturers' perceptions and students' views of benefits and challenges (Dorji, 2026; Tamang et al., 2026). The wider South Asian literature is concentrated in Nepal and Bangladesh (Ghimire et al., 2024; Hasib & Islam, 2025). Applying a TPB-based instrument to Bhutanese students therefore addresses a specific gap in a setting with a national values-education policy that this line of research has not yet examined.

Conceptual Framework

TPB (Ajzen, 1991) provides the study's core lens. It has predicted students' dishonest intentions and self-reported behavior since its earliest applications (Beck & Ajzen, 1991; Harding et al., 2007), and models that add cheating justifications to the core constructs have accounted for 47% (Stone et al., 2009) and 40.8% (Rajah-Kanagasabai & Roberts, 2015) of the variance in self-reported misconduct. Following this precedent, Moral Rationalization is treated here as distinct from attitudes.

Applied to generative AI, positive attitudes toward misconduct and AI, together with subjective norms, predicted intention to misuse AI tools, while a higher perceived likelihood of detection predicted lower intention (Baig & Paparo, 2026). In a pre-registered study of 2,883 students from 15 countries, an extended TPB model accounted for 18.7% of the variance in whether students reported any intention to misuse AI and 47.8% of the variance in the intensity of that intention, and past misconduct also predicted both (Koscielniak et al., 2026); Senali (2026) linked instructor involvement, detection awareness, AI-related risk perceptions, and perceived behavioral control to Australian students' contract-cheating intentions and behavior; and in the Philippines, Giray et al. (2026) used TPB to explore students' motivations for cheating on writing tasks with generative AI. The Institutional Enforcement construct draws on McCabe et al.'s (2001) review, which found that contextual factors, above all peers' behavior, shape cheating more than individual factors do, and that institutional policies such as honor codes can significantly influence it. This matters especially in Bhutan, where AI-specific institutional policy is still being developed.

Moral Rationalization draws on Sykes and Matza's (1957) account of neutralization, in which people invoke justifications such as denial of responsibility or denial of injury to reconcile rule-breaking with a self-image as honest. Hawdon et al. (2026) found that cheating-specific and general cyber-neutralization techniques, along with deviant peers, predicted AI-assisted cheating among U.S. undergraduates, and Huang et al. (2025) found in focus groups that peer influence and personal ethics strongly shaped cheating with generative AI and that students looked to instructors' class policies more than to institutional ones. Where students have been taught under EdGNH to treat honesty as a value, neutralization may need to work harder, or take different forms, than elsewhere, although this study's data can speak to that possibility only indirectly, since EdGNH exposure was not measured.

Several of the model's constructs also correspond to conditions that teachers and institutions can influence, which makes the framework useful for educational practice as well as for theory. Rule Clarity reflects how clearly courses and institutions state what AI use is allowed, something set in course outlines and assignment briefs. Institutional Enforcement reflects whether rules are seen to be applied consistently, a matter of institutional governance. Academic Pressure reflects workload and deadlines, which assessment design and scheduling shape. Behavioral Control reflects students' confidence that they can complete work without AI, which depends partly on the skills that teaching builds. Subjective

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Norms and Moral Rationalization reflect the classroom and peer climate around integrity, which teachers can address directly. Linking each construct to a lever in this way allows the results to be read as guidance for assessment, course policy, and institutional governance, while recognizing that cross-sectional associations cannot show that changing a lever will change behavior.

The study tests two hypotheses. H1: AI Misuse will be predicted by AI Familiarity (positively), Rule Clarity (negatively), Misuse Acceptability (positively), Subjective Norms (negatively), Moral Rationalization (positively), Academic Pressure (positively), and Behavioral Control (negatively). H2: Compliance Intention will be predicted by Rule Clarity, Subjective Norms, and Institutional Enforcement (all positively), Moral Rationalization (negatively), and Behavioral Control (positively). Productive AI Use and Learning Impact were included as exploratory predictors of both outcomes without directional hypotheses, given the absence of prior grounds for predicting their sign in this context. The mediation and moderation analyses were likewise exploratory and carried no formal hypotheses.

Methodology

Research design

The study used a quantitative, cross-sectional survey design. As in the companion study, AI Misuse and Compliance Intention were treated as related but distinct outcomes and modeled separately. Data were collected with an anonymous, self-administered questionnaire of seven-point Likert-type items (1 = strongly disagree, 7 = strongly agree), with demographic items covering age, gender, year and field of study, institution, and self-reported academic performance.

Participants

A total of 713 students from Bhutanese higher education institutions completed the questionnaire. All passed the embedded attention check, and no responses had missing data, so the full sample was retained. Participants were 18 to 31 years old (M = 21.32, SD = 2.17); 51.3% were female, 46.0% were male, and 2.7% did not disclose their gender. Most attended public institutions (86.4%). Years 1 to 4 were evenly represented (22.0% to 22.7% each), and graduate students made up 10.4%. Most respondents described their institution as teaching-focused (69.1%), with smaller shares describing it as research-intensive (8.3%) or saying they were unsure (22.6%). STEM was the largest field of study (27.2%), followed by Social Sciences (18.5%), Business/Economics (17.4%), Other (15.3%), Humanities (12.6%), and Medicine/Health (9.0%). Most rated their academic performance as average (47.4%) or above average (26.8%). Table 1 gives the full sample characteristics.

Table 1: Participant Characteristics (N = 713)

Characteristic	Category	n	%
Gender	Female	366	51.3
	Male	328	46.0
	Prefer not to say	19	2.7
Year of Study	Year 1	157	22.0
	Year 2	162	22.7
	Year 3	162	22.7
	Year 4	158	22.2
	Graduate	74	10.4
Field of Study	STEM	194	27.2
	Social Sciences	132	18.5
	Business / Economics	124	17.4
	Other	109	15.3
	Humanities	90	12.6
	Medicine / Health	64	9.0
Institution Type	Public	616	86.4
	Private	97	13.6
Institution Focus	Teaching-focused	493	69.1

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Characteristic	Category	n	%
	Not sure	161	22.6
	Research-intensive	59	8.3
Academic Performance (self-reported)	Average	338	47.4
	Above average	191	26.8
	Below average	74	10.4
	Top 10%	62	8.7
	Prefer not to say	48	6.7

Note. Age ranged from 18 to 31 years (M = 21.32, SD = 2.17). Percentages may not sum to 100 because of rounding.

Instrument

The questionnaire was adapted from the instrument used in the companion study (Swanson, 2026a) and measured the twelve constructs defined in Table 2. Composite scores were computed by averaging each construct's items after recoding reverse-coded items. Item F6, which asked whether respondents knew classmates who had misused AI, was excluded from the AI Misuse composite because it captures peers' behavior rather than the respondent's own. An embedded attention-check item (AC1) directed participants to select a specified response. Because of social-desirability concerns, the AI Misuse items were preceded by a statement that there were no right or wrong answers. Exact item wordings and reverse-coded items are listed in Supplementary Table S1.

Table 2: Construct Definitions

Construct	Items	Conceptual Definition
AI Familiarity	B1–B3	Students' self-reported knowledge of, comfort with, and prior exposure to generative AI tools.
Rule Clarity	C1–C3	Students' perceived clarity of their institution's rules and expectations governing acceptable AI use.
Productive AI Use	D1–D4	Students' self-reported use of AI tools for legitimate academic support, such as brainstorming, editing, or explaining concepts.
Learning Impact	E1–E3	Students' perceptions of how using AI affects their own learning, skill development, and academic growth.
AI Misuse	F1–F5 (F6 excluded from composite)	Students' self-reported engagement in unauthorized uses of AI for coursework, such as submitting AI-generated work as their own.
Misuse Acceptability	G1–G4	Students' general attitudes toward how acceptable or justifiable unauthorized AI use is, independent of institutional rules.
Subjective Norms	H1–H4	Students' perceptions of whether peers and other important people approve or disapprove of unauthorized AI use.
Institutional Enforcement	I1–I4	Students' perceptions of how consistently and effectively their institution enforces AI-related academic integrity policies.
Moral Rationalization	J1–J4	Students' tendency to justify, minimize, or excuse unauthorized AI use through neutralizing beliefs.
Academic Pressure	K1–K4	Students' perceived workload, performance pressure, and time constraints related to coursework.
Behavioral Control	L1–L3	Students' perceived confidence and ability to complete academic work successfully without relying on AI.
Compliance Intention	M1–M3	Students' stated intention to follow their institution's policies governing appropriate AI use.

Procedure

The questionnaire was built in KoboToolbox and distributed to students at participating institutions as a non-probability convenience sample, mainly via QR code, since Bhutan's comparatively high connectivity allowed mainly digital distribution. Printed copies were also offered given Bhutan's terrain and dispersed settlement. Because English is the medium of instruction in

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Bhutanese higher education, the questionnaire was administered in English. Data were collected in June 2026.

Data analysis

Analyses were conducted in Python, using pandas and NumPy for data handling, statsmodels for the regression models and diagnostics, SciPy for statistical tests, scikit-learn for the principal component analysis, factor_analyzer for the exploratory factor analysis, and maximum-likelihood estimation in SciPy for the CFA. The data were screened for completeness, attention-check performance, and entry errors. The measurement structure was tested with a twelve-factor confirmatory factor analysis (CFA), supplemented by an exploratory factor analysis with oblique (oblimin) rotation. Convergent and discriminant validity were assessed with composite reliability (CR), average variance extracted (AVE), the Fornell–Larcker criterion (Fornell & Larcker, 1981), and the heterotrait–monotrait ratio (HTMT; Henseler et al., 2015), and common method variance with Harman's single-factor test (Podsakoff et al., 2003) and a marker-variable adjustment (Lindell & Whitney, 2001). Reliability was assessed with Cronbach's alpha and with McDonald's omega computed from the CFA loadings (McDonald, 1999), followed by Pearson correlations with a Benjamini–Hochberg false discovery rate (FDR) correction (Benjamini & Hochberg, 1995). Two multiple regression models, with AI Misuse and Compliance Intention as outcomes, each included the other ten constructs as predictors; significance was judged at a two-tailed $\alpha = .05$, and multicollinearity was checked with variance inflation factors (VIFs). Because 20 coefficients were tested across the two models, their p-values were also checked with a Benjamini–Hochberg correction, and both models were re-estimated with heteroscedasticity-robust (HC3) standard errors and with demographic controls. Assumptions were checked with the Shapiro–Wilk test (Shapiro & Wilk, 1965), the Breusch–Pagan test (Breusch & Pagan, 1979), Cook's distance (Cook, 1977), and Mahalanobis distance (Tabachnick & Fidell, 2019), and a sensitivity analysis estimated the smallest interaction detectable with 80% power (Cohen, 1988). A moderated regression tested whether academic level moderated the association between Misuse Acceptability and AI Misuse, and indirect associations through Compliance Intention were tested with percentile bootstrap confidence intervals (5,000 resamples; Preacher & Hayes, 2008), with Sobel tests (Sobel, 1982) reported for comparison.

Ethical considerations

The study was an anonymous, non-interventional survey. Before recruitment, the president and the faculty member responsible for research at each participating institution authorized the study. Participation was voluntary; respondents were told the study's purpose, that their responses were anonymous, and that they could withdraw at any time. No identifying information was collected. Completing and submitting the questionnaire after reading this information was taken as consent. The author was informed that Bhutan has no formal research ethics policy applicable to this study, which is why permission was sought from each participating university.

Results

Measurement structure

A twelve-factor CFA, in which each of the 44 items used in the composites (all substantive items except F6) loaded only on its assigned construct, fit the data well: $\chi^2(836) = 1{,}000.02$, $p < .001$, CFI = .982, TLI = .980, RMSEA = .017, SRMR = .031. The significant chi-square is expected with $N = 713$, and the other indices meet conventional cutoffs (CFI and TLI $\geq .95$, RMSEA $\leq .06$; Hu & Bentler, 1999). Standardized loadings ranged from .54 to .81, all $p < .001$. A supplementary exploratory factor analysis of all 45 substantive items (maximum likelihood, oblimin rotation, 12 factors) supported the intended structure: every item loaded most strongly on its assigned construct's factor, and no cross-loading exceeded .11. F6 loaded on the AI Misuse factor but more weakly than F1 to F5 (.39 vs. .58 to .74), consistent with its exclusion from the composite. CR ranged from .739 to .820. AVE ranged from .466 to .531 and fell slightly below the .50 benchmark for eight constructs, so convergent validity is modest, although CR exceeded .70 for every construct. Discriminant validity was supported: the square root of each construct's AVE (minimum .683) exceeded the largest factor correlation (.406), and

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no HTMT ratio exceeded .41, well under the .85 threshold (Henseler et al., 2015). Full CFA and EFA loadings, CR, AVE, and HTMT values are given in Supplementary Tables S2 to S4.

Common method bias

In Harman's single-factor test, an unrotated principal component analysis of all 45 items produced a first component explaining 12.6% of the variance, well below the 50% threshold commonly used in practice; the first five components together explained 37.9%. Because the test is insensitive and cannot rule out common method variance (Podsakoff et al., 2003), this result is a minimal screen rather than conclusive evidence. As a further check, a marker-variable adjustment using the smallest positive correlation among the constructs ($r = .01$) as the estimate of method variance (Lindell & Whitney, 2001) changed no correlation by more than .01, and every correlation that was significant before the adjustment remained so.

Reliability and descriptive statistics

Cronbach's alpha ranged from .735 (Rule Clarity) to .819 (AI Misuse), so every scale cleared the conventional .70 threshold, including the three-item Behavioral Control ($\alpha = .759$) and Compliance Intention ($\alpha = .747$) scales (Table 3). McDonald's omega, computed from the CFA standardized loadings, tracked alpha closely (.739 to .820), so the reliability estimates do not depend on alpha's tau-equivalence assumption. All scales also cleared .70 in the companion study ($\alpha = .715$ to .789; Swanson, 2026a). Productive AI Use, Behavioral Control, and Compliance Intention had the highest means, and Misuse Acceptability and AI Misuse the lowest, suggesting little personal engagement in unauthorized use alongside favorable views of legitimate use and rule-following. The below-midpoint Rule Clarity mean is consistent with the limited AI-specific guidance described in the most recent available evidence (Dendup, 2024; Dorji, 2026). Skewness and kurtosis showed no substantial departures from normality. In terms of prevalence, 29.2% of students at least slightly agreed (5 to 7) with one or more of the five misuse items and 8.4% agreed or strongly agreed (6 or 7) with at least one, whereas 61.7% at least slightly agreed that they knew classmates who had misused AI (item F6).

Table 3: Reliability and Descriptive Statistics ($N = 713$)

Construct	Items	α	*M*	*SD*	Skew	Kurtosis
AI Familiarity	3	.772	5.04	0.98	−0.17	−0.30
Rule Clarity	3	.735	3.72	1.03	−0.03	−0.39
Productive AI Use	4	.784	5.24	0.93	−0.33	−0.06
Learning Impact	3	.748	4.31	1.01	−0.03	−0.35
AI Misuse	5[1]	.819	2.90	0.93	0.27	−0.26
Misuse Acceptability	4	.781	2.39	0.84	0.46	−0.29
Subjective Norms	4	.784	4.83	0.93	−0.23	−0.39
Institutional Enforcement	4	.816	4.21	1.03	−0.04	−0.15
Moral Rationalization	4	.776	3.67	0.96	−0.01	−0.15
Academic Pressure	4	.787	4.99	0.96	−0.15	−0.31
Behavioral Control	3	.759	5.08	0.98	−0.14	−0.46
Compliance Intention	3	.747	5.07	0.97	−0.26	−0.35

Note. AI Misuse is based on items F1 to F5; item F6 was excluded from the composite.

Correlations

Given 66 pairwise tests, correlations were corrected for FDR, and 34 of the 36 correlations significant at raw $p < .05$ survived (Supplementary Table S7). Misuse Acceptability ($r = .33$), Moral Rationalization ($r = .27$), and Academic Pressure ($r = .25$) correlated most strongly with AI Misuse. Subjective Norms correlated negatively with AI Misuse ($r = −.20$) and was the strongest correlate of Compliance Intention ($r = .29$). Institutional Enforcement correlated weakly with AI Misuse ($r = −.08$), an association that did not survive FDR correction (adjusted $p = .058$), and more strongly with Compliance Intention ($r = .19$).

Predictors of AI Misuse

The model predicted AI Misuse significantly, $R^2 = .245$, adjusted $R^2 = .234$, $F(10, 702) = 22.81$, $p < .001$ (Table 4). Misuse Acceptability was the strongest predictor ($\beta = .215$, $p < .001$), followed by

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Journal of Education and Learning Reviews, 3 (6): November-December 2026. ISSN: 3057-0387
Website: https://so19.tci-thaijo.org/index.php/JELS/about
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AI Familiarity (β = .163, $p < .001$), Rule Clarity (β = −.163, $p < .001$), Academic Pressure (β = .156, $p < .001$), and Moral Rationalization (β = .146, $p < .001$). Subjective Norms (β = −.098, $p = .005$) and Learning Impact (β = −.096, $p = .006$) were negatively associated with AI Misuse. Productive AI Use, Institutional Enforcement, and Behavioral Control were not significant predictors.

Table 4: Multiple Regression Predicting AI Misuse ($N = 713$)

Predictor	β	*B*	*SE*	*t*	*p*	95% CI	VIF
AI Familiarity	.163	0.155	0.033	4.705	< .001	[0.091, 0.220]	1.12
Rule Clarity	−.163	−0.147	0.031	−4.798	< .001	[−0.208, −0.087]	1.08
Productive AI Use	.027	0.027	0.036	0.743	.458	[−0.044, 0.099]	1.23
Learning Impact	−.096	−0.088	0.032	−2.746	.006	[−0.152, −0.025]	1.13
Misuse Acceptability	.215	0.240	0.040	6.060	< .001	[0.162, 0.318]	1.17
Subjective Norms	−.098	−0.097	0.035	−2.810	.005	[−0.165, −0.029]	1.12
Institutional Enforcement	−.023	−0.021	0.032	−0.669	.504	[−0.083, 0.041]	1.13
Moral Rationalization	.146	0.142	0.035	4.084	< .001	[0.074, 0.210]	1.18
Academic Pressure	.156	0.152	0.034	4.530	< .001	[0.086, 0.218]	1.11
Behavioral Control	−.015	−0.015	0.032	−0.458	.647	[−0.077, 0.048]	1.05

Note. β = standardized coefficient; *B* = unstandardized coefficient; CI = confidence interval for B; VIF = variance inflation factor.

Predictors of Compliance Intention

The model also predicted Compliance Intention significantly, $R^2 = .196$, adjusted $R^2 = .184$, $F(10, 702) = 17.07$, $p < .001$ (Table 5). Subjective Norms (β = .200, $p < .001$) and Rule Clarity (β = .188, $p < .001$) were the strongest positive predictors, followed by Behavioral Control (β = .105, $p = .002$), Productive AI Use (β = .095, $p = .012$), and Institutional Enforcement (β = .086, $p = .016$, $sr^2 = .007$, about 0.7% of unique variance). Moral Rationalization was negatively associated (β = −.135, $p < .001$). AI Familiarity, Learning Impact, Misuse Acceptability, and Academic Pressure were not significant. Institutional Enforcement and Behavioral Control therefore predicted Compliance Intention but not AI Misuse, whereas in the companion study both predicted both outcomes (Swanson, 2026a). This cross-study contrast sets significant coefficients beside non-significant ones and was not formally tested.

Table 5: Multiple Regression Predicting Compliance Intention ($N = 713$)

Predictor	β	*B*	*SE*	*t*	*p*	95% CI	VIF
AI Familiarity	.031	0.030	0.035	0.858	.391	[−0.039, 0.100]	1.12
Rule Clarity	.188	0.177	0.033	5.355	< .001	[0.112, 0.241]	1.08
Productive AI Use	.095	0.099	0.039	2.524	.012	[0.022, 0.175]	1.23
Learning Impact	.056	0.054	0.035	1.560	.119	[−0.014, 0.122]	1.13
Misuse Acceptability	−.041	−0.047	0.042	−1.116	.265	[−0.131, 0.036]	1.17
Subjective Norms	.200	0.207	0.037	5.565	< .001	[0.134, 0.280]	1.12
Institutional Enforcement	.086	0.082	0.034	2.407	.016	[0.015, 0.148]	1.13
Moral Rationalization	−.135	−0.137	0.037	−3.665	< .001	[−0.210, −0.063]	1.18
Academic Pressure	−.051	−0.052	0.036	−1.435	.152	[−0.123, 0.019]	1.11
Behavioral Control	.105	0.104	0.034	3.036	.002	[0.037, 0.172]	1.05

Note. β = standardized coefficient; *B* = unstandardized coefficient; CI = confidence interval for B; VIF = variance inflation factor.

Regression diagnostics

All VIFs were below 1.24. Residuals did not depart meaningfully from normality on the Shapiro–Wilk test (AI Misuse: $W = .996$, $p = .051$; Compliance Intention: $W = .997$, $p = .187$), and Breusch–Pagan tests found no heteroscedasticity (LM = 15.33, $p = .120$, and LM = 16.15, $p = .095$). The largest Cook's distances were .026 and .015, well below 1, and the largest Mahalanobis distance ($D^2 = 26.56$) was below the $p < .001$ critical value of 29.59. Both models were robust to three further checks. All 13 significant coefficients remained significant after a Benjamini–Hochberg correction

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across the 20 coefficients (largest adjusted p = .025, for Institutional Enforcement); none changed significance with HC3 standard errors; and adding 18 demographic indicator variables (gender, year of study, field, institution type and focus, and self-reported performance) added little explained variance (ΔR^2 = .021, p = .385, and ΔR^2 = .016, p = .722). None of the demographic variables were significant, and no predictor changed significance (Supplementary Table S5).

Moderation by academic level

As an exploratory test, a mean-centered interaction term (Misuse Acceptability × Graduate; n = 74 graduate and n = 639 undergraduate students) was added to the AI Misuse model. Neither the interaction (B = −0.063, SE = 0.125, t = −0.505, p = .614, ΔR^2 = .0003) nor graduate status (B = 0.004, p = .966) was significant. A sensitivity analysis (Cohen, 1988) showed that the interaction would have needed to be about 5.6 times larger ($B \approx 0.35$) for 80% power, so this null result is inconclusive rather than evidence of no moderation.

Indirect associations through Compliance Intention

Although the two outcomes were modeled in parallel, classic TPB specifies that beliefs shape intention, which in turn shapes behavior. Following Baron and Kenny (1986), Compliance Intention was therefore added to the AI Misuse model. It was significantly associated with AI Misuse in the direction TPB predicts (B = −0.10, SE = 0.035, p = .004), raising R^2 from .245 to .254 (ΔR^2 = .009). Percentile bootstrap confidence intervals (5,000 resamples) for the six predictors associated with Compliance Intention excluded zero for all six indirect paths: Rule Clarity (ab = −.018, 95% CI [−.033, −.005]), Subjective Norms (ab = −.021 [−.038, −.006]), Moral Rationalization (ab = .014 [.004, .027]), Behavioral Control (ab = −.010 [−.022, −.002]), Productive AI Use (ab = −.010 [−.021, −.002]), and Institutional Enforcement (ab = −.008 [−.019, −.001]); see Supplementary Table S6. The more conservative Sobel tests (Sobel, 1982) showed significant indirect paths for Rule Clarity (z = −2.522, p = .012), Subjective Norms (z = −2.542, p = .011), Moral Rationalization (z = 2.254, p = .024), and Behavioral Control (z = −2.081, p = .037), with Productive AI Use and Institutional Enforcement marginal (.05 < p < .07). After FDR correction, the paths for Rule Clarity, Subjective Norms, and Moral Rationalization remained significant, and the path for Behavioral Control did not (p = .056). All indirect effects were small ($|ab| \leq .021$).

Discussion

Principal findings

The models explained 24.5% of the variance in AI Misuse and 19.6% in Compliance Intention, somewhat less for both outcomes than in the companion study (28.4% and 21.5%; Swanson, 2026a). Rule Clarity and Moral Rationalization predicted both outcomes in the expected directions. Beyond this shared core, AI Misuse was also associated with Misuse Acceptability, AI Familiarity, Academic Pressure, Learning Impact, and Subjective Norms, while Compliance Intention was also associated with Subjective Norms, Behavioral Control, Productive AI Use, and Institutional Enforcement. H1 was therefore partly supported: six of its seven predicted associations were significant in the expected direction, but Behavioral Control was not. H2 was supported: all five predicted associations were significant in the expected direction. Because the design is cross-sectional and most variance remains unexplained, the interpretations below concern associations, not causes.

Factors associated with AI Misuse

Misuse Acceptability was the strongest predictor of AI Misuse (β = .215): students who evaluated unauthorized AI use more favorably also agreed more strongly with items describing their own misuse. This fits the attitudinal core of TPB (Ajzen, 1991), its earlier applications to academic dishonesty (Beck & Ajzen, 1991; Harding et al., 2007), and its extension to generative AI (Baig & Paparo, 2026). AI Familiarity was positively associated with misuse (β = .163), unlike in the companion study, where it predicted neither outcome (Swanson, 2026a). Because the association held with Misuse Acceptability controlled, it is unlikely to reflect attitudes alone; greater opportunity, or misuse-building familiarity, are more plausible explanations. The Academic Pressure association fits Ogbaga et al.'s (2026) finding that academic pressure can outweigh potential sanctions, and the Moral Rationalization association fits Sykes and Matza's (1957) neutralization account. The protective association of

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Subjective Norms, which did not appear in the companion study, is notable in light of EdGNH: one possible explanation is that a values-education tradition gives peers' disapproval more behavioral traction, although this is speculative because EdGNH exposure was not measured. Rule Clarity (β = −.163) and Learning Impact (β = −.096) were also negatively associated with misuse. Because higher Learning Impact scores indicate a belief that AI supports rather than replaces one's own learning (Supplementary Table S1), this association suggests that students who see AI as a learning aid are less likely to report using it in prohibited ways. Behavioral Control, significant in the companion study, was not associated with misuse here once other predictors were held constant.

Factors associated with Compliance Intention

Subjective Norms (β = .200) and Rule Clarity (β = .188) were the strongest predictors of Compliance Intention, consistent with McCabe et al. (2001) and with the normative component of Baig and Paparo's (2026) model. The Behavioral Control association fits Ajzen's (1991) account of perceived control as a determinant of intention. Institutional Enforcement was also positively and independently associated (β = .086), a result taken up below. Moral Rationalization was the strongest negative predictor (β = −.135), extending the neutralization logic above. Productive AI Use predicted Compliance Intention but not misuse, the reverse of the companion study, where it predicted misuse but not compliance (Swanson, 2026a).

Interpreting the pattern in the Bhutanese context

Three results stand out against Bhutan's combination of high connectivity, a national values-education policy, and AI governance under construction. First, Institutional Enforcement had only a small association with Compliance Intention (about 0.7% of unique variance) and none with misuse, whereas in the companion study it predicted both outcomes (Swanson, 2026a). A significant coefficient in one study set beside a non-significant one in another is not itself evidence of a difference, and no test of coefficient differences across the studies was possible. The pattern is consistent with, but does not show, the possibility that students register enforcement that is visibly taking shape, such as RUB's drafting of AI policy (Dendup, 2024), in their intentions before it shows in their conduct. Data were collected in June 2026, about two years after that report, and the sources reviewed here do not show whether the policy had been finalized or communicated to students by then. Second, Behavioral Control was not associated with misuse here, whereas Subjective Norms was, the reverse of the companion study; again, this difference was not formally tested. One reading, consistent with EdGNH (Gyamtso et al., 2017), is that where honesty has been taught as a shared value from the early school years, others' disapproval may restrain misuse more than a student's confidence in working without AI, although without a measure of EdGNH exposure this reading is speculative. Third, the small indirect association through Compliance Intention, which the companion study did not test, is consistent with, though far from proof of, a sequential TPB process (beliefs → intention → behavior). Because intention and misuse were measured at the same time, intention could also follow from behavior; given this and the small indirect effects, the finding is a candidate for replication rather than an established feature of the Bhutanese context.

Implications for teaching, assessment, and governance

Read through the levers described in the Conceptual Framework, the results suggest where course and institutional effort is most likely to matter. Rule Clarity was the only institutional factor associated with both outcomes, and unclear rules were common: only 35.2% of students at least slightly agreed that AI expectations were clear in most of their courses, while 47.3% reported that instructors set different rules and 45.6% that it was often unclear what AI use was allowed. This is the lever most directly under teachers' control. Academic Pressure was among the stronger correlates of misuse (β = .156), and 46.7% of students agreed at least slightly that AI rules were unrealistic given academic demands, which points to assessment load and the timing of deadlines, not only to individual integrity. Subjective Norms and Moral Rationalization were associated with both outcomes in opposite directions, suggesting that the classroom climate around AI, including the excuses students find acceptable, is part of the picture. Institutional Enforcement was associated with intention but not with reported misuse, which fits the view that enforcement alone, and especially detection-led enforcement given the unreliability of AI-text detectors (Hadra et al., 2026), is unlikely to be enough. Integrity policies can

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Article ID: e4077

also drift away from practice when sanctions are quietly softened (Verri, 2026), so consistent application may matter as much as the written rules. Finally, Productive AI Use was associated with stronger intention to comply and Learning Impact with less misuse, so encouraging legitimate, learning-centered AI use appears compatible with integrity rather than opposed to it.

Limitations and future research

The cross-sectional design permits only association. The AI Familiarity finding fits equally well with familiarity enabling misuse or misuse building familiarity, and longitudinal designs are needed to distinguish them. Self-reports of prohibited conduct are prone to social-desirability bias despite anonymity and framing, so the AI Misuse mean (M = 2.90) is best read as a floor; combining surveys with institutional records or observation would help. Because rules were often unclear (the Rule Clarity mean was below the scale midpoint), students may also differ in what they count as unauthorized use, which limits the precision of the AI Misuse measure. AVE fell slightly below .50 for eight constructs, so convergent validity is modest. The questionnaire was offered in English only; although English is the medium of instruction, some students may have answered more precisely in Dzongkha. Participants were a convenience sample; no response rate could be calculated, and the findings should not be generalized to Bhutanese higher education without probability sampling. Both models left most variance unexplained, and the moderation test could detect only an interaction several times larger than the one observed. Bootstrapped confidence intervals excluded zero for all six indirect paths, but only three survived FDR correction under the more conservative Sobel tests, and all were small despite N = 713, so the indirect pathway is modest. The study did not measure EdGNH exposure, so it cannot test whether the policy shapes these associations; students were nested within institutions, but institution identifiers were not recorded, so standard errors could not be adjusted for clustering, although results were unchanged with demographic controls and robust standard errors. Finally, the differing roles of Institutional Enforcement and Behavioral Control relative to the companion study were not formally tested and need replication. Qualitative work on what these constructs mean to Bhutanese students, and on whether EdGNH is experienced as connected to AI rules, would help clarify the mechanisms. Longitudinal or quasi-experimental designs that vary how policy is communicated could test whether the Institutional Enforcement association reflects an effect of visible policy formation.

Knowledge Contribution

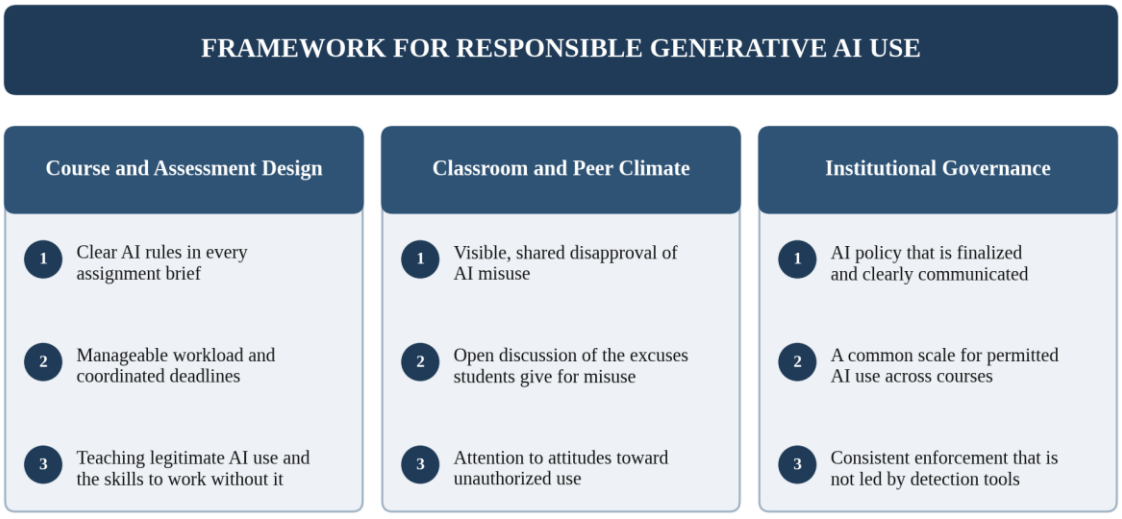


Figure 1. Framework for Responsible Generative AI Use in Bhutanese Higher Education

As Figure 1 shows, the factors associated with AI misuse and compliance intention fall into three levels at which Bhutanese teachers and institutions can act. At the level of course and assessment design, clear AI rules for each assignment, a manageable spread of workload and deadlines, teaching that builds students' ability to work without AI, and guidance on legitimate AI use correspond to Rule Clarity, Academic Pressure, Behavioral Control, and Productive AI Use. At the level of the classroom

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and peer climate, making shared disapproval of misuse visible and discussing the excuses students use correspond to Subjective Norms, Moral Rationalization, and Misuse Acceptability. At the level of institutional governance, finalizing and communicating AI policy, describing permitted AI use on a common scale across courses, and applying rules consistently correspond to Institutional Enforcement and Rule Clarity, with detection tools treated as a supplement to human judgment rather than the basis for decisions.

For educational research, the study contributes in three ways. Theoretically, it extends a TPB model augmented with institutional enforcement, moral rationalization, and academic pressure to a setting where honesty is named in national education policy, although the policy's influence was not measured. Empirically, it offers what appears to be the first evidence on the correlates of generative AI misuse and compliance intention among Bhutanese university students, and a comparison with a companion study in Myanmar showing which associations recur across the two sites (Rule Clarity with both outcomes; Misuse Acceptability, Moral Rationalization, and Academic Pressure with misuse; Subjective Norms with compliance intention) and which differ (Institutional Enforcement, Behavioral Control, and AI Familiarity). For educational policy and practice, it links each finding to the level, whether course design, classroom climate, or institutional governance, at which teachers and institutions can act on it.

Conclusion

This study examined the attitudinal, normative, and institutional factors associated with self-reported generative AI misuse and compliance intention among 713 university students in Bhutan. Students' self-reported AI-related behavior and intentions were associated with several features of their academic environment, not with exposure to the technology alone. Compliance intention was associated jointly with policy clarity, the normative climate around integrity, and perceived institutional enforcement. The association between AI Familiarity and misuse, which did not appear in the companion study, is a reason to pair efforts to build students' comfort with generative AI with attention to norms and responsible use. For Bhutanese higher education, the most promising starting points are clear AI rules in every assignment, assessment schedules that avoid concentrated pressure, classroom attention to the excuses that make misuse feel acceptable, and institutional policy that is finalized, communicated, and applied consistently. Technologies, national policies, and the capabilities of generative AI tools will keep changing, in Bhutan as everywhere else. The underlying educational task will not: helping students build the judgment to use increasingly capable tools responsibly, whatever institutional and cultural conditions they find themselves in.

Recommendation

Institutional policy and governance

For RUB and other institutions, the results support finalizing AI policy and communicating it in terms students can apply to specific tasks, not only as a general prohibition. Because Institutional Enforcement was associated with stated intentions but not with reported misuse, and because AI-text detectors are unreliable (Hadra et al., 2026) and lecturers doubt their performance on Dzongkha content (Dorji, 2026), policy should present detection results as one input to human judgment rather than as evidence in themselves. Institutions could also give staff a common way to describe permitted AI use, such as the AI Assessment Scale (Perkins et al., 2024), so that rules do not differ arbitrarily between courses, a problem reported by nearly half of the students surveyed. The experience of Ghanaian universities, where the absence of formal AI policy left assessment practices inconsistent (Adjei et al., 2026), suggests that the cost of delay falls on teaching and assessment, not only on discipline.

Assessment and course design

Because Rule Clarity was associated with both outcomes, every assignment brief could state which AI uses are permitted, such as brainstorming or language editing, and which are not, with a short reason tied to the task's learning outcomes. Because Academic Pressure was among the stronger correlates of misuse, programs could coordinate deadlines across courses and check whether assessment loads cluster at the same points in the semester, consistent with evidence that pressure and low perceived

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detection risk can outweigh sanctions (Ogbaga et al., 2026). Assessments that include drafts, in-class components, or reflection on process, approaches Bhutanese lecturers already report using (Dorji, 2026) and that secondary school teachers elsewhere have adopted for similar reasons (Mendiola et al., 2026), may also strengthen students' confidence that they can complete work without AI.

Classroom practice

Because Subjective Norms and Moral Rationalization were associated with both outcomes, short class discussions of the common excuses for misuse, such as heavy workload or the sense that many students break the rules, may help, and teachers in Bhutan can connect these discussions to the honesty students have been taught under EdGNH (Gyamtso et al., 2017). Because Productive AI Use was associated with stronger compliance intention, teaching students how to use AI legitimately appears compatible with integrity, although the AI Familiarity association suggests that building comfort with AI should be paired with explicit attention to its limits. All of these associations are cross-sectional, so each recommendation is a starting point for local evaluation rather than a proven intervention.

Declaration — Author Form

1. Conflict of Interest

State any conflicts of interest. If none, declare that no conflict exists.

Statement: The author declares that there are no conflicts of interest.

2. Generative AI and AI-assisted Technologies

State the AI tool used and its purpose. If none was used, state accordingly.

AI tool: Claude (Anthropic), Opus 5.5, September 2026.

Purpose: Editing, formatting, data analysis, reference verification, figure preparation, and editorial advice. The author directed all AI use, reviewed and edited every AI-assisted change, verified all statistical results against the underlying dataset, and takes full responsibility for the final content.

3. Data Availability Statement

State the availability and source of the data or materials used in the study.

Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

4. Ethics Statement

State the ethics approval and approval number, if applicable. If not applicable, provide a brief explanation.

Statement: This study was an anonymous, non-interventional survey. Before recruitment, permission to conduct the study was obtained from the university research authorities at each participating institution (the president and the faculty member responsible for research). The author was informed that Bhutan has no formal research ethics policy applicable to this study, which is why permission was sought from each participating university; no ethics committee approval number therefore applies. Participation was voluntary; respondents were told the study's purpose and that they could withdraw at any time, and no identifying information was collected. Completing and submitting the questionnaire after reading this information was taken as consent.

5. Funding

State the funding source and grant/project number. If no funding was received, state accordingly.

Statement: This research received no funding.

6. Contributor Role Taxonomy (CRediT)

State each author's contribution according to the CRediT roles.

Author(s) and role(s): Brian A. Swanson: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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