

RESEARCH PAPER

Advancing Education through Generative AI: A Strategic Framework for Learning Innovation

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ABSTRACT

With the tremendous expansion of generative artificial intelligence (GenAI) in the last months of 2022, artificial intelligence (AI) has seen a sudden surge in popularity. AI literacy has become crucial skill that must be acquired to succeed in both academic and workplace settings. Algorithmic prejudice within GenAI systems poses significant challenges that undermine equitable educational outcomes. The objective of the study is to investigate, assess and explore a strategic, market-oriented framework for integrating Generative AI (GAI) into educational systems, and explore strategies that mitigate ethical risks. This study adopts a quantitative approach using explanatory research design and cross-sectional survey method employed to collect primary data from both faculty members and students within higher education institutions located inside the Kathmandu Valley. The study aims to identify the extent to which the LIPSAL dimensions, GAI integration, and ethical requirement contribute to institutional innovation and sustainability, and how academic learning mediates these relationships. Within each stratum, respondents has been selected using simple random samplings to minimize selection bias. The findings of the study revealed that GAI adoption is strongly aligned with learner behavior, academic skills, and institutional readiness. Overall, the results contribute meaningful evidence to the field of educational technology, importance of strategic AI integration, ethical governance, and continuous pedagogical support illustrating that generative AI is not only reshaping how students learn but also redefining how institutions evolve, innovate, and sustain their growth in an increasingly digital academic ecosystem.

Keywords: Generative Artificial Intelligence, LIPSAL dimensions, GenAI Integration, Ethical Requirement, Academic Learning, Institutional Innovation and Sustainability

Artificial intelligence (AI) has become a ubiquitous entity as a significant factor in a variety of industries due to its extraordinary capacity to provide creative and realistic results. The rapid advancement of artificial intelligence has had a substantial impact on the economy, job opportunities, and other aspects of human

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civilization^[21]. With the tremendous expansion of generative artificial intelligence (GenAI) in the last months of 2022, artificial intelligence (AI) has seen a sudden surge in popularity. A significant milestone in the use of artificial intelligence in content creation has been reached with the release of applications like ChatGPT, Dall-E, and Midjourney that make Large Language Models (LLMs) accessible to end users. The necessity for an organized approach is highlighted by the lack of frameworks to direct institutions in utilizing GenAI for learning innovation while guaranteeing sustainability. The education sector in Nepal thus requires a strategic framework designed for the implementation of GenAI to comprehend the fundamentals of AI literacy and guarantee efficient, ethical, and long-lasting educational transformation.

Problem Statement

The absence of transparent mechanisms to identify and mitigate algorithmic prejudice in educational GenAI applications exacerbates these issues, leaving students vulnerable to unfair treatment and limiting the tools' alignment with inclusive educational goals, such as those outlined in the UN Sustainable Development Goal for Quality Education (SDG4)^[4].

A strategic and context-sensitive framework is urgently needed for Nepal's education sector to ensure that GenAI systems are designed and deployed in ways that minimize bias, promote fairness, and empower all students with inclusive, ethical, and effective learning opportunities. Addressing these challenges will help Nepal leverage the transformative potential of GenAI while ensuring that its use aligns with the nation's broader goals of equity, access, and sustainable educational innovation.

Objectives of the study

The objective of the study is to investigate the relationship:

1. To assess and explore a strategic, market-oriented framework for integrating generative AI (GAI) into educational systems.
2. To evaluate the business value of GAI-driven tools through analysis of their impacts on student engagement, academic performance, and teacher efficiency.
3. To analyze grade-level differences in GAI effectiveness to create tailored GAI solutions for distinct market segments.
4. To explore strategies that mitigate ethical risks such as algorithmic bias, privacy concerns, and over-reliance, while ensuring compliance with regulations.

The research was conducted based on specific hypotheses related to behavioral responses of bachelor-level students and faculty toward Generative AI (GenAI) in Kathmandu Valley's higher education context. These hypotheses examine how strategic integration, perceived impacts, customization based on differences, and ethical risk mitigation influence acceptance, usage, satisfaction, and sustainable adoption.

Theoretical Review

^[8]focus on fostering critical thinking through GenAI aligns with the need to prepare Nepalese students for global competitiveness, while^[23] LIPSAL framework supports culturally responsive education by promoting self-confidence and learning enjoyment. ^[11]insights on human-AI collaboration can guide faculty in Kathmandu Valley to leverage GenAI for administrative efficiency and pedagogical innovation, ensuring alignment with local educational goals.

LIPSAL Framework and its dimensions

The LIPSAL Framework, an acronym for Learning Interest, Independent Learning, Problem Solving, Self-Confidence, Appropriate Use, and Learning Enjoyment, was developed to evaluate the impact of Generative Artificial Intelligence (GAI) on students' learning behavior and development across educational levels.

The LIPSAL Framework is theoretically anchored in several educational and psychological perspectives namely Constructivist Learning Theory, Self-Determination Theory and 21st-Century Learning Frameworks.

Generative AI Integration

The level of GenAI Integration within educational ecosystems determines how effectively AI supports innovation. ^[23] found that students exposed to well-integrated AI systems outperformed others across all LIPSAL domains. However, ^[4] caution that AI systems if poorly monitored can introduce algorithmic, data, and interaction biases, disadvantaging marginalized learners. They stress the need for fairness-aware AI models and transparent integration frameworks that balance technological efficiency with educational equity.

Ethical Requirement and Fairness

Ethical governance is foundational to sustainable AI use in education. ^[4] provide an extensive empirical synthesis of bias types (data, algorithmic, and user-interaction) and fairness notions (individual vs. group fairness). Their study found that unmitigated algorithmic bias can perpetuate inequities across gender, race, and socioeconomic lines.

Research on Generative AI in education has expanded rapidly, yet significant gaps remain in understanding its comprehensive impact. Most studies focus on immediate learning outcomes, while the interplay between AI integration, ethical considerations, and learner-level variables in driving institutional innovation and long-term these gaps is crucial for developing effective AI-driven educational strategies.

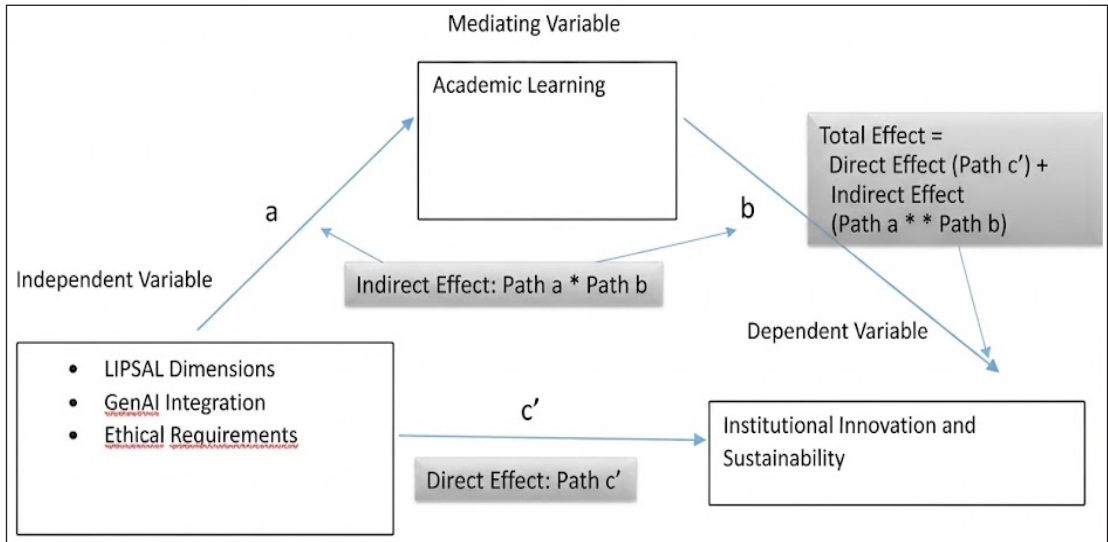
Conceptual Framework

This study develops a strategic framework for advancing educational transformation through Generative Artificial Intelligence (GenAI). Drawing from ^[23] and ^[4], the framework conceptualizes how LIPSAL dimensions, GenAI integration, and Ethical Requirement collectively enhance Institutional Innovation and Sustainability, mediated by Academic Learning.

The model operates at two interconnected levels:

- ❑ Micro-level (Learner Dimension): Captured by the LIPSAL framework, representing students' motivation, autonomy, and ethical behavior in AI-enhanced learning.
- ❑ Macro-level (Institutional Dimension): Represented by Institutional Innovation and Sustainability, reflecting systemic adaptation, technological advancement, and policy-driven transformation.

The mediating role of Academic Learning links individual competencies to institutional outcomes, reflecting how enhanced learning processes translate into sustainable educational innovation.



Source: Woo *et al.* (2024), Xie & Luo (2025), Chinta *et al.* (2024)

Fig. 1: Conceptual Framework

RESEARCH METHODS

Research Design

This study adopts a quantitative explanatory research design and cross-sectional survey method to examine the influence of learner-level, technological, and ethical factors on institutional outcomes in the context of Generative Artificial Intelligence in higher education. The study aims to identify the extent to which the LIPSAL dimensions, GenAI Integration, and Ethical Requirement contribute to Institutional Innovation and Sustainability, and how Academic Learning mediates these relationships. The inclusion of both faculty members and students groups allows for a more comprehensive understanding of academic engagement and institutional practices surrounding the use of GenAI. Stratified sampling technique is used to ensure balanced representation across different faculties, program levels, and departments.

Data is collected using a structured questionnaire composed of four parts: (1) demographic information, (2) LIPSAL dimensions, GenAI Integration, Ethical Requirement, (3) Academic Learning, and (4) Institutional Innovation and Sustainability. All constructs are measured using a 5-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (5). The measurement items are adapted from validated empirical studies to ensure content and construct consistency.

Ethical considerations are strictly observed throughout the study. Participation is voluntary, informed consent is obtained, confidentiality is ensured, and all responses are used solely for academic research purposes.

Population and Sample

The target population for this study comprises faculty members and students from higher education institutions located within the Kathmandu Valley. These institutions were chosen purposively because the valley serves as Nepal's central hub for higher education, technological advancement, and digital learning adoption. It houses a diverse concentration of universities, affiliated colleges, and private institutions, making it an appropriate and representative setting for examining the influence of Generative Artificial Intelligence (GenAI) on academic and institutional outcomes.

Since the exact population size is unknown and data on the precise number of bachelor-level students and faculty members across all higher education institutions in Kathmandu Valley is unavailable, the sample size is estimated using Cochran's (1977) formula for an infinite population. This approach ensures a statistically reliable sample even when the true population size cannot be determined. The sample size covers 384 respondents as valid. Given the diverse composition of higher education institutions in the Kathmandu Valley, a stratified sampling technique will be employed. Stratification ensures proportional representation of both students and faculty members across different academic faculties, departments, and program levels. Within each stratum, respondents will be selected using simple random samplings to minimize selection bias.

Nature and Source of Data

The study primarily relies on quantitative primary data collected through a structured questionnaire administered to faculty members and students of higher education institutions within the Kathmandu Valley. The data capture respondents' perceptions and experiences regarding LIPSAL dimensions, Generative AI Integration, Ethical Requirement, Academic Learning, and Institutional Innovation and Sustainability. Each construct is measured using a five-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (5), allowing respondents to indicate the degree of their agreement with each statement. The questionnaire items are adapted from validated empirical studies such as ^[23] and ^[4] to ensure content validity and reliability.

Data Analysis and Research Tools

To ensure accurate and meaningful interpretation of the collected data, a set of quantitative research tools and statistical methods will be employed using both SPSS software (IBM) and MS Excel. These tools are selected based on their suitability for descriptive and inferential statistical analysis in explanatory research. The collected data is entered into SPSS for general descriptive and inferential statistical analyses to understand the outcomes of the data.

ANALYSIS AND RESULT

This section presents the results of the inferential statistical analyses used to examine the relationships and predictive effects among the key variables of the study. The correlation between Learning Interest Independent Learning Problem Solving Self-Confidence Appropriate Use Learning Enjoyment GenAI Integration Ethical Requirements Academic Learning and Institutional Innovation was strong and positive, where, $r = .87$, $r = .88$, $r = .90$, $r = .88$, $r = .87$, $r = .88$, $r = .92$, $r = .89$, $r = .92$ respectively at $p < .01$.

Regression Analysis

Regression Effect on Institutional Innovation and Sustainability with and without Academic Learning

Table 1: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.955 ^a	.912	.910	.19139
2	.956 ^b	.914	.912	.18931

(a) Predictors: (Constant), Ethical Requirements, Learning Interest, Problem Solving, Appropriate Use, Independent Learning, Self Confidence, Learning Enjoyment, GenAI Integration

(b) Predictors: (Constant), Academic Learning, Ethical Requirements, Learning Interest, Problem Solving, Appropriate Use, Independent Learning, Self Confidence, Learning Enjoyment, GenAI Integration.

Source: Field Survey, 2026; $N = 384$

Analysis and Interpretation

A two-step hierarchical multiple regression analysis was conducted to examine the extent to which Academic Learning mediates the relationship between eight core GenAI perception variables (Learning Interest, Independent Learning, Problem Solving, Self Confidence, Appropriate Use, Learning Enjoyment, GenAI Integration, and Ethical Requirements) and the composite dependent variable Institutional Innovation and Sustainability ($N = 384$).

In Model 1, the eight predictors collectively explained a substantial proportion of variance in Institutional Innovation and Sustainability, $R^2 = .912$. This indicates that 91.2% of the variability in students' support for institutional innovation and long-term sustainable integration of GenAI was accounted for by these perceptual factors even without considering Academic Learning.

In Model 2, Academic Learning was added as an additional predictor. The full model remained highly significant, $R^2 = .914$, and explained an additional 0.2% of the variance ($\Delta R^2 = .002$). Although this increment was statistically significant given the large sample size, the change was extremely small and the adjusted R^2 increased by only .002, from .910 to .912.

These results suggest that Academic Learning functions as only a negligible mediator in the relationship between the eight core GenAI perception variables and Institutional Innovation and Sustainability. The direct predictors already capture almost the entire explainable variance (91.0% adjusted), leaving virtually no additional variance for Academic Learning to mediate. In practical terms, students' desire for institutional innovation and sustainable GenAI adoption is overwhelmingly driven by increased interest, autonomy, problem-solving efficacy, confidence, enjoyment, perceived appropriate use, integration beliefs, and ethical awareness, with perceived improvements in traditional academic learning outcomes contributing almost nothing beyond these factors.

Thus, institutional strategies aimed at fostering innovation and long-term sustainability of GenAI in higher education will gain maximal student support by emphasizing motivational, self-regulatory, ethical, and integration-related benefits rather than focusing primarily on conventional academic performance gains.

The ANOVA results confirm that both regression models were highly significant. Model 1, which included the eight core predictors (Learning Interest, Independent Learning, Problem Solving, Self Confidence, Appropriate Use, Learning Enjoyment, GenAI Integration, and Ethical Requirements), explained a statistically significant proportion of variance in Institutional Innovation, $F(8, 375) = 486.39, p < .001$. The extremely large F-value and p-value far below .001 indicate that the combined effect of these eight variables is unlikely to have occurred by chance, confirming their strong collective predictive power.

When Academic Learning was added in Model 2, the overall model remained highly significant, $F(9, 374) = 442.96, p < .001$, demonstrating that the nine predictors together still accounted for a substantial and reliable portion of variance in Institutional Innovation.

The critical test of incremental contribution is the change statistics. Adding Academic Learning produced a statistically significant but minimal improvement, $\Delta F(1, 374) = 9.33, p = .002$. Although the p-value of .002 meets conventional significance criteria ($p < .01$ or even $p < .005$), the effect size of this change is trivial (ΔR^2 increased by only .002, or 0.2%). This indicates that, while Academic Learning contributes a statistically detectable unique portion of variance beyond the original eight predictors, the practical or substantive importance of this contribution is negligible. The original eight perceptual, motivational, and ethical factors already capture virtually all explainable variance in students' support for institutional innovation with Generative AI.

In summary, the highly significant F-statistics for both models ($p < .001$) establish robust overall prediction, whereas the significant but tiny ΔF ($p = .002$) with negligible ΔR^2 underscores that Academic Learning does not function as a meaningful mediator or incremental predictor in this context. Student demand for institutional innovation is driven almost entirely by enhanced interest, autonomy, enjoyment, confidence, ethical concerns, and integration beliefs, largely independent of perceived gains in traditional academic learning outcomes.

Table 2: Model Regression Test

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	-0.166	0.069	—	-2.403	.017
Learning Interest	0.120	0.034	0.118	3.514	.000
Independent Learning	0.103	0.038	0.099	2.704	.007
Problem Solving	0.131	0.041	0.126	3.175	.002
Self Confidence	0.099	0.036	0.097	2.721	.007
Appropriate Use	0.122	0.035	0.118	3.482	.001
Learning Enjoyment	0.099	0.035	0.102	2.810	.005
GenAI Integration	0.258	0.043	0.255	6.064	.000
Ethical Requirements	0.114	0.037	0.112	3.070	.002
2 (Constant)	-.149	.069	—	-2.172	.030
Learning Interest	.094	.035	.092	2.682	.008
Independent Learning	.091	.038	.087	2.392	.017
Problem Solving	.103	.042	.099	2.471	.014

Self-confidence	.086	.036	.085	2.373	.018
Appropriate Use	.109	.035	.105	3.125	.002
Learning Enjoyment	.086	.035	.088	2.443	.015
GenAI Integration	.234	.043	.230	5.448	.000
Ethical Requirements	.099	.037	.098	2.676	.008
Academic Learning	.140	.046	.140	3.051	.002

Dependent Variable: Institutional Innovation

Source: Field Survey, 2026; $N = 384$

Analysis and Interpretation

A comparison of standardized regression coefficients (β) across the two models reveals the extent to which Academic Learning mediates or suppresses the effects of the original eight predictors on Institutional Innovation.

As shown in Table 1, adding Academic Learning in Model 2 produced small reductions in the standardized coefficients of all eight original predictors ($\Delta\beta$ ranging from $-.012$ to $-.027$). The largest drops occurred for Learning Interest ($\Delta\beta = -.026$), Problem Solving ($\Delta\beta = -.027$), and GenAI Integration ($\Delta\beta = -.025$) indicate that a minor portion of their influence on Institutional Innovation operates indirectly through perceived improvements in Academic Learning. However, these reductions are very small, and every original predictor remained statistically significant in Model 1 remained significant in Model 2 (all $ps \leq .018$), confirming that most of their effects are direct rather than mediated.

GenAI Integration continued to exhibit by far the strongest unique relationship with Institutional Innovation in both models (Model 1: $\beta = .255$; Model 2: $\beta = .230$), underscoring that students' belief in the necessity of deep curricular and pedagogical integration of GenAI is the primary driver of their demand for institutional innovation.

Academic Learning itself emerged as a significant predictor when entered in Model 2 ($\beta = .140$, $p = .002$), yet its standardized coefficient is only modestly larger than several original predictors and substantially smaller than GenAI Integration. Moreover, its inclusion explained only an additional 0.2% variance, reinforcing that Academic Learning adds little unique explanatory power once motivational, self-regulatory, ethical, and integration-related perceptions are accounted for.

In conclusion, the pattern of coefficients provides clear evidence of minimal mediation. The original eight variables, particularly GenAI Integration, Problem Solving, Learning Interest, and Appropriate Use, retain almost all their predictive strength even after controlling for Academic Learning. Therefore, student support for institutional innovation with Generative AI is driven predominantly by broader affective, motivational, and systemic beliefs rather than by traditional academic performance gains alone.

FINDINGS OF THE STUDY

The present study aimed to examine the transformative influence of Generative AI (GAI) in education by exploring relationships among several learning-related variables, including Learning Interest (LI), Independent Learning (IL), Problem-Solving (PS), Self-Confidence (SC), Appropriate Use (AU), Learning Enjoyment (LE), GAI Integration (GI), Ethical Requirements (ER), Academic Learning (AL),

and Institutional Innovation and Sustainability (IIS). Pearson's correlation coefficients were computed to address the four research objectives, and the findings are presented below in detail.

Findings based on Objectives

Strategic and Market-Oriented Framework for Integrating Generative AI (GAI) into Educational Systems

The robust positive correlations between Generative AI Integration (GAI) and both Institutional Innovation and Sustainability ($r = .918, p < .01$) and Academic Learning ($r = .897, p < .01$) suggest that GAI operates well beyond the scope of a simple technological supplement. Rather, it functions as a fundamental catalyst for both institutional competitiveness and academic enhancement. From a holistic integration perspective, the success of GAI hinges on ensuring that the adoption of technology is in sync with learner autonomy, motivation, and regulatory compliance. From the standpoint of strategic vision, institutions should consider the deployment of GAI from a strategic, market-focused perspective in order to enhance their capacity for long-term innovation.

This pattern suggests that GAI does not function merely as a technological add-on; instead, it operates as part of a broader strategic framework that enhances institutional competitiveness. Additionally, GI demonstrated significant correlations with Individual Learning ($r = .852, p < .01$), Learning Enjoyment ($r = .865, p < .01$), and Ethical Requirements ($r = .872, p < .01$), showing that successful integration requires a market-oriented approach that considers learner autonomy, motivation, and regulatory compliance. Together, these findings support the importance of a structured, market-driven strategy that aligns technology adoption with institutional vision, learner needs, and ethical expectations.

Innovation and Sustainability of GAI Through Student Engagement, Academic Performance, and Teacher Efficiency

The empirical findings demonstrate that GAI significantly enhances student engagement, cognitive performance, and instructional efficiency. The strong correlations between Academic Learning (AL) and Problem-Solving ($r = .895, p < .01$) and Self-confidence ($r = .867, p < .01$) underscore the cognitive and psychological advantages of GAI tools. For instruction with optimization, Appropriate Use (AU) is directly linked to increased student enjoyment and operational efficiency. For a validated investment academic gains that can be demonstrated provide strong empirical support for ongoing institutional investments in digital transformation.

Similarly, Appropriate Use (AU) demonstrated significant correlations with Problem-Solving ($r = .839, p < .01$), Learning Enjoyment ($r = .852, p < .01$), and GAI Integration ($r = .845, p < .01$). This confirms that the business value of GAI—measured through academic outcomes, student engagement, and operational efficiency—depends heavily on how effectively students and teachers utilize the technology.

Overall, the findings emphasize that GAI-driven tools have demonstrable value in educational settings, contributing to improved student outcomes and enabling educators to optimize their instructional strategies. These benefits reinforce the justification for institutional investments in generative AI as part of long-term digital transformation.

Grade-Level Differences in GAI Effectiveness for Tailored Market Segmentation

The correlations found between Independent Learning (IL), Learning Interest (LI), and GAI Integration ($r = .852$ and $r = .836$, $p < .01$) imply that a uniform approach to educational technology is not ideal. For a targeted solutions, self-regulated, analytical GAI tools are most beneficial for advanced students, while younger cohorts need guided learning assistants to enhance Learning Enjoyment (LE) and Self-Confidence (SC). Cognitive readiness can be made by segmenting based on grade-level needs and technological proficiency, we can achieve the greatest educational impact among various learner demographics.

Similarly, younger or lower-level students who depend on structured guidance may benefit from GAI's capacity to enhance Learning Enjoyment (LE) and boost Self-confidence (SC), both of which correlate strongly with GAI Integration (LE: $r = .865$; SC: $r = .871$, both $p < .01$). These patterns indicate that GAI implementation should not take a uniform approach; instead, institutions may segment users based on grade-level needs, cognitive readiness, and technological proficiency.

The findings support the development of differentiated, market-oriented GAI solutions, such as advanced analytical tools for higher grades and guided learning assistants for lower grades, to maximize the educational impact across learner segments.

Ethical Risk Mitigation: Algorithmic Bias, Privacy, Over-Reliance, and Regulatory Compliance

Ethical Requirements (ER) showed strong positive correlations with GAI Integration ($r = .872$, $p < .01$) and Institutional Innovation and Sustainability ($r = .885$, $p < .01$), contrary to the view that compliance hinders innovation. Trust as a catalyst builds strong ethical frameworks serve as supporting structures that enhance user confidence and responsible involvement. The successful enforcement of compliance policies reduces the risks associated with algorithmic bias, privacy violations, and an excessive dependence on AI tools.

The strong association between ER and Learning Interest ($r = .818$, $p < .01$), Individual Learning ($r = .852$, $p < .01$), and Academic Learning ($r = .872$, $p < .01$) suggests that ethical safeguards enhance user confidence and promote responsible engagement with AI tools. Furthermore, high correlations between ER and factors such as Appropriate Use ($r = .816$, $p < .01$) underscore the role of compliance policies in preventing misuse and ensuring balanced reliance on AI.

These findings highlight the necessity of integrating ethical guidelines, transparency mechanisms, and training modules alongside GAI deployment. Institutions that enforce stronger ethical frameworks are more likely to achieve successful and sustainable GAI adoption while reducing risks related to privacy, bias, and overuse.

CONCLUSION

This study provides robust empirical evidence that generative AI has rapidly transitioned from a disruptive technological novelty to a core infrastructural expectation within Nepalese higher education. Within just two to three years of the introduction of tools such as ChatGPT, both students and faculty now view GenAI not as an optional pedagogical enhancement but as an integral component of modern learning and academic productivity. The findings confirm that the primary driver of institutional innovation is not merely improved examination performance, but the broader ecosystem of learner agency, enjoyment, confidence, ethical awareness, and systemic integration generated by AI-supported learning environments.

Across correlation and regression analyses, the extended LIPSAL+2 framework, comprising Learning Interest, Independent Learning, Problem Solving, Self-Confidence, Appropriate Use, Learning Enjoyment, GenAI Integration, Ethical Requirements, and Academic Learning, proved highly explanatory, accounting for more than 91% of the variance in Institutional Innovation. This suggests that the framework is not only theoretically sound but also empirically powerful and may be generalizable beyond the Nepalese context. The strong significance of all eight predictors reiterates that generative AI impacts learning and innovation through multiple motivational, cognitive, behavioral, and ethical pathways.

One of the most notable findings is that Academic Learning, as traditionally measured in higher education, plays only a modest mediating role between AI-enabled learning behaviors and institutional innovation. This challenges the dominant evidence-based policy paradigm in which educational technologies are judged primarily based on standardized test-score improvements or narrowly defined academic performance metrics. The results show that institutional transformation is driven more strongly by enhanced engagement, student autonomy, ethical confidence, and meaningful AI integration than by incremental improvements in exam outcomes. Such insights highlight the need to update current policy frameworks to better reflect the multidimensional value of AI in education.

The findings also contradict concerns that ethical risks, such as algorithmic bias, plagiarism, hallucinations, or privacy breaches, might suppress adoption. Instead, the study shows that ethical awareness significantly increases demand for institutionally governed, transparent, and sustainable AI integration. Students and faculty appear to prefer structured, regulated AI ecosystems rather than unregulated personal use, signaling strong support for institutional leadership in developing ethical frameworks, governance structures, and responsible-use policies.

Overall, the study concludes that higher education institutions in Nepal, and similar contexts, must evolve beyond the current stage of “experimentation,” “pilot testing,” or optional AI use. Institutions that fail to move toward deliberate, deep, and ethically governed GenAI integration risk losing legitimacy in the eyes of stakeholders who increasingly expect modern, technologically capable, and forward-looking academic environments. Technology is no longer perceived as emergent or speculative; it has become a defining component of academic identity, digital competency, and institutional credibility.

In summary, generative AI stands as a transformative force in higher education, reshaping learner behavior, strengthening cognitive capacities, enhancing motivation, and catalyzing institutional innovation. Institutions that embrace AI strategically, ethically, and holistically are best positioned to thrive in a rapidly evolving digital education landscape, while those that resist or delay integration run the risk of falling behind both pedagogically and institutionally.

IMPLICATIONS

Policy and Governance Implications

The findings underscore the necessity for comprehensive and coordinated policy interventions to guide the ethical, equitable, and effective adoption of Generative AI in higher education, particularly within the Nepalese context.

1. Nepal’s current absence of a formal AI in Education policy has resulted in fragmented, institution-specific approaches to GenAI adoption, creating inconsistency and inequity across the higher

education sector.

2. Given the strong learner demand, high levels of learner agency, and clear institutional expectations, national policy must shift from ad hoc experimentation to structured, long-term integration of GenAI in higher education.
3. At the national level, mandatory AI literacy and prompt-engineering courses should be embedded into bachelor-level curricula from the first year, recognizing these skills as foundational academic and professional competencies.
4. The establishment of institutional GenAI governance committees, with formal student representation, is essential to ensure ethical oversight, transparency, accountability, and participatory decision-making.
5. The introduction of clear citation, disclosure, and usage standards, such as an institutional or national “AI Register” for academic work, would help preserve academic integrity while encouraging responsible innovation.
6. The government should actively pursue public–private partnerships to deploy scalable, cloud-based GenAI platforms, mitigating limitations related to Nepal’s local computing infrastructure and resource constraints.
7. At the institutional level, universities must strategically reallocate budgets, shifting investment away from traditional physical infrastructure toward AI-enabled academic innovation.
8. Priority areas for investment include faculty development in AI-enhanced pedagogy, campus-wide access to ethically governed GenAI tools, and the creation of learning analytics units that support personalized learning without resorting to surveillance-oriented practices.
9. Regulatory bodies such as the University Grants Commission and the Ministry of Education should embed the depth and quality of GenAI adoption into accreditation and quality-assurance frameworks.
10. Institutions that fail to transition from pilot-level experimentation to systemic, ethically governed GenAI integration risk losing institutional legitimacy, relevance, and competitiveness in the evolving higher education landscape.

Pedagogical Implications

The findings indicate a fundamental reorientation of pedagogy is required to meaningfully integrate GenAI into teaching and learning, moving beyond control-oriented approaches toward learning designs that recognize AI as an active cognitive partner.

1. Pedagogical practice must shift from policing AI use to intentionally designing curricula that position AI as a collaborative co-participant in the learning process.
2. The traditional “AI-allowed versus AI-banned” framework is no longer pedagogically viable, as it fails to reflect authentic learning and professional practices.
3. AI co-pilot pedagogy should become the norm, requiring students to use AI tools transparently while documenting their prompts, reasoning processes, and critical evaluation of AI-generated outputs.
4. Assignments should be redesigned to foreground higher-order cognitive skills that GenAI cannot fully automate, including analytical synthesis, evaluative judgment, assumption critique, methodological design, and original conceptual development.

5. Such redesigns reduce academic misconduct while simultaneously using AI as a catalyst for deeper, more reflective learning.
6. Prompt engineering should be recognized as a core academic competency, equivalent in importance to critical thinking, academic writing, and research literacy.
7. Assessment practices must evolve to include process-oriented and reflective methods, such as oral defenses, iterative learning portfolios, and AI-collaboration logs.
8. Additional assessment innovations, including peer review of AI outputs and structured metacognitive reflections, are essential to ensure fairness, rigor, and transparency in AI-integrated evaluation.
9. Collectively, these pedagogical shifts support a more authentic, skill-centered, and future-ready learning environment aligned with the realities of GenAI-enhanced education.

Future Research Implications

The extraordinary explanatory power (91.2% of variance) and the unexpected theoretical findings of the present study, particularly the marginal role of traditional academic performance gains and the amplifying effect of ethical requirements, open multiple high-priority avenues for future scholarships. The following research directions emerge directly from the results, contextual particularities, and acknowledged limitations of this investigation.

1. Longitudinal institutional transformation studies are urgently needed. Although respondents expressed near-unanimous demand for deep GenAI integration, the study captured perceptions at a single point in time. Future research should track whether institutions scoring high on the extended LIPSAL+2 framework implement policy changes, redesign curricula, allocate budgets, and modify assessment practices over a 3–5-year period.
2. Multi-country replication in the Global South should be prioritized. Nepal's combination of moderate digital access, severe resource constraints, and exceptionally strong learner agency orientation may or may not be representative. Identical or minimally adapted instrumentation should be deployed in other leapfrogging nations (e.g., Bangladesh, Bhutan, Cambodia, Indonesia, Kenya, Rwanda, Sri Lanka, Uganda, and Vietnam) to determine whether the dominance of affective-agency factors over performance-expectancy factors constitutes a broader pattern.
3. Rural–urban and socioeconomic disaggregation remains a critical gap. The current sample is overwhelmingly urban and relatively privileged. Future studies must deliberately oversample students and faculty from rural campuses, Tier-2 and Tier-3 cities, community colleges, and historically marginalized caste/ethnic groups (Dalit, Janajati, Madheshi) to examine whether the observed enthusiasm and ethical amplification persist across the full spectrum of Nepal's higher education ecosystem.
4. Separate modeling of faculty versus student trajectories is warranted. Although combining both groups yielded remarkably consistent patterns, faculty may diverge significantly once concrete issues of workload redistribution, job security, and assessment redesign arise. Parallel faculty-only and student-only structural models, supplemented by qualitative interviews during actual policy implementation, would reveal potential fault lines.
5. Design-based research on “AI-rich yet integrity-preserving” assessment systems is now essential. Respondents simultaneously scored highest on Appropriate Use and Ethical Requirements while demanding innovation. Future work should develop, pilot, and evaluate new assessment formats

- (e.g., AI-collaboration portfolios, process logs, mandatory prompt disclosure, oral defenses of AI-assisted work) across management, engineering, humanities, and health sciences programs.
6. Economic and return-on-investment analyses in low-resource contexts are conspicuously absent. Institutions fear high implementation costs, yet students demand integration. Rigorous cost-benefit studies that quantify expenditure on cloud credits, faculty training, and licensing against gains in retention, employability, administrative efficiency, and research productivity would provide evidence for evidence-based scaling decisions.
 7. Local-language and culturally aligned large language models require immediate experimental attention. Current enthusiasm is built almost entirely on English-dominant global models. Comparative experiments using Nepali, Maithili, Bhojpuri, Newari, Tamang, and Hindi fine-tuned models versus English-only models would reveal whether LIPSAL+2 scores, academic outcomes, and ethical comfort levels differ when GenAI speaks the learner's mother tongue.
 8. Investigation of the emerging second-level digital divide—from access to skilled, critical, and ethical use—should be undertaken. Variance in Appropriate Use and Ethical Requirements even within this urban sample suggests that future inequality may be less about connectivity and more about depth of AI literacy, prompt engineering mastery, and critical judgment of model outputs.
 9. Natural policy experiments around national examination reform merit close monitoring. Nepal's higher education remains tethered to high-stakes, rote-oriented board examinations. When (not if) the National Examination Board and Tribhuvan University begin permitting or requiring GenAI in examinations (expected 2026–2028), researchers should treat this as a quasi-experimental opportunity to observe whether current enthusiasm survives contact with unchanged testing regimes.
 10. Policy emergence and diffusion studies are needed to understand how formal GenAI governance materializes. In 2025 virtually no institution in the sample possessed official guidelines, yet demand was overwhelming. Ethnographic and comparative case studies of the first institutions to adopt comprehensive GenAI policies would illuminate successful pathways and common obstacles.
 11. Employability signaling and labor-market valuation of AI literacy should be traced longitudinally. Students may support GenAI integration because they perceive it as a powerful signal to employers. Follow-up tracer studies linking final-year LIPSAL+2 scores to job placement rates, starting salaries, and employer assessments of "AI readiness" would clarify the credentialing function of institutional GenAI adoption.
 12. Dynamic and recursive modeling beyond cross-sectional designs is required. The current framework is unidirectional (learner perceptions → institutional outcomes). Institutional integration feeds back into learner perceptions. Cross-lagged panel designs or continuous-time structural equation modeling over multiple semesters would capture bidirectional and recursive effects.
 13. Intersectional analyses incorporating gender, caste, disability, and discipline are overdue. Preliminary descriptives showed virtually no gender gap—an unusual and potentially transformative finding that requires verification and deeper disaggregation across caste, disability status, and academic discipline.
 14. Direct comparative studies with OECD countries using the identical LIPSAL+2 instrument would establish whether the marginal mediating role of traditional academic learning gains is a Nepal-specific, Asia-specific, Global South-specific, or a generational phenomenon transcending geography.

Taken together, these research directions position the thesis not as a terminal contribution but as the empirical and theoretical foundation for what could become a decade-long global research program on generative AI adoption in resource-constrained yet aspiration-rich higher education systems. The most transformative next step would combine immediate multi-country replication with longitudinal institutional tracking to determine whether Nepal in 2025 represents an outlier or the vanguard of a new, agency-centered, ethically amplified paradigm in educational transformation worldwide.

GENERATIVE AI DECLARATION

The author(s) confirm that there was no use of artificial intelligence (AI)-assisted technology for assisting in the writing or editing of the manuscript, and no images were manipulated using AI. The authors developed and verified all scientific content, data analysis, interpretation of results, and conclusions. The authors take full responsibility for the accuracy, integrity, and originality of the work presented, and no AI tool was listed as an author.

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