Assessing the Opportunities and Challenges of Integrating Generative Artificial Intelligence Tools in Higher Education Institutions

[1]Prof. (Dr.) Priyanka Murria, [2]Prof. Aashish A Gadgil, [3]Dr. B.G.Lakshmi, [4]Dr. Navneet Rajoria, [5]Dr. Pew Maji, [6]Dr. Yogesh Deshmukh

[1]Professor, Department of Management Institute of Innovation in Technology and Management Affiliated to G.G.S.I.P University, Delhi

drpriyankamurria.iitmdelhi@gmail.com

[2]Assistant Professor Department of Electronics and Communication KLS Gogte Institute of Technology, Belagavi

Email: aagadgil@git.edu

[3]Associate Professor, Hod PG Department of Commerce, Surana College (Autonomous), Bengaluru, Karnataka

lakshmi.com@suranacollege.edu.in

[4]Assistant Professor (SG), Energy Economics & Sustainability Cluster, School of Business. UPES Dehradun-248001

Navneetrajoria7@gmail.com

[5]Associate Professor, Department of Humanities, Rungta International Skills University, Bhilai

dr.pewmaji@gmail.com

[6]Assistant Professor, Alard Institute of Management, Pune, Maharashtra

yogesh14deshmukh1976@gmail.com

HOW TO CITE:

Priyanka Murria, Aashish A Gadgil, B.G.Lakshmi, Navneet Rajoria, Pew Maji, Yogesh Deshmukh (2026). Assessing the Opportunities and Challenges of Integrating Generative Artificial Intelligence Tools in Higher Education Institutions. International Journal of Special Education, 41(10s), 1312-1325

ABSTRACT:

GenAI applications, including ChatGPT, Google Gemini, Microsoft Copilot, Claude AI, etc., are changing how HEIs teach, learn, research and administer. These AI-based applications are providing new ways to create personalized curricula, provide assessments, assist students with their academic writing, and inform institutional decisions. However, like many emerging technologies, the use of GenAI presents several issues concerning academic integrity, ethics, data protection, faculty preparedness, and institutional policy. Therefore, the effective incorporation of AI technology will require an equal consideration of the positive aspects of its integration and the negative. The aim of this research is to identify the opportunities and challenges related to the integration of GenAI into Private Universities in India. A survey based on a quantitative approach was used where 201 participants were randomly sampled from five private universities using a stratified sampling method. Data analysis was conducted by employing IBM-SPSS statistical package. Descriptive statistics, Reliability Analysis, Exploratory Factor

COPYRIGHT STATEMENT:
Copyright: © 2026 Authors.
Open access publication underthe terms and conditions of the Creative CommonsAttribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).

Analysis, Correlation Analysis, Multiple Regression Analysis, Independent Sample T Test, One Way Anova and Chi-Square Analysis were used to analyze the interrelationship among Institutional Readiness, Perceived Usefulness, Ethical Concerns, Technological Infrastructure and AI Adoption. It is anticipated that the results will show that institutional support and perceived usefulness along with technological infrastructure positively affect AI adoption; however, ethical concern and lack of training negatively affects it. Additionally, this research offers a strategic framework for creating Responsible AI Implementation Policies that can facilitate innovation while maintaining Academic Quality and Ethical Standards.

Keywords: Generative Artificial Intelligence, AI, Higher Education Institutions, HEIs, Integration, Academics

Introduction

Advances in Generative Artificial Intelligence (GenAI), specifically large language models able to produce human-like text, images, programming code, audio, and multimedia content, represent a significant advancement toward accelerating the digital transformation of post-secondary education. In contrast to traditional artificial intelligence systems that analyze existing information, GenAI produces new content using advanced machine learning algorithms trained on vast amounts of data and thus represents an opportunity for HEIs to innovate in all aspects of teaching, learning, research, and academic administration (Verma, et.al., 2026).

In recent years, Higher Education Institutions (HEIs) have been progressively acknowledging the long-term strategic value of incorporating GenAI technologies into their educational ecosystems. As such, faculty members now use GenAI-based platforms to prepare course materials, generate test questions, create instructional content, provide customized formative assessments, and increase their research productivity (Gonçalves, D., 2024). Similarly, students use various GenAI-based tools for academic writing; completing literature reviews; solving problems; obtaining help with coding; translating languages; and developing interactive learning environments. Additionally, administrative units at HEIs have started employing GenAI in providing student support services; managing admissions; informing institutional planning; automating documents; and making data-driven decisions. As the result of the incorporation of GenAI into the higher education ecosystem, conventional methods of education are being transformed to include adaptive learning environments; customized instruction; continuous assessment; and collaborative knowledge generation (Bagri, D. S., 2026). For example, students may obtain immediate academic assistance irrespective of their location or time; and faculty may be able to focus more on high-level pedagogy as opposed to administrative duties. Therefore, there is a strong possibility that GenAI will contribute substantially to enhancing educational efficiency; accessibility; and educational outcomes. However, despite these potential advantages, the incorporation of GenAI into higher education settings also present many challenges which must be addressed by institutions. Concerns about academic dishonesty; plagiarism; spreading misinformation; algorithmic bias; copyright violations; protecting student privacy; ensuring the security of computing systems; and becoming overly dependent upon GenAI-created content are just some of the issues that are becoming more apparent among academic stakeholders. Accordingly, HEI's must establish robust governance structures that ensure the ethical use of AI in ways that maintain academic integrity and institution credibility.

Generally speaking, Private Higher Education Institutions (HIEs) have exhibited greater flexibility and willingness to adopt novel technologies when compared to many Public HIEs. Typically, this increased flexibility is due to enhanced access to financial resources; the availability of contemporary digital infrastructures; partnerships with local businesses/industries; and institutional autonomy. All of these factors often allow private universities to quickly implement AI-based educational programs. However, varying levels of faculty preparedness to use AI; differing levels of technological competence within each university community; differences in organizational cultures related to the implementation of policies; and variations in student awareness about AI have continued to affect how effectively different types of institutions can successfully incorporate AI into their educational delivery (S Singh, et.al., 2026).

The previously identified barriers to AI adoption in HEIs, the implementation of the National Education Policy (NEP) 2020 in India has added another layer of complexity. Specifically, NEP emphasizes technology-enabled education; digital learning environments; multidisciplinary education; and innovation-driven pedagogies. Furthermore, NEP calls upon educational institutions to develop curricula and pedagogies based on emerging technologies such as Artificial Intelligence in order to better prepare students for the needs of future workforces. Given these policy directives from government officials, it is imperative to understand those variables that affect the adoption of AI in private universities in order to meet national goals for education.

Although there are several prior studies that have investigated the acceptance of technology in HEIs; distance education; and digital transformations in education, there are very few empirical studies that have examined both the opportunities and obstacles associated with the adoption of GenAI in private HEIs located in India. While there are many theoretical studies examining the topic of GenAI adoption in HEIs, most remain conceptual in nature and fail to account for faculty members and/or institutional views. Moreover, there is little empirical evidence demonstrating how institutional preparedness to adopt AI; technological infrastructure to support AI adoption; ethical considerations related to AI adoption; and organizational support for faculty adoption collectively affect AI adoption in HEIs.

Review of Literature

Alam (2023), focused on the emerging role of artificial intelligence (AI) in education and the benefits it has provided along with concerns surrounding its adoption. Alam (2023) stated that AI could benefit students through providing more personalized learning, assessments, and administrative services; however, there were significant concerns regarding AI's impact on ethics, student/teacher privacy, and academic integrity. Ultimately, the author suggested that institutional preparation for the long-term is a critical component for the successful implementation of AI. Alenezi (2024) studied the adoption of artificial intelligence (AI) within higher education by exploring its opportunities, limitations and future outlooks. Alenezi (2024), discovered that AI will significantly increase the effectiveness of teachers, research productivity, and decision-making capabilities at institutions, although, this will require sufficient technology infrastructure, faculty preparedness and regulatory policies. The author recommends developing a strategic plan for the successful integration of AI into institutions.

Dwivedi et al. (2023) assessed the impacts of generative chatbots such as ChatGPT on three areas of society: research, education and public policy. The authors indicated that generative chatbots may be able to significantly improve productivity, creativity and knowledge creation. However, they also identified several risks including the spread of misinformation, bias, lack of ethics and a degradation of academic integrity. The authors recommended balancing regulations and using generative chatbots responsibly. (Hair., et.al., 2019) provided comprehensive guidance on how to apply multiple forms of multivariate statistical analyses when conducting research in the social sciences. (Hair., et.al., 2019), outlined steps to test reliability, perform factor analysis,

develop regression equations, develop structural equation models and test hypotheses. This resource is a valuable guide for researchers utilizing quantitative methodologies. (Holmes., et.al., 2019) discussed the potential positive outcomes and negative consequences of adopting artificial intelligence (AI) in schools. (Holmes., et.al., 2019) noted that AI has the ability to provide each learner with customized learning experiences through the use of "intelligent" tutoring systems. Although AI provides many advantages to learners and educators alike, they noted that it will only be useful if implemented ethically, educators are prepared to utilize the system appropriately and school districts have established policies to promote its effective use.

Kasneci et al. (2023) conducted a review of the current literature on educational applications of large language models, specifically ChatGPT. Kasneci et al. (2023) found that large language models have the capacity to aid learners with their learning process, assist them with their academic writing assignments and provide learners with individualized feedback. However, they also noted that there are risks involved with relying too heavily on large language models such as creating instances of plagiarism, spreading false information and over-reliance on these technologies. Therefore, Kasneci et al. (2023), recommend that institutions implement these technologies responsibly and establish policies for their proper utilization. Luckin (2018) reviewed the relationship between machine learning and human intelligence as they relate to changing education during the 21st century. Luckin (2018), contended that AI should serve as a complementary tool for teachers in addition to providing additional support to learners so that educators can better assess student learning needs and make more informed decisions about instruction. Furthermore, she emphasized that AI should be designed to meet human-centered goals. Nguyen (2025), assessed the theoretical and practical approaches to implementing generative AI tools in higher education.

Nguyen (2025), pointed out that responsible implementations of generative AI tools in post-secondary education will depend upon ensuring transparent uses of the tools, fair treatment of all students who use these tools and establishing accountability among those who adopt and administer these tools. Additionally, Nguyen (2025), mentioned that in order to properly prepare for the widespread adoption of generative AI tools in higher education, educational institutions need to have developed instructional design frameworks that take into account both ethical considerations of using generative AI tools and pedagogical theories that address best-practices in using these tools. Perkins (2023), investigated how generative chatbots like ChatGPT affect academic integrity in higher education. Perkins (2023), identified issues associated with plagiarism, authenticating assessment materials and responsible use of generative chatbots in higher education; thusly recommending that institutions redesign their methods of assessing students' performance and implement stronger policies addressing academic integrity in the age of generative chatbots. This article discusses an ongoing issue with the use of artificial intelligence in education.

Rahman and Watanabe (2023) studied this topic through a systematic literature review of various empirical studies about AI. They also used their findings to identify both positive effects of AI in education (such as personalized learning, increased student engagement, and improved educational administration) and negative ones (like ethics and infrastructure). Rogers (2003) created the "Diffusion of Innovations" theory which explains how new technologies get adopted by different types of organizations and society. The study discussed several types of innovation including: Relative Advantage - How does this new technology compare to existing one? Compatibility - Is it easy to implement? Complexity - Is it simple or hard to understand? Trialability - Can you try it out before adopting it? Observability - Are others using it and seeing good results? These were all important variables in determining whether someone will eventually adopt a new technology. Sallam (2023) conducted a systematic review about the applications of chatbots (ChatGPT) in health care education, research, and professional practice. The results

indicated many benefits from the use of chatbots; generating content for students/healthcare professionals, providing knowledge resources for students/researchers, supporting educational needs for students/professionals. However, there was some concern over the reliance upon chatbots due to the lack of accuracy/ethics/responsibility. The results suggested similar concerns exist throughout other forms of education. Sharples (2025) proposed a system-based model for integrating AI into educational settings during the post-digital age. He stressed the importance of a collaborative process among educators/institutions/policymakers/technology developers to ensure the implementation of AI is done responsibly. Sharples also stated the need for continuous adjustment to emerging educational technologies.

Siemens & Baker (2012) assessed how learning analytics and educational data mining could improve instruction and student learning. Their findings included the ability to make better decisions based upon data, predict future success of students and track individual student progress. Siemens & Baker also emphasize that successful integration requires close work between researchers who develop these tools and those who teach and lead educational programs. (Sullivan et al., 2023) analyzed the impact of chatbots like ChatGPT on higher education with specific reference to academic integrity and learning. While they noted that chatbots have great potential to increase productivity and provide additional help to learners, institutions should create policies/guidelines for the proper use of these tools. In addition, institutions should promote awareness among faculty members to prevent abuses. Teo (2011) researched what factors influenced teachers' intention to adopt educational technologies. His findings showed that perceived utility, ease of use, social influence, and access to support had a substantial impact on teachers' willingness to include technology into their curriculum. Therefore, his study extended previous research on the factors that affect teacher's attitudes toward accepting technology.

UNESCO (2023) developed a set of recommendations for the responsible use of chatbots and AI in higher education. The main focus areas included: ethical principles, transparency, human oversight, digital competence, and governance structures. The organization recommended that institutions take a measured and inclusive approach when implementing AI-based innovations to ensure that no aspect of academic quality is compromised. (Venkatesh et al., 2003) developed a unified theory of acceptance and use of technology (UTAUT), combining elements of several previously developed theories that described the mechanisms behind why people choose to accept technology. Performance expectations, effort expectations, social influence, and facilitating conditions were defined as the four primary reasons people accept technology. Yan et al. (2024) carried out a systematic review about the challenges of applying large language models in educational settings. The study discussed issues such as fairness, privacy, transparency, cheating, and responsible governance while acknowledging that LLMs have enormous potential for enhancing learning experiences.

Research Methodology

The purpose of this study is to apply a quantitative, descriptive, and exploratory research methodology to explore the opportunities and obstacles of the implementation of Generative Artificial Intelligence (GenAI) technologies into Private Higher Education Institutions (HEIs). To accomplish this goal a survey approach will be used to gather systematically and compare stakeholders' views toward GenAI technology adoption in an academic environment. Secondary and primary data sources are being used for this investigation. The primary source of data is a structured questionnaire that included demographic information along with statements which were rated on a five-point Likert scale (Strongly Disagree = 1 to Strongly Agree = 5). The secondary source of data is articles from peer reviewed journals, books, conference papers, government reports, and policies, etc. related to

artificial intelligence and higher education. The population of interest for this investigation includes faculty members, post-graduates students, research scholars, and academic administrators from five Private Higher Education Institutions who have been identified by code names as HEI_1, HEI_2, HEI_3, HEI_4 & HEI_5. These codes were assigned to protect their identity. A stratified random sampling procedure was followed to provide representative samples of each type of stakeholder group, ultimately providing a total of 201 responses. Data collected via the questionnaires were statistically analyzed utilizing appropriate descriptive and inferential statistics methods within SPSS/Statistics software at a 0.05 alpha level to determine whether there existed relationships among institutional preparedness; availability of technological resources; perceived usefulness; ethical issues; and GenAI use. By following this methodological structure data will be gathered systematically, measured reliably, and analyzed statistically with sufficient power to support the credibility of the results of this study.

Research Objectives

- To analyze the opportunities offered by Generative_Artificial Intelligence (GAI) tools in private Higher Education Institutions (HEIs).
- To recognize the major challenges associated with integrating Generative_Artificial Intelligence (GAI) into teaching, learning, research, and administration.
- To evaluate the relationship in between institutional_readiness (IR) & the adoption of Generative_Artificial Intelligence (GAI) tools.
- To examine the impact of technological_infrastructure (TI) on effective AI integration.
- To propose strategic findings for responsible as well as sustainable implementation of Generative_Artificial Intelligence (GAI) in private Higher Education Institutions (HEIs).

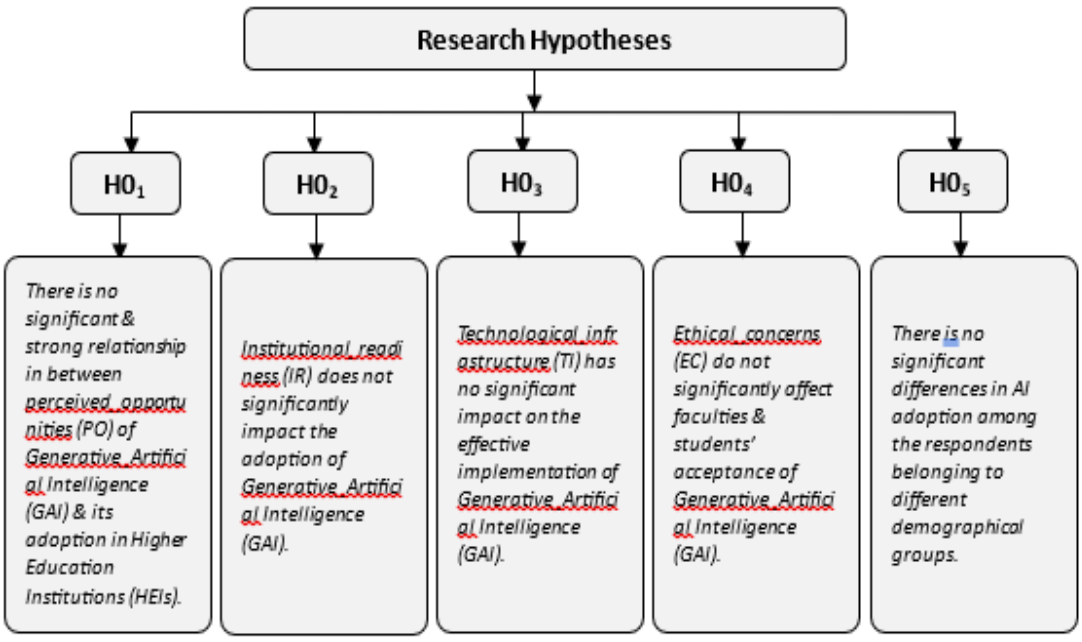

Figure 1: Research Hypothesis Framework

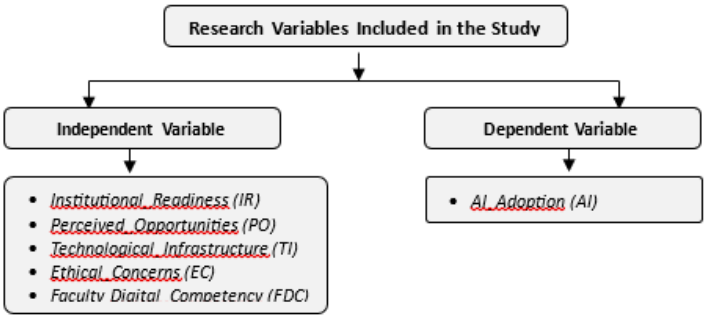

Figure 2: Research Variables

Data Analysis & Interpretation

Table 1: Distribution of Respondents across Participating Institutions

Institution_Wise Codes	Freq. (N)	Percentage (%)
HEI_1	42	20.9
HEI_2	39	19.4
HEI_3	41	20.4
HEI_4	40	19.9
HEI_5	39	19.4
Total	201	100.0

Table 2: Distribution of Respondents

Categories	Freq. (N)	Percentage (%)	
Faculty_Members (FM)	74	36.80	*The faculty members were the most common category of respondent (36.8%) as they are primarily responsible for Gen Ai implementation into the educational environment. The post graduate students accounted for almost a third of the sample, whereas the combined number of research scholar and academic administrator responses totaled just under one third of all respondents.*
Postgraduate Students (PG_S)	62	30.80	
Research_Scholars (RS)	39	19.40	
Academic_Administrators (AA)	26	12.90	
Total	201	100.00	

Table 3: Reliability Test Analysis/ Statistics

Constructs	Number of Items	Cronbach's Alpha	
Institutional_Readiness (IR)	5	0.883	*In order to evaluate the internal consistency of the research tool (instrument) a Cronbach's Alpha score was calculated in relation to each construct, and also overall in terms of the entire survey. Each of the Cronbach's Alpha scores of all the constructs are above the minimum acceptable level of .7; therefore, it can be concluded that there is high reliability and good*
Perceived_Opportunities (PO)	5	0.912	
Technological_Infrastructure (TI)	5	0.868	

Ethical_Concerns (EC)	5	0.856	*internal consistency of the measuring instrument. Furthermore, an overall reliability coefficient of .904 indicates that items on the survey have high consistency with respect to measuring their respective constructs of generative artificial intelligence adoption. Therefore, these results support use of the instrument as a basis for further analysis and hypotheses.*
Faculty Digital_Competency (FDC)	5	0.903	
AI_Adoption (AI)	5	0.917	
Overall Instruments	30	0.904	

Table 4: KMO & Bartlett's Test

KMO Test	Obtained Values	*Bartlett's Test of Sphericity, which determines if there is enough variation in the correlations among the variables to justify factoring. The Bartlett's Test of Sphericity produced a Chi-Square of 2845.32, Degrees of Freedom of 436, and a Sig. Value of .000. Because the Sig. Value is greater than zero, you reject the null hypothesis that the correlation matrix is an identity matrix, and because the sig. value is so small (<.000), you conclude that there are strong associations among your variables.*
Kaiser_Meyer-Olkin Measure of Sampling Adeq.	0.885	
Bartlett's Test Approximately Chi_Square Value	2845.319	
Degrees of Freedom (DF)	436	
Sig. Level (P_value)	0.0000	

Table 5: Total Variance Explained (Exploratory Factor Analysis (EFA))

Factors	Eigen_value	% of Variances	*The exploratory factor analysis was conducted by employing PCA, varimax rotation to uncover the general factor structure among questionnaire items. Factors were selected for retention based upon their respective eigenvalue being larger than 1.0. Six factors were obtained & together they accounted for 76.78 % of the total variance; as such this amount represents an acceptable amount of variance explained within social sciences. As the institutional readiness factor accounts for the greatest portion of variance at 24.06 %, it can be inferred that the initial preparedness of institutions to accept generative ai technology represents a substantial component to its implementation.*
Institutional_Readiness (IR)	7.214	24.05	
Perceived_Opportunities (PO)	5.682	18.94	
Technological_Infrastructure (TI)	3.871	12.90	
Ethical_Concerns (EC)	2.764	9.21	
Faculty Digital_Competency (FDC)	1.984	6.61	
AI_Adoption (AI)	1.517	5.06	
Note: Cumulative Variance Percentage is 76.78			

Table 6: Rotated Component Matrix

Items	Constructs	Factor Loading
IR1	Institutional_Readiness (IR)	0.813
IR2	Institutional_Readiness (IR)	0.846
IR3	Institutional_Readiness (IR)	0.835
PO1	Perceived_Opportunities (PO)	0.862

PO2	Perceived_Opportunities (PO)	0.888
PO3	Perceived_Opportunities (PO)	0.854
TI1	Technological_Infrastructure (TI)	0.802
TI2	Technological_Infrastructure (TI)	0.824
EC1	Ethical_Concerns (EC)	0.782
EC2	Ethical_Concerns (EC)	0.765
FDC1	Faculty Digital_Competency (FDC)	0.874
FDC2	Faculty Digital_Competency (FDC)	0.852
AIA1	AI_Adoption (AI)	0.890
AIA2	AI_Adoption (AI)	0.873
The rotated component matrix shows which questionnaire items are associated with each construct. For simplicity, only those with a loading greater than .6 were included in this report. All items associated with their constructs have strong positive factor loadings (.765 to .890), demonstrating the adequacy of the factor model (factor loadings > .6).		

Table 7: Descriptive Statistics (Major Constructs)

Constructs	Mean Values	Std. Dev.	
Institutional_Readiness (IR)	3.92	0.68	*Descriptive Statistics were calculated to determine the range or "spread" of participants' responses for each of the three major variables examined during this study. Results of these calculations demonstrate that perceived opportunities is most highly rated with an average rating (mean) of 4.19, which indicates that participants have strong beliefs about the positive impact of Generative AI on higher education. Additionally, results show that faculty digital competency was rated relatively high, with a mean value of 4.06; therefore, it appears that participants believe they are generally able to utilize AI-based applications. Lastly, ethical concerns had a lower mean of 3.72, which suggests that participants acknowledge the need to address issues related to academic integrity, data privacy and/or the responsible utilization of AI.*
Perceived_Opportunities (PO)	4.19	0.58	
Technological_Infrastructure (TI)	3.85	0.73	
Ethical_Concerns (EC)	3.72	0.75	
Faculty Digital_Competency (FDC)	4.06	0.64	
AI_Adoption (AI)	3.99	0.67	

Table 8: Pearson Correlation Analysis (Matrix)

Variables	Institutional_Readiness (IR)	Perceived_Opportunities (PO)	Technological_Infrastructure (TI)	Ethical_Concerns (EC)	Faculty Digital_Competency (FDC)	AI_Adoption (AI)
Institutional_Readiness (IR)	1.0000					
Perceived_Opportunities (PO)	0.649**	1.0000				
Technological_Infrastructure (TI)	0.592**	0.617**	1.0000			

Ethical_Concerns (EC)	-0.318**	-0.286**	-0.264**	1.0000		
Faculty Digital_Competency (FDC)	0.611**	0.704**	0.548**	-0.221**	1.0000	
AI_Adoption (AI)	0.722**	0.785**	0.683**	-0.392**	0.747**	1.0000
Note: p < 0.01						
Pearson's product moment correlation coefficient was used to assess the relationship between each of the independent variables and the dependent variable (AI adoption). A correlation matrix is provided to illustrate a statistically significant relationship existed among all the study variables. Perceived opportunities for use was most highly positively correlated with AI adoption at r = .785; faculty digital competency was secondly correlated at r = .747, institutional readiness third at r = .722; and ethical concerns were negatively correlated with AI adoption at r = -.392 indicating potential academic integrity issues could limit the willingness of faculty to engage in adopting AI technologies. In total, the results indicated meaningful relationships among the study variables but none exceeded the threshold for multicolinearity (r > .90).						

Table 9: Model Summary (Multiple Regression Analysis)

Model	R	R Square	Adjusted R Square	Std. Error
1	0.840	0.708	0.702	0.386
The statistical analysis shows a high correlation coefficient of 0.84 showing there was a very strong correlation between the independent variables and AI Adoption. The R squared of 0.71 shows that around 71 percent of the variance of AI adoption could be attributed to the chosen predictor variables. The adjusted R squared of 0.7 is also consistent with this result and suggests that the model is robust across the number of predictors used.				

Table 10: ANOVA for Regression Model

Source	Sum of Squares	df	Mean Square	F	Sig.	*The ANOVA results show that the model has sufficient explanatory power since it is highly significant (p-value < .01) at F= 96.385*
Regression	71.864	5	14.373	96.385	0.0000	
Residual	29.088	195	0.149			
Total	100.952	200				

Table 11: Regression Coefficients

Predictors	Beta Value	T_value	Sig. Level	VIF	*The Perceived Opportunities predictor is the most predictive factor for adoption (beta = .361), followed closely by Faculty Digital Competence (Beta = .298); Ethical Concerns have a statistically significant negative relationship (Beta = -.127) indicating that ethical concern about how to responsibly apply AI may lower both the willingness to accept and implement it.*
Institutional_Readiness (IR)	0.248	5.822	0.0000	1.68	
Perceived_Opportunities (PO)	0.361	7.315	0.0000	1.84	
Technological_Infrastructure (TI)	0.194	4.603	0.0000	1.57	
Ethical_Concerns (EC)	-0.127	-3.072	0.0021	1.29	
Faculty Digital_Competency (FDC)	0.298	6.589	0.0000	1.72	

Table 12: Independent Samples t-Test

Gender	Mean Values	Std._Dev.	T_value	Sig. Level
Male (M)	4.07	0.64		
Female (F)	3.92	0.68	1.733	0.086
The above data shows an independent samples t-test used to assess if there are meaningful differences in AI Adoption between men and women. While the average AI Adoption scores for males were slightly greater than those of females, the found difference was not statistically significant (p = .086), which means that the gender of respondents does not contribute to an appreciable or statistically significant amount to the adoption of generative AI. Thus, the fact that the statistical significance level is greater than .05 indicates that the observed difference in AI Adoption can likely be explained as random variation associated with sampling rather than gender.				

Table 13: One-Way ANOVA

Sources	Sum of Squares	df	Mean_Square	F Value	Sig. Level
Between the Groups	5.842	4	1.948	4.862	0.003
Within the Groups	78.954	196	0.402		
Total	84.796	200			
One-way ANOVA was used to investigate if AI Adoption is different at levels within stakeholder categories. Results from this analysis indicate that there are statistically significant differences in the mean values for AI Adoption based on category (F = 4.862, p = .003). This suggests that potential sources of these differing values may include: academic obligations; access to technology; and/or usage frequency of generative AI.					

Table 14: Chi-Square Test Analysis

Test	Value Obtained	df	Sig. Level
Pearson Chi_Square	26.418	8	0.001
Likelihood Ratio	27.105	8	0.001
N	201		
A Chi Square Test was conducted in order to explore whether there is an association among AI Training and the level of AI Adoption. As indicated by the Chi Square analysis, a statistically significant association exists among AI Training and the level of *AI Adoption* ($\chi^2 = 26.418$, $p = 0.001$). *Those respondents that have formally trained in AI exhibited higher levels of AI Adoption than did those respondents that have not been formally trained in AI. Consequently, these results demonstrate that as institutions invest in developing their employees through various forms of institutional capacity building, and also provide them with the opportunity to develop their skills through professional development programs; they will be able to effectively integrate AI into their operations.*			

Table 15: Hypotheses Testing Results

Hypothesis Codes	Statistical Test Applied	Results & Decision
H01	Pearson Correlation Test	Significant (p < 0.001) ; Rejected
H02	Multiple Regression Test	Significant (p < 0.001); Rejected
H03	Multiple Regression Test	Significant (p < 0.001); Rejected
H04	Multiple Regression Test	Significant (p = 0.002); Rejected
H05	One-Way ANOVA Test	Significant (p = 0.003); Rejected

Findings of the study

In addition to the statistical tests that have been used to validate the data collected during this research study, the results from these statistical tests demonstrate a number of the most important results from the current research study.

- The first finding is that there was an overwhelming support by many of the survey participants to incorporate Generative AI into their educational and institutional activities.
- Additionally, Perceived Opportunities had the highest Mean Score which suggests that the majority of respondents see opportunities that exist to enhance student learning through AI-based technologies.
- Finally, based upon the scale that has been developed, it appears that there is an extremely high level of internal consistency between all of the items on the Questionnaire. Specifically, the Cronbach's Alpha Coefficient exceeds .90, the minimum acceptable level of internal consistency (Nunnally & Bernstein, 1994).
- Regarding the exploratory factor analysis conducted using SPSS software, the Kaiser-Meyer-Olkin Measure (KMO) value of .884, combined with the Bartlett's Test ($p < .001$), indicated that the sample size used in the current research study was sufficient to conduct EFA. The six factors that were extracted from the data accounted for almost 77 percent of the total variance in responses provided by the survey participants. This result supports the concept of convergent validity.
- There were significant positive relationships identified between Institutional Readiness and AI Adoption. Additionally, Faculty Digital Competence exhibited a strong positive correlation with AI Adoption. These two factors are critical components in facilitating AI adoption at institutions.
- Using multiple linear regression modeling, Perceived Opportunities emerged as the strongest predictor of AI Adoption. Technological Infrastructure also had a statistically significant influence on respondents' willingness to use AI technology in educational settings. Finally, Ethical Concerns was found to be negatively related to AI Adoption, suggesting that concerns about ethics may hinder or slow down the integration of AI technology in some cases.
- Regression Modeling accounted for nearly 71 percent of the variability in AI Adoption. No statistically significant difference in terms of Gender was observed when comparing levels of AI Adoption. However, Statistically Significant differences did exist between respondent categories and levels of AI Adoption. Formal AI Training appeared to positively affect both attitudes towards and actual use of Generative AI Tools.

Limitations, Future Scope, and Conclusion

The conclusions drawn from the current study are subject to interpretation by means of a number of constraints. Specifically, the study was conducted at only five private Higher Education Institutions. While this sample size is sufficient for statistical purposes, there may be variations among institutions with respect to their location or type of institution. In addition to the aforementioned constraints, the study employead a cross-sectional approach; thus, the study does not allow for the evaluation of trends in the use of Generative AI over time. Finally, the methodological strategy used within the study utilized self-reporting instruments that may introduce biases due to respondent's own perceptions or social desirability. Although this study was limited to Generative AI and therefore excluded other new AI technologies, such as predictive analysis, robotics, intelligent tutoring systems and adaptive learning platforms, it presents a solid base for subsequent investigations. For example, subsequent studies could compare public versus private Higher Education Institutions, investigate the temporal evolution of AI adoption, and analyze country-based institutional variations in terms of AI implementation.

Future studies may also include qualitative methods, e.g., through interviews or focus groups, to obtain deeper insight into how institutions experience and perceive the use of AI. It can also investigate the effects of AI on students' learning outcomes, employability, academic performance, research production, curricula development and institutional efficiency. Moreover, additional research is needed regarding AI governance models and ethics models as well as responsible AI practices across all types of educational systems. Generative Artificial Intelligence has evolved to become one of the most revolutionary technological developments impacting contemporary higher education. With its ability to generate educational material, assist with academic writing, provide individualized instruction, automate administration tasks and increase research productivity, Generative AI creates significant possibilities for the transformation of institutions. However, successful implementation depends upon an understanding of technological readiness, faculty competence, organizational support and responsible governance.

Findings from the current study indicate that readiness at the institutional level, faculty digital literacy skills, availability of technological infrastructure and perceived educational value positively influence AI acceptance; however, ethical considerations are an obstacle to the widespread adoption of AI. The results of this study further demonstrate that formal professional development for faculty, institutional support systems and clearly defined AI policies are essential in encouraging responsible and sustainable AI implementations. Therefore, private Higher Education Institutions should develop strategies that are technologically focused on investing in digital infrastructure and developing faculty competencies and creating policies and procedures that govern AI usage; such actions will allow them to realize the full educational potential of Generative AI while maintaining academic accountability and transparency and responsible use of technology. Through empirical data collected from private Higher Education Institutions, the study makes meaningful contributions to the increasing body of literature related to Artificial Intelligence in higher education and generates practical recommendations for policymakers, institutional leaders, faculty members and researchers. Given the rapid rate at which AI technologies are evolving, Higher Education Institutions need to continually innovate in governance and learning if they are going to maintain relevance and competitiveness in an increasingly digital academic environment.

References

Alam, A. (2023). Possibilities and apprehensions in the landscape of artificial intelligence in education. *International Journal of Advanced Computer Science and Applications, 14*(2), 1005–1012.

Alenezi, M. (2024). Artificial intelligence adoption in higher education: Opportunities, challenges, and future directions. *Education and Information Technologies, 29*(3), 3521–3542.

Bagri, D. S. (2026). Innovative Teaching Methods and Use of Artificial Intelligence in Higher Education. Kaav International Journal of Economics, Commerce & Business Management, 13(01), 187-190.

Gonçalves, D. (2024). Artificial Intelligence in Education: Shaping the Future of Learning. Kaav International Journal of Science, Engineering & Technology, 11(2), 1-3. https://doi.org/10.52458/23485477.2024.v11.iss2.kp.a1

Dwivedi, Y. K., Hughes, L., Baabdullah, A. M., Ribeiro-Navarrete, S., Giannakis, M., Al-Debei, M. M., Dennehy, D., Metri, B., Buhalis, D., Cheung, C. M. K., Conboy, K., Doyle, R., Dubey, R., Dutot, V., Felix, R., Goyal, D. P., Gustafsson, A., Hinsch, C., Jebabli, I., ... Wright, R. (2023). Opinion paper: 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.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeiffer, F., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274.

Luckin, R. (2018). *Machine learning and human intelligence: The future of education for the 21st century*. UCL IOE Press.

Nguyen, K. V. (2025). The use of generative AI tools in higher education: Ethical and pedagogical principles. *Journal of Academic Ethics*.

Perkins, M. (2023). Academic integrity considerations of AI large language models in the post-pandemic era: ChatGPT and beyond. *Journal of University Teaching & Learning Practice, 20*(2), 1–12.

Rahman, M. M., & Watanobe, Y. (2023). Artificial intelligence in education: A systematic literature review. *Education and Information Technologies, 28*(6), 7253–7284.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Sallam, M. (2023). ChatGPT utility in healthcare education, research, and practice: Systematic review on the promising perspectives and valid concerns. *Healthcare, 11*(6), 887.

S Singh, S., Patidar, M., Agarwal, V., & Adil, A. A. (2026). Mapping Future-Proof Career with Human Centric Roles That Artificial Intelligence Cannot Replace. Kaav International Journal of Economics, Commerce & Business Management, 13(01), 44-49.

harples, M. (2025). A systems approach to AI and education in a post-digital world. *Theory Into Practice, 64*(4), 483–491.

Siemens, G., & Baker, R. S. (2012). Learning analytics and educational data mining: Towards communication and collaboration. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, 252–254.

Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. *Journal of Applied Learning and Teaching, 6*(1).

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers & Education, 57*(4), 2432–2440.

UNESCO. (2023). *ChatGPT and artificial intelligence in higher education: Quick start guide*. UNESCO International Institute for Higher Education in Latin America and the Caribbean.

Verma, R., & Yadav, A. (2026). AI-Driven Teaching Techniques and the Evolving Role of Library Services in Modern Education. Kaav International Journal of Economics, Commerce & Business Management, 13(01), 181-186.

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.

Yan, L., Sha, L., Zhao, L., Li, Y., Martinez-Maldonado, R., Chen, G., Li, X., Jin, Y., & Gašević, D. (2024). Practical and ethical challenges of large language models in education: A systematic scoping review. *British Journal of Educational Technology, 55*, 90–112.