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The Factors Influencing AI Adoption Willingness Among English Language Students in Jordanian Private Universities

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***Abstract*—This study examined the factors influencing English language students' willingness to adopt artificial intelligence (AI) in Jordanian private universities. Three key factors were investigated, specifically ease of use, time and psychological risks associated with AI, and task–technology fit (TTF). The study hypothesized that these factors would have a significant positive impact on students' AI adoption. A quantitative technique was utilized to collect data using a survey. The study sample consisted of 130 English language students. The findings revealed significant positive correlations between students' willingness to use AI and perceived ease of use as well as perceived time and psychological risks. Contrary to expectations, TTF did not have a significant impact on students' willingness to use AI. These findings provide valuable insights into the potential for AI adoption in the field of education and the factors that nurture or hinder the integration of this technology.**

***Index Terms*—artificial intelligence, English language learning, technology adoption, student perceptions, Jordan**

I. Introduction

The rapid progress of technology, most notably the rise of the internet, has dramatically reshaped the field of education (Alrashed et al., 2023; Algerafi et al., 2023; Jdaitawi et al., 2022; Jdaitawi et al., 2023; Al-Mawadiah & Al-Zoubi, 2020; Jdaitawi & Kan'an, 2022). Within this dynamic environment, the prominence of artificial intelligence (AI) has skyrocketed, demonstrating significant potential to revolutionize learning and especially higher education (Li, 2023). Growing evidence indicates that AI-powered platforms and applications cater to learners' individual needs and thereby enable more effective teaching methodologies (Kuleto et al., 2021; Sandu & Gide, 2019; Aleedy et al., 2022). Additionally, several studies have revealed that technologies such as augmented reality and AI can enhance student engagement, motivation, and communication and therefore foster positive learning experiences (Jdaitawi et al., 2023; Muhaidat et al., 2022; Sánchez-Prieto et al., 2020; Huang et al., 2022).

The potential of AI for English language learning has also been well documented (Lin et al., 2023). Studies have consistently supported the effectiveness of using AI technology in formal and informal language learning contexts because it fosters enthusiasm among language learners and sustains their interest in language acquisition (Crompton et al., 2014; Kim, 2014; Cheng et al., 2018; Tolksdorf et al., 2021).

While AI offers numerous advantages, its integration into education also presents challenges and concerns. The most controversial issues relate to privacy, security, user trust, and appropriate pedagogical integration of AI (Vincent-Lancrin & van der Vlies, 2020; Rodway & Schepman, 2023; Li & Gu, 2023). Moreover, despite the growing literature examining the role of AI in English language learning (Rodway & Schepman, 2023; Li & Gu, 2023), further exploration is required to understand the factors influencing students' experiences with this new technology as well as their perceptions and feedback (Kumar & Bajaj, 2016; Malkawi et al., 2024; Sun et al., 2023). This need is particularly notable in the Jordanian context. Jordanian universities have demonstrated a commitment to promoting e-learning and investing in integrating AI into the learning process, yet, this area remains underexplored, especially in relation to learners' perspectives (Rababah, 2025a, 2025b).

This study aims to fill this gap by investigating AI integration into English language learning as well as identifying and analyzing the determinants of students' adoption of AI in the Jordanian context (Al-Khasawneh et al., 2024; Rababah, 2024). The aim of this research is to inform educators, policymakers, and technology developers about effective AI implementation strategies (Amaireh & Rababah, 2024).

II. Literature Review and Hypotheses

A pivotal subfield of computer science, artificial intelligence (AI) is focused on the creation of computer applications capable of producing intelligent behavior by enhancing the abilities of the human (Naqvi, 2020). This proven capability has earned AI widespread adoption across various fields, including economics, healthcare, and education (Suh & Ahn, 2022; Garcia-Madurga & Grillo-Mendez, 2023; Kapa, 2023; Mukherjee, 2022; Owan et al., 2023). The merit of AI in education is its ability to offer innovative solutions that improve the process of teaching and learning (Wang et al., 2023).

Using the technology acceptance model (TAM), most studies have focused on exploring specific variables influencing the actual or potential adoption of AI, such as ease of use, time and psychological risks, and task–technology fit.

Perceived ease of use, or the extent to which users believe that a particular technology is simple, straightforward, and effortless to use and thereby will positively impact their performance of a given task, is a crucial factor influencing learners' willingness to adopt AI (Davis, 1989). According to the TAM, ease of use is a strong determinant of a user's intention to adopt and utilize AI. Thus, the more user-friendly the technology, the more likely the user will adopt it (Salleh et al., 2022; Mensah et al., 2021). Based on existing literature, we propose that perceived ease of use has a significant positive impact on Jordanian university students' willingness to adopt AI systems for learning English.

Perceived risk is another key factor that is well documented in literature as a strong predictor of users' adoption of AI. This variable refers to possible negative consequences that users associate with a particular technology (Bauer, 1960). In the context of AI in education, several studies have noted the necessity of analyzing the possible risks that students perceive, namely concerns about time investment and possible psychological issues (Zhang et al., 2021; Shin et al., 2017; Kim & Gu, 2012; Kim, 2019). These studies have integrated decision hypothesis models with theories of perceived risks to examine students' acceptance of such technology in their learning activities. We hypothesize that these perceived time-related and psychological risks have a significant impact on students' intention to adopt AI.

The third major variable is related to the concept of task–technology fit (TTF). This model explains the tripartite correlation between the abilities of the users, the functionality of the technology, and the requirements of the tasks being performed (Yang et al., 2017; Salleh, 2016). The TTF model underscores the vital importance of aligning these three variables. Technology is adopted when the user perceives a strong fit between the technology and the task they must perform such that the technology effectively achieves the task. The stronger the fit, the more likely the user will accept the technology (Alyoussef, 2021; Goodhue & Thompson, 1995). Based on this understanding, we propose that a positive TTF increases students' willingness to use AI for learning English.

Research Questions and Hypotheses

Based on the reviewed literature, the following three hypotheses are proposed, as illustrated in Figure 1:

1- Perceived ease of use has a significant positive impact on students' willingness to adopt AI.
2- Time and psychological risks have a significant influence on students' willingness to adopt AI.
3- Task–technology fit has a positive influence on students' willingness to adopt AI.

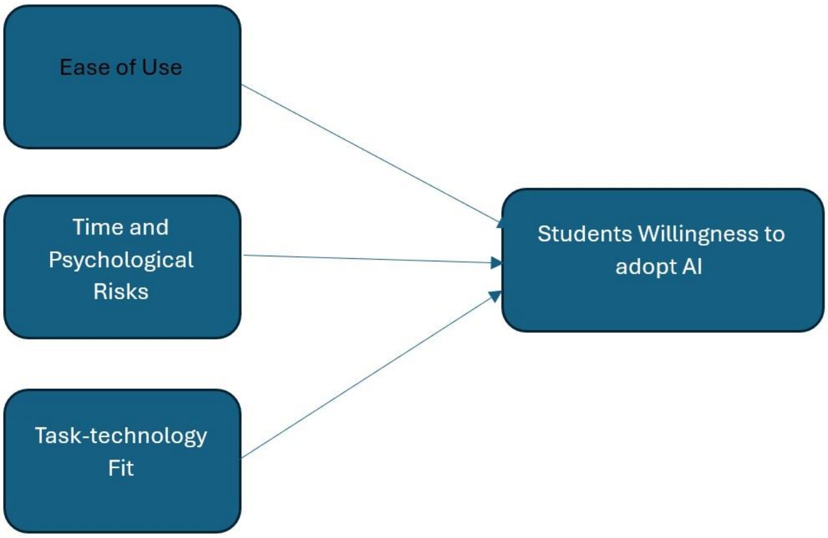

Figure 1. Study Model

III. METHODOLOGY

This study employed a quantitative research design to examine the factors influencing English language students' willingness to adopt AI at Jordanian universities. The data collection method was a survey questionnaire administered to 130 participants. The questionnaire approach was chosen for its efficiency in gathering standardized information from a large sample.

A. Study Participants and Sampling

The target population for this study consisted of 130 English language students enrolled at private universities in Irbid and Ajloun, Jordan. These two universities were selected due to their efforts to promote digital education and technology use among students. Participants were chosen based on their active use of technology and familiarity with AI in their daily lives. All participants were majors in English language and ranged in age between 18 and 22 years old. The sample size was determined based on the recommendations of Hair et al. (2010), who stipulated a minimum of 100 survey respondents for studies using structural equation modeling with five or fewer constructs. Thus, this study's sample size provides sufficient representation within the scope of the study.

Before data collection, ethical approval was obtained from the Ethics Committee and the Dean of Scientific Research at both universities. Data collection was conducted through voluntary participation, with students' providing verbal consent in the presence of university staff. Students were assured that their responses would be kept confidential and used solely for research purposes. These actions ensured the study's adherence to ethical research standards and protection of participants' rights.

B. *Measurement Instruments*

The survey questionnaire was designed based on validated scales from previous studies. These measurement instruments were adopted and adapted to fit the context of AI in English language learning. More specifically, the questionnaire included the following measures:

1. Perceived Ease of Use: Adapted from Davis (1989), this three-item scale assesses students' perceptions of how easy it is to use AI in their learning.
2. Time and Psychological Risks: Based on the work of Featherman and Pavlou (2003), this six-item scale measures students' perceptions of potential risks related to time investment and psychological discomfort while using AI.
3. Task- Technology Fit: Adapted from Goodhue and Thompson (1995), this two-item scale evaluates students' perceptions of the extent to which AI capabilities and the requirements of their language learning tasks are aligned.
4. Willingness to Use AI: Developed based on Sudaryanto et al. (2023), this three-item scale measures students' overall readiness to adopt AI in their English language learning.

The first section of the questionnaire collected demographic information (age, gender, and computer experience). The subsequent section included scaled response items to measure respondents' perceptions of the factors under investigation. All items were measured on a five-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree".

C. *Reliability and Validity of the Measurements*

To ensure the quality and trustworthiness of the data collected as well as the overall credibility of the findings, we conducted several statistical analyses to accurately assess the reliability and validity of the measurement instruments. Reliability refers to the consistency of the measures, ensuring that the instrument produces stable and consistent results, while validity indicates whether the instrument measures what it is intended to measure.

With regards to the reliability of the questionnaire items, three methods were employed: Cronbach's alpha coefficient, composite reliability (CR), and factor loading coefficients. First, Cronbach's alpha measures the internal consistency of a set of items, indicating the extent to which items within a scale measure the same underlying construct. Cronbach's alpha is expressed as a number between 0 and 1; the higher the values, the greater the reliability. Next, we used factor loadings analysis. Obtained through confirmatory factor analysis (CFA), factor loadings analysis aims to identify the correlation between each item and its corresponding factor, which ultimately provides insights into the internal consistency of the scale. Factor loadings above 0.5 are generally considered acceptable. Stronger relationships between the item and the construct are indicated through higher values. Finally, the composite reliability (CR) model was utilized as an additional measure of internal consistency to assess the overall consistency of the scale. Using structural equation modeling techniques, CR is a robust measure of reliability that considers the different outer loadings of the indicator variables. CR values are expressed as a number between 0 and 1; the higher the value, the more reliable the construct.

As illustrated in Table 1, these reliability measures yielded the following results. Cronbach's alpha values for all constructs surpassed the recommended threshold of 0.60, demonstrating good internal consistency. Specifically, Cronbach's alpha was 0.759 for willingness to adopt AI, 0.753 for ease of use, 0.824 for time and psychological risks, and 0.849 for TTF. Furthermore, the factor loadings analysis provided additional evidence of the reliability of the measurement items. All items analyzed had a value above 0.40. The CR test provided further evidence of reliability. The yielded values for all the constructs surpassed the recommended threshold of 0.60, thereby demonstrating strong internal consistency (willingness to adopt AI: 0.857, ease of use: 0.858, time and psychological risks: 0.928, task–technology fit: 0.851).

In addition to the above-mentioned measures, we applied convergent validity analysis to assess the extent to which multiple measures of the same convergent validity. Convergent validity was assessed using the average variance extracted (AVE), which measures the amount of variance captured by each construct. An AVE value superior to 0.50 is an indicator of satisfactory convergence and establishes that the construct explains more than half of the variance in its indicators. As shown in Table 1, convergent validity for all four items was confirmed through the following values: willingness to adopt AI (AVE = 0.670), ease of use (AVE = 0.503), time and psychological risks (AVE = 0.865), and task–technology fit (AVE = 0.656). Overall, these findings confirm that the measurement instruments employed in this study were both reliable and valid. This enhances the credibility of the collected data.

TABLE 1
CONSTRUCT VALIDITY AND RELIABILITY OF THE MEASUREMENT

Variable	**α**	**CR**	**AVE**
Willingness	.759	.857	.670
Ease of Use	.753	.858	.503
Time and Psychological Risks	.824	.928	.865
Task Technology Fit	.849	.851	.656

IV. RESULTS AND DISCUSSION

To examine the correlations that govern the three factors under study and English language students' willingness to use AI, two major analyses were conducted: Pearson product–moment correlation and path analysis. The findings are detailed below.

Initially, a correlation analysis was performed to explore the relationships between the study variables. As summarized in Table 2, the analysis revealed significant positive correlations between students' willingness to adopt AI and the three key factors.

- *Perceived Ease of Use:* A strong positive correlation was observed between perceived ease of use and willingness to use AI ($r = 0.694$, $p < 0.05$). This means that students who perceive AI as user-friendly and easy to manipulate are more inclined to adopt it in their English language learning.
- *Perceived Time and Psychological Risks:* A significant positive correlation was also revealed between perceived time and psychological risks and students' willingness to use AI ($r = 0.646$, $p < 0.05$). In other words, if students have only minimal concerns about excessive time investment and potential psychological discomfort in using AI, they are more willing to incorporate AI into their English language learning.
- *Task–Technology Fit:* A positive correlation was noted between TTF and willingness to use AI ($r = 0.383$, $p < 0.05$). However, as the values suggest, the correlation was weaker compared to the other two factors.

These findings underscore the crucial importance of the factors of perceived ease of use and perceived time and psychological risks for students' willingness to use AI, while TTF plays a lesser yet still notable role. The findings of this study shed light on the various factors that influence students' willingness to adopt AI as an English language learning tool within the Jordanian higher education context. Consistent with previous studies that identify these factors as key determinants of students' adoption intentions (Sudaryanto et al., 2023; Omar et al., 2022), the research findings demonstrate the significant influence of perceived ease of use as well as the perceived time and psychological risks that students associate with this transformative technology. These findings suggest that in order to achieve effective integration of AI into English language learning, both educators and technology developers need to ensure the user-friendliness of the technology as well as address the practical and psychological challenges of integration.

The findings clearly support the hypothesis that perceived ease of use has a positive impact on students' willingness to incorporate AI into their learning. This finding is consistent with the TAM postulated by Davis (1989), and it accurately aligns with recent studies in the field of educational technology adoption (e.g., Salleh et al., 2022; Mensah et al., 2021). This significant positive correlation emphasizes the key importance of user-friendly AI tools in enhancing the English language-learning experience. Given that ease of use is a key determinant of student acceptance of new technology, educators and tech developers should design accessible, intuitive, and navigable AI-generated learning tools and platforms to accelerate AI adoption rates among students.

TABLE 2
PEARSON PRODUCT-MOMENT CORRELATION ANALYSIS

Variable	1	2	3	4
Ease of Use	--			
Time and Psychological Risks	0.672	--		
Task Technology Fit	0.421	0.468	--	
Willingness	0.694	0.646	0.383	--

To further elucidate the direct impact of these variables on AI adoption, a path analysis was performed using PLS-AMOS. As illustrated in Figure 2, the path model revealed only two significant direct paths between the study factors and willingness to use AI.

- *Perceived Ease of Use:* The analysis demonstrated that students' perception of AI's ease of use had a direct and significant positive influence on their willingness to adopt this technology in their English language learning activities ($\beta = 0.467$, $p < 0.05$), which corroborates Hypothesis 1. This finding confirms that the perception of AI as easy to use directly supports students' intention to adopt it.
- *Perceived Time and Psychological Risks:* Similarly, the findings revealed that perceived time and psychological risks also had a direct and significant positive impact on students' inclination to adopt AI ($\beta = 0.313$, $p < 0.05$). This finding strongly supports Hypothesis 2 and suggests that students' concerns about time commitment and psychological outcomes directly affect their willingness to use AI.

- *Task–Technology Fit:* Contrary to the first two factors, the path analysis demonstrated that task–technology fit did not have a significant direct path to the willingness to use AI (β = 0.040, p > 0.05). Thus, this finding fails to support Hypothesis 3 which indicates that students did not take this variable into serious consideration when they planned whether to use or not to use AI in their English language learning.

In summary, both the correlation and path analyses support that students' perceptions of AI's ease of use and its associated time and psychological risks are strong predictors of their willingness to use AI as part of their learning. In contrast, while task–technology fit did exhibit a positive correlation, the variable did not have a significant direct impact on students' intention to incorporate AI into their learning of the English language. Hypothesis 2, which predicted that users' perceived time and psychological risks have a significant impact on their adoption intentions, is therefore confirmed by the study findings. These findings resonate with established literature on technology adoption, which underscores students' consideration of time investment and the psychological discomfort risks associated with the use of AI for learning (Kim & Gu, 2012; Zhang et al., 2021). The correlation is negative when students have negative associations with the risks of AI and positive when students do not associate any risks with AI.

Contrary to our initial hypothesis, this study did not find a significant correlation between task–technology fit and students' AI adoption intentions. This unexpected result is a notable departure from previous research that identified task–technology fit as a key factor in AI adoption (Goodhue & Thompson, 1995; Alyoussef, 2021). This finding warrants further examination of the nuanced interplay between task–technology fit and students' willingness to use AI as well as investigation of other factors that could play a more vital role. These factors include limited AI exposure among students, which prevents them from being able to accurately assess alignment of the technology with their learning tasks. Likewise, the rapidly evolving nature of AI technologies may cause uncertainty among users and add an extra burden to learning new skills.

TABLE 3
RESULTS OF THE PATH COEFFICIENTS OF THE MODEL

Hypotheses	B	t-value	Sig.	Results
Ease of Use – Willingness	5.419	5.419	0.000	Supported
Time and Psychological Risks – Willingness	0.313	3.597	0.000	Supported
Task Technology Fit – Willingness	0.040	0.566	0.572	Supported

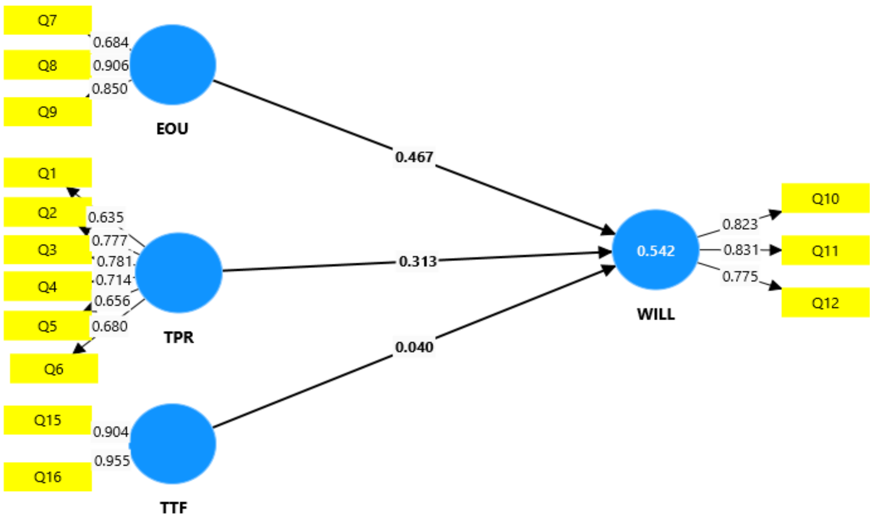

Figure 2. Path Model

V. CONCLUSION

This study provides significant insights into the complex variables that influence students' willingness to use AI to learn English within the Jordanian higher education context. The findings highlight the key importance of perceived ease of use as well as perceived time and psychological risks and their significant correlation with students' AI adoption intentions. Unexpectedly, the findings show no significant impact of task–technology fit. These practical insights can inform the strategies of technology developers, educators, and policymakers to ensure effective AI integration into English language. Such strategies need to prioritize user-friendly design and risk mitigation in order to cater to students. As AI-integrated education gains more ground, this research provides a solid foundation for evidence-based implementation. Future studies should experiment with combined approaches, include larger samples, and explore cross-cultural comparisons to further optimize AI's potential in language learning.

A. Findings and Implications

This study makes several significant contributions to the discourse on AI adoption in English language learning. By investigating the interplay of various variables that determine students' willingness to adopt AI technologies, this research contributes to the attempt to gain a comprehensive understanding of the complex dynamics at play. A key theoretical contribution is the integration of multifaceted aspects from the technology acceptance model (TAM), perceived risk theory, and the task–technology fit (TTF) model. Consistent with previous research, the findings demonstrate the applicability of TAM in educational contexts, as evidenced by the positive correlation between AI's ease of use and students' willingness to embrace it for learning. Moreover, incorporating time-related and psychological risks into the model further enriched our understanding of these factors and their role in promoting or impeding AI adoption. Likewise, the insignificant impact of TTF calls for a more nuanced investigation into the variables influencing AI adoption along with a deeper understanding of the precise impact of TTF.

In addition to its theoretical contributions, this study has significant practical implications. Firstly, the strong correlation between ease of use and students' willingness to use AI gives clear guidance to technology developers for fine-tuning their technologies and making them more accessible, user-friendly, and customized to the needs of English language learners. Similarly, students' perception of the potential time and psychological risks in using AI was proven to be of critical importance. Thus, educational institutions must prioritize addressing such risks. Potential solutions include introducing orientation programs and training, promoting AI literacy programs, and developing ongoing support mechanisms (Sun et al., 2022; Kumar, 2023; Sol et al., 2024). A smart gradual integration of AI platforms and tools that cater to the specific needs and skills of the students is also a plausible approach. Differentiated programs that address students' individual needs are also essential. An additional practical implication relates to policymakers in higher education, who rely on the effective integration of AI into English language learning in particular and education at large (Li & Gu, 2023; Sun et al., 2022; Kumar, 2023; Sol et al., 2024). This research-enlightened AI investment would effectively modernize education and ensure efficient achievement by addressing issues of accessibility, practicality, and data privacy as well as ethical and psychological considerations regarding AI use.

B. Limitations and Future Research

While this research provides several insightful contributions to the research topic, it has a few limitations that should be considered and addressed in future research. One limitation is the study's exclusive reliance on quantitative survey methodology. Future studies could benefit from taking an integrated combined approach by incorporating interviews, classroom observations, and/or focus group discussions. This methodological enrichment can capture a deeper understanding of the determinants of AI adoption. Additionally, although sufficiently representative, the study sample had a limited size of 130 students within the context of higher education in Jordan. Expanding the sample to include more students from various public and private institutions within Jordan and potentially other countries would enhance the generalizability of the findings. Performing a cross-cultural comparison could shed further light on the peculiarities of AI adoption in different contexts.

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