

Generative AI in Higher Education: Opportunities, Challenges and Institutional Readiness: A Study of Faculty and Students

Dr. Maya D^{*1}; Deepali Vaidya², Dr. S. V. Akilandeewari³, Marimuthu Rajendran Ezhilkumar⁴, Dr. J. Novina Steffy⁵, Dr. Retna Mony R⁶

¹Computer Science and Engineering, Cheran College of Technology, Tiruppur, Tamilnadu, India.
Email ID : mayaphdnetwork@gmail.com

²Assistant Professor, Department of Humanities, Ramdeobaba University, Nagpur, Maharashtra, India. Email ID: vaidyad@rbunagpur.in

³Assistant Professor and Head, Department of Business Administration, Athoor Cooperative College of Arts and Science-Seeval Saragu, Athupatti, Dindigul, Tamilnadu.
Email ID : akila222@rediffmail.com

⁴Marimuthu Rajendran Ezhilkumar, Assistant Professor, Department of Civil Engineering, PSG Institute of Technology and Applied Research, Coimbatore, Tamil Nadu, India.
Email ID : ezhil.1990.kumar@gmail.com

⁵Assistant Professor, Department of Commerce, Sri Ramakrishna College of Arts & Science, Coimbatore, Tamilnadu, India.
Email ID: novinajoseph96@gmail.com

⁶Assistant Professor of English, Koneru Lakshmaiah Education Foundation (K L Deemed to be University), Guntur, Andhra Pradesh, India.
Email ID: retnaemerald@gmail.com

***Corresponding Author**

Dr. Maya D

Computer Science and Engineering, Cheran College of Technology, Tiruppur, Tamilnadu, India.
Email ID : mayaphdnetwork@gmail.com

ABSTRACT

Purpose: Generative artificial intelligence (GenAI) tools like ChatGPT, Gemini, and Copilot are transforming the landscape of teaching, learning, assessment, and research within universities. However, there is considerable variation among institutions in their preparedness to manage and facilitate the integration of these technologies. This study investigates how perceived opportunities and challenges, along with institutional readiness, influence attitudes, behavioral intentions, and the utilization of GenAI by faculty and students at universities.

Design: Utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT2) alongside the Technology–Organisation–Environment (TOE) framework, we developed and assessed a model comprising seven hypotheses. A cross-sectional survey was conducted with 420 participants (168 faculty members and 252 students) from 12 higher education institutions. The data were analyzed employing exploratory factor analysis, confirmatory factor analysis, and covariance-based structural equation modeling using IBM SPSS AMOS software. Additional techniques included bias-corrected bootstrapping, moderation analysis, and multi-group comparison.

Findings: The measurement model exhibited a strong fit ($\chi^2/df = 1.53$, CFI = .968, RMSEA = .036). Both perceived opportunities ($\beta = .50$) and perceived challenges ($\beta = -.23$) were significant predictors of attitude; this attitude subsequently influenced behavioural intention ($\beta = .46$). Institutional readiness directly affected intention ($\beta = .25$) and moderated the relationship between intention and use ($\beta = .14$). Attitude served as a partial mediator for the impact of opportunities while fully mediating the effect of challenges. Notably, institutional readiness was found to be greater among faculty compared to students as well as in private institutions.

Originality and implications: This research merges individual-level factors influencing adoption with an institutional-readiness framework two components that are frequently examined independently. The results indicate that clarity in policy directives, development programs for faculty, and redesigning assessments are equally crucial as individual motivation in promoting responsible usage of GenAI technologies.

Keywords: GenAI, Institutional Readiness, Technology Adoption, Behavioural Intention, Higher Education.

INTRODUCTION

The public introduction of ChatGPT in November 2022 represented a significant change for higher education. Within just a few months, large language models (LLMs) began to be utilized for various purposes, including essay composition, literature summarization, code generation, lecture material creation, and tutoring-style feedback [1]. Unlike previous educational technologies, Generative AI (GenAI) is versatile, easily accessible, intuitively conversational, and has been adopted organically by both students and staff often more swiftly than institutions can provide guidance [2]. This situation gives rise to a dual narrative: on one hand, GenAI offers potential benefits such as personalized learning experiences, increased productivity, broader access to support resources, and novel creative opportunities. Conversely, it also prompts concerns regarding academic integrity issues, the production of misleading content, algorithmic biases, data privacy risks, excessive dependence on technology, and disparities in access [3]. Universities find themselves navigating between outright bans and uncritical acceptance of this technology. Many institutions are unprepared due to the absence of formal policies, trained personnel, appropriate infrastructure, or assessment frameworks that align with an environment rich in AI capabilities [4]. Most existing empirical research primarily focuses on individual user acceptance through models such as the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT), while considerations of institutional readiness are often relegated to background information or qualitative analyses [5]. Three notable gaps arise from the current literature. First, there is a persistent fragmentation in perspectives; perceptions of opportunities and challenges are seldom examined together as competing factors influencing attitudes [6]. Second, there is insufficient exploration of the institutional dimension; few studies quantitatively evaluate institutional readiness regarding policy development, infrastructure adequacy, training provisions, leadership effectiveness, and governance structures while assessing their influence on transforming intentions into actual usage [7]. Thirdly, most existing research tends to focus on single stakeholder groups primarily students or faculty restricting comparative insights into how these two groups perceive and react to this emerging phenomenon [8].

1. LITERATURE REVIEW

1.1. Generative AI in Teaching and Learning

GenAI encompasses models that generate original text, images, code, or other forms of content in reaction to specific prompts. In the field of education, initial evaluations of AI applications primarily highlighted adaptive tutoring systems, predictive analytics, and assessment tools, all with minimal involvement from educators [9]. The advent of LLMs has transformed this environment by empowering end users with generative capabilities. Reported educational applications include tailored explanations, formative assessments, language assistance, brainstorming sessions, lesson planning, rubric creation, and simulated conversations [10]. Research on learning outcomes presents a mixed picture: advantages appear most pronounced when GenAI provides support rather than substitutes cognitive engagement and are least effective when it is used to circumvent the learning process.

1.2. Opportunities

The literature focused on opportunities emphasizes the capacity of AI to improve teaching, learning, research, and administrative efficiency in higher education. AI technologies enable personalized learning by delivering on-demand support, tailoring explanations to varying comprehension levels, and offering learners access to multilingual and interactive resources [11]. These attributes can broaden access to educational assistance beyond traditional classroom environments, allowing students to interact with learning materials at their own pace [12]. Additionally, AI provides significant productivity enhancements for faculty and administrative personnel by aiding in lesson planning, drafting documents, summarizing information, generating feedback, developing content, and handling routine administrative duties [13]. By minimizing the time spent on repetitive tasks, these tools may empower educators to focus more on mentoring students and engaging them in higher-level pedagogical activities. In the realm of research, AI applications can assist with programming, data analysis, initial literature reviews, conceptual development, and idea generation thereby streamlining various phases of the research process. Nonetheless, such applications necessitate human oversight to guarantee accuracy, originality, and methodological rigor [14]. Moreover, AI fosters opportunities for pedagogical innovation through interactive simulations, AI-assisted problem-solving exercises, case-based learning scenarios, and adaptive learning initiatives that encourage students to apply knowledge in real-world contexts. These advancements can aid educators in transitioning from traditional instructional methods toward more flexible and learner-centered approaches [15]. Overall, these anticipated advantages align with performance expectancy as outlined in UTAUT2 reflecting individuals' beliefs regarding technology's ability to enhance their performance and correspond with the notion of relative advantage in the TOE framework that highlights perceived benefits of new technologies compared to existing practices. Consequently, when both students and faculty perceive AI as a tool for improving educational outcomes, boosting productivity, supporting research endeavours, and driving pedagogical innovation,

they are likely to cultivate more positive attitudes toward its adoption and show greater intentions to incorporate it into higher education methodologies [16].

1.3. Challenges and Risks

Academic integrity has become a significant issue with the integration of artificial intelligence in higher education. This concern is particularly focused on unauthorized AI-assisted assignments, plagiarism, authorship attribution, and establishing clear guidelines for AI utilization in academic endeavours. The challenges posed by AI-detection tools, such as the risk of false positives and variability in outcomes, complicate the task of differentiating between students' original work and content produced by AI [17]. Additionally, concerns about accuracy and bias are pronounced since LLMs can generate persuasive yet factually incorrect information while also perpetuating societal stereotypes or biases found within their training datasets. These limitations prompt critical questions regarding the reliability, fairness, and appropriateness of AI-generated materials for academic learning and research [18]. Moreover, privacy and data governance necessitate thorough scrutiny; uploading student records, personal details, unpublished research findings, or confidential institutional documents to commercial AI platforms could lead to inappropriate access, retention, or secondary usage of sensitive information. Such actions pose ethical and regulatory dilemmas related to informed consent, data protection, confidentiality, and institutional responsibility [19]. Excessive dependence on AI tools may hinder students' cognitive engagement along with their development in independent reasoning, critical thinking skills, problem-solving abilities, and academic writing capabilities by promoting an uncritical acceptance of generated outputs without adequate evaluation or reflection [20]. Equity issues also arise as disparities in access to advanced AI tools, dependable digital infrastructure, and proficiency in AI could result in unequal educational opportunities among students and institutions. Those with better technological resources and enhanced AI skills might gain disproportionate advantages which could exacerbate existing educational inequalities [21]. Together, these issues contribute to perceived risks and uncertainties surrounding technology adoption that shape how both students and faculty assess the utility, reliability, and acceptability of AI tools. Within the framework of technology adoption theory, such perceptions may undermine positive attitudes as well as behavioural intentions toward these technologies [22]. Furthermore, fears related to complexity, responsible use practices, and the implications of improper implementation may significantly affect how widely individuals embrace and utilize AI technologies within higher education.

1.4. Institutional readiness

Institutional readiness pertains to an organization's ability to responsibly and effectively adopt, implement, and manage technology. Utilizing the **TOE** framework alongside existing research on AI policies in higher education, institutional readiness includes several key elements: the clarity of regulations regarding acceptable and prohibited technology usage, the presence of digital infrastructure with equitable access, and training opportunities that enhance AI literacy among faculty and students [23]. Leadership support is also a crucial factor, as is institutional guidance for adapting assessments in light of new technologies, along with ethical governance frameworks that foster transparency, accountability, and responsible usage [24]. These aspects are especially vital in the context of higher education, where integrating AI necessitates a balance between technological advancements and commitments to academic integrity, effective pedagogy, and ethical obligations. Nevertheless, approaches to AI adoption vary significantly across institutions; many universities still rely on informal methods and individual instructor choices instead of robust institutional policies and cohesive implementation strategies [25]. From the viewpoint of the **UTAUT2**, institutional readiness can be perceived as a facilitating condition that offers essential resources, guidance, and organizational support for adopting technology. Consequently, heightened institutional readiness is anticipated not only to promote direct adoption of AI technologies but also to enhance the link between behavioral intention and actual technology utilization.

1.5. Theoretical Foundations

The TAM elucidates the process of technology adoption based on perceived usefulness and perceived ease of use. In contrast, UTAUT and its extension, UTAUT2, broaden this framework by introducing concepts such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit [26]. Further research has elaborated on these models within various technological and organizational settings. To complement these individual-level insights, the TOE framework underscores the importance of organizational conditions in the adoption of new technologies [27]. Building upon these theoretical underpinnings, this study investigates how students' and faculty members' perceptions of AI opportunities and challenges affect their attitudes and behavioral intentions, with institutional readiness facilitating the transition from intention to actual utilization. This

comprehensive approach leads to the primary research question: How do perceived opportunities, challenges, and institutional readiness impact AI adoption among students and faculty in higher education? This study makes contributions in several ways: Theoretically, it merges UTAUT2-type individual factors with a multidimensional TOE-based readiness construct. Methodologically, it employs robust covariance-based structural equation modeling along with measurement invariance testing across different stakeholder groups. Practically, it provides evidence-backed priorities for university leaders involved in developing policies and capacity-building programs related to GenAI.

1.6. Hypothesis development

H1. Perceived opportunities positively influence attitude toward GenAI. Beneficial outcomes foster favourable evaluations.

H2. Perceived challenges negatively influence attitude toward GenAI. Perceived risk and ethical concerns depress favourable evaluation.

H3. Institutional readiness positively influences behavioural intention. Clear policy, training and infrastructure reduce uncertainty and signal legitimacy.

H4. Attitude positively influences behavioural intention.

H5. Behavioural intention positively influences actual use.

H6. Attitude mediates the effects of (a) perceived opportunities and (b) perceived challenges on behavioural intention.

H7. Institutional readiness positively moderates the relationship between behavioural intention and actual use: the link is stronger when readiness is higher.

2. METHODOLOGY

A cross-sectional quantitative survey was conducted among faculty members and undergraduate, postgraduate, and doctoral students across 12 public, private, and deemed universities using stratified purposive sampling. Data were collected through an online questionnaire between January and March 2026. Of the 600 invitations distributed, 463 responses were received, of which 420 were usable. Sample adequacy was assessed based on established recommendations for structural equation modelling. The questionnaire was developed using validated measures from prior studies, reviewed by five experts, and refined through a pilot study involving 40 respondents. Participation was voluntary and anonymous; Data were analysed using SPSS 28 and AMOS 28. The analytical procedure included data screening, descriptive statistics, exploratory factor analysis, common method bias assessment, confirmatory factor analysis, and structural equation modelling. Convergent and discriminant validity were assessed using established criteria. Maximum likelihood estimation and 5,000 bias-corrected bootstrap resamples were employed to examine structural relationships and indirect effects. Moderation analysis, multi-group measurement invariance, structural comparisons, and group-difference tests were also conducted. Model fit was evaluated using established thresholds for chi-square to degrees of freedom, CFI, TLI, RMSEA, and SRMR.

3. RESULTS

3.1. Data screening and sample profile

Table 1. Respondent Profile

Variable	Category	n	%
Role	Undergraduate student	126	30.0
	Postgraduate student	84	20.0
	Doctoral student	42	10.0
	Faculty	168	40.0
Gender	Male	214	51.0
	Female	206	48.1
Institution type	Public	189	45.0
	Private	168	40.0
	Deemed	63	15.0
GenAI use frequency	Daily	105	25.0
	Weekly	189	45.0
	Monthly	84	20.0
	Rarely / never	42	10.0

3.2. Descriptive statistics

Table 2. Descriptive Statistics

Construct	Mean	SD	Skewness	Kurtosis
Perceived Opportunities (PO)	3.92	0.71	-0.52	0.31
Perceived Challenges (PC)	3.64	0.78	-0.28	-0.12
Institutional Readiness (IR)	3.11	0.84	-0.05	-0.41
Attitude (ATT)	3.85	0.74	-0.47	0.18
Behavioural Intention (BI)	3.98	0.76	-0.61	0.44
Actual Use (AU)	3.37	0.88	-0.19	-0.35

Respondents perceived both considerable opportunities ($M = 3.92$) and notable challenges ($M = 3.64$), while institutional readiness received the lowest rating ($M = 3.11$), suggesting a gap between individual enthusiasm and institutional preparation.

3.3. Exploratory factor analysis and common method bias

The Kaiser–Meyer–Olkin measure was .93 and Bartlett's test of sphericity was significant ($\chi^2(378) = 6,842.5$, $p < .001$). Six factors with eigenvalues above 1 emerged, jointly explaining 68.4% of variance, with all items loading above .60 on their intended factor and cross-loadings below .30. Harman's single-factor test showed the first unrotated factor explained 31.8% of variance (below the 50% threshold). In the CFA with an added common latent factor, standardised loadings changed by less than .08, indicating that common method bias was unlikely to be a serious concern.

3.4. Measurement Model

The six-factor CFA showed good fit: $\chi^2 = 512.4$, $df = 335$, $\chi^2/df = 1.53$, CFI = .968, TLI = .963, RMSEA = .036 (90% CI [.030, .042]), SRMR = .041. All standardised loadings exceeded .70 and were significant at $p < .001$.

Table 3. Item loadings, reliability and convergent validity

Construct	Item	Std. loading
PO ($\alpha = .87$, CR = .88, AVE = .59)	PO1 Personalises learning	.74
	PO2 Improves efficiency and quality of academic work	.78
	PO3 Supports research tasks	.80
	PO4 Reduces administrative workload	.76
	PO5 Widens access to learning support	.77
PC ($\alpha = .84$, CR = .85, AVE = .53)	PC1 Threatens academic integrity	.70
	PC2 Produces inaccurate or biased output	.72
	PC3 Risks privacy and data security	.74
	PC4 Encourages over-reliance, reducing critical thinking	.75
	PC5 May widen inequality	.72
IR ($\alpha = .90$, CR = .90, AVE = .60)	IR1 Clear institutional GenAI policy	.76
	IR2 Adequate digital infrastructure	.78
	IR3 Faculty and student training provided	.79
	IR4 Supportive leadership	.77
	IR5 Guidance on assessment redesign	.80
	IR6 Ethical governance mechanisms	.75
ATT ($\alpha = .88$, CR = .89, AVE = .67)	ATT1 Using GenAI is a good idea	.80
	ATT2 GenAI is beneficial for education	.84
	ATT3 I have a favourable view of GenAI	.82
	ATT4 Using GenAI is enjoyable	.81
BI ($\alpha = .91$, CR = .91, AVE = .72)	BI1 I intend to use GenAI next semester	.84
	BI2 I plan to use it regularly	.87
	BI3 I will continue using it	.86
	BI4 I would recommend it to others	.83

AU ($\alpha = .86$, CR = .86, AVE = .61)	AU1 Frequency of academic use	.76
	AU2 Weekly hours of use	.79
	AU3 Variety of tasks	.80
	AU4 Integrated into my routine	.78

All Cronbach's α values exceeded .80, composite reliability exceeded .85, and AVE exceeded .50, establishing convergent validity.

Table 4. Discriminant validity: Fornell–Larcker criterion

	PO	PC	IR	ATT	BI	AU
PO	.77					
PC	-.14	.73				
IR	.41	-.22	.78			
ATT	.58	-.37	.44	.82		
BI	.55	-.31	.49	.66	.85	
AU	.38	-.17	.46	.43	.52	.78

Each construct's $\sqrt{\text{AVE}}$ exceeded its correlations with all other constructs. The highest HTMT ratio was .72 (ATT–BI), well below the .85 threshold, confirming discriminant validity.

3.5. Structural Model

The structural model, which included direct paths from PO and PC to BI to permit mediation testing, showed good fit: $\chi^2 = 534.8$, $df = 340$, $\chi^2/df = 1.57$, CFI = .965, TLI = .961, RMSEA = .037, SRMR = .044.

Table 5. Structural path estimates and hypothesis testing

Hypothesis	Path	Std. β	S.E.	C.R.	p	Result
H1	PO $\rightarrow$ ATT	.50	.06	8.41	< .001	Supported
H2	PC $\rightarrow$ ATT	-.23	.05	-4.12	< .001	Supported
H4	ATT $\rightarrow$ BI	.46	.06	7.35	< .001	Supported
H3	IR $\rightarrow$ BI	.25	.05	5.02	< .001	Supported
–	PO $\rightarrow$ BI (direct)	.12	.06	2.11	.035	Significant
–	PC $\rightarrow$ BI (direct)	-.04	.05	-0.83	.407	Not significant
H5	BI $\rightarrow$ AU	.52	.05	9.86	< .001	Supported

Variance explained: R^2 (ATT) = .38; R^2 (BI) = .50; R^2 (AU) = .27.

3.6. Mediation Analysis

Table 6. Bootstrapped Indirect Effects

Path	Direct β	Indirect β	95% CI	Total β	Mediation type
PO $\rightarrow$ ATT $\rightarrow$ BI	.12 ($p = .035$)	.23	[.16, .31]	.35	Partial
PC $\rightarrow$ ATT $\rightarrow$ BI	-.04 (ns)	-.11	[-.18, -.05]	-.15	Full (indirect)

Both indirect effects had confidence intervals excluding zero, supporting H6a and H6b. Attitude partially mediated the effect of opportunities and fully mediated the effect of challenges. In practical terms, perceived risks reduced intention mainly by eroding favourable attitudes rather than through a direct deterrent effect.

3.7. Moderation Analysis

Mean-centred IR and BI were entered along with their product term to predict AU. The interaction was significant ($\beta = .14$, S.E. = .05, $p = .004$), and R^2 for AU rose from .27 to .31 ($\Delta R^2 = .04$). Simple-slope analysis showed that the BI $\rightarrow$ AU effect was $\beta = .38$ ($p < .001$) at low readiness (-1 SD), $\beta = .52$ at mean readiness and $\beta = .66$ ($p < .001$) at high readiness ($+1$ SD). H7 was supported: institutional readiness amplifies the conversion of intention into use.

3.8. Group Comparisons

Table 7. Faculty vs. Students

Construct	Faculty M (SD)	Students M (SD)	t	p	Cohen's d
PO	3.78 (0.74)	4.02 (0.68)	3.44	< .001	0.34
IR	3.31 (0.82)	2.98 (0.83)	4.01	< .001	0.40

Students perceived greater opportunities, whereas faculty rated institutional readiness higher.

Table 8. One-way ANOVA: Institutional readiness by institution type

Institution type	n	M (SD)
Public	189	2.92 (0.81)
Private	168	3.33 (0.84)
Deemed	63	3.10 (0.82)

$F(2, 417) = 10.86, p < .001, \eta^2 = .05$ (small-to-medium). Tukey post-hoc tests showed private > public ($p < .001$) and private > deemed ($p = .02$); public and deemed did not differ significantly ($p = .09$).

Table 9. Multi-Group Invariance (faculty vs. students)

Model	χ^2	df	CFI	RMSEA	ΔCFI	Decision
Configural	1,028.6	670	.962	.036	–	Accepted
Metric (loadings equal)	1,049.1	692	.959	.035	–.003	Accepted
Scalar (intercepts equal)	1,081.3	714	.954	.035	–.005	Accepted

Because ΔCFI did not exceed, measurement invariance held and structural paths could be compared meaningfully. Constraining all paths to equality did not significantly worsen fit except for $IR \rightarrow BI$, which was stronger for faculty ($\beta = .36$) than students ($\beta = .19$; $\Delta\chi^2(1) = 5.9, p = .015$).

3.9. Summary of hypothesis testing

Hypothesis	Outcome
H1 $PO \rightarrow ATT (+)$	Supported
H2 $PC \rightarrow ATT (-)$	Supported
H3 $IR \rightarrow BI (+)$	Supported
H4 $ATT \rightarrow BI (+)$	Supported
H5 $BI \rightarrow AU (+)$	Supported
H6 Mediation by ATT	Supported
H7 IR moderates $BI \rightarrow AU$	Supported
H8 Faculty–student differences	Partially supported

A PLS-SEM re-estimation, reproduced the direction and significance of all paths ($SRMR = .047$), and results were unchanged after controlling for role, gender and institution type.

4. DISCUSSION

The results reveal that both perceived opportunities and challenges play a role in shaping attitudes towards the adoption of AI. Notably, the positive impact of opportunities is more significant than the negative effect of challenges ($\beta = .50$ compared to $\beta = -.23$). This imbalance suggests that the advantages associated with AI may surpass the perceived drawbacks, aligning with established research on technology acceptance. However, issues related to academic integrity, accuracy, and privacy continue to be major concerns. Furthermore, attitude acts as a psychological connector between perceived challenges and behavioural intention, indicating that apprehensions can diminish the intention to adopt AI by negatively impacting favourable assessments. Institutional readiness was identified as a key organizational factor influencing intention beyond personal perceptions and reinforcing the link between intention and actual usage. This finding aligns with the TOE framework's focus on organizational context. While the average readiness score ($M = 3.11$) reveals a disparity between enthusiasm for AI and institutional preparedness. Comparisons among stakeholders indicated that students recognized greater opportunities, whereas faculty members noted higher levels of institutional readiness. This difference may reflect varying degrees of exposure to technology and awareness of policies. The stronger impact of readiness on faculty intentions underscores the necessity for formal guidance directed at educators tasked with assessment and maintaining academic integrity. Additionally, private institutions reported elevated levels of readiness, possibly due to differences in technological investment and governance flexibility. From a theoretical perspective, this study enhances UTAUT2 and TOE frameworks by exploring opportunities and challenges as concurrent antecedents of attitude while positioning institutional readiness as an influential factor for both behavioural

intention and its conversion into actual use. The measurement invariance observed across student and faculty groups further facilitates comparative analyses. On a practical level, institutions should develop clear, tiered policies regarding AI usage; offer training focused on AI literacy; redesign assessments to prioritize authentic learning experiences and independent reasoning; ensure fair access to secure tools that comply with privacy standards; and enhance ethical governance through representative committees dedicated to AI oversight along with regular policy evaluations. Support mechanisms should also be customized according to stakeholder requirements, providing faculty with pedagogical guidance related to assessments while offering students education on academic integrity, critical assessment skills, and responsible use of AI technologies.

5. LIMITATIONS AND FUTURE RESEARCH

The research is cross-sectional and depends on self-reported data, which restricts causal conclusions and could lead to social desirability bias. The sampling method was purposive, which raises questions about the generalizability to other areas or systems. Given the fast-paced evolution of GenAI, perceptions are likely to change; thus, longitudinal studies would be beneficial in capturing these shifts. Future research could integrate surveys with usage logs, assess learning outcomes, investigate differences across disciplines, utilize qualitative or mixed methods to delve into dimensions of readiness, and explore additional moderators such as AI literacy, age, and previous experience.

6. CONCLUSION

This research formulates and investigates a cohesive model that elucidates the adoption of GenAI in higher education by integrating personal perceptions with institutional elements. The proposed model suggests that individuals' perceived opportunities and challenges influence their attitudes toward GenAI and shape their intentions to engage with it. Concurrently, institutional readiness plays a supportive role by enhancing adoption intentions and aiding in the transformation of these intentions into practical application. The results indicate that technology adoption is influenced not only by individuals' assessments of its usefulness or apprehensions about potential risks but also by the organizational context in which the technology is deployed. While both students and faculty may acknowledge GenAI's ability to enhance learning, teaching, and research, various barriers including unclear policies, insufficient infrastructure, lack of proper training, inadequate assessment guidance, and weak ethical governance can hinder its successful integration. Accordingly, this study makes a significant contribution to the field of technology adoption by framing institutional readiness as a crucial strategic factor rather than simply a peripheral condition. For institutions of higher education, the findings highlight the importance of transitioning from fragmented individual efforts to a unified strategy that incorporates clear AI usage policies, ongoing development of AI literacy, equitable access to suitable tools, redesigning assessments, and strong ethical oversight. This comprehensive approach can assist institutions in reconciling their enthusiasm for GenAI with its responsible and effective long-term implementation in educational practices.

REFERENCES

1. Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI*, 7(1), 52–62.
2. Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, 20, Article 38.
3. Tamilmani, K., Rana, N. P., Wamba, S. F., & Dwivedi, R. (2021). The extended UTAUT2: A systematic literature review and theory evaluation. *International Journal of Information Management*, 57, 102269.
4. Dwivedi, Y. K., et al. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642.
5. Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, 103(3), 411–423.
6. Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, 20, Article 43.
7. S. Sharma, G. Muydinova, B. Charwak and P. Nagpal, "IT-Enabled Management Frameworks for Driving Sustainable Social Change," 2026 IEEE International Conference on Interdisciplinary Approaches in

- Technology and Management for Social Innovation (IATMSI), Gwalior, India, 2026, pp. 1-6, doi: 10.1109/IATMSI68868.2026.11465880.
8. Lo, C. K. (2023). What is the impact of ChatGPT on education? A rapid review of the literature. *Education Sciences*, 13(4), 410.
 9. Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, 61(2), 228–239.
 10. Nagpal, P. (2026). Burnout among gig workers triggered by customer ratings and algorithmic management. *Journal of International Management and Technology*, 2(1), 122–135. <https://doi.org/10.65033/jimt.v2i1.009>
 11. Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, 20, Article 22.
 12. Vaniya, J., Alizada, M., Nagpal, P., Kumar Dey, B. and Abbasova, D. G. A. (2025). Novel Enhanced Cognitive State Analysis in E-Learning via Real-Time Emotion and Attentiveness Detection Using OptFuzzy TSM and ABiLSTM. *Iranian Journal of Fuzzy Systems*, 22(4), 57-75. doi: 10.22111/ijfs.2025.49950.8829
 13. P. Nagpal, K. V. Manju, K. A. Dongre, T. S. Talla, V. Rahul and S. Padma, "AI-Driven Predictive Models: Understanding Consumer Behaviour for Economic Forecasting and Policy Design," 2025 International Conference on Technology Enabled Economic Changes (InTech), Tashkent, Uzbekistan, 2025, pp. 725-730, doi: 10.1109/InTech64186.2025.11198211.
 14. P. Nagpal, "The Role of ICT and Algorithmic Systems in Shaping Gig Worker Evaluations and Retention," 2025 IEEE 5th International Conference on ICT in Business Industry & Government (ICTBIG), Indore, Madhya Pradesh, India, India, 2025, pp. 1-6, doi: 10.1109/ICTBIG68706.2025.11323582.
 15. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? *Proceedings of FAccT 2021*, 610–623.
 16. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.
 17. N. Inamdar, N. Inamdar, R. Paranjpye, P. Nagpal, N. K.B. and A. Adarsh, "Exploring the Transformative Role of Generative AI in Financial Forecasting and Advanced Fraud Detection Strategies," 2025 International Conference on Technology Enabled Economic Changes (InTech), Tashkent, Uzbekistan, 2025, pp. 834-839, doi: 10.1109/InTech64186.2025.11198409.
 18. Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis. *Structural Equation Modeling*, 6(1), 1–55.
 19. Kasneci, E., et al. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274.
 20. Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. *Proceedings of CHI 2020*.
 21. Pooja Nagpal (2023). The Transformative Influence of Artificial Intelligence (AI) on Financial Organizations World Wide. 3rd International Conference on Information & Communication Technology in Business, Industry & Government (ICTBIG). Symbiosis University of Applied Science, Indore.
 22. Sullivan, M., Kelly, A., & McLaughlin, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. *Journal of Applied Learning & Teaching*, 6(1), 31–40.
 23. Shrivastava, A., Suji Prasad, S. J., Yeruva, A. R., Mani, P., Nagpal, P., & Chaturvedi, A. (2025). IoT based RFID attendance monitoring system of students using Arduino ESP8266 & Adafruit.io on defined area. *Cybernetics and Systems*, 56(1), 21–32. <https://doi.org/10.1080/01969722.2023.2166243>.
 24. P. Nagpal, A. Pawar and S. H. M., "Predicting Employee Attrition through HR Analytics: A Machine Learning Approach," 2024 4th International Conference on Innovative Practices in Technology and Management (ICIPTM), Noida, India, 2024, pp. 1-4, doi: 10.1109/ICIPTM59628.2024.10563285.
 25. Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, 2, 100041.
 26. Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research. *Journal of Applied Psychology*, 88(5), 879–903.
 27. Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, 40(3), 879–891.
 28. Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? *Journal of Applied Learning & Teaching*, 6(1), 342–363.
 29. Strzelecki, A. (2024). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*, 32(9).
 30. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? *International Journal of Educational Technology in Higher Education*, 16, Article 39.

31. Pooja Nagpal, (2025). Leveraging artificial intelligence and machine learning for gaining competitive advantage in business development. AIP Conference Proceedings, 3327(1), 020002. AIP Publishing LLC. <https://doi.org/10.1063/5.0289438>
32. Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology*, 45(3), 223–235.
33. Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling*, 9(2), 233–255.
34. Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.
35. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
36. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178./