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Exploring UAE Student Perspectives on Utilising AI Tools in Higher Education: A Quantitative Analysis

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Abstract

The increasing integration of Artificial Intelligence (AI) technologies in higher education has transformed teaching and learning practices worldwide. In the United Arab Emirates (UAE), where digital innovation and AI adoption are strategic national priorities, understanding students' perspectives toward AI tools is essential for effective educational implementation. This study investigates the factors influencing the acceptance and adoption of AI tools among higher education students in the UAE. Drawing on the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB), the study examines the effects of perceived usefulness, perceived ease of use, subjective norms, and attitudes toward AI on students' behavioural intentions to adopt AI technologies.

A quantitative research design was employed, and data were collected through a structured questionnaire distributed to 100 higher education students in the UAE. The data were analysed using Jamovi and WarpPLS software to assess the measurement and structural models. The findings revealed that perceived usefulness and attitudes toward AI tools significantly and positively influence students' intentions to adopt AI technologies. In contrast, perceived ease of use and subjective norms did not demonstrate a statistically significant effect on behavioural intention. The model explained 82% of the variance in students' intentions to adopt AI applications, indicating strong explanatory power.

The study contributes to the growing body of literature on AI adoption in higher education by providing empirical evidence from the UAE context. The findings highlight the importance of demonstrating the educational value of AI tools and fostering positive student attitudes toward their use. Practical implications are provided for educational institutions, policymakers, and technology developers seeking to enhance AI integration in higher education. Future research is recommended to explore AI adoption across diverse educational contexts and through mixed-method approaches.

1 Introduction

1.1 Research Background, Rationale, and Context

The growing adoption of artificial intelligence (AI) in education worldwide has changed teaching and learning paradigms and affected many educational institutions (Bates et al., 2020). The UAE government prioritises digital innovation and supports the strategic use of AI technology in education (UAE Government, 2021). Research to inform policy and enable AI integration in education is crucial to the UAE's goal of being a leading knowledge-based economy (Rashid, 2023). Stakeholders can ensure that the digital transformation in education meets the region's educational goals and cultural norms by studying student attitudes towards AI technologies (Abulibdeh et al., 2024). An in-depth research of how higher education students perceive and use AI technologies will help developers construct AI-driven instructional solutions that meet student needs and expectations (Chan & Hu, 2023).

The choice of the UAE as a study setting is strategic, given its role as a regional leader in technology integration and policy support for AI advancements (Al-Kfairy et al., 2022). Additionally, the diverse

student population in UAE higher education institutions provides a rich spectrum of insights into AI usage, enriching the research data and enhancing the study's relevance (Ashour, 2020). This setting not only aligns with the UAE's economic objectives of fostering a technology-driven economy but also offers a unique opportunity for comparative research, contributing to a broader understanding of global trends in AI-enhanced education.

1.2 Research Problem

Despite the potential benefits of AI tools in enhancing educational outcomes, there persists a reluctance among the higher education (HE) workforce and students to adopt these technologies (Abbas et al., 2023). This reluctance hinders the effective integration of AI tools into educational curricula, limiting their capacity to optimise student engagement and learning outcomes in culturally and technologically dynamic environments (Kuleto et al., 2021). Educators and policymakers lack comprehensive empirical data on student perspectives, particularly among UAE students, regarding the specific factors that influence the acceptance and utilisation of AI tools (Alhumaid et al., 2023). Understanding these factors, including students' perceptions of AI tools' ease of use and usefulness, subjective norms, and their own attitudes, is essential for developing strategies to overcome this reluctance and effectively integrate AI technologies into higher education (Alzahrani, 2023). Such insights are essential for ensuring that AI tools enhance learning without exacerbating existing educational disparities.

1.3 Research Aims

The primary aim of this study is to explore the factors affecting students' use of AI tools. It also aims to understand the levels of acceptance, usage patterns, and factors that influence students' attitudes towards AI technologies in their educational environment. To achieve this, the study intends to provide empirical data that can guide educators, policymakers, and technology developers in improving the effective integration of AI into educational practices, aligning with the UAE's strategic educational and technological objectives.

1.4 Paper Structure

This paper is structured to explore the utilisation of AI tools by students in higher education within the UAE. The roadmap for this investigation's progression is as follows: Introduction: Introduces the research by outlining its background, problem, context, and aim. Literature Review: Reviews existing research on AI in education, identifying gaps to be addressed. Methodology: Details quantitative methods for data collection and analysis, including questionnaire design and statistical tools. Results: Presents questionnaire findings with graphs and tables, discussing levels of AI tool acceptance among students. Discussion: Interprets results in relation to literature, exploring implications for educational policy and practice. Conclusion and Recommendations: summarises key insights, offers recommendations for AI integration in education, and suggests future research areas. References: Lists all cited sources. Appendices: contain supplementary materials like questionnaires and consent forms.

Figure 1. Paper Structure

2 Literature Review

2.1 Conceptualization

This study defines essential constructs from the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour to fully comprehend UAE students' views on using AI tools in higher education. PEOU, PU, SN, AI attitudes, and BI are these constructs. First, perceived ease of use (PEOU) is a person's belief that a system is easy to use (Davis, 1989). Research shows that customers prefer simpler, more intuitive technologies (Venkatesh & Bala, 2008). However, perceived usefulness (PU) is "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). This concept claims that technology will improve education (Venkatesh & Davis, 2000). Sun & Zhang (2006) found that PU strongly predicts behavioural intentions and system use, modulating PEOU's effect on users' attitudes and behaviours.

Subjective norms (SN) and AI attitudes (A) influence behavioural intentions (BI), which indicate an individual's willingness to use AI tools (Ajzen, 1991). Perceived social pressure to do or not perform the behaviour is particularly intense in the UAE due to strong collective standards, according to Ajzen (1991). Student adoption of AI tools can be influenced by faculty endorsement and peer popularity (Fishbein & Ajzen, 2010). PEOU and PU affect students' AI attitudes, which encompass their total affective reactions to the technology (Ajzen, 1991). Positive experiences, perceived advantages, and effective execution and peer endorsements improve attitudes (Venkatesh & Davis, 1996). An individual's total judgement of a behaviour, including its pros and negatives, is called behaviour intention (Ajzen 1991). However, these notions describe how numerous aspects affect students' AI tool intentions and use in higher education. Thus, by identifying and addressing these variables, UAE educational institutions can better integrate AI technology into their curricula, improving educational outcomes and student experiences in a digitally changing world.

Together, these concepts explain how various factors influence students' intentions and the actual use of AI tools in higher education. By understanding and addressing the interplay between these factors, educational institutions in the UAE can better facilitate the integration of AI technologies into their curricula, thereby enhancing educational outcomes and student experiences in a digitally evolving landscape.

2.2 Theoretical Framework

The Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) are used to examine UAE students' views on using AI tools in higher education. Both theories are crucial to understanding technology adoption and use (Ruiz-Herrera et al., 2023), making them essential to studying how UAE higher education students perceive and use AI tools.

2.2.1 Technology Acceptance Model (TAM)

TAM, developed by Davis in 1989, is a leading theory of technology adoption prediction and explanation. The model states that Perceived Usefulness (PU) and Perceived Ease of Use (PEU) drive technology adoption. Perceived usefulness is the extent to which a person thinks a system would improve their job performance, whereas perceived ease of use is the extent to which little effort is required (Venkatesh & Davis, 2000). This model can help determine how AI tool effectiveness and operational simplicity affect student engagement and acceptability in education.

Positive perceptions of AI's effectiveness and ease of use can enhance student engagement and willingness to use these tools, thereby improving learning outcomes such as knowledge acquisition and skill development (Terblanche et al., 2023). On the other hand, if students find the AI tools challenging to use, this may hinder their learning process and diminish the potential educational benefits (Burkhard, 2022). Moreover, Alzahrani (2023) identified factors influencing students' attitudes and behavioural intentions to use AI in education, including performance expectancy and facilitating conditions.

2.2.2 Theory of Planned Behaviour (TPB)

In addition to the Technology Acceptance Model (TAM), Icek Ajzen (1991)'s Theory of Planned Behaviour (TPB) helps explain and forecast technology uptake. Attitudes, subjective standards, and perceived behavioural control drive human behaviour, according to TPB. Saadé (2008) noted that attitude affects information technology acceptance, a critical component of TPB. Mak (2003) revealed that attitude, subjective norm, and perceived behavioural control predicted leisure learners' desire to use instructional technology, supporting TPB's application in technology adoption. These studies show that TPB can predict technological uptake.

By combining TAM and TPB, this research will delve deeper into understanding how student attitudes, perceived utility, ease of use, social norms, and institutional support together determine the patterns of AI adoption in higher education. This integrated framework is key to identifying gaps and opportunities for developing more effective AI-based educational tools aligned with students' expectations and the UAE's strategic educational objectives.

2.3 Empirical Review and Hypothesis Development

2.3.1 Perceived Ease of Use of AI in Higher Education

Joo et al. (2018) found that perceived ease of use increases acceptance and incorporation of user-friendly solutions into daily academic tasks. UAE higher education AI tools must be simple and intuitive. A 2019 Khan et al. study on AI adoption in higher education indicated that simplicity of use greatly affects students' views towards technology, increasing their chance to adopt it. This supports past hypotheses that easier-to-use technology facilitate initial inquiry and greater educational integration (Venkatesh et al., 2016). However, opposing views show that PEOU's importance may vary by user demographic and time. Al-Emran et al. (2018) found that ease of use greatly influences beginners'

technology use intentions, but as they gain experience, it fades, suggesting a shift towards functionality-oriented characteristics like perceived utility. This fading influence shows how complicated technology adoption is, where early simplicity of use attracts users and ongoing advantages and learning outcomes sustain use.

Given the robust findings from recent research and their relevance to the educational technology landscape in the UAE, the proposed hypothesis for this study is as follows:

H1: Students' perceptions of ease of use have a significant influence on the behaviour intention of AI tools in higher education in the UAE.

2.3.2 Perceived Usefulness of AI Tools in Higher Education

Perceived Usefulness (PU), as originally defined by Davis (1989), describes "the degree to which a person believes that using a particular system would enhance his or her job performance." This translates to how students perceive the benefits of AI tools for improving their academic performance in higher education. Technology adoption studies still focus on perceived usefulness (Venkatesh et al., 2016). Recent studies stress the importance of perceived utility in educational AI tool adoption. Abbas et al. (2023) and Zhou et al. (2024) found that students' evaluations of AI tools' academic benefits, such as tailored learning and efficiency, strongly predict their propensity to utilise them. Perceived utility motivates technology adoption across educational contexts (Ibrahim & Shiring, 2022). There are conflicting data on how much perceived utility influences adoption decisions compared to perceived ease of use or subjective norms. Al-Samarraie et al. (2018) found that perceived utility predicted technology adoption, while social factors were stronger in some educational settings. This implies that perceived utility is important but can have an impact.

We propose the following hypothesis in light of these considerations:

H2: Students' perceptions of the usefulness of AI tools have a positive impact on their adoption in UAE higher education contexts.

2.3.3 Subjective Norms and Intentions to Use AI

Recent studies highlight the pivotal role of subjective norms in shaping students' behavioural intentions towards technology use. For example, Al-Mamary and Al-Shammari (2023). found that in educational settings, both the overt recommendations of faculty and the implicit approval of peers strongly influence students’ decisions to adopt new technologies. This effect is often amplified in environments where communal or collectivist values are predominant, such as in many Middle Eastern cultures, including the UAE (Faqih 2020). Furthermore, the rise of digital social networks has also altered the landscape of subjective norms. As Chiu et al. (2018) noted, online peer interactions can significantly enhance or undermine the perceived value of educational technologies, depending on the prevailing sentiment within these networks. This online peer influence can sometimes act more powerfully than traditional in-

person educational influences, especially among younger demographics who frequently engage with social media and other digital platforms (Soh et al., 2018).

The examination of the literature thus leads to the formulation of the following hypothesis for this study:

H3: Favourable subjective norms (e.g., peer influence) positively predict students' intentions to use AI tools.

2.3.4 Attitudes and Behavioural Intentions Towards AI Tools

Attitudes Towards AI Tools refers to students' overall affective response to using AI technologies in their educational processes. This construct, as part of Ajzen's Theory of Planned Behaviour (1991), indicates that positive attitudes towards a behaviour (such as using AI tools) are likely to result in higher intentions to engage in that havior. A study by Sukkeewan et al. (2024) demonstrated that students' positive attitudes towards AI-enabled learning platforms significantly predicted their intention to use these tools, reinforcing the pivotal role of attitudinal factors in technology adoption. Similarly, research by Wu and Chen (2017) found that positive attitudes towards innovative educational technologies, including AI, were crucial predictors of students' willingness to adopt these technologies for learning purposes. However, external factors may influence attitudes in contexts with high novelty or uncertainty related to technology, such as emerging AI tools. Brewer (2022) found that news use, science fiction viewing, and discussing technology can shape these attitudes, with technology news use predicting changes in support for AI. Yang (2023) delved deeper into the influence of trust on attitudes, discovering a correlation between stronger support for AI and trust in key actors, especially among conservatives.

Based on this analysis, we propose the following hypothesis:

H4: Positive attitudes towards AI tools lead to stronger student behavioural intentions to use them.

3 Methodology

3.1 Research Design

Using a quantitative methodology, this study investigates how students at UAE universities perceive and make use of AI resources. According to Boud and Falchikov (1989), quantitative approach facilitates the collection of numerical data for statistical analysis, enabling the identification of trends, patterns, and relationships among the studied variables (Boud & Falchikov, 1989).

3.2 Population and Sample

The research is conducted in the UAE, targeting over 80 students studying mainly in universities. The sample size of 80 participants is considered adequate for conducting quantitative analysis and drawing meaningful conclusions (Cohen 2013). Additionally, a simple random sampling technique will be

employed to ensure representation from different universities and academic disciplines within higher educational institutions (Noor et al., 2022).

3.3 Data Collection Instrument

UAE students were surveyed using Google Forms to test hypotheses. Electronic questionnaires were provided to students for the survey. The questionnaire, based on the Technology Acceptance Model (TAM) and Theory of Planned Behaviour (TPB), covers perceived ease of use, perceived usefulness, subjective norms, attitudes towards AI, and behavioural intentions to utilise AI tools. The items scored on a Likert scale from strongly disagree (1) to strongly agree (5). Likert scales measure views, attitudes, perceptions, and behaviours. This standardised method lowers survey response biases and subjective interpretations (Creswell & Creswell, 2017).

3.4 Variables Measurement

The factors in this study were quantitatively assessed utilising items from recognised field research. These changes make the measures contextually relevant and scientifically robust, laying the groundwork for empirical research.

The measures evaluating perceived usefulness (PU) and perceived ease of use (PEOU) were derived from Chatterjee et al. (2021), Lee et al. (2003), and Yousafzai (2007). These modifications were chosen for their reliability and validity in assessing technology uptake across contexts. Next, subjective norm measurements were derived from Ivanov et al. (2024), which shed light on societal influences on technology adoption. The views towards AI measures were adapted from Ivanov et al. (2024) to provide theoretical coherence for social factors and individual views. Finally, Chatterjee et al. (2021), known for their rigorous technological acceptance research, provided the measurements for AI adoption intentions.

3.5 Data Analysis and Hypothesis Testing

The researchers formulated the hypotheses based on the relationships between the independent variables PU, PEOU, SN, A, and IAA. Thus, we used descriptive, inferential, and correlation analysis to draw conclusions from the data (Nardi 2018). According to Shi and Conard (2009), regression analysis is a sophisticated statistical tool for examining the connection between a dependent variable and one or more independent variables. In this study, the researchers used regression analysis to examine the association between behaviour intention (a dependent variable) and PU, PEOU, SN, A, and IAA. This method also reveals how each independent variable affects the dependent variable (Gogtay, Deshpande & Thatte 2017). Regression analysis is suitable for modelling these interactions and assessing their strength and direction (Lee 2022).

The analysis utilised the latest JAMOVI statistical software, noted for its user-friendly interface and significant analytical capabilities (Şahin & Aybek 2019). This solution optimised data management and processing, providing a rigorous and precise evaluation of UAE student opinions on AI tools in higher education (Caldwell 2022).

3.6 Ethical Considerations

This study follows strict ethical guidelines to ensure research integrity. We fully explained the study's purpose and dangers to participants before they consent. This initial step requires student agreement, verifying their informed and voluntary commitment.

To protect the confidentiality and privacy of participant data, we employed robust security measures. Data is anonymized to eliminate personally identifiable information and stored securely to prevent unauthorised access. The study was inclusive and non-discriminatory, following ethical norms that forbid bias based on race, gender, religion, or other personal factors. All data used for study, stored securely, and accessed by allowed staff. The researchers will also disclose their techniques, data sources, and findings to other experts and the public. This includes peer-reviewed journal publication and data availability for replication studies. By guaranteeing a broad and representative sample, this strategy improves research fairness, reliability, and generalizability.

4 Data Analysis

This study employed two statistical software packages, WarpPLS version 8 and Jamovi version 2.2.5, chosen for their reliability and compatibility with our research goals. Academic research generally acknowledges WarpPLS for its effectiveness in managing structural equation modelling (SEM) and its ability to evaluate discriminant validity and detect common method bias through thorough collinearity tests (Kock, 2019). On the other hand, Jamovi is open-source software that has proven to be highly useful in academic environments because of its ease of use and the wide range of statistical tests it provides (Şahin & Aybek, 2019).

The study commenced with the use of Jamovi, a statistical software, to do descriptive statistics (see Appendix A). This facilitated the provision of an initial overview of the data (Alvo et al., 2014; Turner & Haoule, 2019). Following that, we used WarpPLS to evaluate the measurement and structural model (see Appendix B), taking advantage of its specialist characteristics to comprehensively analyse the links within our model.

1.1 Descriptive Statistics

The descriptive statistics in this study offer a comprehensive summary of the age distribution, gender, and highest qualification of the participants. According to the data, the largest proportion of respondents (40%) belong to the age range of 35–44 years. In total, 79% of the participants are below the age of 45.

Table 1
Descriptive Statistics.

Characteristics		Counts	% of Total
Age Group	18–24 years old	16	16.0%
	25–34 years old	23	23.0%
	35–44 years old	40	40.0%
	45–54 years old	17	17.0%
	55 and above	4	4.0%
Gender	Male	16	16.0%
	Female	84	84.0%
Highest qualification	Bachelor's Degree	35	35.0%
	Postgraduate Diploma	8	8.0%
	Master's Degree	39	39.0%
	Doctoral or PhD Degree	18	18.0%

As for gender, the female population constitutes 84% of the total, and the male population is 16% of the whole. This suggests that the distribution exhibits a pronounced skewness in favour of females. The respondents possess a diverse variety of educational qualifications, with the highest concentration being among those who hold a master's degree.

1.2 Hypotheses Testing

To test the hypotheses, we evaluate both the measurement and structural models to determine the validity and reliability of the latent constructs and the relationships among them, respectively. The measurement model pertains to the reliability and validity of the underlying constructs (Hajjar, 2018). It entails testing the consistency of the measurement scales across different instances, ensuring that they accurately capture the constructs they are intended to measure. Following the measurement model validation, the structural model assessment focuses on the relationships between the constructs (Anderson, 1987).

1.2.1 Assessment of Measurement Model

The measurement model is being assessed to determine the validity and reliability of the latent constructs. Reliability testing is an essential step to ensure the consistency of the measuring scales employed in research. The term "testing procedure" in this context pertains to the extent to which a specific measurement yields consistent outcomes when employed in comparable scenarios (Babu & Kohli, 2023). To assess the reliability of the constructs, two metrics were used: Cronbach's alpha (α) and composite reliability, as defined by Haddoud et al. in 2022. Kilic (2016) states that a higher value of

Cronbach's α and composite reliability implies a higher degree of scale reliability. Values beyond 0.7 are often deemed satisfactory; values surpassing 0.8 imply strong reliability; and values exceeding 0.9 indicate outstanding reliability.

On one side, Cronbach's alpha (α) values for the constructs are as follows:

Table 2
Cronbach's Alpha (α) values.

Construct	Cronbach's Alpha (α) value
Perceived Usefulness (PU)	0.814
Perceived Ease of Use (PEOU)	0.771
Subjective Norms (SN)	0.892
Attitude Toward the Technology (ATTD)	0.937
Intention to Adopt AI Applications (IAA)	0.930

These values indicate a high level of internal consistency for each construct, as they all exceed the commonly accepted threshold of 0.7 for social science research. The PU scale has a Cronbach's α of 0.814, reflecting high reliability; the PEOU scale has a Cronbach's α of 0.771, indicating acceptable reliability; the SN scale has a Cronbach's α of 0.892, denoting high reliability; the ATTD scale has a Cronbach's α of 0.937, signifying excellent reliability; and the IAA scale has a Cronbach's α of 0.928, also indicating excellent reliability. These reliability analyses confirm that the scales used for PEOU, PU, SN, ATTD, and IAA are reliable measures for this study.

On the other side, composite reliability scores were calculated to further validate the consistency of the constructs, as displayed in Table 3.

Table 3
Composite Reliability values.

Construct	Composite Reliability
Perceived Usefulness (PU)	0.882
Perceived Ease of Use (PEOU)	0.854
Subjective Norms (SN)	0.933
Attitude Toward the Technology (ATTD)	0.951
Intention to Adopt AI Applications (IAA)	0.950

These scores, which exceed the 0.7 criterion, validate the constructs' strong dependability, further supporting the consistency and stability of the scales used in this investigation. Composite reliability ratings that are closer to 1.0 imply a higher level of internal consistency among the indicators within

each construct, which confirms the strength and reliability of the measurement instruments used (Osburn, 2000).

While reliability guarantees the consistency and stability of data (Nelson, 1980), validity ensures that the data appropriately measure their intended purpose (Twycross & Shields, 2004). Validity refers to the degree to which a set of indicators collectively measure input or output (Heale & Twycross, 2015). Validity is commonly evaluated by examining convergent and discriminant validity (Henseler et al., 2015). Convergent validity is assessed by analysing the Average Variance Extracted (AVE) coefficient and the item loadings, both of which must exceed 0.5 in order to establish convergent validity.

The Average Variance Extracted (AVE) values for each construct are as follows:

Table 4
Average Variance Extracted (AVE) values.

Construct	Average Variance Extracted (AVE)
Perceived Usefulness (PU)	0.661
Perceived Ease of Use (PEOU)	0.594
Subjective Norms (SN)	0.822
Attitude Toward the Technology (ATTD)	0.762
Intention to Adopt AI Applications (IAAA)	0.827

As shown above, the AVE values exceed the 0.5 criterion, indicating that their corresponding constructs explain a substantial percentage of the variability in the observed variables. This confirms the presence of robust convergent validity. Regarding the item loading, all items have robust loadings on their corresponding constructions, surpassing the 0.5 criterion in a significant manner. This suggests that the items effectively measure the constructs they are designed to assess.

Table 5. Combined Loadings and Cross-loadings.

	PU	PEOU	SN	ATTD	IAAA	Type	SE	P value
PU1	(0.926)	-0.076	0.029	0.027	-0.201	Reflective	0.078	<0.001
PU2	(0.920)	-0.093	0.067	0.245	-0.273	Reflective	0.078	<0.001
PU3	(0.817)	0.049	-0.026	0.031	0.023	Reflective	0.080	<0.001
PU4	(0.520)	0.223	-0.129	-0.528	0.803	Reflective	0.087	<0.001
PEOU1	0.208	(0.770)	-0.263	0.074	0.054	Reflective	0.081	<0.001
PEOU2	0.143	(0.826)	0.039	-0.016	-0.253	Reflective	0.080	<0.001
PEOU3	-0.257	(0.707)	0.054	0.159	0.029	Reflective	0.083	<0.001
PEOU4	-0.125	(0.774)	0.171	-0.202	0.190	Reflective	0.081	<0.001
SN1	0.090	0.132	(0.887)	0.120	-0.299	Reflective	0.079	<0.001
SN2	-0.063	-0.006	(0.940)	0.035	0.061	Reflective	0.077	<0.001
SN3	-0.023	-0.124	(0.893)	-0.156	0.233	Reflective	0.078	<0.001
ATTD1	0.261	0.008	0.080	(0.851)	-0.286	Reflective	0.079	<0.001
ATTD2	0.316	-0.058	0.003	(0.902)	-0.464	Reflective	0.078	<0.001
ATTD3	-0.194	0.050	-0.040	(0.894)	0.067	Reflective	0.078	<0.001
ATTD4	-0.207	0.013	-0.103	(0.884)	0.176	Reflective	0.079	<0.001
ATTD5	-0.236	0.065	-0.033	(0.881)	0.468	Reflective	0.079	<0.001
ATTD6	0.069	-0.083	0.104	(0.825)	0.040	Reflective	0.080	<0.001
IAA1	0.115	0.016	0.043	0.184	(0.893)	Reflective	0.078	<0.001
IAA2	0.076	0.029	-0.014	-0.044	(0.912)	Reflective	0.078	<0.001
IAA3	-0.248	-0.010	-0.048	-0.306	(0.909)	Reflective	0.078	<0.001
IAA4	0.057	-0.034	0.019	0.166	(0.924)	Reflective	0.078	<0.001

The discriminant validity of a construct is assessed by comparing the square root of the average variance extracted (AVE) with the correlations between different constructs (Raykov, 2011). This serves the objective of ascertaining the distinctiveness of a construct in comparison to other constructs.

Table 6. Correlations among latent variables and errors.

	PU	PEOU	SN	ATTD	IAA
PU	(0.813)	0.385	0.349	0.740	0.782
PEOU	0.385	(0.771)	0.476	0.409	0.435
SN	0.349	0.476	(0.907)	0.452	0.448
ATTD	0.740	0.409	0.452	(0.873)	0.876
IAA	0.782	0.435	0.448	0.876	(0.910)

The correlation coefficient between PU and PEOU is 0.385. The correlation coefficient between PU and SN is 0.349. The correlation coefficient between PU and ATTD is 0.740. Lastly, the correlation coefficient between PU and IAA is 0.782. The largest correlation that PU has with another construct is with IAA, with

a value of 0.782. However, this value is still lower than the square root of AVE for IAA, which is 0.910. When comparing each construct, PEOU has a maximum correlation of 0.476 with SN, which is lower than its own square root of AVE, 0.771. The strongest correlation observed between SN and another construct is 0.476 with PEOU, which is much lower than SN's square root of AVE, 0.907. The correlation between ATTD and IAA is 0.876. Although this value is high, it is still less than the square root of AVE for IAA, 0.910, but slightly higher than the square root of AVE for ATTD, 0.873, indicating a potential issue with discriminant validity between ATTD and IAA.

Most constructs exhibit a square root of AVE that is greater than any of their correlations with other constructs, thereby demonstrating their discriminant validity. This suggests that each construct is unique and evaluates a distinct notion or dimension compared to the others in our model, with the exception of ATTD and IAA. The correlation between ATTD and IAA is slightly higher than the square root of AVE for ATTD, indicating a potential issue with discriminant validity between these two constructs. However, the statistical significance of these correlations, indicated by the P values ($p < 0.001$), provides additional evidence for the importance and robustness of these interactions. Despite the noted exception, the distinct nature of the correlations for the other constructs confirms the ability to differentiate between most constructs, thereby validating their discriminant validity for the majority of the model.

The study also evaluated the collinearity. Kock (2012) and Gunst (1984) both highlight the significance of evaluating collinearity in structural equation modelling. High collinearity can negatively impact the reliability of statistical analysis, resulting in erroneous and unstable coefficient estimates in regression models (McGiffen et al., 1988).

Table 7
Collinearity Statistics.

Construct	**Collinearity (VIF)**
Perceived Usefulness (PU)	2.688
Perceived Ease of Use (PEOU)	1.415
Subjective Norms (SN)	1.451
Attitude Toward the Technology (ATTD)	4.538
Intention to Adopt AI Applications (IAAA)	5.312

In general, VIF values that are less than 5 suggest a modest level of collinearity, which can be effectively managed in structural equation modelling (SEM) assessments. Our analysis found that PU, PEOU, and SN have low collinearity, as indicated by their VIF values being significantly below the threshold of 5. This suggests that there are few difficulties with collinearity.

The ATTD construct has a VIF value that exceeds 4, nearing the threshold of 5, indicating a significant amount of collinearity. Additionally, the IAA construct has a VIF value of 5.312. Although not currently

causing any issues, it is important to carefully examine these numbers to verify that the collinearity does not introduce any bias into the model's estimates. Since none of the VIF values exceed 10, the amount of collinearity in our model does not reach the levels normally associated with severe multicollinearity problems (Kock & Lynn, 2012). Nevertheless, the ATTD and IAA values indicate the need for a thorough examination of these constructs. This might involve consolidating overlapping indicators or modifying the model structure to minimise potential collinearity effects.

Overall, the model displays a certain level of collinearity, specifically in the constructs ATTD and IAA. However, this collinearity is still within acceptable boundaries for conducting dependable SEM analysis. Regular monitoring and potential modifications in model specifications or data handling can improve the reliability and interpretive precision of our findings.

1.2.2 Assessment of the Structural Model

The assessment of the structural model usually involves three main measures: significance (p-value), path coefficient (β), and R square (R^2) (Hair et al., 2021). P values less than 0.05 are considered acceptable. The values of the β coefficients indicate both the magnitude and direction of the relationship. The value approached ± 1 to a higher degree when the connection was more robust. The direction of the relationship is controlled by the sign of the value, which might be positive or negative. As per Hair et al. (2021), the R^2 value is a statistical metric that quantifies the extent to which the independent variables impact the dependent variable.

Table 8
Hypotheses Testing Results.

H1	Hypothesis	Path Coefficients (β)	P-value	Supported
	PU ◊ IAA	**0.30**	**p < 0.01**	**Yes**
H2	PEOU ◊ IAA	0.05	P = 0.30	No
H3	SN ◊ IAA	0.01	P = 0.48	No
H4	ATTD ◊ IAA	0.64	P < 0.01	Yes

The p-value for Hypothesis 1 (H1), which examines the relationship between PU and IAA, is less than 0.01, indicating that PU significantly affects IAA. This demonstrates that the probability of students wanting to utilise artificial intelligence technology rises in direct correlation to their perception of the usefulness of these technologies. Conversely, the p-value for H2, which represents the relationship between PEOU and IAA, is 0.30, indicating that the impact of PEOU on IAA is not statistically significant. This implies that the level of user friendliness may not be a reliable indicator of students' willingness to adopt artificial intelligence in this specific situation. Similarly, the impact of SN on IAA is not statistically significant. This suggests that social constraints or the perceived expectations of others have minimal impact on individuals' intent to use artificial intelligence technologies. The ATTD construct has a significant and positive impact on IAA. The most influential predictor in the model is the positive attitude towards technology, which strongly suggests a big desire to embrace it.

The dependent variable's R^2 value is 0.82, indicating that the model's four predictors account for 82% of the variance in the intention to employ artificial intelligence applications in relation to the dependent variable. Given the high R^2 value, it is clear that the model is highly effective in explaining the intention to adopt apps that use artificial intelligence.

The coefficient of determination (R^2) for the dependent variable is 0.82, indicating that 82% of the variability in the intention to adopt AI applications can be accounted for by the four predictors included in the model. The high R^2 value indicates that the model is highly effective in elucidating the intention to embrace AI applications.

2 Discussion

The results of this study offer a valuable understanding of the aspects that impact the acceptability and use of AI tools in higher education by students in the UAE. Notably, the findings underscore the significant impact of perceived usefulness and attitudes towards technology on students' intentions to adopt AI applications, while perceived ease of use and subjective norms were less influential. When considered in the context of relevant and current previous studies, these findings improve our comprehension of the factors that influence student attitudes towards technology-enhanced learning environments.

2.1 Perceived Usefulness and Student Engagement

The findings confirm a strong correlation between students' perceptions of AI tools' effectiveness and their adoption in educational settings. This aligns with Abbas et al. (2023), who found that students' recognition of educational benefits predicts their usage likelihood. Similarly, Zhou et al. (2024) noted that customized learning experiences foster positive attitudes towards AI's usefulness. Our study reiterates that perceived usefulness is key in AI adoption, suggesting that tangible benefits increase students' willingness to use AI technologies.

In the UAE context, the integration of AI tools in education is heavily influenced by the government's focus on establishing a knowledge-based economy, which enhances the perceived usefulness of these technologies among students (Lakshmi et al., 2023). Additionally, the UAE's advanced digital infrastructure and widespread acceptance of technology foster a conducive environment for adopting educational innovations (Alwaely et al., 2022), making AI tools more appealing to students.

Educational strategies in the UAE often feature cutting-edge technologies at their core, which elevates the utility of AI tools in fulfilling educational objectives like critical thinking and digital literacy (Akour et al., 2023). Consequently, when students recognise the usefulness of AI tools, their engagement increases as they view these technologies as essential for achieving superior academic results and preparing for competitive job markets. This dynamic underscores the direct impact of perceived usefulness on student engagement in the UAE's unique educational and cultural context.

2.2 The Limited Role of Perceived Ease of Use

While the Technology Acceptance Model generally emphasises the importance of perceived ease of use (Davis, 1989), our findings suggest that this factor plays a limited role in the adoption of AI tools by students in the UAE. This may be indicative of a higher level of technological sophistication among these students, who seem to prioritise functionality and outcomes over mere user-friendliness. Evidence of this sophistication can be seen in the UAE's rapid digital transformation initiatives and high rates of technology adoption across educational institutions.

For instance, the UAE has one of the highest smartphone penetration rates globally (Ameen et al., 2018) and significant investments in digital infrastructure (Bing & Al-Mutawakel, 2018), reflecting a populace that is highly familiar with technology. Furthermore, the UAE's education sector has been at the forefront of incorporating advanced technology into the classroom, with initiatives like the Mohammed Bin Rashid Smart Learning Programme and the adoption of virtual and augmented reality tools for educational purposes (Xanthidis et al., 2020). Such developments suggest that students are accustomed to engaging with technology at a level where ease of use is a basic expectation rather than a barrier. This environment fosters a discernment in technological adoption where functionality and tangible benefits are more crucial than simplicity, aligning with our findings.

2.3 The Influence of Subjective Norms

Although previous research, such as the study conducted by Al-Mamary and Al-Shammari (2023), frequently highlights the influence of subjective norms on technology adoption, our results did not support this assertion. The diminished role of subjective norms in influencing the adoption of AI tools among students in the UAE suggests a cultural shift towards more individualistic decision-making within the educational context. This change could be driven by several factors, including the increasingly multicultural nature of the UAE's higher education environment and the strong emphasis on personal achievement and technological proficiency in the UAE's educational policy (Ashour, 2020). Evidence of this shift can be observed in the diverse composition of the student body in UAE universities, which includes a significant percentage of international students. This diversity introduces a variety of perspectives and reduces the impact of traditional social endorsements typical of a more homogenous society. Additionally, research indicates a global trend where younger generations, particularly in technologically advanced societies, exhibit a greater tendency towards individualism, influenced by digital communication and social media (Mayer et al., 2020; Nastoiashcha, 2019). In the UAE, where digital engagement is exceptionally high, this trend may be accentuated, leading to a lesser impact of subjective norms on educational technology adoption. Such insights align with our findings, illustrating a significant cultural and behavioural evolution in the UAE’s educational sector.

2.4 Attitudes Toward AI Tools

Our analysis confirms that positive attitudes towards AI tools are the most influential predictor of their adoption, as suggested by Sukkeewan et al. (2024). This finding underscores the importance of

addressing students' emotional and cognitive responses to AI technologies and highlights the emotional and cognitive dimensions of technology integration. Interventions aimed at enhancing student experiences and perceptions of AI can foster more positive attitudes, thereby increasing their openness to utilising these tools in educational contexts. It suggests that students are more influenced by their personal feelings and the perceived intellectual enrichment from AI tools than by external social pressures or ease of use considerations.

This discussion not only contextualises our findings within the broader landscape of AI in education but also provides a foundational basis for future interventions aimed at optimising the integration of AI tools in UAE higher education. By understanding and addressing these key factors, educational institutions can tailor their approaches to better meet the needs and expectations of their students, ultimately enhancing the educational experience and outcomes.

3 Conclusion

The primary aim of this study was to investigate the determinants that impact the acceptance and utilisation of AI technologies in higher education among students in the UAE. This involved evaluating the degree of acceptance, patterns of usage, and influential elements that shape their attitudes. This analysis effectively discovered and analysed these aspects, offering a comprehensive grasp of the intricacies involved in the adoption of AI technologies.

The results definitively show that the perceived usefulness of AI tools significantly impacts their adoption. This means that as students recognize more benefits, they are more likely to use these technologies in their educational activities. Additionally, our findings confirm that positive attitudes towards AI tools are the most influential predictor of their adoption. Contrary to the existing literature, our research discovered that the perceived ease of use did not have a significant impact on the adoption of AI tools among the surveyed students. This unforeseen effect emphasises a potential change in emphasis from simple usability to more significant outcome-based assessments of technology tools among students. Our findings also confirms that positive attitudes towards AI tools are the most influential predictor of their adoption.

In addition, subjective norms, which usually have a substantial impact in collective cultures, were not observed to have a significant influence on the adoption of AI tools in this particular situation. This implies a perhaps distinctive characteristic of the student body or a shifting cultural influence on the adoption of technology in educational environments in the UAE.

By addressing these specific aspects of AI tool use and acceptance among UAE students, this study not only fulfils its primary objective but also contributes significantly to the broader discourse on educational technology adoption, providing actionable insights and raising questions for further investigation. The results form a robust basis for understanding how educational institutions can better integrate AI tools to enhance learning outcomes and student engagement, effectively aligning with the UAE’s strategic educational and technological objectives.

4 Implications

The study's findings have several theoretical and practical implications for educational policymakers, technology developers, and educators in the United Arab Emirates.

4.1 Practical Implications

Enhancing Educational Strategies

The findings of this study underscore the necessity for educational institutions to prioritise the integration of AI technologies that demonstrate tangible benefits to students. This may include the adoption of AI-powered tools to tailor learning experiences according to individual student needs or the use of AI for providing immediate feedback on assignments. Specifically, institutions can implement AI systems that develop personalised learning plans based on student performance and learning styles. Additionally, AI can be utilised to deliver real-time feedback on assignments, aiding students in promptly refining their skills and understanding their mistakes. Further, the deployment of AI tutors can provide round-the-clock individualised assistance to explain complex topics in depth. AI can also be used to monitor and analyse student engagement during online sessions, allowing for the dynamic adaptation of teaching methods.

Development of AI Tools

Developers should focus on creating AI tools that align with the educational objectives of UAE universities and meet the specific needs of their students. This involves actively engaging with students and educators to identify practical requirements and desired outcomes. Strategies should include organising sessions with students and instructors to gather direct feedback on AI tools, thereby shaping future developments, and initiating pilot programmes to evaluate new AI tools in classroom settings, utilising feedback for iterative improvements. Including educators and students in development teams ensures that the tools not only meet educational goals but also enhance the user experience. Regular distribution of these tools for extensive feedback allows for a broader data set for AI tool refinement, and integrating direct feedback features within AI tools enables users to suggest improvements and rate their experiences seamlessly.

Training and Support Systems

To foster a positive attitude towards AI, it is critical for institutions to offer comprehensive training programs for both students and faculty. These programmes should aim to demystify AI technologies, highlight their benefits, and provide guidance on how to effectively utilise them in various academic contexts.

4.2 Theoretical Implications

Revising Technology Acceptance Models

The unexpected findings on the constrained impact of perceived ease of use on AI adoption provide a challenge to current models of technology acceptance. This indicates a requirement for theoretical models to potentially include elements that represent advanced levels of technological literacy and evolving student characteristics, such as technological self-confidence or anticipated outcomes.

Cultural Influence on Technology Adoption

The limited influence of subjective norms on the adoption of AI in a society that is traditionally collectivist, such as the UAE, warrants additional theoretical investigation into the ways in which culture affects the acceptance of technology. Potential future research might investigate the ways in which the global exposure and multicultural atmosphere of higher education in the UAE are influencing and transforming conventional cultural influences on technology usage.

Attitude and behavioural intentions

The significant impact of attitudes on the adoption of AI tools highlights the crucial role of affective aspects in technology adoption theories. This may promote a transition towards more comprehensive models that take into account both cognitive and emotional reactions to technology, potentially resulting in a deeper understanding of user behaviour in educational technology research.

These theoretical and practical implications not only serve as a guide for immediate measures, but they also serve to enrich ongoing academic conversations and future research on the incorporation of artificial intelligence in education, particularly in circumstances that are comparable to those that will be encountered in the United Arab Emirates. They suggest a dynamic interplay between technology, user attitudes, and cultural contexts, which must be taken into consideration in the process of making policies as well as in the process of developing academic theories.

5 Limitations and Future Recommendations

While our study provides important insights, it is not without limitations. The sample, while sufficient for statistical analysis, was restricted to a specific demographic and educational setting, potentially impacting the applicability of the findings to other locations or diverse educational institutions. Furthermore, the study's abstract quantitative design restricts our ability to establish causal relationships and fully understand the underlying reasons for the findings. To overcome these limitations, future research could benefit from incorporating both qualitative and quantitative approaches, providing a more comprehensive analysis of the variables involved.

Our findings also suggest that future research should focus on examining the long-term effects of AI technologies on learning outcomes and student engagement in a wider range of educational environments. Additional research could investigate the varying effects of cultural influences on the acceptability and use of AI technology in education, perhaps providing comparative analysis between countries that prioritise individualism and those that emphasise collectivism. Finally, it would be

advantageous to analyse the relationship between faculty endorsements and student adoption of AI technologies, taking into account the limited impact of subjective norms identified in this study.

Overall, this research makes a substantial contribution to our understanding of the factors that influence the adoption of AI tools in higher education in the UAE. It also provides a basis for future efforts to improve the incorporation of AI into educational practices. This study explores the practical consequences and acknowledges the limitations of using AI technology to enhance educational experiences and outcomes, contributing to a better understanding of how to effectively utilise AI in education.

Declarations

This study received ethical approval from the British University in Dubai (BUiD) Research Ethics Committee prior to data collection. All participants were provided with information about the study and participated voluntarily. Informed consent was obtained from all participants, and all data were collected, stored, and analyzed in accordance with the ethical guidelines and requirements of the British University in Dubai.

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Figures

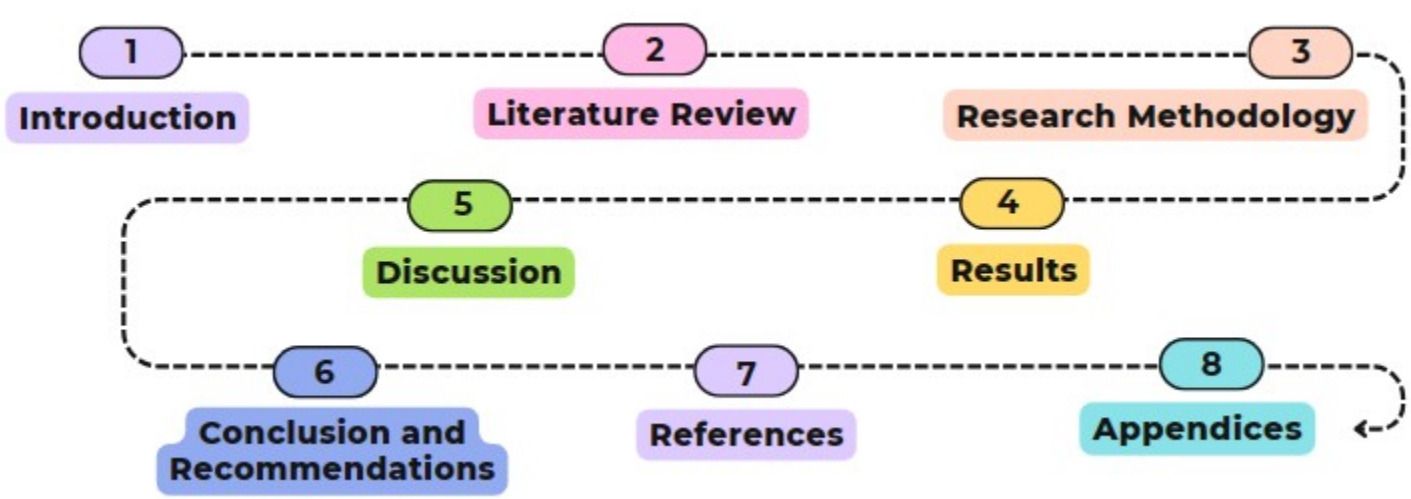


Figure 1

Fig.1. Paper Structure

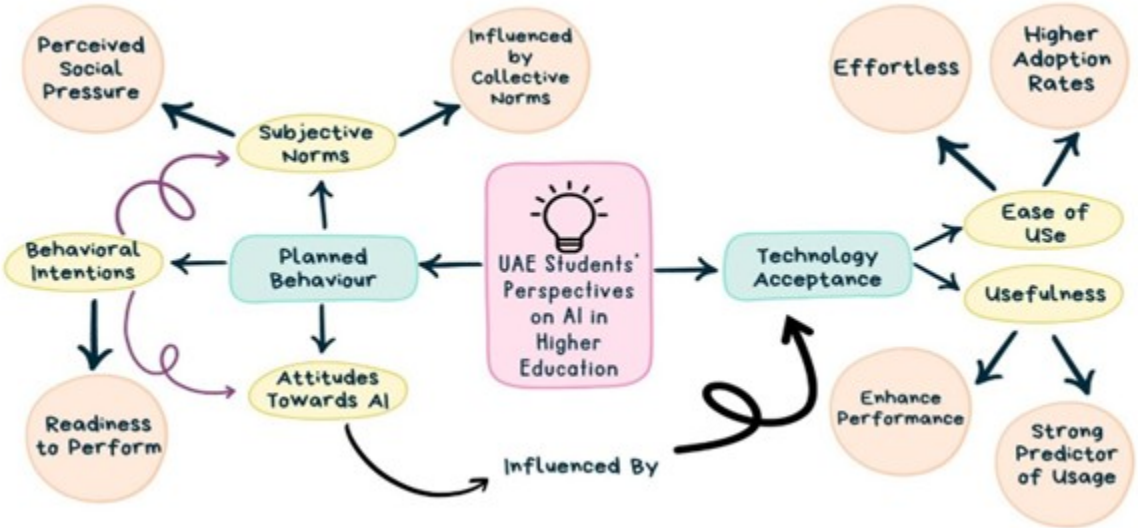


Figure 2

Fig. 2. Concept Mapping

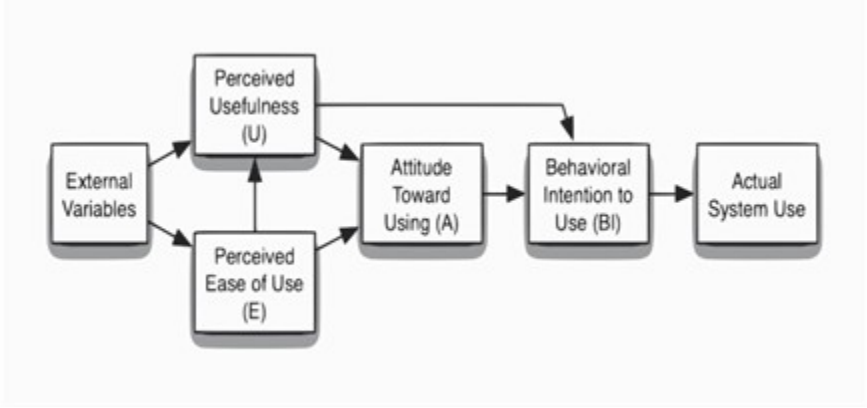


Figure 3

Fig. 3. Technology Acceptance Model (Davis, 1989)

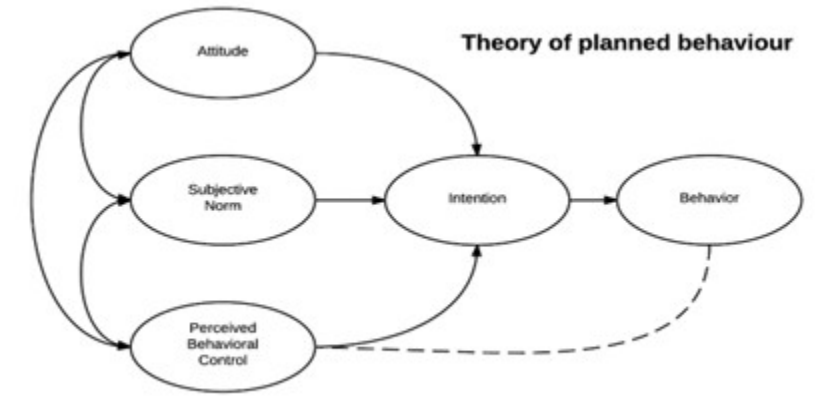


Figure 4

Fig. 4. Theory of planned Behaviour (1991)

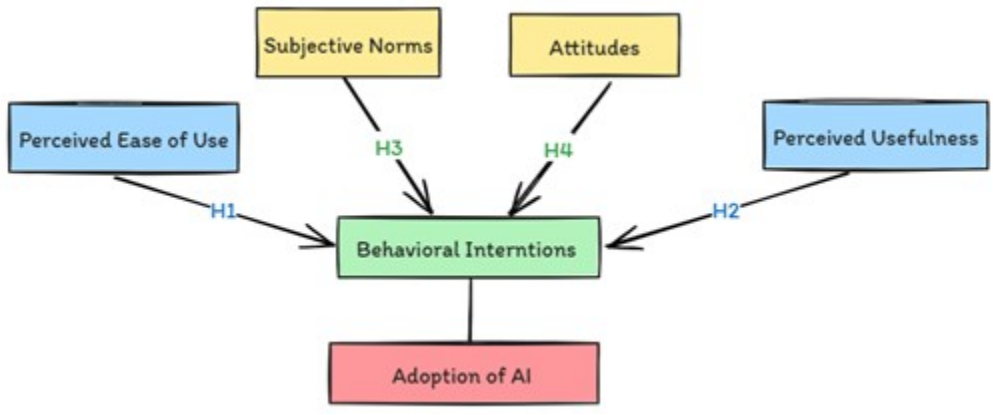


Figure 5

Fig. 5. Research Model

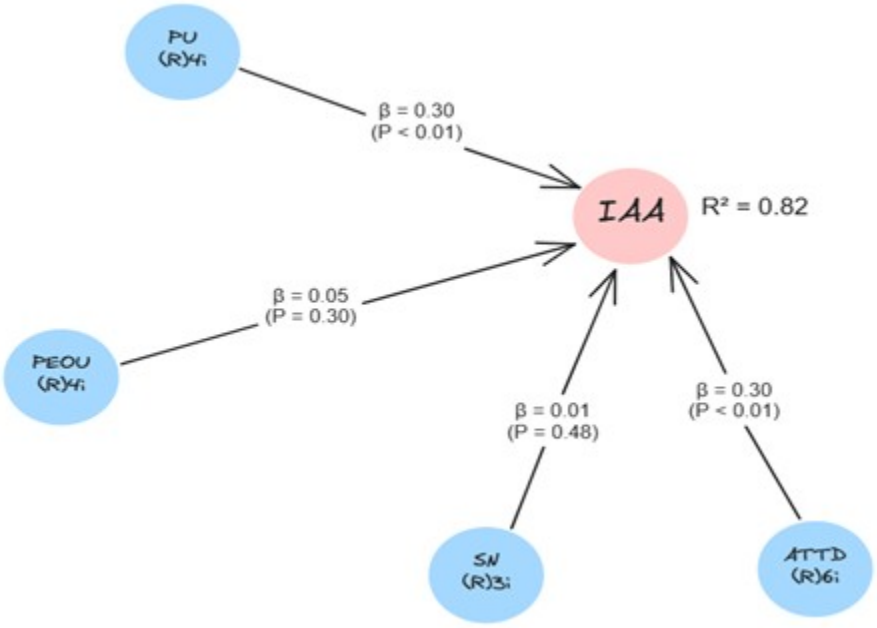


Figure 6

Fig. 1. The structural Model.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Appendices.docx