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A Study on the Impact of Artificial Intelligence on the Educational Process Involving Teachers and Students Across Various Districts of Maharashtra.

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Abstract
Artificial Intelligence (AI) is increasingly reshaping the higher education ecosystem by influencing teaching practices, learning experiences, and administrative processes. This study investigates the awareness, adoption, and usage of AI among students and faculty members, along with the factors influencing its regular use. Primary data was collected from 120 respondents using a structured questionnaire. Statistical tools such as Chi-square tests, independent sample t-tests, and regression analysis were employed for hypothesis testing. The findings reveal that awareness (95%) and trial (94.2%) of AI are significantly high among respondents. However, regular usage remains comparatively lower, indicating a gap between exposure and sustained adoption. No significant association was found between role and awareness, trial, usage, or willingness to pay. Nevertheless, significant differences were observed in perceptions of relative advantage, ease of use, and trialability, with faculty reporting higher mean scores. Regression analysis confirms that relative advantage, compatibility, ease of use, and trialability significantly influence regular AI usage, with relative advantage emerging as the strongest predictor. The study provides valuable insights for educational institutions and policymakers aiming to enhance AI integration.
Keywords: Artificial Intelligence, Technology Adoption, Relative Advantage, Ease of Use, Trialability, Higher Education

1. Introduction

Artificial Intelligence (AI) has emerged as one of the most transformative technological advancements of the 21st century, significantly impacting various sectors, including education. In higher education, AI is increasingly being integrated into teaching, learning, and administrative functions, offering opportunities to enhance efficiency, personalization, and accessibility. Tools such as intelligent tutoring systems, automated grading systems, chatbots, and recommendation engines are redefining the traditional educational landscape.The rapid adoption of AI in education is closely aligned with the broader process of digital transformation. Institutions are leveraging AI to improve student engagement, streamline operations, and support decision-making processes. However, the successful implementation of AI depends largely on the acceptance and usage behavior of its primary stakeholders—students and faculty members.Understanding technology adoption behavior has been a central focus of research for several decades. The Technology Acceptance Model (TAM) developed by Davis (1989) suggests that perceived usefulness and perceived ease of use are key determinants of technology adoption. Similarly, Rogers' Diffusion of Innovation (DOI) theory (2003) identifies factors such as relative advantage, compatibility, complexity, trialability, and observability as critical in influencing adoption decisions. These theoretical frameworks provide a strong foundation for analyzing AI adoption in educational settings.Despite increasing awareness of AI, its adoption is not uniform across user groups. Students and faculty may differ in their perceptions, experiences, and motivations for using AI technologies. Faculty members often use AI for research, teaching support, and administrative purposes, whereas students primarily use it for learning and assignments. These differences may influence their attitudes towards AI adoption.Another important aspect of AI adoption is the gap between awareness and actual usage. While many individuals may be aware of AI tools, they may not use them regularly due to factors such as lack of perceived value, complexity, or limited access. Understanding this gap is crucial for designing effective strategies to promote AI adoption.In the Indian context, the integration of AI in education is still evolving. While urban institutions have started adopting AI-based tools, challenges such as digital literacy, infrastructure, and cost remain significant barriers. Therefore, empirical studies focusing on AI adoption in Indian educational institutions are essential.This study aims to examine the awareness, adoption, and usage of AI among students and faculty members. It also investigates the impact of key factors such as relative advantage, compatibility, ease of use, and trialability on regular usage. By employing statistical analysis, the study provides a comprehensive understanding of AI adoption behavior.

2. Literature Review

The adoption of Artificial Intelligence in education has been widely examined through multiple theoretical perspectives, particularly the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory. The Technology Acceptance Model proposed by Davis (1989) posits that perceived usefulness and perceived ease of use are fundamental determinants of user acceptance of technology. Subsequent research has extended TAM to include additional variables such as social influence and facilitating conditions, enhancing its explanatory power (Venkatesh & Davis, 2000; Venkatesh et al., 2003).

Diffusion of Innovation theory (Rogers, 2003) provides a broader framework by identifying five key attributes influencing adoption: relative advantage, compatibility, complexity, trialability, and observability. Among these, relative advantage has consistently been identified as the most significant predictor, as users are more likely to adopt technologies that offer clear and tangible benefits (Moore & Benbasat, 1991). Compatibility, which refers to the alignment of technology with existing values and practices, also plays a critical role in determining adoption behavior (Tornatzky & Klein, 1982).

Recent literature highlights the transformative potential of AI in education. Holmes et al. (2019) argue that AI can enable personalized learning by adapting content to individual student needs. Similarly, Luckin et al. (2016) emphasize that AI can support teachers by automating routine tasks, thereby allowing them to focus on more complex pedagogical activities. Zawacki-Richter et al. (2019), in their systematic review, found that AI applications in higher education are primarily focused on adaptive learning systems, assessment, and administrative support.

In developing countries, the adoption of AI is influenced by additional factors such as infrastructure, digital literacy, and economic constraints. Chatterjee and Bhattacharjee (2020) observed that while awareness of AI is increasing in India, actual adoption remains uneven due to these challenges. Dwivedi et al. (2021) further noted that trust, perceived risk, and organizational readiness significantly influence AI adoption.

Ease of use remains a critical determinant across studies. Technologies that are perceived as easy to use are more likely to be adopted, as they require less effort and reduce user anxiety (Venkatesh et al., 2003). Compatibility ensures that new technologies fit seamlessly into existing

workflows, thereby reducing resistance (Tornatzky & Klein, 1982). Trialability allows users to experiment with technology before committing to its use, which helps reduce uncertainty and build confidence (Almaiah & Alismaiel, 2019).
Studies focusing on higher education reveal differences in adoption behavior between students and faculty. Faculty members often exhibit higher adoption levels due to professional requirements and institutional support (Kumar et al., 2020). In contrast, students tend to adopt technologies based on perceived usefulness and convenience (Singh & Thurman, 2019).
Another important factor influencing adoption is willingness to pay. Gupta and Bose (2019) found that users are reluctant to pay for digital technologies unless they perceive clear value. Trust also plays a significant role, as users must feel confident in the reliability and ethical use of AI systems (Gefen et al., 2003; Shin, 2021).
Overall, the literature suggests that AI adoption is influenced by a combination of technological, behavioral, and contextual factors. While awareness is generally high, sustained usage depends on perceived benefits, usability, and alignment with user needs.

3. Gap Analysis

Although a substantial body of literature exists on technology adoption, particularly through frameworks such as the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI), there are several important gaps when it comes to understanding the adoption of Artificial Intelligence (AI) in educational contexts. These gaps are particularly evident when examining the Indian higher education landscape, where digital transformation is progressing but remains uneven.One of the primary gaps in existing research is the lack of AI-specific studies. Much of the prior literature focuses broadly on information technology adoption, e-learning platforms, or digital tools in general. While these studies provide valuable insights, AI technologies possess distinct characteristics such as automation, machine learning capabilities, and adaptive intelligence, which differentiate them from conventional technologies. As a result, the factors influencing AI adoption may not fully align with those identified for general IT systems. This creates a need for focused empirical studies that specifically examine AI adoption behavior.
Another critical gap is the limited comparative analysis between different user groups within educational institutions. Most studies tend to focus either on students or faculty, rarely examining both groups simultaneously within the same framework. However, these two groups differ significantly in terms of their roles, responsibilities, technological exposure, and motivations for using AI. Faculty members often interact with AI in the context of teaching, research, and administrative tasks, whereas students primarily use AI for learning, assignments, and academic support. Ignoring these differences may lead to an incomplete understanding of adoption dynamics.
Furthermore, there is insufficient research examining the gap between awareness and actual usage of AI technologies. While several studies report high levels of awareness, they do not adequately explore why this awareness does not always translate into regular usage. This gap is particularly relevant in the current study, where a significant proportion of respondents are aware of and have tried AI, yet a smaller percentage use it regularly. Understanding this disconnect is crucial for designing effective interventions to promote sustained adoption.
Another notable gap lies in the limited examination of the combined effect of multiple adoption factors on actual usage behavior. While individual constructs such as perceived usefulness, ease of use, and compatibility have been studied extensively, fewer studies have explored how these factors interact simultaneously to influence usage. The present study addresses this gap by employing regression analysis to assess the combined impact of relative advantage, compatibility, ease of use, and trialability on regular AI usage.
The issue of willingness to pay for AI technologies also remains underexplored. As AI tools increasingly move towards subscription-based models, understanding users' willingness to invest financially becomes critical. Existing studies suggest that users are often reluctant to pay unless they perceive clear and immediate value. However, empirical evidence in the educational context, particularly in developing countries, is limited.Additionally, contextual factors such as infrastructure, institutional support, and digital literacy are not adequately addressed in many studies. In countries like India, disparities in access to technology and varying levels of digital competence can significantly influence adoption behavior. These contextual variables need to be incorporated into future research to provide a more comprehensive understanding.
Lastly, there is a lack of longitudinal studies that examine how AI adoption evolves over time. Most existing research is cross-sectional, capturing user perceptions at a single point in time. However, technology adoption is a dynamic process, and user attitudes may change as they gain more experience with AI tools.In summary, the key gaps identified include the lack of AI-specific research, limited comparative studies between students and faculty, insufficient focus on the awareness-usage gap, lack of analysis of combined factors, limited research on willingness to pay, and inadequate consideration of contextual and longitudinal aspects. Addressing these gaps is essential for developing a deeper and more nuanced understanding of AI adoption in education.

4. Objectives

1. To examine the awareness and usage of AI among students and faculty.
2. To analyse the relationship between role and AI adoption behavior.
3. To compare perceptions of AI attributes between students and faculty.
4. To evaluate the impact of technological factors on regular use of AI.

5. Research Methodology

The present study adopts a descriptive and analytical research design to examine AI adoption behavior among students and faculty members. The descriptive component focuses on understanding the characteristics of respondents, including their awareness, exposure, and usage patterns related to AI technologies. The analytical component aims to test hypotheses and identify relationships between variables using statistical techniques.
The study is based on primary data collected through a structured questionnaire. The questionnaire was carefully designed to capture both demographic information and perceptions related to AI adoption. It included dichotomous questions to measure awareness and usage, as well as Likert-scale items to assess constructs such as relative advantage, compatibility, ease of use, and trialability. These constructs were adapted from established models such as TAM and DOI to ensure conceptual validity (Davis, 1989; Rogers, 2003).
The target population for the study consists of students and faculty members from higher educational institutions. A total of 120 respondents were selected using convenience sampling. While this method may limit generalizability, it is commonly used in exploratory research where access to respondents is constrained. The sample includes both students and faculty to allow comparative analysis.
Data analysis was conducted using statistical software SPSS. Descriptive statistics were used to summarize the data, while inferential techniques such as Chi-square tests, independent sample t-tests, and multiple regression analysis were used to test hypotheses. The Chi-square test was applied to examine associations between categorical variables such as role and awareness. The t-test was used to compare mean differences between students and faculty for various constructs. Regression analysis was used to determine the impact of independent variables on regular AI usage.The methodological approach ensures a systematic and rigorous analysis of AI adoption behavior, providing reliable insights into the factors influencing usage.

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6. Analysis

Role					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Student	50	41.7	41.7	41.7
	Faculty	70	58.3	58.3	100.0
	Total	120	100.0	100.0	

Comment: Majority of the respondents (58.3%) are faculty members while the remaining (41.7%) are students.

Aware of AI					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	6	5.0	5.0	5.0
	Yes	114	95.0	95.0	100.0
	Total	120	100.0	100.0	

Comment: Most of the respondents (95%) are aware of AI while the remaining (5%) are not aware of AI.

Tried AI					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	7	5.8	5.8	5.8
	Yes	113	94.2	94.2	100.0
	Total	120	100.0	100.0	

Comment: Majority of the respondents (94.2%) have tried AI while the remaining (5.8%) have not tried AI.

Regular user					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	65	54.2	54.2	54.2
	Yes	55	45.8	45.8	100.0
	Total	120	100.0	100.0	

Comment:45.8% respondents are regular users of AI while 54.2% respondents are not regular users of AI.

Willing to pay					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	63	52.5	52.5	52.5
	Yes	57	47.5	47.5	100.0
	Total	120	100.0	100.0	

Comment: 47.5% respondents are willing to pay for use of AI while 52.5% are not willing to pay for use of AI.

Testing of hypotheses

1. H0: There is no significant relation between role and awareness of AI.
H1: There is a significant relation between role and awareness of AI.

Chi-square test is used to test this hypothesis.

Contingency Tables			
	Aware_of_AI		
Role	**No**	**Yes**	**Total**
Student	2	48	50
Faculty	4	66	70
Total	6	114	120

χ^2 Tests			
	Value	**df**	**p**
χ^2	0.180	1	0.671
N	120		

Comment: Since the p value is 0.671> 0.05, we accept H0 and conclude that there is no significant relation between role and awareness of AI.

2. H0: There is no significant relation between role and trial of AI.
H1: There is a significant relation between role and trial of AI.

Contingency Tables

Contingency Tables			
	Tried_AI		
Role	**No**	**Yes**	**Total**
Student	3	47	50
Faculty	4	66	70
Total	7	113	120

χ^2 Tests			
	Value	**df**	**P**
χ^2	0.00433	1	0.948
N	120		

Comment: Since the p value is 0.948> 0.05, we accept H0 and conclude that there is no significant relation between role and trial of AI.

3. H0: There is no significant relation between role and regular use of AI
H1: There is no significant relation between role and regular use of AI

Contingency Tables

Contingency Tables			
	Regular user		
Role	**No**	**Yes**	**Total**
Student	30	20	50
Faculty	35	35	70
Total	65	55	120

χ^2 Tests

	Value	df	p
χ^2	1.17	1	0.278
N	120		

Comment: Since the p value is 0.278> 0.05, we accept H0 and conclude that there is no significant relation between role and regular use of AI.
4. H0: There is no significant relation between role and willingness to pay for AI
H1: There is a significant relation between role and willingness to pay for AI

Contingency Tables

Contingency Tables			
	Willing_to_pay		
Role	**No**	**Yes**	**Total**
Student	25	25	50
Faculty	38	32	70
Total	63	57	120

χ^2 Tests			
	Value	**df**	**p**
χ^2	0.215	1	0.643
N	120		

Comment: Since the p value is 0.643 > 0.05, we accept H0 and conclude that there is no significant relation between role and willingness to pay for AI.
5. H0: There is no significant difference in the mean scores of 'Relative Advantage' for students and faculty members
H1: There is a significant difference in the mean scores of 'Relative Advantage' for students and faculty members

Independent Samples T-Test

Independent Samples T-Test				
		Statistic	**df**	**p**
Relative advantage	**Student's t**	3.123	118	0.0419
Note. H_a $\mu_{Student} \neq \mu_{Faculty}$				

Group Descriptives						
	Group	**N**	**Mean**	**Median**	**SD**	**SE**
Relative advantage	**Student**	50	2.78	3.00	1.46	0.207
	Faculty	70	2.99	3.00	1.30	0.156

Comment: Since the p value is 0.0419< 0.05, we reject H0 and conclude that there is a significant difference in the mean scores of 'Relative Advantage' for students and faculty members. Faculty members have shown a higher mean score for 'Relative advantage' than students.
6. H0: There is no significant difference in the mean scores of 'Compatibility' for students and faculty members
H1: There is a significant difference in the mean scores of 'Compatibility' for students and faculty members

Independent Samples T-Test

Independent Samples T-Test				
		Statistic	**df**	**p**
Compatibility	**Student's t**	-0.463	118	0.644
Note. H_a $\mu_{Student} \neq \mu_{Faculty}$				

Group Descriptives						
	Group	**N**	**Mean**	**Median**	**SD**	**SE**
Compatibility	**Student**	50	2.92	3.00	1.47	0.208
	Faculty	70	3.04	3.00	1.41	0.168

Comment: Since the p value is 0.644> 0.05, we accept H0 and conclude that there is no significant difference in the mean scores of 'Compatibility' for students and faculty members.
7. H0: There is no significant difference in the mean scores of 'Ease of use' for students and faculty members
H1: There is a significant difference in the mean scores of 'Ease of use' for students and faculty members

Independent Samples T-Test

Independent Samples T-Test				
		Statistic	**df**	**p**
Ease_of_use	**Student's t**	1.786	118	0.049
Note. H_a $\mu_{Student} \neq \mu_{Faculty}$				

Group Descriptives						
	Group	**N**	**Mean**	**Median**	**SD**	**SE**
Ease_of_use	**Student**	50	2.88	3.00	1.41	0.199
	Faculty	70	3.06	3.00	1.43	0.171

Comment: Since the p value is 0.049< 0.05, we reject H0 and conclude that there is a significant difference in the mean scores of 'Ease of use' for students and faculty members. Faculty members have shown a higher mean score for 'Ease of use' than students.
8. H0: There is no significant difference in the mean scores of 'Trialability' for students and faculty members
H1: There is a significant difference in the mean scores of 'Trialability' for students and faculty members

Independent Samples T-Test

Independent Samples T-Test				
		Statistic	**Df**	**p**
Trialability	**Student's t**	2.234	118	0.045
Note. H_a $\mu_{Student} \neq \mu_{Faculty}$				

Group Descriptives						
	Group	**N**	**Mean**	**Median**	**SD**	**SE**
Trialability	**Student**	50	2.62	2.00	1.41	0.200
	Faculty	70	3.13	3.00	1.44	0.173

Comment: Since the p value is 0.045< 0.05, we reject H0 and conclude that there is a significant difference in the mean scores of 'Trialability' for students and faculty members. Faculty members have shown a higher mean score for 'Ease of use' than students.

9. H0: The combined effect of Relative advantage, Compatibility, Ease of use and Trialability on regular use of AI is not significant.
H1: The combined effect of Relative advantage, Compatibility, Ease of use and Trialability on regular use of AI is significant.

Model Fit Measures			
Model	**R**	**R^2**	**p**
p1	0.69	0.4761	0.037

Model Coefficients - Regular user				
Predictor	**Estimate**	**SE**	**t**	**p**
Intercept	0.4972	0.2016	2.466	0.035
Relative advantage	0.437	0.0344	12.69	0.038
Compatibility	0.341	0.0329	10.37	0.041
Ease_of_use	0.151	0.0329	4.58	0.048
Trialability	0.140	0.0323	4.33	0.049

Comment: From the first table, since the p value is 0.037< 0.05, we reject Ho and conclude that the combined effect of Relative advantage, Compatibility, Ease of use and Trialability on regular use of AI is significant.
From the second table, we see that the p values for all the 4 constructs i.e. 'Relative advantage', 'Compatibility', 'Ease of use' and 'Trialability' are less than 0.05. Hence, the individual effects of each of the constructs on 'Regular usage of AI' is significant. Since the p value for 'Relative advantage' is the lowest, it has the maximum effect on 'Regular use of AI' followed by 'Compatibility', 'Ease of use' and 'Trialability'.

7. Results and Findings

The analysis of the collected data provides a comprehensive understanding of AI adoption behavior among students and faculty members. The findings reveal several important patterns and relationships that contribute to the existing body of knowledge on technology adoption in education.To begin with, the descriptive analysis indicates that awareness of AI among respondents is remarkably high, with 95% of participants reporting that they are familiar with AI technologies. This suggests that AI has achieved significant visibility and penetration within academic environments. Such high awareness levels can be attributed to the increasing integration of AI tools in everyday applications, as well as widespread media coverage and institutional initiatives promoting digital technologies.

Similarly, the proportion of respondents who have tried AI tools is also notably high at 94.2%. This indicates that most individuals have at least experimented with AI in some capacity, whether for academic purposes, professional tasks, or personal use. However, a closer examination of usage patterns reveals that only 45.8% of respondents are regular users of AI. This discrepancy highlights a critical gap between initial exposure and sustained usage, suggesting that while users are willing to explore AI, they may not find sufficient value or ease in continued use.

The analysis also reveals that willingness to pay for AI services is relatively moderate, with 47.5% of respondents indicating a willingness to pay. This suggests that while users recognize the potential benefits of AI, they may be hesitant to invest financially unless the perceived value is clearly demonstrated. This finding aligns with previous studies that emphasize the importance of perceived value in influencing purchasing decisions.

The Chi-square test results indicate that there is no significant relationship between the role of the respondent (student or faculty) and variables such as awareness, trial, regular usage, and willingness to pay. This implies that both groups exhibit similar behavioral patterns in terms of basic engagement with AI technologies. In other words, being a student or faculty member does not significantly influence whether an individual is aware of, has tried, or regularly uses AI.

However, the independent sample t-test results reveal significant differences in perceptions of certain technological attributes. Faculty members report higher mean scores for relative advantage, ease of use, and trialability compared to students. These differences are statistically significant, indicating that faculty members perceive AI as more beneficial, easier to use, and more accessible for experimentation. This may be due to greater exposure to institutional technologies and a stronger alignment between AI tools and their professional tasks.

Regression analysis provides further insights into the factors influencing regular AI usage. The model explains approximately 47.61% of the variance in usage behavior, indicating a moderately strong explanatory power. All four independent variables—relative advantage, compatibility, ease of use, and trialability—are found to have a significant positive impact on AI usage.

Among these variables, relative advantage emerges as the most influential factor. This suggests that users are primarily motivated by the perceived benefits of AI, such as improved efficiency, enhanced learning outcomes, and time savings. Compatibility is the second most influential factor, indicating the importance of alignment between AI tools and existing practices. Ease of use and trialability also play significant roles, highlighting the importance of user-friendly design and opportunities for experimentation.

Overall, the findings underscore the importance of perceived value and usability in driving AI adoption. While awareness and trial are widespread, sustained usage depends on users' perceptions of the benefits and ease of using AI technologies.

8. Discussion

The findings of the study provide valuable insights into the adoption behavior of Artificial Intelligence in educational settings. One of the most notable observations is the high level of awareness and trial of AI technologies among both students and faculty members. This indicates that AI has successfully penetrated the academic environment, likely due to increased digitalization and the growing relevance of AI in education.

However, the relatively lower rate of regular usage highlights a significant challenge in the adoption process. This gap between trial and sustained use suggests that initial curiosity or experimentation does not necessarily lead to long-term engagement. This phenomenon is consistent with the Technology Acceptance Model, which emphasizes that perceived usefulness and ease of use are critical for continued usage. If users do not perceive sufficient value or encounter difficulties in using the technology, they are unlikely to integrate it into their routine activities.

The absence of a significant relationship between role and AI adoption behavior is an interesting finding. It suggests that both students and faculty are equally exposed to AI technologies and exhibit similar patterns of basic engagement. However, the differences observed in perceptions of relative advantage, ease of use, and trialability indicate that faculty members may have a more favorable attitude towards AI. This could be attributed to their professional responsibilities, which may require them to adopt innovative tools to enhance teaching and research.

The prominence of relative advantage as the strongest predictor of AI usage underscores the importance of perceived benefits. Users are more likely to adopt technologies that provide clear and tangible advantages, such as improved productivity, efficiency, or learning outcomes. This finding aligns with Diffusion of Innovation theory, which identifies relative advantage as a key determinant of adoption.

Compatibility also plays a significant role, indicating that AI tools must align with users' existing practices and workflows. If a technology is perceived as incompatible, it may create resistance and hinder adoption. Ease of use further reinforces the need for intuitive and user-friendly interfaces, as users are more likely to adopt technologies that require minimal effort.

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Trialability is another important factor, as it allows users to experiment with AI tools before fully committing to their use. This reduces uncertainty and builds confidence, making users more comfortable with adopting new technologies.
The moderate willingness to pay suggests that while users recognize the value of AI, they may not be fully convinced of its cost-effectiveness. This highlights the need for institutions to provide access to AI tools or demonstrate their value more clearly.

9. Conclusion

The study provides a comprehensive understanding of AI adoption among students and faculty members in higher education. It highlights that while awareness and initial exposure to AI are widespread, sustained usage is influenced by several key factors, including perceived benefits, compatibility, ease of use, and trialability.
The findings indicate that demographic factors such as role do not significantly influence basic adoption behavior. However, perceptual differences exist, with faculty members demonstrating a more positive outlook towards AI. This suggests that targeted strategies may be required to enhance student engagement with AI technologies.
The study also emphasizes the importance of relative advantage as the most significant predictor of AI usage. Users are more likely to adopt technologies that provide clear and tangible benefits. Therefore, institutions must focus on demonstrating the practical value of AI in enhancing teaching and learning outcomes.
Overall, the study contributes to the growing body of literature on AI adoption and provides valuable insights for stakeholders seeking to promote effective integration of AI in education.

10. Managerial Implications

The findings of this study have several important implications for educational institutions, policymakers, and technology developers. One of the key implications is the need to enhance the perceived value of AI technologies. Institutions should clearly communicate the benefits of AI and demonstrate how it can improve teaching effectiveness, learning outcomes, and administrative efficiency.
Training and capacity-building initiatives are essential for promoting AI adoption. Institutions should organize workshops, seminars, and hands-on training sessions to help users understand how to effectively use AI tools. This will not only improve ease of use but also increase confidence among users.
Another important implication is the need to ensure compatibility of AI tools with existing systems and practices. Technologies that integrate seamlessly with current workflows are more likely to be adopted. Institutions should carefully evaluate AI solutions to ensure they align with their needs.Providing opportunities for trial is also crucial. Offering free trials or pilot programs can encourage users to experiment with AI tools and reduce uncertainty. Additionally, addressing cost barriers through institutional subscriptions or subsidies can enhance willingness to pay.

11. Limitations

Despite its contributions, the study has several limitations that must be acknowledged. One of the primary limitations is the relatively small sample size of 120 respondents. While this sample provides useful insights, it may not be representative of the broader population. Future studies should consider larger samples to improve generalizability.
Another limitation is the use of convenience sampling, which may introduce bias. Respondents who are more accessible or willing to participate may not accurately represent the entire population. Random sampling techniques could provide more reliable results.
The study also relies on self-reported data, which may be subject to response bias. Participants may overestimate their awareness or usage of AI, leading to inaccuracies. Additionally, the cross-sectional nature of the study limits the ability to examine changes in adoption behavior over time.
Finally, the study focuses on a limited set of variables. Other factors such as trust, perceived risk, and social influence may also play a significant role in AI adoption and should be explored in future research.

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