

Examining The Interrelationships Between Technology Acceptance, AI-Based Tools Usage, And Technology-Based Tutoring Systems And Their Impact: A Study Of Higher Education Institution In Lucknow

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ABSTRACT

The integration of technology into education has ushered in a new era of learning and teaching, with AI-based tools emerging as potential game-changers. Understanding how these tools are accepted, used, and impact student outcomes and organizational performance is crucial for maximizing their potential benefits. This study investigate the interrelationships between technology acceptance, the level of use of AI-based tools, and the adoption of technology-based tutoring systems, student performance and organizational performance. Using a research survey design and employing quota sampling technique, primary data was collected from a sample of 546 students from Lucknow-based Higher Education Institutions using a structured Likert scale questionnaire. Data was gathered over three months (March-May 2024) via Google Forms. The instrument's validity and reliability were established. Data analysis involved frequency, descriptive, correlation, and regression analyses using SPSS 25. The results showed that Technology acceptance significantly influences AI tool usage and technology-based tutoring, both of which positively impact student performance. Improved student performance subsequently contributes to enhanced organizational outcomes.

Keywords: Technology Acceptance, Level of use of AI based tools, Technology based Tutoring System, Organizational Performance, and Students' Performance

1. INTRODUCTION

In recent years, the integration of technology into educational systems has garnered significant attention due to its transformative potential in enhancing teaching and learning experiences. As educational institutions strive to keep pace with technological advancements, understanding the dynamics of technology acceptance and its implications for educational outcomes becomes crucial. The current study aims to explore these dynamics within the context of higher education institutions in Lucknow city, focusing on the interrelationships between technology acceptance, the usage of AI-based tools, and technology-based tutoring systems, and their impact on both students' and organizational performance.

The concept of technology acceptance has been extensively studied, emphasizing its critical role in determining the extent to which new technologies are embraced and utilized (Venkatesh et al., 2003). Recent research highlights the importance of users' attitudes and perceptions in influencing the adoption and effective use of technology, particularly in educational settings (Davis, 1989; Agarwal & Karahanna, 2000). In the realm of higher education, the use of AI-based tools has been recognized for its potential to revolutionize learning environments by providing personalized and adaptive learning experiences (Kumar, 2019; Cox et al., 2019). These tools not only enhance the learning experience but also contribute to the efficiency of educational processes (Chaudhary, 2017).

Furthermore, technology-based tutoring systems have emerged as significant components in modern education, offering innovative approaches to support student learning and academic achievement (Ocaa-Fernández et al., 2019). These systems

are designed to address diverse educational needs and improve student outcomes through interactive and tailored learning experiences (Ma et al., 2018; Khare et al., 2018). However, the effectiveness of these technologies is closely linked to their acceptance and integration by both students and educators.

This study seeks to examine how technology acceptance influences the usage of AI-based tools and technology-based tutoring systems, and how these factors, in turn, impact students' academic performance and the overall performance of educational institutions in Lucknow city. By utilizing regression analysis, this research aims to provide insights into the interplay between these variables and their implications for enhancing educational practices and outcomes in the region.

1.1 Objectives of the study

The following objectives guided the study-

- To examine the impact of Technology Acceptance (Independent Variable) on the Level of Use of AI-Based Tools (Dependent Variable).
- To assess the impact of the Level of Use of AI-Based Tools (Independent Variable) on Students' Performance (Dependent Variable).
- To evaluate the effect of Technology Acceptance (Independent Variable) on Technology-Based Tutoring Systems (Dependent Variable).
- To determine the influence of Technology-Based Tutoring Systems (Independent Variable) on Students' Performance (Dependent Variable).
- To analyze the effect of Students' Performance (Independent Variable) on Organizational Performance (Dependent Variable).

1.2 Rationale and Significance of the study

The rationale behind this study is rooted in the critical need to understand how technology acceptance and the use of AI-based tools and technology-based tutoring systems impact both students and organizational performance within higher education institutions. As educational institutions increasingly adopt advanced technologies to enhance learning outcomes and operational efficiency, it becomes essential to evaluate their effectiveness comprehensively. This study aims to bridge the gap in current research by examining the interplay between technology acceptance, AI tool usage, and tutoring systems, and their subsequent effects on student performance and organizational success. By providing insights into these relationships, the study contributes to a better understanding of how technology-driven interventions can be optimized to improve educational and administrative practices, thus offering actionable recommendations for policy makers, educators, and administrators in Lucknow city and beyond.

2. LITERATURE REVIEW

The integration of Artificial Intelligence (AI) in higher education is increasingly recognized as pivotal for enhancing educational quality and efficiency. This section examines the literature on AI's impact and its transformative potential within educational settings. In current Information Technology literature, the adoption of modern technology by users is often highlighted as a key study topic (Williams et al., 2009). In India, there is an acute need for a paradigm shift in the teaching-learning environment and administrative operations at the higher education level (Menon et al., 2014). Ensuring the quality of education necessitates paying particular attention to fundamental factors (Kremer et al., 2013), with rapid implementation of Artificial Intelligence (AI) and other cutting-edge technologies being crucial in Indian higher education (Croxford & Raffe, 2015). AI-powered libraries and applications can enhance the learning experience by personalizing it for students (Cox et al., 2019; Kumar, 2019).

Chaudhary (2017) notes that AI benefits both students and instructors by facilitating a collaborative educational environment. This perspective is supported by Ocaa-Fernández, Valenzuela-Fernández, and Garro-Aburto (2019), who suggest that AI and modern technologies can enrich the educational experience and provide valuable information for achieving excellence. Furthermore, AI's potential to positively impact student success is highlighted by Khare, Stewart, and Khare (2018), who found that AI applications could enhance the fundamental responsibilities of educational institutions in teaching, learning, and research.

Despite AI's capabilities, Gamoura et al. (2018) argue that technical and ethical barriers prevent absolute machine autonomy in decision-making. Nevertheless, AI applications, such as chatbots, can provide customized assistance and effectively address student inquiries (Chrisinger, 2019; Kumar, 2019). The use of AI in creating intelligent content, such as digitalized textbooks and adaptive learning interfaces, is also emphasized (Ahmad, 2019).

The rising number of learners and the increasing workload necessitate advanced technology implementation, including AI, to realize its benefits (Andrea et al., 2015). AI has created new opportunities and challenges for India's higher education system (Silander & Stigmar, 2019), with significant potential to improve government efficiency (Nasrallah, 2014). In the

context of Indian higher education, AI is defined as computer systems capable of human-like activities essential for completing complex tasks (Stefan & Sharon, 2017).

Incentivizing stakeholders to adopt AI is crucial for enhancing India's higher education system (Norris & Phillips, 2013). Governments worldwide are utilizing contemporary technologies, including AI, to improve education quality (Cremer & Bettignies, 2013). AI can update student evaluation systems and promote higher education through increased funding (Bigg & Tang, 2007; Buckner, 2011).

Studies show that AI-assisted learning is superior to traditional methods (Scieluna et al., 2012; Nasrallah, 2014), with personalized teaching systems proving effective (Kulik & Fletcher, 2016). Explainable AI (XAI) is particularly relevant in education, providing essential feedback for both students and instructors (Gunning, 2017; Hattie & Timperley, 2007). This feedback process fosters learning and instructional development (Boyer, 1990; Kreber, 2005).

The use of data to present institutional performance profiles is crucial for ongoing improvement (Drake & Walz, 2018). Business intelligence tools aid decision-making and personalize instruction in AI-enhanced educational systems (Self et al., 1999). The primary goal of AI in education is to develop intelligent tutoring systems that replicate the benefits of one-on-one human instruction (Bloom, 1984). These systems are driven by learner-centered models that adapt based on student interactions (Koedinger et al., 1997; Mitrovic, 2003).

Open Learner Models (OLMs) provide students with insights into their learning progress, promoting control and responsibility (Bull & Kay, 2016; Khosravi et al., 2021). Addressing unfairness in AI models is critical for broader adoption in education (Chounta et al., 2021).

Sanusi et al. (2022) emphasize the importance of competencies in AI education for K-12 students, focusing on cognition, ethics, and collaboration. Chu, Hwang, and Tu (2022) explore the research trends of AI-Robots in education, noting their potential in enhancing learning performance and behavior. Al-Badi, Khan, and Eid-Alotaibi (2022) find positive attitudes towards AI in personalized learning among students and teachers in Oman.

Dai and Feng (2022) review AI's transformative potential in education, particularly in simulation-based learning. a et al. (2022) highlight the importance of Explainable AI in addressing concerns about justice, accountability, and transparency in education, thus supporting learner autonomy and integrity.

3. RESEARCH METHODOLOGY

The present survey research was based on primary data collected from sample of 546 students of government and private HEIs in Lucknow by employing quota sampling technique. Primary data was collected with the help of a close ended structured questionnaire having Likert scale based questions. The validity of the instrument was taken care by experts by ensuring the face and content validity of the tool. Reliability was assessed with help of Cronbach's alpha value. Data was collected for a period of three months from March, 2024 to May 2024 through scheduling, and google form link was created and was also sent to the students through emails and WhatsApp.

After the data collection, creating and coding process, level of dimensions of the study were calculated namely for- Technology Acceptance, Level of use of AI based tools, Technology based Tutoring System, Students' Performance & Organizational performance, an index was developed for all the dimensions. Z scores of the data were computed and added for all dimensions. Range, minimum and maximum scores were calculated and based on range, class interval was computed by diving range by 5 for all dimension. The data was then analyzed by applying frequency analysis, descriptive analysis, correlation analysis & regression analysis with the help of SPSS version 25. To ensure, research ethics, participants were informed about the pourpose of the study and their consent was taken at their free will and confidentiality of the data was maintained.

4. RESULTS AND DISCUSSION

4.1 Reliability analysis of the data

Table 1- Reliability Statistics

Reliability Statistics		
Scale	Cronbach's Alpha	N of Items
Technology Acceptance	.711	7
Level of use of AI based tools	.709	11
Technology based Tutoring System	.616	10

Students' Performance	.738	5
Organizational performance	.609	5

Source- Author's own compilation of primary data analysis

Results- The reliability statistics indicate that most scales exhibit acceptable internal consistency. Technology Acceptance ($\alpha = 0.711$) and Level of Use of AI-Based Tools ($\alpha = 0.709$) show good reliability, suggesting consistent measurement. Students' Performance ($\alpha = 0.738$) also demonstrates good internal consistency. However, Technology-Based Tutoring System ($\alpha = 0.616$) and Organizational Performance ($\alpha = 0.609$) have moderate reliability, indicating some variability but still providing reasonably reliable measures.

4.2 Descriptive analysis of the data

Table 2- Descriptive Statistics

Descriptive Statistics			
	Mean	Std. Deviation	N
Level of use of AI based tools	3.09	.869	546
Technology Acceptance	3.51	1.082	546
Technology based Tutoring System	2.67	.826	546
Students' Performance	4.04	.779	546
Organisational Performance	3.07	1.111	546

Source- Author's compilation of primary data analysis

4.3 Demographic Profile of the Respondents

Table 3- Age of respondents (students)

Age (in years)		Frequency	Percent
Valid	19 years to 24 years	442	81.0
	25 years to 30 years	104	19.0
	Total	546	100.0
Gender		Frequency	Percent
Valid	Male	318	58.2
	Female	228	41.8
	Total	546	100.0
Course		Frequency	Percent
Valid	Graduation	159	29.1
	Post-graduation	277	50.7
	PhD	67	12.3
	Other	43	7.9
	Total	546	100.0
Department		Frequency	Percent
Valid	Engineering	150	27.5
	Commerce and	198	36.3

	Management		
	Humanities	148	27.1
	Science	50	9.2
	Total	546	100.0
Institute/University		Frequency	Percent
Valid	Government University/Institute	312	57.1
	Private University/Institute	234	42.9
	Total	546	100.0

Source- Author's own compilation of primary data analysis

Results- The table provides a demographic breakdown of the respondents.

- **Age Distribution:** The majority of respondents, 81.0% (442 students), fall within the 19 to 24 years age bracket, indicating that this age group is the most prevalent among the surveyed students. In contrast, 19.0% (104 students) are between 25 and 30 years old. This distribution highlights a predominantly younger student population.
- **Gender Distribution:** The gender distribution shows that 58.2% (318 students) of the respondents are male, while 41.8% (228 students) are female. This suggests a higher proportion of male students compared to female students in the sample.
- **Course Enrollment:** Among the respondents, 50.7% (277 students) are enrolled in post-graduate programs, making it the largest group. Graduates constitute 29.1% (159 students), PhD students make up 12.3% (67 students), and those in other courses represent 7.9% (43 students). This distribution indicates a strong representation of post-graduate students within the sample.
- **Departmental Affiliation:** The majority of respondents are from the Commerce and Management department, accounting for 36.3% (198 students). The Engineering and Humanities departments have similar representation at 27.5% (150 students) and 27.1% (148 students), respectively. The Science department has the smallest representation at 9.2% (50 students). This suggests a diverse departmental representation with a notable concentration in Commerce and Management.
- **Institution Type:** A significant majority, 57.1% (312 students), are from Government universities or institutes, whereas 42.9% (234 students) are from Private universities or institutes. This distribution reflects a slightly higher representation of students from Government institutions in the sample.

4.4 Regression Analysis of Technology Acceptance, Level of Use of AI-Based Tools, Technology-Based Tutoring System, and Their Impact on Students' and Organizational Performance

- **H₀ 1:** There is no significant Impact of Technology Acceptance (IV) on Level of use of AI based tools (DV).
- **H₀ 2:** There is no significant impact of Level of use of AI based tools (IV) on Students' Performance (DV).
- **H₀ 3:** There is no significant impact of Technology Acceptance (IV) on Technology based Tutoring System (DV).
- **H₀ 4:** There is no significant impact of Technology based Tutoring System (IV) on Students' Performance (DV).
- **H₀ 5:** There is no significant impact of Students' Performance (IV) on Organisational Performance (DV).

Table 4- Regression Analysis of Technology Acceptance, Level of Use of AI-Based Tools, Technology-Based Tutoring System, and Their Impact on Students' and Organizational Performance

Independent Variable	Dependent Variable	Correlation	Sig.	R ²	Standardized Beta Coefficient	Sig.
Technology Acceptance	Level of use of AI based tools	.415	.000*	.172	.415	.000*
Level of use of AI	Students'	.133	.001*	.018	.133	.002*

based tools	Performance					
Technology Acceptance	Technology based Tutoring System	.426	.000*	.182	.426	.000*
Technology based Tutoring System	Students' Performance	.183	.000*	.033	.183	.000*
Students' Performance	Organisational Performance	.247	.000*	.061	.247	.000*
* indicates impact is significant at 0.05 level of study						

Source- Author's own compilation of primary data analysis

Result- The above table shows that Technology Acceptance significantly affects the Level of use of AI-based tools. With a correlation coefficient of 0.415 and a significance level of 0.000, this indicates a strong positive relationship. The R^2 value of 0.172 implies that Technology Acceptance explains approximately 17.2% of the variance in the Level of use of AI-based tools. The standardized beta coefficient of 0.415 further highlights this impact, indicating that a one-standard-deviation increase in Technology Acceptance is associated with a 0.415 standard-deviation increase in the use of AI-based tools. This suggests that as students' acceptance of technology increases, their use of AI-based tools also rises significantly leading to the **rejection of $H_0 1$** .

In addition, the Level of use of AI-based tools has a notable impact on Students' Performance. The correlation of 0.133 and significance level of 0.001 reflect a positive but modest relationship. The R^2 value of 0.018 indicates that the Level of use of AI-based tools accounts for 1.8% of the variance in Students' Performance, demonstrating a small yet significant effect on student outcomes. The standardized beta coefficient of 0.133 indicates that a one-standard-deviation increase in the Level of use of AI-based tools is associated with a 0.133 standard-deviation increase in Students' Performance, reflecting a modest but significant impact leading to the **rejection of $H_0 2$** .

Technology Acceptance also significantly influences the Technology-based Tutoring System, with a correlation of 0.426 and a significance level of 0.000. This result, coupled with an R^2 value of 0.182, suggests that Technology Acceptance explains 18.2% of the variance in the use of Technology-based Tutoring Systems. The standardized beta coefficient of 0.426 indicates that a one-standard-deviation increase in Technology Acceptance leads to a 0.426 standard-deviation increase in the use of these systems, highlighting a strong positive and significant influence, leading to the **rejection of $H_0 3$** .

Furthermore, the Technology-based Tutoring System has a positive impact on Students' Performance, as indicated by a correlation coefficient of 0.183 and a significance level of 0.000. The R^2 value of 0.033 shows that this system explains 3.3% of the variance in Students' Performance. Although the effect size is small, it is significant, suggesting that improvements in tutoring systems can positively influence student performance. The standardized beta coefficient of 0.183 means that a one-standard-deviation increase in the use of Technology-based Tutoring Systems is associated with a 0.183 standard-deviation increase in Students' Performance, reflecting a modest positive and significant effect, therefore **$H_0 4$ is rejected**.

Finally, Students' Performance significantly affects Organizational Performance, with a correlation of 0.247 and a significance level of 0.000. The R^2 value of 0.061 indicates that Students' Performance explains 6.1% of the variance in Organizational Performance. The standardized beta coefficient of 0.247 shows that a one-standard-deviation increase in Students' Performance leads to a 0.247 standard-deviation increase in Organizational Performance. Thus, **$H_0 5$ is rejected**, which suggests that better student performance contributes positively to overall organizational outcomes, highlighting the importance of student success for organizational achievements.

5. CONCLUSION

The study provides compelling evidence for the interconnectedness of technology acceptance, the level of AI-based tool usage, technology-based tutoring systems, student performance, and organizational performance. The results consistently demonstrate significant relationships among these variables, supporting the research hypotheses.

A central finding is the strong positive relationship between technology acceptance and the level of AI-based tool usage. This indicates that students who are more receptive to technology are more likely to adopt and utilize AI-based tools. This relationship is crucial as it underlines the importance of fostering a positive attitude towards technology for successful AI implementation.

Besides, the study reveals that the level of AI-based tool usage has a positive, albeit modest, impact on student performance. This suggests that while AI-based tools can contribute to improved student outcomes, their influence is not solely determinative. Other factors, such as teaching methodologies, curriculum design, and individual student characteristics,

likely play significant roles in student success.

The role of technology-based tutoring systems is also noteworthy. These systems were found to have a positive influence on student performance, albeit small. This indicates that while technology-based tutoring can supplement traditional teaching methods, it is essential to consider its limitations and integrate it effectively into the overall learning process.

The study also highlights the importance of student performance in achieving organizational goals. The positive relationship between student performance and organizational performance emphasizes the need for institutions to prioritize student success as a key driver of overall institutional effectiveness.

The results of this study offer valuable insights into the complex interplay between technology acceptance, AI-based tool usage, technology-based tutoring systems, student performance, and organizational performance. The findings emphasize the potential benefits of AI-based tools in education but also emphasize the need for a comprehensive approach that considers multiple factors influencing student success and institutional outcomes.

6. IMPLICATIONS OF THE STUDY

The findings of this research highlight several critical implications. Firstly, cultivating a positive attitude towards technology, or technology acceptance, is pivotal for the successful integration of AI-based tools in educational settings. Secondly, while AI-based tools can positively influence student performance, their impact is moderate, suggesting that they should be used in conjunction with other pedagogical strategies. Thirdly, the study emphasizes the role of technology-based tutoring systems in enhancing student outcomes, albeit with a modest effect. Lastly, the research underscores the importance of student success as a key determinant of organizational performance.

7. RECOMMENDATIONS

Based on the study's findings, several recommendations can be made. Firstly, institutions should invest in initiatives to foster technology acceptance among educators and students. Secondly, there is a need for continued development and implementation of AI-based tools that are specifically designed to address the unique learning needs of different student populations. Thirdly, ongoing evaluation and refinement of technology-based tutoring systems are essential to maximize their effectiveness. Lastly, strategies to improve overall student performance should be a core focus for institutions seeking to enhance organizational outcomes.

8. LIMITATIONS OF THE STUDY

It is important to acknowledge the limitations of this research. The study's focus on Lucknow city alone limits the generalizability of its findings to other geographical areas of different educational settings. Additionally, the cross-sectional survey employed in the study provides a snapshot of the variables at a single point in time, rather than capturing changes over time. Besides, the research did not account for other potential factors that might influence student performance and organizational outcomes.

9. FUTURE RESEARCH DIRECTIONS

To expand upon the findings of this study, future research could explore the causal relationships between the variables through experimental designs. Additionally, investigating the impact of different types of AI-based tools on various student populations would provide valuable insights. Longitudinal studies could examine the long-term effects of AI-based tool usage on student performance and organizational outcomes. Finally, comparative studies across different educational contexts would contribute to a broader understanding of the factors influencing the successful integration of AI in education.

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