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# A Study on Factors Affecting Usage of Artificial Intelligence Among Students

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**Abstract**
*The rapid integration of Artificial Intelligence (AI) in education has significantly transformed the way students learn, access information, and complete academic tasks. This study examines the factors influencing AI usage among students, with a particular focus on self-efficacy, perceived ease of use, perceived usefulness, and information quality. The research aims to understand how these factors contribute to the adoption and effective utilization of AI technologies in academic environments. Primary data were collected from student respondents through a structured questionnaire, and the data were analyzed using various statistical techniques through Jamovi software. The findings indicate that perceived ease of use and information quality play a major role in influencing students' adoption of AI technologies. The study also reveals that students generally perceive AI as a supportive tool that enhances learning efficiency, accessibility to information, and academic engagement. However, certain concerns related to dependency on AI tools and the effective integration of AI into educational practices were also identified. The findings support the Technology Acceptance Model (TAM) and DeLone and McLean's Information Systems Success Model, emphasizing the importance of usability and quality information in encouraging AI adoption among students. The study provides valuable implications for educators, AI developers, and policymakers in designing effective and user-friendly AI-based educational systems. In conclusion, AI has considerable potential to improve academic learning experiences and support student development when implemented responsibly and effectively within educational environments.*
***Keywords:*** *artificial intelligence, self-efficacy, perceived ease of use, perceived usefulness, information quality, technology acceptance model*

## 1. INTRODUCTION

Artificial Intelligence (AI) has become an integral part of modern digital environments, particularly in education, where students increasingly rely on AI tools for academic and learning purposes. AI-based applications such as chatbots, virtual assistants, and automated content generators are widely used to complete assignments, conduct research, and enhance understanding of complex concepts, contributing to improved efficiency, accessibility, and convenience in learning.

Despite growing adoption, the extent to which students utilise these tools effectively depends on several underlying factors. Key factors such as self-efficacy, perceived ease of use, perceived usefulness, and information quality play a significant role in determining how students interact with AI systems. Although AI adoption is increasing rapidly, limited structured empirical studies examine the combined effect of these factors using a quantitative and analytical approach. This study addresses that gap.

### 1.1 Background

The advancement of digital technologies has transformed education, leading to increased integration of AI in learning environments. AI tools now support personalized learning, automate repetitive tasks, and provide instant access to information. Theoretical frameworks such as the Technology Acceptance Model (TAM) highlight the importance of perceived usefulness and perceived ease of use in influencing technology adoption. Variables such as self-efficacy and information quality further enhance understanding of user behaviour in technology-driven environments.

### 1.2 Statement of the Problem

Students are increasingly using AI tools for academic purposes; however, the factors influencing their usage are not fully understood. There is insufficient empirical evidence explaining how self-efficacy, perceived ease of use, perceived usefulness, and information quality collectively influence AI usage among students. The absence of such analysis limits the effective implementation and improvement of AI technologies in educational settings.

### 1.3 Objectives

Primary Objective: To identify the key determinants influencing the adoption and usage of AI tools among students.

Secondary Objectives: (i) To examine the relationship between perceived ease of use and AI usage; (ii) To analyse the relationship between perceived usefulness and AI usage; (iii) To assess the effect of self-efficacy on AI adoption; and (iv) To evaluate the influence of information quality on students' decision to use AI.

### 1.4 Hypotheses

H1: Technological self-efficacy has a significant positive influence on students' intention to use AI tools.

H2: Perceived usefulness has a significant positive influence on students' intention to use AI tools.

H3: Perceived ease of use has a significant positive influence on students' intention to use AI tools.

H4: Information quality has a significant positive influence on students' trust in AI tools.

## 2. REVIEW OF LITERATURE

Artificial Intelligence has become a transformative force in higher education, fundamentally altering how students learn, access information, and engage with academic content (Siemens, 2018; Holmes, 2019). AI tools such as intelligent tutoring systems, chatbots, and adaptive learning platforms are increasingly embedded in academic environments (Davenport & Kirby, 2016; Brynjolfsson & McAfee, 2017).

The Technology Acceptance Model (TAM), developed by Davis (1989), posits that perceived usefulness and perceived ease of use are primary determinants of technology adoption. TAM has been extensively validated in educational technology contexts (Davis, 1989; Venkatesh & Davis, 2000; Roca et al., 2006). Building on TAM, Venkatesh et al. (2003) proposed UTAUT, incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions, offering a more holistic perspective on technology acceptance.

Bandura (1977, 1986) introduced self-efficacy theory, establishing that individuals' confidence in their abilities significantly influences behaviour and performance. Venkatesh and Davis (1996) confirmed that self-efficacy significantly influences perceived ease of use. Talwar (2021) found that self-efficacy significantly influences students' intention to use AI tools. Ullah and Sreedevi (2024) further confirmed a positive relationship between AI usage and student self-efficacy.

DeLone and McLean (1992, 2003) proposed the Information Systems Success Model, emphasising information quality, system quality, and user satisfaction as determinants of IS success. Straub (2009) and Pavlou (2018) confirmed information quality as a major factor influencing user trust in digital systems. Ifenthaler and Seel (2020) and Crockett (2022) further established that trust in AI is strongly influenced by the reliability and quality of AI-generated information.

Recent empirical studies affirm growing AI adoption among students. The Digital Education Council (2024) reported that 86% of students globally use AI tools, with ChatGPT being the most widely used platform. The Higher Education Policy Institute (2025) reported that AI adoption among UK university students rose from 66% in 2024 to 92% in 2025. Von Garrel and Mayer (2023) found that nearly two-thirds of university students use AI for understanding complex concepts. Black and Tomlinson (2025) and Basch et al. (2025) highlighted growing awareness of AI, while noting significant gaps in ethical AI literacy.

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## 3. METHODOLOGY

### 3.1 Research Design

The study adopts a quantitative, descriptive, and analytical research design. A survey method was used, with a structured questionnaire distributed online via Google Forms. The quantitative approach enables examination of relationships between variables using statistical techniques.

### 3.2 Sampling

The target population consisted of students using AI tools for academic purposes. A sample of 200 respondents was selected using convenience sampling, providing sufficient data for basic statistical analysis and pattern identification.

### 3.3 Research Instrument

Primary data was collected using a five-section structured questionnaire (Sections B–F) covering Self-Efficacy (10 items), Perceived Usefulness (5 items), Perceived Ease of Use (5 items), Information Quality (10 items), and Usage of AI (10 items). Respondents indicated agreement on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The instrument was grounded in established theoretical frameworks (TAM; DeLone & McLean Model). Secondary data was gathered from academic journals, research papers, and online resources related to AI, technology acceptance, and digital learning.

### 3.4 Reliability

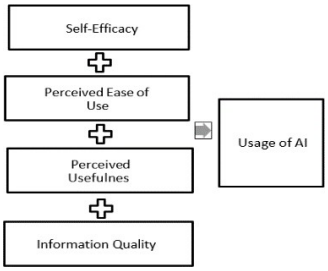
Reliability was assessed using Cronbach's Alpha via Jamovi software. Content validity was ensured by grounding questionnaire items in established literature and theoretical frameworks.

### 3.5 Data Analysis

Statistical analyses included: (i) descriptive analysis (mean, median, standard deviation); (ii) reliability analysis (Cronbach's Alpha); (iii) linear regression to identify predictors of AI usage; and (iv) independent samples t-test to examine gender differences. Data was analysed using Jamovi software.

## 4. CONCEPTUAL MODEL

Figure 1 presents the conceptual model for this study. Self-efficacy, perceived ease of use, perceived usefulness, and information quality are the independent variables; usage of AI is the dependent variable, consistent with TAM and DeLone & McLean's IS Success Model.




*[Figure 1: Conceptual Model]*

*Self-Efficacy → Perceived Ease of Use → Usage of AI ← Perceived Usefulness ← Information Quality*

## 5. DATA ANALYSIS AND FINDINGS

### 5.1 Demographic Analysis

The sample comprised 200 student respondents. Table 1 shows the gender distribution: 104 males (52%) and 96 Females (48%), providing a near-balanced sample minimizing Gender bias.

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| Gender | Count | % of Total |
|---|---|---|
| Male | 104 | 52% |
| Female | 96 | 48% |
| **Total** | **200** | **100%** |

*Table 1: Gender Distribution of Respondent*

### 5.2 Reliability Analysis

Table 2 presents Cronbach's Alpha coefficients for all study constructs. All values exceeded the recommended threshold of 0.70, confirming acceptable to excellent internal consistency.

| Variable | Type | Cronbach's Alpha |
|---|---|---|
| Self-Efficacy | IV 1 | 0.907 |
| Perceived Usefulness | IV 2 | 0.759 |
| Perceived Ease of Use | IV 3 | 0.869 |
| Information Quality | IV 4 | 0.932 |
| Usage of AI | DV | 0.924 |

*Table 2: Reliability Analysis (Cronbach's Alpha)*

### 5.3 Descriptive Statistics

All variables recorded mean scores above the neutral midpoint (3.0) on the five-point Likert scale, indicating generally positive perceptions of AI tools. Usage of AI recorded the highest mean (M = 4.02, SD = 0.648), followed by Perceived Ease of Use (M = 3.97, SD = 0.700), Self-Efficacy (M = 3.92, SD = 0.655), Information Quality (M = 3.83, SD = 0.719), and Perceived Usefulness (M = 3.71, SD = 0.544). These results indicate that students frequently engage with and hold favourable attitudes toward AI technologies.

| Variable | Mean | SD | Min–Max |
|---|---|---|---|
| Self-Efficacy | 3.92 | 0.655 | 1.00–5.00 |
| Perceived Usefulness | 3.71 | 0.544 | 1.60–5.00 |
| Perceived Ease of Use | 3.97 | 0.700 | 1.00–5.00 |
| Information Quality | 3.83 | 0.719 | 1.00–5.00 |
| Usage of AI | 4.02 | 0.648 | 1.00–5.00 |

*Table 3: Descriptive Statistics (N = 200)*

### 5.4 Linear Regression Analysis

A linear regression analysis was conducted to determine the impact of the four independent variables on AI usage. The model demonstrated strong fit ($R = 0.826$, $R^2 = 0.683$), indicating that the four predictors collectively explain 68.3% of the variance in AI usage (N = 200). Table 4 presents the regression coefficients.

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| Predictor | β | SE | t | p |
|---|---|---|---|---|
| Intercept | 0.669 | 0.193 | 3.46 | <.001 |
| Information Quality | 0.294 | 0.062 | 4.76 | <.001* |
| Perceived Ease of Use | 0.334 | 0.078 | 4.28 | <.001* |
| Perceived Usefulness | 0.100 | 0.076 | 1.32 | .187 |
| Self-Efficacy | 0.137 | 0.072 | 1.90 | .059 |

*Table 4: Linear Regression – Predictors of AI Usage (* p < .05)*

Perceived Ease of Use was the largest predictor (β = 0.334, t = 4.28, p < .001), confirming that students who find AI tools easy to use are considerably more likely to adopt them. Information Quality was the second most significant predictor (β = 0.294, t = 4.76, p < .001), underscoring the importance users place on accurate, reliable AI-generated information. Both findings align with established TAM frameworks. Perceived Usefulness did not reach statistical significance (p = .187), possibly due to multi-collinearity with related predictors. Self-Efficacy approached but did not reach significance (p = .059), suggesting a trend that may emerge in larger samples.

## 6. DISCUSSION

The findings strongly support H3 and H4, confirming that perceived ease of use and information quality are the most significant drivers of AI adoption among students. This indicates that students are more likely to use AI technologies when the tools are simple to understand, easy to operate, and capable of providing accurate, reliable, and relevant information. These results highlight the growing importance of user-friendly AI platforms in educational settings, as students tend to prefer technologies that reduce complexity and improve learning efficiency. H1 (self-efficacy) demonstrated a marginal but positive trend, suggesting that students who feel confident in their technological abilities are more willing to engage with AI tools for academic purposes. H2 (perceived usefulness) was not found to be independently significant, indicating that students may prioritize accessibility and information quality over performance benefits alone when adopting AI technologies.

The regression model demonstrated strong explanatory power with an $R^2$ value of 0.683, indicating that the selected variables explained a substantial proportion of the variation in students' AI usage behaviour. This is a significant result because it shows that the study variables provide a strong and reliable framework for understanding the factors influencing AI adoption among students. The high explanatory power also strengthens the validity of the research model and confirms that the identified factors play a meaningful role in shaping students' acceptance and use of AI technologies in academic environments.

The findings are consistent with the Technology Acceptance Model and the DeLone and McLean Information Systems Success Model, reinforcing the importance of ease of use and high-quality information in technology adoption. The gender-neutral findings further demonstrate that AI technologies are becoming increasingly accessible and accepted among students regardless of gender, reflecting greater inclusivity and equal opportunities in digital learning environments. This is particularly important for educational institutions because it suggests that AI-based learning initiatives and training programs can be implemented broadly without the need for gender-specific strategies. The study also highlights the broader impact of AI in education, as effective AI adoption can improve learning efficiency, enhance academic engagement, support independent learning, and

provide faster access to educational resources. As AI technologies continue to evolve, their integration into education has the potential to transform traditional learning methods by creating more personalized, interactive, and flexible learning experiences. Therefore, educational institutions, AI developers, and policymakers should focus on developing reliable, ethical, and student-friendly AI systems that maximize academic benefits while encouraging responsible and effective usage.

## 7. CONCLUSION

This study empirically investigated the factors affecting AI usage among 200 student respondents. Perceived Ease of Use and Information Quality emerged as the two most significant determinants of AI adoption, collectively explaining 68.3% of the variance in AI usage. Self-Efficacy demonstrated a marginal positive influence, while Perceived Usefulness did not independently predict usage when other variables were controlled. Gender had no significant influence on any study variable, indicating gender-neutral AI adoption patterns.

For educators and institutions, the findings suggest promoting user-friendly AI tools and ensuring high-quality AI-generated content will significantly enhance adoption. AI developers should prioritise intuitive design and accurate outputs. Policymakers can implement standardised digital literacy programmes for all students. Future research should include larger, geographically diverse samples, longitudinal designs, and additional constructs such as trust, social influence, and perceived risk to provide a more comprehensive understanding of AI adoption in education.

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