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Research Article

Understanding Technology Acceptance in Higher Education Institutions: A Comparative Study of Teacher and Student Perspectives in Lucknow

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ABSTRACT

Understanding Technology Acceptance (TA) in higher education is vital in today's information-driven era, as rapid technological advancements reshape educational landscapes. Effective evaluation of factors influencing technology adoption is essential to ensure that new innovations are successfully integrated and not wasted. Therefore, to address this gap, the study explores the critical factors influencing TA in Higher Education Institutions (HEIs) from the perspectives of both teachers and students in Lucknow and also assesses the associations between these two groups. An exploratory research design with a quantitative approach was used and primary data was collected from a sample of 461 teachers & 546 students of government and private HEIs in Lucknow using quota sampling. The research tool was constructed and validated and then administered to the respondents in both online and offline mode. Data analysis included factor analysis & chi-square tests using SPSS version 25. The study revealed that two primary factors influence teachers' acceptance of technology: the perceived value of investing time and energy in learning new tools and their ease of use, which enhances teaching effectiveness. Similarly, students' acceptance is driven by the ease of learning new tools and their time-saving benefits, alongside awareness and actual use of technology for academic purposes. These findings indicate that enhancing awareness and providing training on technology tools can boost acceptance among teachers and students. Institutions should focus on strategies that highlight the benefits and necessity of technology integration to improve academic performance.

Keywords: Technology Acceptance, Education, HE, Teachers, Students.

1 Introduction

Understanding TA in HEIs has become increasingly crucial in our information-driven era. The rapid advancement and integration of innovative technologies have transformed the landscape of education, prompting a need for effective evaluation of how these tools are adopted. Without comprehensive data on the factors influencing the acceptance or rejection of technology, introducing new innovations can prove ineffective and wasteful. Ignoring these acceptance factors during the development process raises critical questions about how new technologies can be enhanced and how individuals cognitively engage with these innovations.

In response to this need, Davis, F. D. (1989) introduced the TA Model (TAM) to provide valid metrics for understanding the acceptance of computer-related technologies, specifically email. The original formulation of TAM included two primary determinants: perceived usefulness (PU) and perceived ease of use (PEU). Subsequently, an 'attitude toward using' component was integrated into the model as a function of PU and PEU (Davis, F. D., 1993). This foundational framework has been widely employed to predict TA across various contexts, leading to significant expansions of the model over the years. For instance, Davis and Venkatesh, V., & Davis, F. D. (1996) highlighted the necessity for a deeper exploration of PEU to devise effective interventions aimed at enhancing user acceptance.

Today, TAM stands as a globally recognized framework for examining technology acceptance, especially in educational settings. The model has gained renewed attention in light of the COVID-19 pandemic, which

necessitated rapid technological adaptation in HE. Consequently, there has been a notable surge in TAM-related studies, emphasizing its relevance and applicability in understanding the shifting dynamics of technology adoption.
This study aims to explore the factors crucial for TA from the perspectives of both teachers and students in HEIs in Lucknow. By comparing these viewpoints, we seek to identify commonalities and divergences in their experiences and attitudes toward technology, contributing to a deeper understanding of the adoption landscape in this region. As we analyze these perspectives, we will also consider how the insights gained can inform future strategies for enhancing technology integration in educational practices.
In the light of the above discussion, the present study is focused on fulfilling the following two objectives-

1.1 Objectives of the study

- To explore the most important factors of TA for Teachers & Students of HEIs in Lucknow.
- To evaluate the association between students & teachers for TA in HEIs in Lucknow.

1.2 Significance of the study

This study is significant as it addresses critical factors influencing TA among teachers and students in HEIs in Lucknow. By exploring the key variables that affect both groups' willingness to adopt AI tools, the research provides valuable insights that can guide educators and administrators in enhancing technology integration. Additionally, evaluating the association between students and teachers regarding TA fosters a collaborative approach to technology use in educational settings. The findings can inform policy decisions and training programs, ultimately improving teaching effectiveness and student learning outcomes in an increasingly digital educational landscape.

2. Literature Review

Numerous studies have examined the factors influencing TA in HE, highlighting various aspects such as PU, EoU, and IS. Understanding these determinants is crucial for enhancing the effectiveness of TA environments. Al-Mushasha (2013) identified PU, EoU, IS., university support, and C-SE as significant determinants of TA among students in HE. This foundational understanding has been further developed by Khodadad, et al., (2023), who emphasized the impact of instructor characteristics and teaching materials on the intention to use e-learning, with PU emerging as the most critical factor. However, they noted that the design of learning content did not significantly affect perceived EoU, indicating that other elements might overshadow its importance.
Fathema, et al., (2015) confirmed the relevance of the TA Model (TAM) in understanding faculty attitudes towards Learning Management Systems (LMSs), revealing that system quality, perceived self-efficacy, and facilitating conditions were pivotal external variables influencing these attitudes. Similarly, Dumpit and Fernandez (2017) found that PU and EoU, alongside subjective norms and playfulness, robustly predicted students' usage behavior. This suggests a multifaceted interaction between personal and contextual factors in technology adoption. Rezaei et al. (2008) demonstrated a positive relationship between students' intention to use e-learning and factors like PU and C-SE, while also noting negative influences from computer anxiety and age. This aligns with Fearnley and Amora's (2020) findings that both system quality and P-SE significantly impacted PU, which in turn influenced attitudes towards technology.
Despite the positive trends, Schoonenboom (2014) highlighted a low intention among instructors to use LMSs, attributing this to the perceived unimportance of tasks and the usefulness and ease of use of the LMS itself. This reflects the complexity of user acceptance and the need for tailored solutions based on specific instructional contexts. Al-Qaysi, , et al., (2021) expanded the discussion by identifying additional factors such as perceived enjoyment and subjective norms that affect SM adoption in HE. They emphasized the importance of understanding these dynamics to assist decision-makers in leveraging SM effectively.
In terms of TA, Binyamin, Rutter, and Smith (2019) confirmed that PU comprises multiple determinants, including content quality and system interactivity. This highlights the intricate relationship between various dimensions of PU and their role in enhancing e-learning adoption. Akman and Turhan (2017) further noted that core and external constructs of TAM predict behavior towards using SM for learning, excluding EoU. Lehmann, et al., (2023) presented a comprehensive model comprising nine latent variables influencing students' behavioral intentions, while Elwood, et al., (2006) identified a third factor, perceived change that affects technology acceptance. This underlines the evolving nature of technological landscapes and the importance of continuous adaptation.
Kabakus, , et al., (2023) examined the role of digital literacy among HE administrative staff, revealing that digital literacy directly affects effort expectancy but does not directly influence the intention to use technology. Pires and Halawi (2020) affirmed the significant relationships among PU, EoU, and BI, reinforcing their roles in mobile TA.
Handoko (2019) found that performance expectancy and quality of service influenced behavioral intentions, though the lecturer's influence was negligible. Alyoussef and Al-Rahmi (2022) emphasized facilitating conditions and perceived risks as key determinants affecting students' attitudes toward big data usage, underscoring the necessity of a supportive environment for technology adoption. Alenezi, et al., (2011)

validated the applicability of TAM in Saudi Arabian HE, indicating that institutional variables significantly contribute to students' acceptance of e-learning. Amron and Noh (2021) added that both perceived EoU and PU are critical for cloud computing adoption, which is echoed by other studies examining diverse technological contexts.

The COVID-19 pandemic highlighted the importance of educational management information systems, as discussed by Bravo et al. (2022), who categorized managers based on their quality perceptions and information system acceptance. Parket al., (2007) found that PU significantly affects BI and actual system usage, emphasizing the role of motivation in TA. Chávez, et al., (2023) identified direct and indirect paths influencing the use of tools like PowerPoint, while Atif et al. (2015) confirmed the relevance of core TAM variables in explaining academic intentions to use technology. Aburagaga, ,et al., (2020) found significant effects of privacy and IS on BI, suggesting that these factors also play a crucial role in social network usage.

Yeou (2016) reaffirmed the relevance of TAM in blended learning environments, emphasizing the significance of C-SE and PU. Mahmodi (2017) linked increased awareness of e-learning systems to higher usage intentions among students. Martínez-Torres et al. (2008) supported the extended TAM in predicting student intentions to use e-learning, while Kripanont and Tatnall (2009) proposed the IAM as a parsimonious framework for understanding technology acceptance.

Finally, Sinha and Bag (2023) indicated that PU and EoU directly impacted students' intentions to use online education platforms, while Rafique et al. (2020) demonstrated the initial acceptance of mobile library applications in Pakistan, highlighting the necessity of integrating external factors and system quality into the TA model.

Overall, these studies collectively emphasize the multifaceted nature of TA in HE, underlining the importance of perceived usefulness, ease of use, and contextual factors in promoting e-learning adoption.

3 Methodology

This exploratory research employs a quantitative, cross-sectional approach. Primary data were collected from a sample of 461 teachers and 546 students from government and private HEIs in Lucknow using a quota sampling technique. A structured questionnaire with closed-ended Likert scale questions was designed for data collection, which was distributed via a Google Form link and sent to teachers through email and social media. SPSS version 25 was used to conduct various analyses, including frequency analysis, cross-tabulation analysis, chi-square analysis, and factor analysis. To assess the level of TA, an index was created by calculating Z scores for the data, summing them, and then dividing the total by five to establish class intervals, resulting in the levels being categorized as very low, low, medium, high, and very high.

4. Data Analysis and Interpretation

4.1 Demographic Profile of Respondents (Teachers & Students)

Table 1: Demographic Profile of Respondents (Teachers & Students)

Demographic Variable	Students	N	%	Teachers	N	%
Age	19 to 24	442	81.00%	21 to 30	113	24.50%
	25 to 30	104	19.00%	31 to 40	109	23.60%
				41 to 50	124	26.90%
				51 to 60	115	24.90%
	Total	**546**	**100.00%**	**Total**	**461**	**100.00%**
Gender	Male	318	58.20%	Male	299	64.90%
	Female	228	41.80%	Female	162	35.10%
	Total	**546**	**100.00%**	**Total**	**461**	**100.00%**
Course/Department	Graduation	159	29.10%	Engineering	201	43.60%
	Post-graduation	277	50.70%	Commerce	134	29.10%
	PhD	67	12.30%	Humanities	93	20.20%
	Other	43	7.90%	Science	18	3.90%
	Total	**546**	**100.00%**	**Total**	**461**	**100.00%**
Institute/University	Government	312	57.10%	Government	123	26.70%
	Private	234	42.90%	Private	338	73.30%
	Total	**546**	**100.00%**	**Total**	**461**	**100.00%**
Designation				Assistant Prof.	235	51.00%
				Associate Prof.	171	37.10%
				Professor	55	11.90%
				Total	**461**	**100.00%**

Interpretation- The demographic profile of teachers reveals a diverse age distribution, with the largest group aged 41 to 50 years (26.9%), followed closely by those aged 51 to 60 years (24.9%). The majority are male (64.9%), indicating a gender imbalance in the teaching profession. In terms of academic departments, most teachers come from engineering (43.6%), while the remaining are distributed among commerce, humanities, and science. The data also shows a strong representation of teachers in private institutions (73.3%) compared to government institutions (26.7%), highlighting a trend toward private education.

In contrast, the student demographic is predominantly younger, with 81.0% aged between 19 and 24 years. The gender distribution is more balanced, with 58.2% male and 41.8% female students. A significant number of students are pursuing post-graduate studies (50.7%), indicating a focus on HE. Additionally, the student body is primarily enrolled in government universities (57.1%), suggesting a preference for public educational institutions. This profile underscores the differences in age, gender, and educational focus between students and teachers within the academic environment.

4.2 Factor Analysis: Identifying the most important factors of Technology Acceptance for Teachers of HEIs

Table 2-K & B Test: Teachers

K &B Test[a]		
K-M-O- MoSA.		.810
Bartlett's Test of Sphericity	Approx. C-S	1876.131
	df	21
	Sig.	.000

Interpretation-The KMO value of .810 indicates adequacy of data and sig value of .000 shows presence of enough correlation.

Table 3- TVE: Teachers

TVE			
	IE		
Component	Total	% of V	C %
1	**3.655**	**52.215**	52.215
2	**1.038**	**14.826**	**67.040**
3	.984	14.063	81.103
4	.757	10.811	91.915
5	.274	3.912	95.827
6	.154	2.199	98.026
7	.138	1.974	100.000

Interpretation- The table shows that the first component explains 52.21% of the variance in TA, and the second component explains 14.826%. Together, these two components account for 67.04% of the total variance & 1st component is the most important among all.

Table 4- RCM: Teachers

RCM		
	Component	
	1	2
20. It is worth to spend money, time and energy on learning to use ICT tools/ AI based systems, than to bear the consequences of not learning.	**.921**	-.048
17. Learning how to use ICT tools/ AI based systems, is not difficult.	**.907**	.099
18. Using ICT tools/ AI based systems, saves time and energy.	**.898**	-.078
21. ICT tools/ AI based systems must be implemented in HEIs.	**.811**	-.133
19. Using ICT tools/ AI based systems, increases effectiveness, efficiency and my academic performance.	**.722**	.197
16. I use ICT tools/ AI based systems for academic purpose.	-.016	**.789**
15. I am aware of ICT tools/ AI based systems, used for academic purpose.	-.016	**-.584**

Findings: The study revealed two main factors that influence teachers' TA. The first factor highlights five important points: the value of investing time and energy in learning new tools, the ease of learning to use them, the time-saving benefits, the need for their use in HE, and their positive impact on teaching effectiveness and academic performance. The second factor focuses on two aspects: the use of these tools for academic purposes and awareness of their availability.

4.3 Factor Analysis: Identifying the most important factors of Technology Acceptance for Students of HEIs

Table 5-K & B Test: Students

K &B Test[a]		
K-M-O- MoSA.		.609
Bartlett's Test of Sphericity	Approx. C-S	779.621
	df	21
	Sig.	.000

Interpretation-The KMO value of .609 indicates adequacy of data and sig value of .000 shows presence of enough correlation.

Table 6–TVE: Students

TVE			
	IE		
Component	Total	% of V	C %
1	**2.516**	**35.940**	35.940
2	**1.268**	**18.120**	**54.060**
3	.981	14.015	68.075
4	.814	11.627	79.702
5	.571	8.150	87.852
6	.558	7.969	95.821
7	.293	4.179	100.000

Interpretation- The table shows that the first component explains 35.940% of the variance in TA, and the second component explains 18.120%. Together, these two components account for 54.06% of the total variance & 1st component is most important among all.

Table 7- RCM: Students

RCM		
	Component	
	1	2
17. Learning how to use ICT tools/ AI based systems, is not difficult.	**.872**	.092
18. Using ICT tools/ AI based systems, saves time and energy.	**.738**	.112
19. Using ICT tools/ AI based systems, increases effectiveness, efficiency and my academic performance.	**.726**	.162
15. I am aware of ICT tools/ AI based systems, used for academic purpose.	.070	**.795**
16. I use ICT tools/ AI based systems for academic purpose.	.281	**.661**
20. It is worth to spend money, time and energy on learning to use ICT tools/ AI based systems, than to bear the consequences of not learning.	-.017	**.618**
21. ICT tools/ AI based systems must be implemented in HEIs.	.187	**.577**

Findings: The study identified two main factors affecting students' TA. The first factor highlights three points: learning to use new tools is easy, these tools save time and energy, and they enhance effectiveness and academic performance. The second factor includes four aspects: awareness of technology for academic purposes, actual use of these tools, the value of investing time and resources in learning them, and the necessity of implementing such tools in HE.

4.4 Chi-Square Analysis: Association between students & teachers for Technology Acceptance in HEIs

H_0 1: There is no significant association between respondents (students & teachers) for TA in HEIs.

Table 8: Crosstab-Respondent * TA

Crosstab								
			TA					
			VLL	LL	ML	HL	VHL	Total
Respondent	Students	Count	26	69	156	191	104	546
		% within	4.8%	12.6%	28.6%	35.0%	19.0%	100.0%
	Teachers	Count	71	77	165	61	87	461
		% within	15.4%	16.7%	35.8%	13.2%	18.9%	100.0%
Total		Count	97	146	321	252	191	1007
		% within	9.6%	14.5%	31.9%	25.0%	19.0%	100.0%

Interpretation:
Out of total **1007** respondents, **546** respondents were **students** and **461** respondents were **teachers**. The percent wise break-up of the level of TA for both students & teachers is as given below-

- **Students:** Out of **546** respondents, 19.0% respondents have VHL, 35.0% respondents have HL, 28.6% respondents have ML, 12.6% respondents have LL and 4.8% respondents have VLL for "Technology Acceptance."
- **Teachers:** Out of **461** respondents, 18.9% respondents have VHL, 13.2% respondents have HL, 35.8% respondents have ML, 16.7% respondents have LL and 15.4% respondents have VHL for "Technology Acceptance."

Table 9- C-S-T

Chi-Square Tests			
	Value	df	Asy. S
P-C-S	83.564[a]	4	.000

Interpretation: It was found that Asy. S for P-C-S comes out to be **less than 0.05**, so we **reject H_0 1** and concluded that **two variables are associated.**

5. Conclusion and Suggestions

This study on TA in HEIs in Lucknow offers valuable insights into the perspectives of both teachers and students regarding the adoption of AI-based tools. For teachers, the analysis highlighted five key variables that influence their acceptance of technology. These include the perceived value of investing time and resources in learning new tools, the ease of use of these tools, and their ability to save time. Additionally, teachers recognized the necessity of integrating these technologies into HE and their positive impact on teaching effectiveness and academic performance. This multifaceted understanding underscores the need for educational institutions to not only provide access to technology but also ensure that educators feel adequately equipped and supported in their efforts to integrate these tools into their teaching practices. From the students' perspective, the study identified three main variables that significantly affect their acceptance of technology. Students emphasized the simplicity of learning to use new tools, their time-saving benefits, and their overall enhancement of academic performance. Moreover, the analysis indicated that awareness of the technology's academic applications, actual usage, and the perceived value of investing time and resources in learning these tools are crucial factors. This finding suggests that students are open to adopting new technologies, provided they receive sufficient information about their benefits and practical applications. The emphasis on ease of use and efficiency indicates that educational institutions should prioritize user-friendly technologies that align with students' academic needs and enhance their learning experience.

The results further revealed a significant association between the TA levels of students and teachers, suggesting a shared understanding of the value and necessity of technology in education. This association points to the importance of variables such as mutual awareness and collaboration in technology adoption. By fostering an environment where both educators and learners actively engage in the technology adoption process, HEIs can create more cohesive strategies for integration that cater to both groups' needs. Ultimately, it is crucial for institutions to prioritize collaborative efforts in training, awareness campaigns, and the development of supportive infrastructures that facilitate effective technology use, thus enhancing the overall educational experience and improving academic outcomes.

5.1 Suggestions

Following suggestions can be provided according to the results-

- Develop tailored training sessions for both teachers and students to improve their skills in using AI-based tools.
- Organize workshops and seminars to inform faculty and students about available technologies and their academic benefits.
- Prioritize the selection of intuitive and easy-to-use technologies that minimize the learning curve for both groups.
- Create opportunities for teachers and students to work together on technology integration projects.
- Implement channels for ongoing feedback from both teachers and students to continually improve technology use.
- Highlight examples of successful technology integration in teaching and learning to motivate wider adoption.
- Provide robust technical support to assist both teachers and students in resolving issues with technology use.
- Integrate the use of AI-based tools into course curricula to normalize their usage and enhance learning outcomes.

6. Future directions

Future research in the context of TA in computer science education should focus on developing enhanced training programs specifically tailored to the unique needs of both teachers and students in using AI-based tools effectively. Additionally, implementing awareness campaigns that include workshops and seminars can significantly improve understanding of available technologies and their academic benefits. A key area of exploration will be the identification and promotion of user-friendly tools that reduce the learning curve, facilitating smoother adoption for all users. The establishment of collaborative learning environments is essential, allowing teachers and students to engage in joint projects that promote technology integration. Furthermore, creating regular feedback mechanisms will ensure continuous improvement in technology usage based on real-time experiences. Future studies should also highlight success stories of technology integration to inspire wider acceptance and motivate others. Robust technical support services must be prioritized to assist users in overcoming challenges related to technology use. Finally, incorporating AI-based tools into the curriculum will be crucial for normalizing their usage and enhancing overall learning outcomes, making technology an integral part of the educational experience in computer science.

List of Abbreviations used

PU	:	Perceived Usefulness
EoU	:	Ease of Use
IS	:	Institutional Support
C-SE	:	Computer Self-Efficacy
P-SE	:	Perceived Self-Efficacy
SM	:	Social Media
BI	:	Behavioral Intention
IAM	:	Internet Acceptance Model
TA	:	Technology Acceptance
AI	:	Artificial Intelligence
IT	:	Information Technology
VLL	:	Very Low Level
VL	:	Low Level
ML	:	Moderate Level
HL	:	High Level
VHL	:	Very High Level
SM	:	Social Media
HE	:	Higher Education
HEIs	:	Higher Education Institutions
P-C-S	:	Pearson Chi-Square
C-S T	:	Chi-Square Tests
Asy. S	:	Asymptotic Significance (2-sided)
K & B	:	KMO & Bartlett's
C-S	:	Chi-Square
K-M-O- MOSA	:	Kaiser-Meyer-Olkin Measure of Sampling Adequacy
TVE	:	Total Variance Explained
IE	:	Initial Eigenvalues
C%	:	Cumulative %
% of V	:	% of Variance
RCM	:	Rotated Component Matrix

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