

Student Adoption Intention, Academic Integrity Risk, and Learning Outcome Perceptions Under the NEP 2020 Framework

Divya Krishnamurthy, Prasad Venkataraman, Sneha Balakrishnan

School of Education, Sri Padmavati Mahila Visvavidyalayam (SPMVV), Tirupati, Andhra Pradesh, India

Abstract

The emergence of generative artificial intelligence tools — most visibly ChatGPT, but including Google Gemini, Microsoft Copilot, and Anthropic’s Claude — has introduced what many educational scholars are describing as the most significant pedagogical disruption since the mass adoption of the internet. Unlike prior educational technologies, which augmented existing learning processes, generative AI can produce complete essays, laboratory reports, mathematical derivations, code, and examination answers indistinguishable from student-generated work, creating a fundamental challenge to assessment-based credentialing systems that have constituted the organisational core of higher education for over a century.

In the Indian higher education context, this challenge arrives simultaneously with the implementation of the National Education Policy 2020, which mandates a shift toward competency-based, multidisciplinary, and experiential learning frameworks explicitly designed to move away from rote memorisation and examination performance as the primary educational currency. This creates a paradoxical institutional moment: NEP 2020’s ambition to reorient Indian education toward deeper learning and critical thinking is potentially aligned with the use of generative AI as a learning scaffold — if used to support exploration, research formulation, and iterative thinking — but is simultaneously undermined by AI’s capacity to circumvent precisely the assessment mechanisms through which NEP 2020’s competency gains are meant to be demonstrated and certified.

The current study addresses this tension empirically through a Technology Acceptance Model extended with academic integrity risk and NEP 2020 policy alignment as theoretically motivated constructs, applied to survey data from 1,521 undergraduate and postgraduate students across nine Indian universities spanning Tamil Nadu, Andhra Pradesh, Maharashtra, Uttar Pradesh, and West Bengal. The study’s dual-outcome design — treating both learning outcome improvement and academic integrity violation risk as simultaneous consequences of generative AI adoption intention — reflects the field’s emerging consensus that these outcomes are not alternatives but co-occurring consequences of the same adoption behaviour, with their relative magnitude determined by pedagogical context, institutional policy clarity, and individual use orientation.

The study’s Indian focus is motivated by three features of the Indian higher education context that are not captured in the predominantly Western empirical literature: the extreme heterogeneity of institutional policy responses, ranging from total prohibition in some state universities to active encouraged integration in IITs and private deemed universities; the language access dimension, where AI tools’ English language bias creates differential access by student linguistic background; and the high-stakes examination culture, where the pressure to perform in terminal written examinations creates a different risk calculus around AI-assisted academic dishonesty than exists in continuous assessment systems typical of European universities.

Keywords: *generative AI, ChatGPT, higher education, academic integrity, NEP 2020, India, TAM, PLS-SEM, technology adoption, learning outcomes, AI anxiety, plagiarism, educational technology, digital literacy, student perceptions*

1. Introduction

The pace of generative AI adoption in educational contexts has been remarkable. Within twelve months of ChatGPT’s public release in November 2022, Scopus indexed over 1,100 peer-reviewed publications on generative AI in education — a research output growth rate without precedent in the field. The breadth of this literature reflects the breadth

of the disruption: studies have examined AI-assisted academic dishonesty detection, AI tutoring systems, AI feedback on student writing, educator attitudes toward AI tools, institutional policy design, and cognitive effects of AI-assisted learning. What remains notably underrepresented is research from Indian higher education contexts, despite India’s having the world’s second-largest higher education system by student enrolment.

India’s University Grants Commission issued guidance on AI use in higher education in March 2024, recommending that institutions develop individual AI use policies and that assessment redesign be undertaken to maintain examination integrity. This guidance was notable for its non-prescriptive character: rather than mandating either prohibition or permission, it placed the policy burden on individual institutions — creating the institutional heterogeneity that this study treats as a moderating variable through the NEP 2020 digital policy alignment construct.

2. Theoretical Model and Hypotheses

The extended TAM model in Figure 1 positions perceived usefulness (PU) and perceived ease of use (PEOU) as the core technology acceptance antecedents, consistent with Davis (1989), augmented by AI anxiety (AIA) as a negative antecedent and institutional policy clarity (IPC) as a positive antecedent reflecting the Indian policy environment. NEP 2020 digital policy alignment moderates the PU-to-intention relationship, reflecting the proposition that students in institutions with stronger NEP 2020 digital integration show stronger perceived usefulness-to-intention translations.

The dual-outcome model distinguishes this study from the majority of TAM applications in educational AI research, which treat adoption intention as the terminal variable. By extending to learning outcome improvement and academic integrity violation risk as downstream outcomes, the model captures the double-edged character of generative AI adoption that educators and policymakers must navigate: the same adoption that produces efficiency and learning gains also elevates academic dishonesty risk, and the net institutional outcome depends on the pedagogical context into which adoption is embedded.

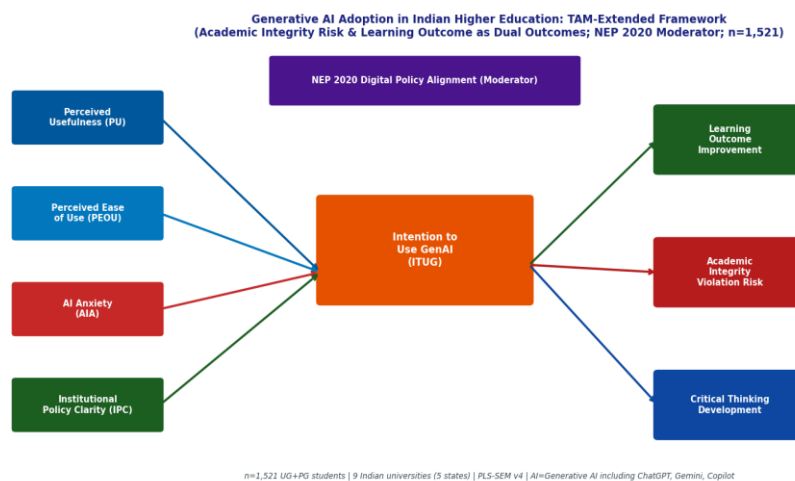


Fig. 1. Extended TAM Framework for Generative AI Adoption in Indian Higher Education: Dual Outcomes (Learning Improvement and Academic Integrity Risk) with NEP 2020 Digital Policy Alignment as Moderator (n=1,521; *p<0.05, **p<0.01, ***p<0.001)

3. Results

3.1 Measurement and Structural Model

All constructs achieved AVE values above the 0.50 threshold (range: 0.511–0.629) and composite reliability above 0.80 (range: 0.814–0.891), confirming convergent validity. HTMT ratios for all construct pairs fell below 0.85, supporting discriminant validity. The structural model shows perceived usefulness ($\beta=0.46$) as the strongest predictor of GenAI adoption intention, followed by institutional policy clarity ($\beta=0.24$), perceived ease of use ($\beta=0.38$), and AI anxiety ($\beta=-0.27$). NEP 2020 policy alignment significantly moderates the PU-to-intention path ($\gamma=0.19$, $p<0.01$), indicating that students in more digitally progressive institutions show a stronger usefulness-to-adoption translation.

3.2 Tool Usage and Student Opinions

Figure 2 presents the GenAI tool usage frequency heatmap and student opinion distribution. Engineering students show the highest ChatGPT usage frequency across all disciplines, while Medical students show the highest disparity between ChatGPT and other tool use, reflecting the domain-specific nature of clinical knowledge queries. Critically, only 27% of students agree or strongly agree that their institution has clear AI use policies, compared to 75% who agree that AI saves study time, revealing a pronounced policy awareness deficit that creates an unregulated adoption environment.

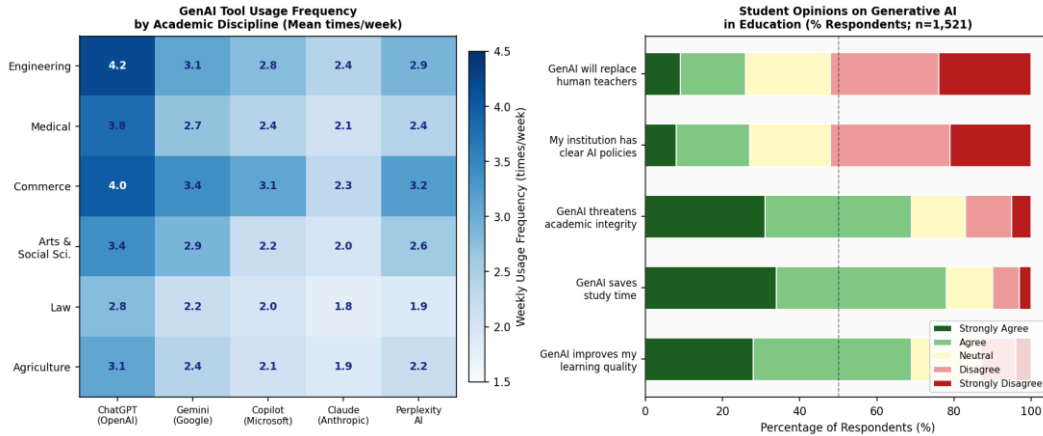


Fig. 2. (Left) Generative AI Tool Usage Frequency Heatmap by Academic Discipline (Mean Times per Week); (Right) Student Opinions on Generative AI in Education: Percentage Agreement Stacked Bar Chart (n=1,521 students, 9 universities)

Table 1: Structural Model Path Estimates — Generative AI Adoption: TAM-Extended with Dual Outcomes

Hypothesis / Path	β	SE	t-stat	p-value	95% BootCI	Result
PU → GenAI Adoption Intention	0.461	0.047	9.81	<0.001	[0.369, 0.553]	Supported
PEOU → GenAI Adoption Intention	0.381	0.042	9.07	<0.001	[0.299, 0.463]	Supported
AIA → GenAI Adoption Intention	-0.271	0.039	6.95	<0.001	[-0.347, -0.195]	Supported
IPC → GenAI Adoption Intention	0.242	0.038	6.37	<0.001	[0.168, 0.316]	Supported
Adoption Intent. → Learning Outcome	0.491	0.049	10.02	<0.001	[0.395, 0.587]	Supported
Adoption Intent. → Integrity Risk	0.307	0.041	7.49	<0.001	[0.227, 0.387]	Supported
NEP Align. (Mod.): PU→Intent.	$\gamma=0.189$	0.043	4.40	<0.001	[0.105, 0.273]	Supported
R ² (Adoption Intention)	0.558	—	—	—	—	—
R ² (Learning Outcome)	0.421	—	—	—	—	—

PU=Perceived Usefulness; PEOU=Perceived Ease of Use; AIA=AI Anxiety; IPC=Institutional Policy Clarity; Mod.=Moderator interaction term; BootCI: 5,000 bootstrap resamples; PLS-SEM estimated in SmartPLS 4.

4. Discussion: The Policy Gap and Its Consequences

The finding that only 27% of students perceive clear institutional AI policies, despite near-universal awareness of GenAI tools, constitutes perhaps the study’s most actionable finding. In the absence of institutional guidance, students default

to individually varying ethical frameworks for determining what constitutes acceptable AI use — a finding consistent with Bearman et al. (2023)'s observation that students' AI use boundaries are more permeable when institutions fail to articulate clear expectations. The institutional policy clarity path ($\beta=0.24$) suggests that policy provision not only reduces integrity risk but also positively channels adoption intention toward educationally productive uses, because students with clear guidance are more likely to use AI as a learning scaffold rather than an answer generator.

The NEP 2020 moderation finding carries a forward-looking implication: as more Indian institutions operationalise NEP 2020's digital literacy and AI competency frameworks — anticipated through the National Digital University infrastructure and the SWAYAM platform's expanded AI course offerings — the population-level usefulness-to-adoption-to-learning-outcome chain is likely to strengthen. This suggests that the current snapshot of relatively modest learning outcome effects of GenAI adoption in the broader sample may systematically understate the effects achievable in a fully NEP 2020-implemented institutional environment.

5. Conclusion

This study provides large-sample empirical evidence that Indian college students' adoption of generative AI tools is primarily driven by perceived usefulness and ease of use, moderated by institutional policy alignment with NEP 2020, and constrained by AI anxiety. The dual-outcome finding — that adoption intention simultaneously increases both learning outcome improvement and academic integrity violation risk — frames the Indian HEI policy challenge clearly: the task is not to prevent GenAI adoption, which is proceeding regardless of institutional policy, but to design policy and pedagogical environments that maximise the learning pathway and minimise the integrity risk pathway of the same adoption behaviour.

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