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Factors influencing students' adoption of AI research tools: A logistic regression analysis

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Abstract
Purpose: This study aims to analyse the factors influencing students' behavioural intention to adopt AI research tools using a logistic regression model.
Study Design / Methodology / Approach: A structured survey was conducted among 350 college students in Coimbatore, aged 18-25. The survey assessed factors such as perceived usefulness, perceived ease of use, social influence, perceived trust, and facilitating conditions. Data were analysed using logistic regression modelling techniques.
Findings: The study found that perceived usefulness and facilitating conditions significantly influence students' behavioural intention to adopt AI research tools. The logistic regression model predicted students' propensity to use AI tools with an accuracy rate of 80.43%.
Originality / Value: This research addresses a notable gap in the literature by providing a comprehensive analysis of the factors influencing students' adoption of AI research tools, offering valuable insights for educators, researchers, and policymakers.

Keywords: AI adoption in education, student behavioural intention, AI research tools, logistic regression model

Introduction
The integration of Artificial Intelligence (AI) in academia is transforming research methodologies. This study explores the factors influencing students' behavioural intention to adopt AI research tools.

Research Gap / Problems Identified
Despite the growing importance of AI, there is a lack of comprehensive analysis on the factors influencing students' willingness to adopt AI research tools.

Operational Definition of Variables
- **Perceived Ease of Use (PEU):** The simplicity and accessibility of AI research tools.
- **Perceived Usefulness (PU):** The benefits and contributions of AI tools to academic work.
- **Social Influence (SI):** The impact of peers, professors, and influential figures.
- **Perceived Trust (PT):** Confidence in the reliability and credibility of AI tools.
- **Facilitating Conditions (FC):** Environmental and technical support available.

Research Questions
1. What is the relationship between perceived ease of use and students' behavioural intention to adopt AI research tools?
2. How does social influence affect students' behavioural intention?
3. What is the influence of perceived trust on adoption willingness?
4. How do facilitating conditions impact behavioural intention?
5. What are the critical factors impacting students' adoption behaviour?

Literature Review
This literature review delves into the factors influencing students' behavioural intention to adopt AI research tools, focusing on hypotheses derived from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

The review synthesizes findings from various studies to provide a comprehensive understanding of the critical factors impacting AI adoption in educational settings.

Hypothesis 1: Perceived Ease of Use Positively Impacts Behavioural Intention

Bilquise *et al*. found that students' perceptions of ChatGPT's ease of use did not significantly influence their adoption of the app. This suggests that while ease of use is often considered a critical factor in technology adoption, it may not always be the primary driver in the context of AI tools for education. Instead, other factors such as perceived usefulness and social presence play a more significant role.

Ban *et al*. (2023) [3] highlighted that perceived ease of use (PEOU) significantly influences students' attitudes and behavioral intentions towards AI-based systems. However, the study noted that learning motivations related to goal achievement and subjective norms were unaffected by students' attitudes towards AI-based systems, indicating that ease of use alone may not be sufficient to drive adoption.

Chiu & Chai (2020) [11] emphasized the importance of structured AI curricula in K-12 education, noting that providing educators with the necessary resources and curriculum design approaches is crucial for meaningful AI learning experiences. This supports the idea that perceived ease of use, facilitated by well-structured curricula, can enhance students' willingness to adopt AI tools.

Hypothesis 2: Perceived Usefulness Positively Impacts Behavioural Intention

Bilquise *et al*. emphasized that perceived usefulness (PU) is a significant factor influencing students' positive attitudes towards using ChatGPT for educational purposes. The study found that students' motivation and enjoyment, along with the tool's perceived usefulness, social presence, and legitimacy, were crucial in shaping their attitudes.

Kelly *et al*. (2023) [18] conducted a systematic review and found that perceived usefulness consistently influences behavioral intentions and willingness to use AI across various industries. This reinforces the importance of perceived usefulness in the adoption of AI tools in educational settings.

Ban *et al*. (2023) [3] further supported this by demonstrating that perceived usefulness significantly impacts students' attitudes, behavioral intentions, and actual use of AI-based systems. The study highlighted that students are more likely to adopt AI tools if they perceive them as beneficial to their academic work.

Marrone *et al*. (2022) [19] found that while students recognize that AI cannot match human creativity, they are open to using AI to enhance their creative abilities. This indicates that perceived usefulness extends beyond practical benefits to include enhancements in creative processes.

Hypothesis 3: Social Influence Positively Impacts Behavioural Intention

Chatterjee & Bhattacharjee (2020) [7] discussed the role of social influence in the adoption of AI in higher education. The study found that stakeholders' views on AI adoption are influenced by various factors, including social influence, which underscores the importance of peer and instructor recommendations in shaping students' behavioral intentions.

Roy *et al*. (n.d.) 2022 [25] used the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Technology Readiness Index (TRI) to investigate the openness of instructors and students to integrating AI-powered robots into the classroom. The study confirmed that social influence plays a significant role in the adoption of AI-driven robotics for innovative teaching.

Chiu *et al*. (2021) **[11]** highlighted the effectiveness of collaborative co-creation processes involving professors, principals, and teachers in implementing AI education. This collaborative approach enhances social influence, encouraging students to adopt AI tools.

Hypothesis 4: Perceived Trust Positively Impacts Adoption Willingness

Bilquise *et al*. noted that perceived trust in the legitimacy and reliability of ChatGPT significantly influenced students' positive attitudes towards its use. This finding highlights the importance of trust in the adoption of AI tools, as students are more likely to use tools they perceive as credible and reliable.

Kelly *et al*. (2023) [18] also found that trust is a critical factor influencing behavioural intentions and willingness to use AI. The study emphasized that trust in AI technology is essential for its acceptance across different demographics and industries.

Y. Y. Wang & Wang (2022) [29] developed the AI Anxiety Scale (AIAS) to measure anxiety related to AI development. The study found that reducing AI anxiety through increased trust and understanding can positively impact motivated learning behaviour, further supporting the importance of perceived trust.

Hypothesis 5: Facilitating Conditions Positively Impact Behavioural Intention

Chatterjee & Bhattacharjee (2020) [7] identified facilitating conditions as a significant factor influencing the adoption of AI in higher education. The study highlighted that the availability of technical support and infrastructure plays a crucial role in encouraging the use of AI tools.

F. Wang *et al*. (2023b) [28] examined the role of supportive environments in motivating students' intentions to learn AI. The study found that higher perceptions of support and expectancy-value beliefs were associated with stronger intentions to learn AI, underscoring the importance of facilitating conditions in AI adoption.

Guleria & Sood (2023) [15] presented a framework for effective career counseling using AI and machine learning techniques. The study emphasized the importance of facilitating conditions, such as technical support and infrastructure, in improving decision accuracy and encouraging the adoption of AI tools.

Zawacki-Richter *et al*. (2019) [30] highlighted the need for ethical considerations and well-defined theoretical frameworks in AI education. The study emphasized that facilitating conditions, including ethical guidelines and theoretical support, are essential for the effective implementation of AI in higher education.

The literature review confirms that perceived usefulness, social influence, perceived trust, and facilitating conditions are significant factors influencing students' behavioral intention to adopt AI research tools. While perceived ease of use is also important, its impact may vary depending on the context and specific AI tool being considered. These findings provide valuable insights for educators, researchers, and policymakers to optimize the integration of AI tools in educational settings.

Research Methodology

The study employs a logistic regression model to analyze students' behavioral intention to adopt AI research tools.

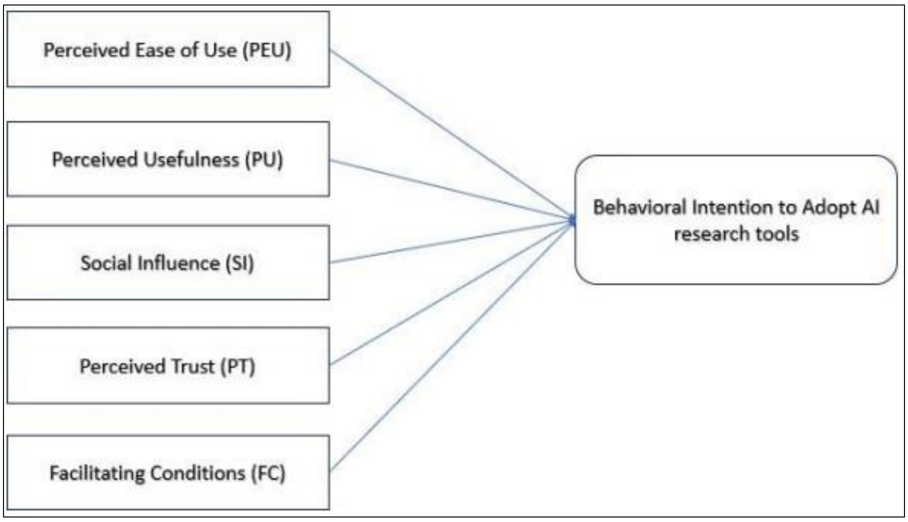
Sampling Design

- **Population:** College students aged 19 to 25 in Coimbatore.
- **Sampling Frame:** Colleges in Coimbatore.
- **Sampling Technique:** Random sampling to ensure representation across various factors.
- **Sample Size:** 383 college students, determined using a sample size calculator to achieve a 95% confidence level with a 5% margin of error.
- **Sampling Unit:** Individual students aged 19 to 25 from colleges in Coimbatore.

Data Collection

- **Instrument:** Structured survey using Likert scales to measure factors such as perceived usefulness, perceived ease of use, social influence, perceived trust, facilitating conditions, and behavioral intention to use AI research tools.
- **Procedure:** Distribute surveys to the target sample and collect responses.

Theoretical Framework



Data Analysis

- **Logistic Regression Model:** Used to analyse the relationship between the independent variables (PEU, PU, SI, PT, FC) and the dependent variable (behavioral intention to adopt AI research tools).
- **Software:** R programming language for data analysis.

Reliability Test

- **Cronbach's Alpha:** Used to test the reliability of the survey instrument. A high Cronbach's Alpha value (0.964) indicates excellent internal consistency.

Interpretation of the Analysis

Output Summary

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-9.24692	1.75997	-5.254	1.49e-07	***
FQ1	0.16980	0.26814	0.633	0.526569	
FQ2	0.26558	0.30223	0.879	0.379553	
FQ3	-0.14742	0.30322	-0.486	0.626835	
FQ4	0.05390	0.24176	0.223	0.823582	
FQ5	0.28828	0.24870	1.159	0.246382	
FQ6	-0.29012	0.26196	-1.107	0.268089	
FQ7	0.73690	0.36791	2.003	0.045181	*
FQ8	-0.31976	0.33561	-0.953	0.340698	
FQ9	0.08256	0.25243	0.327	0.743608	
FQ10	0.28647	0.26819	1.068	0.285444	
FQ11	0.08627	0.34531	0.250	0.802729	
FQ12	-0.19872	0.35108	-0.566	0.571364	
FQ13	-0.35800	0.34788	-1.029	0.303435	
FQ14	-0.09450	0.25906	-0.365	0.715271	
FQ15	0.29402	0.28225	1.042	0.297540	
FQ16	0.55440	0.33087	1.676	0.093818	.
FQ17	-0.58286	0.38877	-1.499	0.133813	
FQ18	-0.01081	0.35975	-0.030	0.976018	
FQ19	0.43186	0.31770	1.359	0.174035	
FQ20	0.10489	0.26248	0.400	0.689460	
FQ21	0.20650	0.33548	0.616	0.538193	
FQ22	0.45268	0.39265	1.153	0.248958	
FQ23	0.03142	0.32248	0.097	0.922384	
FQ24	0.16360	0.31694	0.516	0.605726	
FQ25	0.84171	0.25388	3.315	0.000915	***

Fig 1: Output Significance Levels

Significant Variables

The analysis identified that perceived usefulness (PU) and facilitating conditions (FC) were significant predictors of students' behavioural intention to adopt AI research tools.

Confusion Matrix

The confusion matrix summarizes the model's performance:

True Positives (TP): 61
True Negatives (TN): 13
False Positives (FP): 14
False Negatives (FN): 4

Accuracy

Accuracy Calculation

Sum of correctly predicted instances (TP and TN) Divided by the total number of instances in the dataset. Formula: Accuracy = (TP + TN) / (TP + TN + FP + FN) Accuracy = (61 + 13) / (61 + 13 + 14 + 4) = 74 / 92 ≈ 0.8043

Findings

Model Performance

The logistic regression model accurately predicted students' intention to use AI research tools with an accuracy rate of 80.43%.

Significance of Variables

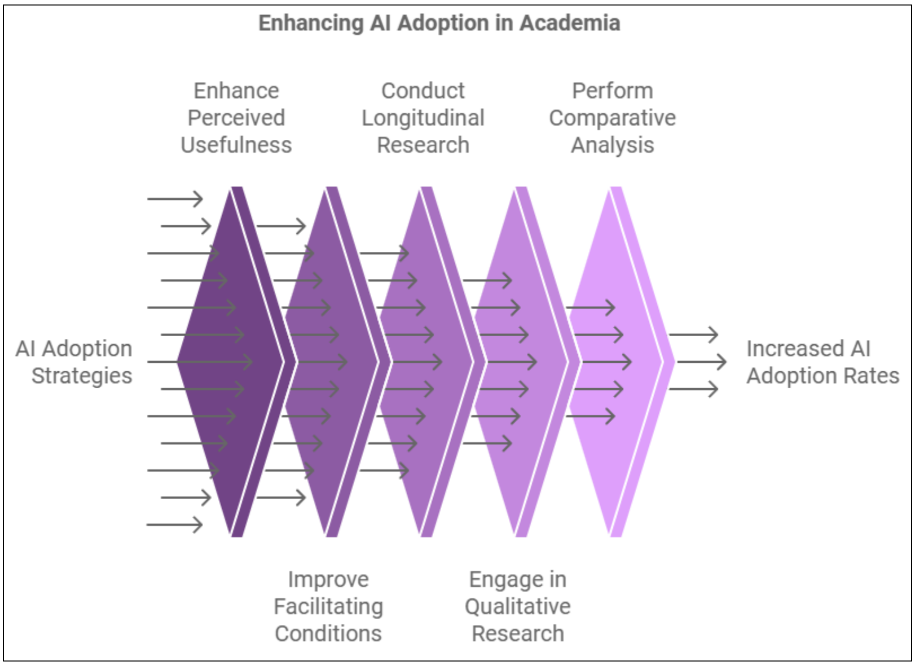
- **Perceived Usefulness (PU):** A critical factor influencing students' adoption of AI tools.
- **Facilitating Conditions (FC):** Access to technical support and infrastructure significantly impacts students' willingness to adopt AI tools.

The study infers that perceived usefulness and facilitating conditions are significant predictors of students' behavioural intention to adopt AI research tools. Students are more likely to adopt AI tools if they perceive them as beneficial and have access to the necessary technical support and infrastructure.

Conclusion

The study's conclusions highlight the importance of several variables affecting students' behavioural intention to use AI research tools. Using a logistic regression model, it was found that students' propensity to embrace AI technologies was significantly influenced by perceived utility and favourable conditions. In particular, if students believe these technologies will help them with their academic work and if there is sufficient technical support and supportive infrastructure available, they are more likely to adopt them. Additionally, the investigation showed that students perceive using AI tools to improve project performance, demonstrating an awareness of the advantages of AI technologies. Furthermore, the perception of the accessibility of required technical support implies that favorable settings promote the use of AI technologies in research.

Roadmap to Improve AI Adoption Rates



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