Investigating the Drivers of Artificial Intelligence Acceptance among Oman University Students

دراسة عوامل تقبل الذكاء الاصطناعي بين الطلبة الجامعيين في سلطنة عمان

Tinashe Ngorima

Sohar University, General Foundation Programme, Sohar University, Sohar,
Al Batinah North, Oman,
ORCID# 0000-0001-6286-3969

Dr. David Mutambara

Sohar University, General Foundation Programme, Sohar University, Sohar,
Al Batinah North, Oman
ORCID# 0000-0002-7953-0172

Received Date: 25-03-2025 Acceptance Date: 13-04-2025

Ngorima, T. & Mutambara, D. (2025). Investigating the Drivers of Artificial Intelligence Acceptance among University Students. *Sohar University Journal of Humanities and Social Sciences*, 2(2), 75-94.

Abstract

This study investigates the key factors influencing the acceptance of artificial intelligence (AI) technologies among university students in Oman. Despite global advancements in AI integration within education, limited research has explored how students in the Middle East, particularly in Oman, perceive and adopt AI applications in higher education. Grounded in the Technology Acceptance Model (TAM), the study examines the effects of perceived usefulness, perceived ease of use, perceived trust, perceived attitude, and perceived social influence on actual AI usage.

A quantitative research design was employed, utilising a structured questionnaire distributed to 310 students from Sohar University, from which 200 valid responses were collected. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results demonstrate that the model explains 81% of the variance in actual AI use ($R^2 = 0.810$), confirming the strong predictive power of the TAM constructs. Perceived trust emerged as the most significant predictor, positively influencing both perceived usefulness ($\beta = 0.450$) and perceived ease of use ($\beta = 0.613$). Perceived ease of use also positively impacted usefulness ($\beta = 0.343$) and showed a medium effect size ($f^2 = 0.293$).

The findings underscore the importance of fostering trust, designing intuitive AI tools, and leveraging peer influence to support AI adoption in Omani universities. The study offers practical implications for educators, developers, and policymakers and contributes to the growing body of literature on AI acceptance in non-Western educational contexts.

Keywords: Acceptance, Artificial intelligence, Drivers, Oman, University students

الملخص: تهدف هذه الدراسة إلى استقصاء العوامل الرئيسة التي تؤثر في تقبل تقنيات الذكاء الاصطناعي بين الطلبة الجامعيين في سلطنة عُمان. على الرغم من التقدم العالمي في دمج الذكاء الاصطناعي في التعليم، إلا أن الأبحاث التي تناولت كيف يتصور الطلبة تطبيقات الذكاء الاصطناعي ويتبنونها في التعليم العالي محدودة في الشرق الأوسط، وخاصة سلطنة عُمان. تستند الدراسة إلى نموذج قبول التكنولوجيا(TAM) ، حيث تستعرض تأثيرات الفائدة المتصورة، وسهولة الاستخدام المتصور، والثقة المتصورة، والموقف المتصور، والتأثير الاجتماعي المتصور على الاستخدام الفعلي للذكاء الاصطناعي.
تم استخدام تصميم البحث الكمي، حيث تم توزيع استبانة على 310 طالبا وطالبة من جامعة صحار، وجُمعت 200 استجابة صالحة. تم تحليل البيانات باستخدام نمذجة المعادلات الهيكلية للمربعات الصغرى الجزئية (PLS-SEM) . وأظهرت النتائج أن النموذج يفسر 81% من التباين في الاستخدام الفعلي للذكاء الاصطناعي ($R^2 = 0.810$)، مما يؤكد القوة التنبؤية لبناء نموذج قبول التكنولوجيا (TAM) . وأظهرت النتائج أن الثقة المتصورة هي أهم مؤشر، حيث يؤثر بشكل إيجابي على كل من الفائدة المتصورة ($\beta = 0.450$) والسهولة المتصورة للاستخدام ($\beta = 0.613$) . كما أن للسهولة المتصورة للاستخدام أيضًا تأثير إيجابي على الفائدة ($\beta = 0.343$) حيث كان حجم الأثر متوسط ($f^2 = 0.293$) .
وتؤكد النتائج على أهمية تعزيز الثقة، وتصميم أدوات الذكاء الاصطناعي البديهية، واستغلال تأثير الأقران لدعم اعتماد الذكاء الاصطناعي في الجامعات العمانية. وتقدم الدراسة مضامين عملية للتربويين والمطورين وصانعي السياسات، كما تقدم الدراسة إضافة للأدبيات التربوية المتعلقة بقبول الذكاء الاصطناعي في السياقات التعليمية غير الغربية.

الكلمات المفتاحية: تقبل، الذكاء الاصطناعي، العوامل، سلطنة عمان، الطلبة الجامعيين.

1. Introduction

Artificial Intelligence (AI) has rapidly transformed the way individuals live, work, and learn.

It continues to revolutionise various sectors, including healthcare, finance, and entertainment (Kelly et al., 2023). Its impact on everyday life is increasingly evident (Gerlich, 2023). Education has not remained untouched by these developments. In higher education, AI has the potential to enhance teaching methodologies (Choung et al., 2023), improve learning experiences (Choi et al., 2023), and optimise administrative processes.

Reaching consensus on a single definition of AI remains challenging, given its widespread influence across diverse sectors (Al Darayseh, 2023; Choi et al., 2023). The term encompasses applications ranging from common gadgets such as smartphones and smart speakers to complex technologies like autonomous vehicles, demonstrating the breadth and ambiguity of its meaning (Kelly et al., 2023; Zhang & Aslan, 2021). Russell and Norvig (2016) define AI as "the study and design of intelligent agents," whereas Kaplan and Haenlein (2020) offer a broader definition that includes systems capable of perceiving their environment, reasoning, learning, and acting to achieve specific goals. In this study, AI refers to the use of intelligent systems and algorithms to support teaching and learning activities. This encompasses adaptive learning platforms, virtual tutors, automated grading systems, and predictive analytics tools that personalise instruction, identify at-risk students, and enhance learning outcomes (Al Darayseh, 2023; Kelly et al., 2023).

AI acceptance refers to the degree to which individuals adopt and utilise AI technologies in their daily routines or professional settings (Kelly et al., 2023). Several studies have examined the barriers and facilitators that influence the adoption of educational technologies in higher education (Granić, 2023; Kelly et al., 2023; Mutambara & Bayaga, 2020). By revealing user preferences, concerns, and expectations, such research informs the design of learner-centred educational tools and teaching approaches aligned with the needs of both educators and learners (Chibisa & Mutambara, 2022; Kelly et al., 2023). Ultimately, these insights contribute to the development of evidence-based practices that support the effective integration of educational technologies and improve learning outcomes (Al Darayseh, 2023; Chibisa & Mutambara, 2022). As such, identifying both the barriers and enablers for AI adoption in education remains crucial, a point repeatedly emphasised in the literature (Chibisa & Mutambara, 2022; Granić, 2023; Kelly et al., 2023; Mutambara & Bayaga, 2020).

Despite the growing interest in AI within education, relatively few studies have focused specifically on the acceptance of AI technologies (Al Darayseh, 2023; Choi et al., 2023; Kelly et al., 2023; Ragheb et al., 2022). For example, Ragheb et al. (2022) investigated the acceptance of chatbots among Egyptian university students, whereas Choi et al. (2023) examined how pedagogical beliefs and trust influence teachers' acceptance of AI tools. Additionally, Choung et al. (2023) utilised the Technology Acceptance Model (TAM) to evaluate student attitudes towards AI-driven assessments in e-learning environments. These studies affirm the importance of identifying factors that influence AI acceptance. However, much of the existing research has primarily focused on technologically advanced regions, such as the United States and Europe (Al Darayseh, 2023; Choung et al., 2023), which limits the applicability of these findings to less technologically developed regions, including the Middle East. This study seeks to bridge that gap.

Additionally, during the inaugural session of the Council of Oman's 8th term, His Majesty

Sultan Haitham bin Tarik highlighted the nation's commitment to harnessing AI technologies across various developmental sectors, with education being a major focus (Albusaidi, 2023). In alignment with this national vision, there is a pressing need for research that identifies the drivers influencing AI adoption in Oman's higher education institutions. A comprehensive understanding of these factors can inform policymaking and facilitate the successful integration of AI in education, thereby contributing to the broader national development goals articulated by His Majesty.

Despite the global interest in AI applications within education, research focused on the acceptance of such technologies by university students in Oman remains limited. Most available studies originate from Western contexts, limiting their relevance to the Omani sociocultural and technological landscape. In light of the national AI agenda and the unique local context, it is crucial to investigate how students in Oman perceive and engage with AI in higher education.

This study addresses this gap by investigating the key factors that influence AI acceptance among university students in Oman. The Technology Acceptance Model (TAM) is employed to examine how perceived usefulness, perceived ease of use, trust, and social influence shape students' attitudes and behaviours toward the adoption of AI in learning environments.

1.1. Study Problem

The integration of artificial intelligence into educational systems is a rapidly evolving phenomenon, offering both opportunities and challenges (Al Darayseh, 2023; Choi et al., 2023). While its potential to improve teaching, learning, and administration is widely recognised (Choung et al., 2023; Kelly et al., 2023), the determinants of AI acceptance and use remain underexplored in many regions, particularly the Middle East.

Existing literature has largely concentrated on technologically advanced countries such as the United States and those in Europe (Al Darayseh, 2023; Choung et al., 2023), with limited attention given to the socio-technological contexts of Gulf nations like Oman. This presents a critical gap in understanding how cultural, infrastructural, and educational factors shape students' willingness to engage with AI technologies. Although Oman has outlined a strategic vision for AI integration across sectors, including education, empirical evidence remains scarce regarding students' perceptions, trust levels, and actual usage of AI tools.

In the absence of locally grounded research, there is a risk that AI initiatives may be misaligned with user needs, leading to low adoption rates, user resistance, and limited educational impact. A deeper understanding of AI acceptance drivers is therefore essential for the successful implementation of AI technologies in Oman's higher education sector.

Accordingly, the present study adopts the Technology Acceptance Model (TAM) to investigate the psychological and contextual factors influencing AI adoption among university students in Oman. TAM is particularly well-suited to this purpose, given its emphasis on perceived usefulness, ease of use, trust, and social influence which are core components in understanding technology acceptance.

1.3. Research Question

What are the drivers of acceptance of AI technologies in education among university students in Oman?

1.4. Significance of the Study

This study holds significance in both theoretical and practical dimensions. Theoretically, it contributes by developing a structural model that identifies the key factors influencing university students' acceptance of AI applications. This model provides a sound theoretical basis for further exploration of AI integration in educational settings and enhances the understanding of learner-technology interaction.

Practically, the study offers valuable insights for policymakers, AI developers, and academic institutions. The findings inform the design of professional development programmes for lecturers and support university departments focused on teaching and learning. In the context of Oman, where AI integration is a national priority, these insights offer timely recommendations for effective and sustainable implementation strategies.

2. Literature Review

2.1. Uses of AI in Higher Education

Artificial intelligence (AI) has the potential to significantly transform traditional teaching methods into personalised and adaptive learning experiences (Choung et al., 2023). It can support differentiated instruction by providing tailored educational content that accommodates individual learning styles and paces (Al Darayseh, 2023). Intelligent Tutoring Systems (ITS) offer personalised feedback and guidance, enabling students to master complex concepts at their own pace (Bradáč & Kostolányová, 2017). This individualised approach enhances retention and understanding by delivering timely and targeted support (Choi et al., 2023). The effectiveness of personalised instruction and support has been well documented (Brusilovsky et al., 2004). In mathematics education, the integration of technology has demonstrated positive outcomes in terms of student achievement and engagement (Çavuş & Deniz, 2022; Poçan et al., 2023). Similarly, AI-based tools support innovative pedagogical approaches, including blended learning and flipped classrooms, thereby enabling more flexible and customised educational delivery (Çavuş & Deniz, 2022).

By creating interactive and engaging learning environments, AI can enhance students' academic experiences (Choi et al., 2023). AI-powered virtual reality (VR) and augmented reality (AR) technologies provide immersive learning experiences, making complex concepts more accessible and engaging (Darling-Hammond, 2019). These technologies allow students to manipulate models, perform virtual experiments, and understand abstract ideas more effectively (Çavuş & Deniz, 2022; Darling-Hammond, 2019). AI-based gamification further promotes critical thinking and motivation (Suresh Babu & Dhakshina Moorthy, 2024). Such platforms individualise challenges and feedback, thereby sustaining student engagement.

Studies have shown that AI-enhanced educational games improve learning outcomes across disciplines, including mathematics and science (Vidanaralage et al., 2022). These games often employ adaptive learning algorithms to adjust difficulty based on learners' performance, striking an optimal balance between challenge and skill (Suresh Babu & Dhakshina Moorthy, 2024).

In addition to supporting instruction, AI driven automation reduces educators' workloads, helping to alleviate stress (González-Calatayud et al., 2021; Huang et al., 2021). This allows teachers to focus more on curriculum development and student interaction, ultimately improving student satisfaction. Furthermore, AI applications facilitate improved data management and analysis, providing decision-makers with valuable insights for institutional planning through the use of big data (González-Calatayud et al., 2021; Granić, 2023).

2.2. Drivers of Acceptance of AI in Higher Education

Several studies have aimed to identify the determinants of AI acceptance in educational settings (Gerlich, 2023; González-Calatayud et al., 2021). Al Darayseh (2023), applying the Technology Acceptance Model (TAM), found that self-efficacy, ease of use, expected benefits, attitudes, and behavioural intentions significantly influence AI acceptance. These results suggest that confidence in using AI, perceptions of its usability, and anticipated benefits play central roles in shaping technology adoption (Brusilovsky et al., 2004; Çavuş & Deniz, 2022).

Similarly, Zhang and Aslan (2021) used TAM to examine AI acceptance among pre-service teachers. Their findings revealed that AI self-efficacy and perceived enjoyment indirectly influenced behavioural intentions through perceived ease of use. Perceived usefulness also mediated the relationship between behavioural intention and factors such as job relevance and social norms. These results indicate that perceptions of enjoyment, practicality, peer expectations, and professional relevance significantly impact willingness to adopt AI technologies.

In a South Korean context, Han and Sa (2022) found that perceived usefulness, perceived ease of use, and perceived trust were significant factors in AI acceptance among teachers. These findings emphasise that understanding the practical benefits of AI, confidence in its ease of use, and establishing trust in the technology are key to encouraging its adoption. Overall, the literature confirms that AI acceptance is a multifaceted construct shaped by individual efficacy, perceived utility, usability, enjoyment, social influence, and trust. This highlights the need for culturally responsive and context-specific strategies to promote AI integration in education.

3. Theoretical Frameworks and Hypotheses

Several theoretical models have been developed to explain the acceptance of new technologies. These include the Diffusion of Innovations Theory (DOI) (Rogers, 1962), the Theory of Planned Behaviour (TPB) (Ajzen, 1991), the Technology Acceptance Model

(TAM) (Davis, 1989), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). DOI identifies five key attributes: relative advantage, compatibility, trialability, observability, and complexity as influencing the rate of technology adoption (Rogers, 1962). TPB proposes that attitudes toward behaviour, subjective norms, and perceived behavioural control predict intention and behaviour (Ajzen, 1991). The TAM, developed by Davis (1989), builds on the Theory of Reasoned Action and posits that perceived usefulness and perceived ease of use are primary determinants of technology acceptance. UTAUT, an extension of TAM, introduced four core constructs namely performance expectancy, effort expectancy, social influence, and facilitating conditions alongside moderating factors such as gender, age, experience, and voluntariness (Venkatesh et al., 2003).

This study adopts the TAM due to its simplicity, adaptability, and extensive validation across diverse research contexts (Davis, 1989; Mutambara & Bayaga, 2020). According to Chibisa and Mutambara (2022), TAM's emphasis on user perceptions is especially relevant for understanding students' acceptance of AI technologies. Moreover, incorporating context-specific external variables enhances the model's explanatory power (Mutambara & Chibisa, 2024), making it particularly suitable for this research.

3.1. The Technology Acceptance Model

The Technology Acceptance Model (TAM), introduced by Davis in 1986 and formalised in 1989, is a theoretical framework developed to explain and predict user acceptance of information technology. It proposes that two key perceptions, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) influence an individual's attitude towards a technology, which in turn affects their behavioural intention to use it.

PU refers to the extent to which a user believes a technology enhances task performance (Davis, 1989), while PEOU relates to the belief that the technology requires minimal cognitive effort. The model suggests that when users perceive a technology as both useful and easy to use, they are more likely to form a positive attitude towards it and ultimately intend to adopt it. TAM also allows for the inclusion of external variables to improve its explanatory capacity (Mutambara & Chibisa, 2024).

3.2. Hypotheses

3.2.1. Perceived Attitude Towards (PAT)

In this study, PAT is defined as the overall affective reaction of a university student to the use of AI tools. Attitude plays a critical role in the decision to accept or reject new technologies (Al Darayseh, 2023). In an educational setting, positive attitudes have been linked to increased acceptance of virtual learning platforms (Chibisa & Mutambara, 2022). Previous studies have shown that perceived attitude significantly influences students' acceptance of AI technologies (Al Darayseh, 2023; Mutambara & Chibisa, 2024). Thus, the following hypothesis is proposed:

H1: Oman university students' PAT predicts their actual use of AI technologies.

3.2.2. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)

PU is defined as the extent to which students believe AI technologies will enhance their academic performance. PEOU refers to the belief that using these technologies requires minimal effort. These are central constructs in TAM and have consistently been associated with positive attitudes and actual technology use (Chibisa & Mutambara, 2022; Mutambara & Chibisa, 2024). It is therefore hypothesised:

H2: Oman university students' PU predicts their actual use of AI technologies.
H3: Oman university students' PU predicts their perceived attitude towards AI technologies.
H4: Oman university students' PEOU predicts their perceived attitude towards AI technologies.
H5: Oman university students' PEOU predicts their perceived usefulness of AI technologies.

3.2.3. Perceived Trust (Trust)

Trust refers to the user's belief that AI tools will reliably help achieve learning goals (Setiawan & Widanta, 2021). Trust has been shown to influence both perceived usefulness and behavioural intentions (Choung et al., 2022; Miltgen et al., 2013). In the context of this study, it is hypothesised:

H6: Oman university students' Trust predicts their actual use of AI technologies.
H7: Oman university students' Trust predicts their perceived attitude towards AI technologies.
H8: Oman university students' Trust predicts their perceived usefulness of AI technologies.

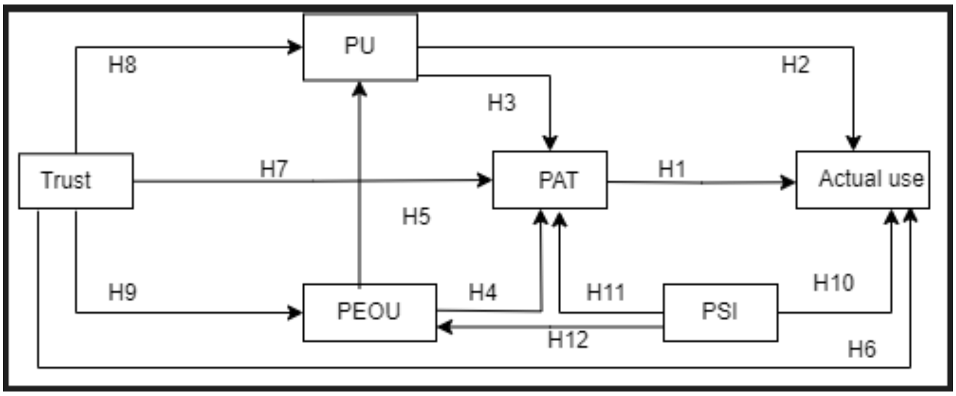
3.2.4. Perceived Social Influence (PSI)

PSI is defined as the extent to which an individual believes that those important to him or her expect them to use a particular technology (Chibisa & Mutambara, 2022). In university contexts, these influential figures may include peers, lecturers, and family members. PSI has been found to influence both behavioural intentions and perceptions of usefulness and ease of use (Venkatesh et al., 2003; Mutambara & Bayaga, 2020). Accordingly:

H9: Oman university students' PSI predicts their actual use of AI technologies.
H10: Oman university students' PSI predicts their perceived attitude towards AI technologies.

A conceptual model combining these hypotheses and latent variables is presented in Figure 1.

Figure 1
The conceptual framework



4. Methodology

4.1 Research Design

A quantitative research methodology was employed to gather demographic data and participant perceptions using a structured survey (Creswell & Poth, 2016). Survey methods are considered suitable for theory testing as they enable the efficient collection of data from large populations. According to Creswell and Poth (2016), surveys are cost-effective and time-efficient, making them ideal for hypothesis-driven research. The hypotheses of this study were examined using Partial Least Squares Structural Equation Modelling (PLS-SEM), a method well suited for theory development and complex predictive models (Sarstedt et al., 2021).

4.2 Participants

Simple random sampling was adopted to ensure that all students at Sohar University had an equal probability of being selected, thereby improving the representativeness of the sample (Creswell & Poth, 2016). As outlined by Creswell (2021), this method ensures each member of the population has an unbiased and independent opportunity for selection. The target population consisted of approximately 9,000 students enrolled during the 2023–2024 academic year. A total of 310 online questionnaires were distributed, yielding 200 valid responses, a response rate of 65%.

Demographic characteristics of the respondents were as follows:

- **Age Range**: Participants ranged in age from 18 to 30 years, with approximately 65% aged between 18 and 24.
- **Field of Study**: Respondents represented diverse disciplines: Engineering (23%), Business (18%), Computing and Information Technology (17%), Law (17%), Language Studies (15%), and Education and Arts (10%).
- **Year of Study**: The sample included students from all academic levels: first year (40%), second year (30%), third year (20%), and final year (10%).

- **Gender**: The survey included 79% female and 21% male respondents.

4.3 Instrument

To investigate the drivers of AI acceptance among university students in Oman, an online questionnaire was administered. The instrument consisted of two sections. The first captured demographic information. The second section employed a seven-point Likert scale (ranging from "strongly disagree" to "strongly agree") to measure six latent constructs: Actual Use, Perceived Attitude Towards (PAT), Perceived Social Influence (PSI), Perceived Usefulness (PU), Perceived Trust (Trust), and Perceived Ease of Use (PEOU).

The measurement items for PSI, PAT, Actual Use, PEOU, and PU were adapted from previously validated studies (Mutambara & Bayaga, 2022). The items used to assess Trust were sourced from Choung et al. (2023). In total, the questionnaire contained 24 items measuring these constructs.

4.4 Analysis Technique

Data were analysed using PLS-SEM, implemented through the R programming language. According to Mutambara and Chibisa (2023), the primary function of PLS-SEM is to predict the target variable, in this case, the actual use of AI technologies by university students in Oman.

The analysis followed the two-step procedure recommended by Sarstedt et al. (2021). First, the measurement model (outer model) was evaluated for reliability and validity, focusing on the relationships between constructs and their indicators. Second, the structural model (inner model) was assessed to determine the significance of the relationships among constructs, the variance explained, and the predictive capabilities of the model (Hair et al., 2012).

5. Data Analysis Results

5.1 Outer Model

The outer model was assessed to determine the reliability and validity of the measurement model. This involved evaluating convergent validity, the extent to which indicators of a specific construct are correlated and discriminant validity, the extent to which a construct is distinct from other constructs (Hair et al., 2012; Chin, 1998; Khan et al., 2019).

As shown in Table 1, all reflective indicators had loadings above 0.70, confirming item reliability (Hair et al., 2012; Sarstedt et al., 2021). Composite Reliability (CR) values exceeded 0.60, and Average Variance Extracted (AVE) values were above 0.50, thereby satisfying the criteria for convergent validity (Sarstedt et al., 2021).

Table 1
Convergent validity results

Construct	Indicator	Loadings	CR	AVE
SI	SI3	0.766	0.737	0.543
	SI4	0.773		
PU	PU3	0.953	0.848	0.687
	PU4	0.977		
Trust	Trust1	0.723	0.874	0.719
	Trust2	0.818		
	Trust3	0.881		
	Trust4	0.768		
AT	AT1	0.78	0.91	0.642
	AT2	0.818		
	AT3	0.898		
	AT4	0.901		
PEOU	PEOU1	0.828	0.84	0.715
	PEOU2	0.821		
	PEOU3	0.758		
AU	AU1	0.935	0.931	0.751
	AU3	0.908		
	AU4	0.887		
	AU5	0.931		

Discriminant validity was assessed using the Fornell-Larcker criterion, which requires that the square root of each construct's AVE exceeds its highest correlation with any other construct (Hair et al., 2012). As shown in Table 2, this condition was met, thereby confirming discriminant validity.

Table 2
Fornell-Larcker criterion

	SI	PU	Trust	AT	PEOU	AU
SI	0.673					
PU	0.471	0.848				
Trust	0.716	0.555	0.821			
AT	0.773	0.590	0.811	0.846		
PEOU	0.765	0.568	0.769	0.828	0.874	
AU	0.721	0.532	0.734	0.809	0.786	0.867

Overall, the measurement model demonstrated adequate reliability and both convergent and discriminant validity, confirming its suitability for assessing the structural model.

5.2 Structural Model

The structural model was evaluated using the five-step procedure outlined by Sarstedt et al. (2021):

Step 1: Multicollinearity Assessment

Variance Inflation Factor (VIF) values were examined to identify potential multicollinearity issues. All VIF values were below 4 (Table 3), indicating the absence of multicollinearity concerns (Hair et al., 2012).

Step 2: Significance of Path Coefficients

Bootstrapping with 5,000 subsamples was used to assess the significance of the path coefficients. Coefficients were deemed significant when their associated *t*-values exceeded 1.96 and *p*-values were ≤ 0.05 (Hair et al., 2012; Sarstedt et al., 2021). Table 3 presents the results of this analysis.

Step 3: Effect Size (f^2)

Effect sizes were evaluated based on thresholds proposed by Chin (1998): 0.02 (small), 0.15 (medium), and 0.35 (large). The path from Trust to PEOU exhibited a large effect size (f^2 = 0.376), while the path from PEOU to PAT indicated a medium effect (f^2 = 0.293). Other paths showed small effect sizes.

Table 3
Structural model results

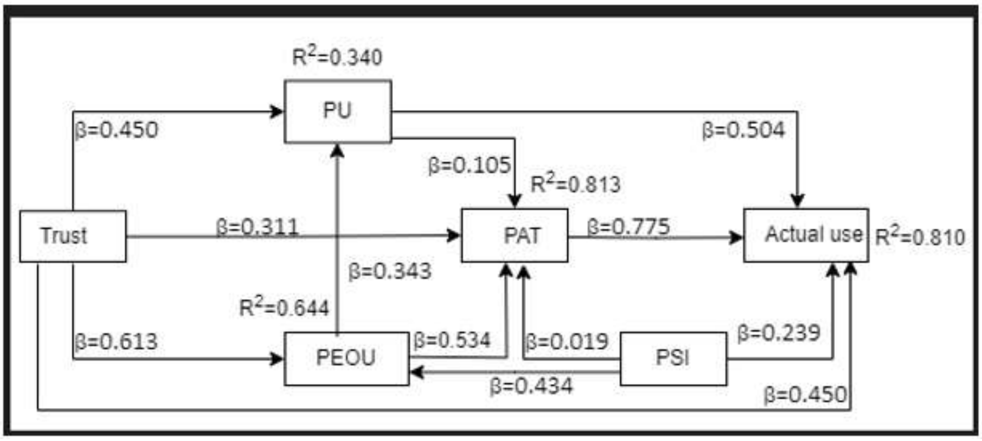
Path	Std Beta	T-Statistics	P-Values	Decision	f-squared	VIF
PEOU => PAT	0.534	5.079	0.000	Accepted	0.285	1.044
PU =>PAT	0.105	2.137	0.033	Accepted	0.011	3.459
PSI => PAT	0.019	1.844	0.065	Rejected	0.048	2.117
Trust => PAT	0.311	2.491	0.013	Accepted	0.097	1.707
PAT => Actual use	0.775	8.462	0.000	Accepted	0.601	2.327
PSI => Actual use	0.239	2.221	0.026	Accepted	0.057	1.203
PSI => PEOU	0.434	3.082	0.002	Accepted	0.188	2.323
Trust => PEOU	0.613	4.170	0.000	Accepted	0.376	1.800
PEOU => PU	0.343	2.5940	0.009	Accepted	0.118	3.934
Trust =>Actual use	0.450	2.712	0.007	Accepted	0.203	1.300
PU=> Actual use	0.504	3.892	0.000	Accepted	0.280	1.324
Trust =>PU	0.450	2.712	0.007	Accepted	0.203	1.300

Step 4: Coefficient of Determination (R^2)

The R^2 values indicate the proportion of variance in the dependent variables explained by the model. Values of 0.67, 0.33, and 0.19 are interpreted as substantial, moderate, and weak, respectively (Sarstedt et al., 2021). As shown in Figure 2:

- **Actual Use (AU)**: R^2 = 0.810 (substantial)
- **Perceived Attitude Towards (PAT)**: R^2 = 0.813 (substantial)
- **Perceived Ease of Use (PEOU)**: R^2 = 0.644 (moderate to substantial)
- **Perceived Usefulness (PU)**: R^2 = 0.340 (moderate)

Figure 2
Structural model



The results indicate that Trust predicted AU, PU, PAT, and PEOU. PSI was found to influence PAT, PEOU, and AU. PEOU predicted PU, and both PEOU and PU predicted PAT, which in turn predicted AU.

Step 5: Predictive Relevance (Q^2)

The Stone-Geisser Q^2 statistic was used to assess predictive relevance. All Q^2 values were above zero, suggesting that the model has predictive relevance in explaining AI acceptance among Omani university students (Sarstedt et al., 2021).

6. Discussion

The results of this study indicate that the structural model effectively explains and predicts the actual use of AI applications. All Q^2 values exceeded zero, confirming the model's predictive relevance concerning the endogenous latent variables (Sarstedt et al., 2021). This demonstrates that the constructs used in the model are strong predictors of AI acceptance among university students in Oman. Specifically, perceived ease of use, perceived usefulness, perceived trust, perceived attitude, and perceived social influence were identified as key determinants. Together, these constructs explained 81% of the variance in actual use ($R^2 = 0.81$), reflecting substantial explanatory power.

Consistent with the findings of Choung et al. (2022), perceived trust was found to significantly influence both perceived usefulness and perceived ease of use. When students have confidence in AI applications, they are more inclined to regard them as user-friendly and beneficial to their academic performance. These results underscore the importance of establishing trust in technological systems prior to promoting their functionality. Additionally, trust was observed to reduce the cognitive load associated with learning how to use AI tools, reinforcing the need for trustworthy system design.

Perceived trust also exerted a significant influence on actual use, aligning with the results of Han and Sa (2022), who identified trust as a critical factor in determining users' willingness to engage with AI technologies. The implication is clear: even if AI tools are perceived as easy to use and useful, the absence of trust may prevent users from adopting them. Trust serves as a foundational driver that shapes both the perception of usefulness and ease of use, which, in turn, influences actual usage (Choung et al., 2023). These findings suggest that institutions seeking to promote AI adoption must prioritise transparency, data protection, and ethical system implementation to establish and maintain user trust.

The influence of perceived ease of use on perceived usefulness was also confirmed, consistent with the Technology Acceptance Model (Davis, 1989) and corroborated by Chibisa and Mutambara (2022) and Mutambara and Chibisa (2024). Students who find AI technologies easy to navigate are more likely to view them as useful tools for enhancing academic performance (Poçan et al., 2023). A likely explanation is that user-friendly systems encourage exploration and discovery of AI's educational benefits.

Consistent with the findings of Kelly et al. (2023), perceived social influence positively influences perceived ease of use. Endorsements or encouragement from peers, instructors, or role models may contribute to students' perceptions of usability (Chibisa & Mutambara, 2022; Kelly et al., 2023). This influence may arise from increased confidence, conformity to social norms, or shared knowledge within peer networks (Mutambara & Bayaga, 2020).

Perceived social influence was also found to have a significant effect on actual use, supporting the findings of Mutambara and Bayaga (2020), Mutambara and Chibisa (2024), and Al Darayseh (2023). Students who experience positive social pressure or observe others using AI tools are more likely to adopt them. Factors such as social conformity, the desire to fit in, or fear of being left behind may contribute to this behaviour.

However, in contrast to earlier findings (Al Darayseh, 2023; Chibisa & Mutambara, 2022), perceived social influence did not have a significant effect on perceived attitude. This suggests that while social cues may prompt behavioural engagement with AI, they do not necessarily shape students' personal evaluations of these technologies. Attitudes may instead be influenced by individual experiences or values.

In line with Gerlich (2023) and the TAM, perceived usefulness was positively associated with actual use. Students who believe that AI tools will enhance academic performance or support daily academic tasks are more likely to incorporate such tools into their learning routines (Choung et al., 2023). Perceived usefulness also influenced attitude towards AI, consistent with Davis (1989) and subsequent studies (Chibisa & Mutambara, 2022). Students who view AI as beneficial are more likely to develop a positive disposition toward its adoption and integration.

Interestingly, contrary to Al Darayseh (2023), perceived ease of use was shown to positively influence perceived attitude. When students perceive AI systems as requiring minimal effort, they tend to hold more favourable attitudes toward them. These results reinforce the importance of designing intuitive, student-centred AI tools to encourage positive engagement.

Overall, perceived attitude, defined as students' overall emotional or evaluative response to AI emerged as a motivational force driving actual usage. Students who hold positive attitudes towards AI are more likely to use it both academically and personally.

6.1. Practical implications

The findings provide actionable guidance for enhancing AI integration in Omani higher education. The TAM-based results show that perceived ease of use significantly affects both perceived usefulness and students' attitudes toward AI technologies. This aligns with previous findings (Davis, 1989; Chibisa & Mutambara, 2022), suggesting that intuitive and accessible design is key to fostering technology adoption. To promote ease of use, higher education institutions should invest in capacity-building initiatives such as workshops, training programmes, and ongoing digital support. These measures can help reduce the learning curve and enhance both competence and confidence among students and faculty.

Another major finding relates to perceived trust, which played a critical role in shaping both attitudes and actual usage. As demonstrated in this study and supported by previous research (Choung et al., 2023; Miltgen et al., 2013), trust is essential for successful technology adoption. In the Omani context, where digital infrastructure is evolving, institutions and developers must emphasise transparency, fairness, and data privacy. Clear policies regarding data handling and the ethical use of AI are essential for fostering enduring trust among students.

Perceived social influence was also a significant predictor of both ease of use and actual adoption. Institutions should strategically promote peer modelling and faculty endorsement by encouraging tech-savvy instructors and students to act as role models. Institutional campaigns, testimonials, and collaborative demonstrations can help cultivate a positive environment around AI use.

Furthermore, policy-level initiatives are vital. Policymakers should support AI adoption by allocating funding for educational AI tools, mandating ethical deployment practices, and integrating AI literacy into the curriculum. Such efforts should align with His Majesty Sultan Haitham bin Tarik's vision for national digital transformation (Albusaidi, 2023), ensuring that AI development is contextually relevant and socially inclusive.

In summary, these findings support a multidimensional strategy for AI integration, one that incorporates usability, trust, social reinforcement, and supportive policies. Without a coordinated approach, adoption may face resistance and fail to realise its transformative potential.

6.2 Limitations and Future Research

This study focused on a single university in Oman. As such, caution should be exercised when generalising the findings to other institutions or broader national contexts. While perceived trust emerged as the strongest predictor of AI acceptance, the specific mechanisms through which trust is developed remain underexplored.

Future studies are encouraged to adopt qualitative or mixed-methods approaches to investigate the underlying factors that shape trust in AI. Insights into cultural, experiential, and cognitive elements of trust formation could inform more effective design and implementation strategies.

7. Conclusion

This study provides a comprehensive understanding of the factors influencing AI acceptance among university students in Oman, offering valuable insights for educational institutions, AI developers, and policymakers. The findings indicate that perceived trust, perceived ease of use, perceived usefulness, and perceived social influence are critical determinants of AI acceptance and actual use among students.

Notably, the structural model reveals that these factors collectively account for a significant proportion of the variance in the actual usage of AI applications, with an R^2 value of 0.810, indicating that 81% of the variance in actual use is explained by the identified predictors. Perceived trust was the most influential predictor, significantly affecting both perceived usefulness ($\beta = 0.450$) and perceived ease of use ($\beta = 0.613$). Perceived ease of use also positively impacted perceived usefulness ($\beta = 0.343$), with a medium effect size ($f^2 = 0.293$).

These quantitative findings underscore the importance of building and maintaining trust in AI technologies through transparency, ethical practices, and robust data security. Institutions must prioritise these aspects to foster a supportive environment for AI adoption. Additionally, the results emphasise that user-friendly AI tools complemented by adequate training and peer engagement can strengthen students' confidence in using AI, thereby shaping more favourable perceptions and attitudes.

By addressing these factors, Omani universities can better prepare students for a future where AI plays an increasingly central role in academic and professional settings. This study contributes to the growing body of literature on AI acceptance in education, particularly within the Middle Eastern context, and offers practical guidance for enhancing the integration of AI in higher education. Future research could expand this work by exploring trust formation mechanisms and evaluating AI adoption across diverse educational institutions in the region.

8. References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Al Darayseh, A. (2023). Acceptance of artificial intelligence in teaching science: Science teachers' perspective. *Computers and Education: Artificial Intelligence*, *4*, 100132.

Albusaidi, B. (2023). *His Majesty's speech opening 8th session of the Council of Oman*. Foreign Ministry of Oman. Retrieved 18-01-2024 from https://www.fm.gov.om/his-majestys-speech-opening-8th-session-of-the-council-of-oman/

Bradáč, V., & Kostolányová, K. (2017). Intelligent tutoring systems. *Journal of Intelligent Systems*, *26*(4), 717-727.

Brusilovsky, P., Karagiannidis, C., & Sampson, D. (2004). Layered evaluation of adaptive learning systems. *International Journal of Continuing Engineering Education and Life Long Learning*, *14*(4-5), 402-421.

Çavuş, H., & Deniz, S. (2022). The effect of technology assisted teaching on success in mathematics and geometry: A meta-analysis study. *Participatory Educational Research*, *9*(2), 358-397.

Chibisa, A., & Mutambara, D. (2022). An Exploration of Stem Students' and Educators' Behavioural Intention to Use Mobile Learning. *Journal of e-Learning and Knowledge Society*, *18*(3), 166-176.

Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. In (pp. vii-xvi): JSTOR.

Choi, S., Jang, Y., & Kim, H. (2023). Influence of pedagogical beliefs and perceived trust on teachers' acceptance of educational artificial intelligence tools. *International Journal of Human–Computer Interaction*, *39*(4), 910-922.

Choung, H., David, P., & Ross, A. (2023). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human–Computer Interaction*, *39*(9), 1727-1739.

Creswell, J. W. (2021). *A concise introduction to mixed methods research*. SAGE publications.

Creswell, J. W., & Poth, C. N. (2016). *Qualitative inquiry and research design: Choosing among five approaches*. Sage publications.

Darling-Hammond, L. (2019). *A license to teach: Building a profession for 21st century schools*. Routledge.

Davis, F. D. (1989). Technology acceptance model: TAM. *Al-Suqri, MN, Al-Aufi, AS: Information Seeking Behavior and Technology Adoption*, *205*, 219.

Dimari, A., Tyagi, N., Davanageri, M., Kukreti, R., Yadav, R., & Dimari, H. (2024). AI-Based Automated Grading Systems for open book examination system: Implications for Assessment in Higher Education. 2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS),

Gerlich, M. (2023). Perceptions and acceptance of artificial intelligence: A multi-dimensional study. *Social Sciences*, *12*(9), 502.

González-Calatayud, V., Prendes-Espinosa, P., & Roig-Vila, R. (2021). Artificial intelligence for student assessment: A systematic review. *Applied sciences*, *11*(12), 5467.

Granić, A. (2023). Technology acceptance and adoption in education. In *Handbook of Open, Distance and Digital Education* (pp. 183-197). Springer.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the academy of marketing science*, *40*, 414-433.

Han, J.-H., & Sa, H. J. (2022). Acceptance of and satisfaction with online educational classes through the technology acceptance model (TAM): The COVID-19 situation in Korea. *Asia Pacific Education Review*, *23*(3), 403-415.

Huang, J., Saleh, S., & Liu, Y. (2021). A review on artificial intelligence in education. *Academic Journal of Interdisciplinary Studies*, *10*(3).

Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Business Horizons*, *63*(1), 37-50.

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, *77*, 101925.

Khan, G. F., Sarstedt, M., Shiau, W.-L., Hair, J. F., Ringle, C. M., & Fritze, M. P. (2019). Methodological research on partial least squares structural equation modeling (PLS-SEM) An analysis based on social network approaches. *Internet Research*, *29*(3), 407-429.

Mutambara, D., & Bayaga, A. (2020). Predicting rural STEM teachers' acceptance of mobile learning in the fourth industrial revolution. *Journal of Construction Project Management and Innovation*, *10*(2), 14-29.

Mutambara, D., & Chibisa, A. (2024). Students' acceptance of online proctor software for assessments: The case of South African higher education. In *Online Teaching and Learning in Higher Education: Issues and Challenges in an African Context* (pp. 219-236). Springer.

Poçan, S., Altay, B., & Yaşaroğlu, C. (2023). The effects of mobile technology on learning performance and motivation in mathematics education. *Education and Information Technologies*, *28*(1), 683-712.

Ragheb, M. A., Tantawi, P., Farouk, N., & Hatata, A. (2022). Investigating the acceptance of applying chat-bot (Artificial intelligence) technology among higher education students in Egypt. *International Journal of Higher Education Management*, *8*(2).

Rogers, E. (1962). *Diffusion of Innovations.* New York: Free.

Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: a modern approach*. Pearson.

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In *Handbook of market research* (pp. 587-632). Springer.

Setiawan, P., & Widanta, A. (2021). The effect of trust on travel agent online use: Application of the technology acceptance model. *International Journal of Data and Network Science*, *5*(3), 173-182.

Suresh Babu, S., & Dhakshina Moorthy, A. (2024). Application of artificial intelligence in adaptation of gamification in education: A literature review. *Computer Applications in Engineering Education*, *32*(1), e22683.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Vidanaralage, A. J., Dharmaratne, A. T., & Haque, S. (2022). AI-based multidisciplinary framework to assess the impact of gamified video-based learning through schema and emotion analysis. *Computers and Education: Artificial Intelligence*, *3*, 100109.

Zhang, K., & Aslan, A. B. (2021). AI technologies for education: Recent research & future directions. *Computers and Education: Artificial Intelligence*, *2*, 100025.