International Journal of Data and Network Science 8 (2024) 823–834

Contents lists available at GrowingScience

International Journal of Data and Network Science

homepage: www.GrowingScience.com/ijds

Artificial intelligence in Jordanian education: Assessing acceptance via perceived cybersecurity, novelty value, and perceived trust

Mazen Alzyoud[a*], Najah Al-Shanableh[a], Saleh Alomar[b], As'ad Mahmoud As'adAlnaser[c], Akram Mustafa[d], Ala'a Al-Momani[e] and Sulieman Ibraheem Shelash Al-Hawary[f]

[a]*Department of Computer Science, Faculty of Information Technology, Al al-Bayt University, Jordan*
[b]*Department of networks and cyber security, The Faculty of Science and Information Technology, Jadara University, Jordan*
[c]*Department of Applied Science, Ajloun University College, Al-Balqa Applied University, Ajloun, Jordan*
[d]*Department of Computer Science, Faculty of Information Technology, Al al-Bayt University, Jordan*
[e]*School of Management, Universiti Sains Malaysia, Malaysia*
[f]*Department of Business Administration, School of Business, Al al-Bayt University Mafraq, Jordan*

C H R O N I C L E

Article history:
Received: November 6, 2023
Received in revised format: November 24, 2023
Accepted: December 23, 2023
Available online: December 23, 2023

Keywords:
Artificial intelligence
Acceptance
Perceived cybersecurity
Novelty value
Perceived trust
AI device use acceptance
Students
Jordan

A B S T R A C T

The growing significance of Artificial Intelligence (AI) across different fields highlights the essential role of user acceptance, as the success of this technology largely depends on its adoption and practical use by individuals. This research aims to examine how perceived cybersecurity, novelty value, and perceived trust affect students' willingness to accept AI in educational settings. The study's theoretical basis is the AI Device Use Acceptance (AIDUA) model. Using structural equation modeling, the study tested hypothesized relationships using data from 526 students at Jordanian universities. The results showed that social influence is positively associated with performance expectancy, while perceived cybersecurity is positively related to both performance and effort expectancy. Novelty value is positively associated with performance expectancy but a negative one with effort expectancy. Additionally, effort and performance expectancy significantly influence perceived trust and the willingness to accept AI. Moreover, perceived trust has a notable positive effect on the willingness to accept AI in education. These findings provide valuable guidance for the creation and improvement of AI-driven educational systems in universities, contributing to the broader understanding of AI technology acceptance in the educational field.

1. Introduction

Recent developments in the fields of technology and digitization have had remarkable, positive effects in varied sectors (Timotheou et al., 2023). They proved to be vital not only for enhancement of differing aspects of business (Ala'a & Ramayah, 2023c) but also for improving performance of individuals and corporations (Ala'a & Ramayah, 2023b). They play a key role in reducing limitations of space and distance and overcoming gaps in time, which stresses their wide-ranging impact (Abu-Shanab et al., 2012a; Abu-Shanab et al., 2012b). On this account, educational systems are gradually incorporating these technologies in their operations, thus taking advantage of their distinctive features and benefits for better learning outcomes (Jarrah & Lahiani, 2021).

In general, artificial intelligence concentrates on building expert computational systems so as to learn from the environment and visualize adaptive and intelligent behavior (Hinojo-Lucena et al., 2019). It occupies an outstanding position in the technology sector and it has already attracted the attention of both the academic and business communities (Ala'a, 2023b). The advancements in AI technology and applications are transforming higher education and changing how the universities involve

* Corresponding author.
E-mail address: malzyoud@aabu.edu.jo (M. Alzyoud)

ISSN 2561-8156 (Online) - ISSN 2561-8148 (Print)

doi: 10.5267/j.ijdns.2023.12.022

the students and support their employees (Sharma et al., 2022a). Wang et al. (2021) highlighted four remarkable advantages of the AI in this context, which are (i) enhancement of the organizational efficiency by analyzing data drawn from various campus systems for decision making; (ii) provision of customized academic tutoring for students; (ii) helping the instructors by providing resources for struggling students; and (iv) provision of individualized support for students throughout the registration process. Moreover, Zawacki-Richter et al. (2019) underlined four major elements of AI that particularly fit to the educational setting, namely, intelligent tutoring systems for collaborative learning, adaptive systems and customization for teaching and learning, assessment tools for grading and feedback, and prediction means for academic decision making.

Viability of utilization of AI in education is not only conditioned upon the technology itself but equally importantly on the user's willingness and readiness to accept and use it (Algerafi et al., 2023). In fact, incorporation of the AI into university programs has high potential to affect student's learning and continual growth positively and thoroughly (Bates et al., 2020). In compliance with the economic trends and changing lifestyles, it is necessary for the universities worldwide to prepare their students and equip them with the necessary tools to keep up with those changes (Algerafi et al., 2023). Artificial intelligence and robotics stand at the front line of the educational conversion, restructuring the basic structure of the higher education systems and institutions and roles of the researchers and teachers (Zhang et al., 2020). However, despite the advancements in technology, there has not been a marked improvement in the existing educational methods (Roy et al., 2022). Consequently, there is currently a bad need for educational strategies that integrate diverse technologies into the educational operations to prioritize student's acquisition of knowledge and skills and performance enhancement (Waris & Hameed, 2023).

As Fig. 1 shows, Jordan ranked the 19th out of 131 countries globally and 4th out of 11 Arab countries in terms of Information and Communication Technology (ICT) skills of individuals in the education systems (Network Readiness Index, 2022). This ranking demonstrates Jordan's strong emphasis on integration of ICT skills in its educational sector. Indeed, the notable position of Jordan in ICT integration among Arab countries underscores its distinguished regional presence in this domain. At the Arab country level, ranking fourth suggests that Jordan has made substantial investments in developing ICT expertise within its educational framework, which is a crucial action and step in the contemporary digital age. Furthermore, ranking 59th globally in the adoption of emerging technologies, according to the same index, reflects the active engagement of Jordan in new technology and its adaptation to it. This adaptability is highly vital in an era characterized by rapid technological advancements that extensively influence all sectors, especially the educational one.

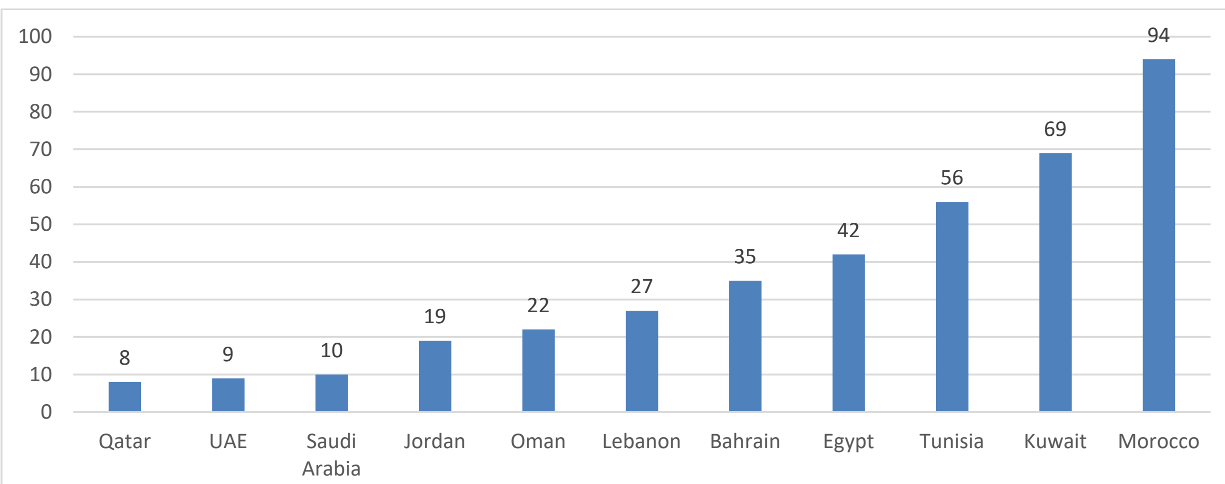

Fig. 1. Ranking of Jordan among Arab countries (Network Readiness Index, 2022)

1.1 Research Gap

Research into adoption of AI in education started appearing in indexed journals in around 1975. Currently, the Scopus database, as one example, lists 3,580 articles that include AI adoption in education in their titles. As Fig. 2 illustrates, there has been a surge in studies focusing on AI acceptance in education, particularly in the past three years. Bibliometric analysis using VOSviewer reveals that the most common keywords in these articles are 'artificial intelligence' (frequency (f) = 1,122), 'artificial intelligence in education' (f = 52), 'cybersecurity' (f = 13), and 'trust' (f = 12). Fig. 3 depicts prevalence of these keywords in a World Cloud form. Nonetheless, a review of the literature unfolded that the AI Device Use Acceptance (AIDUA) framework (Gursoy et al., 2019), which is an essential framework for evaluation of acceptance of AI, is seldom employed in assessment of user's willingness to adopt AI in educational contexts. One recent study which adopted this framework is that of Gerlich (2023), which involved 1,389 users from business schools in the United States, United Kingdom, Germany, and Switzerland. It provided a detailed view on diverse aspects of AI from the standpoints of university students and faculty members using the AIDUA framework. In addition, there is a lack of studies combining key technology adoption factors like perceived cybersecurity (PC), novelty value (NV), and perceived trust (PT) in the AIDUA framework in educational settings. The literature review also uncovered that AI acceptance in education in Jordan has received limited attention and that few local studies looked into this research theme. One such study is that of Bani Ahmad et al. (2023), who explored the extent to which faculty members in Jordanian universities are receptive to use of digital tools in teaching. However, these researchers performed their inquiry based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model of Venkatesh et al. (2003). Thereupon, this study incorporates the PC, NV, and PT into the AIDUA framework to investigate willingness of Jordanian university students to accept AI in the educational setting in Jordan.

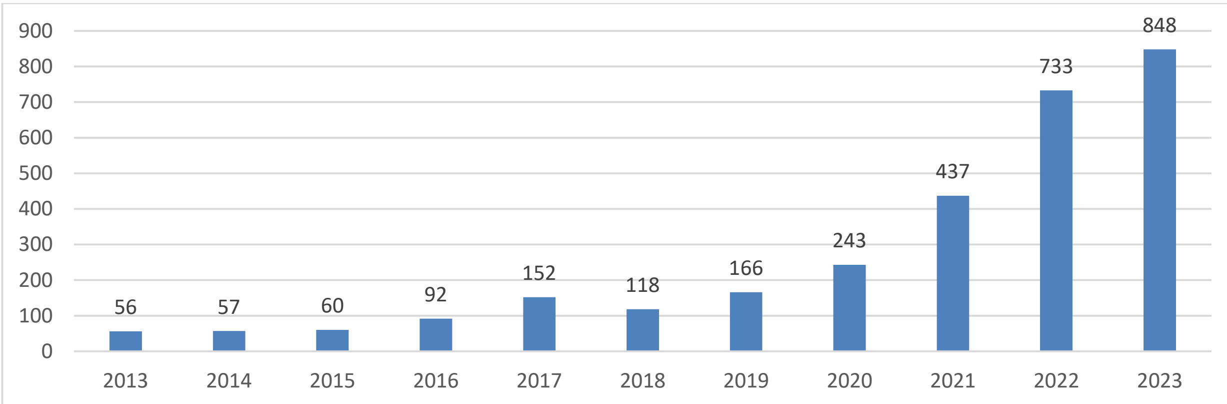

Fig. 2. Number of articles published from 2013 to November 2023 (Scopus database)

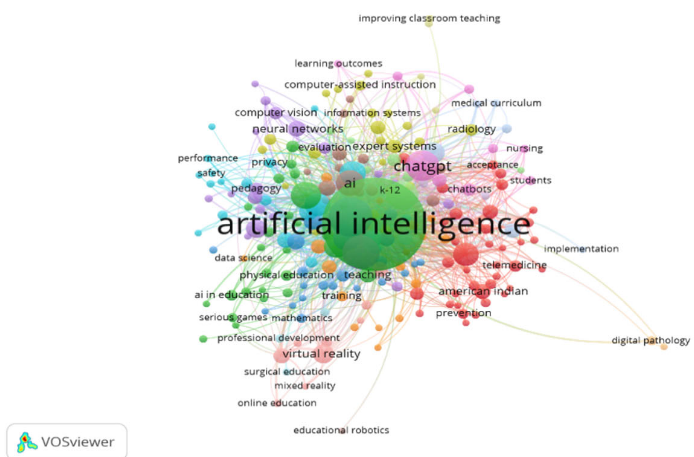

Fig. 3. The most used keywords

2. Theoretical Background and Hypotheses

Considering the distinctive characteristics of the AI technologies like the human-like intelligence, which characterizes them from the traditional technologies, the existent technology acceptance models are usually inadequate for fully capturing the attitudes of the users to AI (Gursoy et al., 2019; Ma & Huo, 2023). For addressing this research gap, Gursoy et al. (2019) suggested the AIDUA framework, which delves into the AI acceptance decision-making process in three phases (Fig. 4). In this framework, emotions are notably emphasized as prime drivers of adoption of the AI service devices, which implies that the behavioral intentions relating to those devices are affected predominantly by emotional factors. But this framework does not account for specific factors that are quite vital in certain environments. Besides, Aaccording to Straub et al. (1997), the technology acceptance frameworks cannot be applied universally across all contexts, which necessitates tailoring those frameworks to the distinct context of every country of interest (Ala'a & Ramayah, 2023a). For example, the high uncertainty avoidance characteristic of the Jordanian population (Hofstede-insights, 2023; Hofstede et al., 2010) influences how people, including students, perceive emerging technologies like AI and engage in them as depicted in Fig. 5. In such a setting, factors like PC and PT may be critical for technology acceptance. Furthermore, in cultures that value achievement and success, individuals are often driven to excel and embrace new opportunities that enhance their skills and status (Hofstede-insights, 2023; Hofstede et al., 2010). Thus, the novel aspect of incorporation of AI in education, which is characterized by its novelty, creativity, and potential to provide superior educational experiences, aligns well with these cultural values in Jordan. Students in this environment may view AI as a tool for achieving academic success. Fig. 6 presents the proposed research model which encompasses these considerations and associated factors.

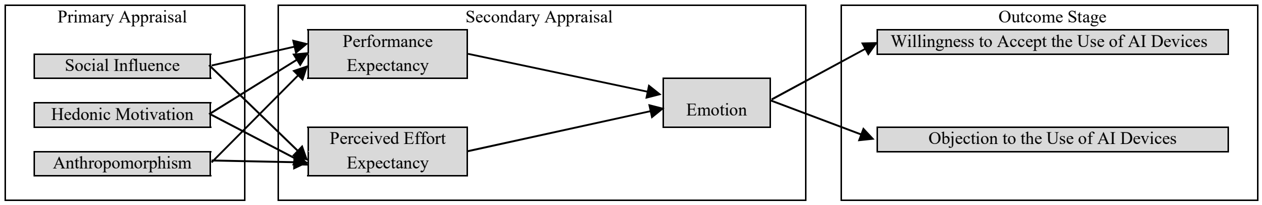

Fig. 4. The AIDUA framework (Gursoy et al., 2019)

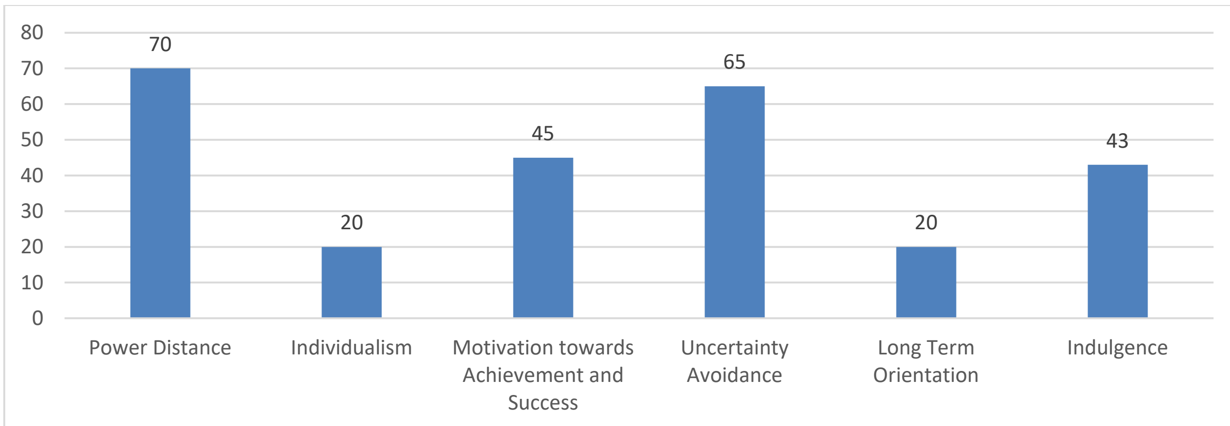

Fig. 5. Hofstede's Jordanian Traits (Hofstede-insights, 2023)

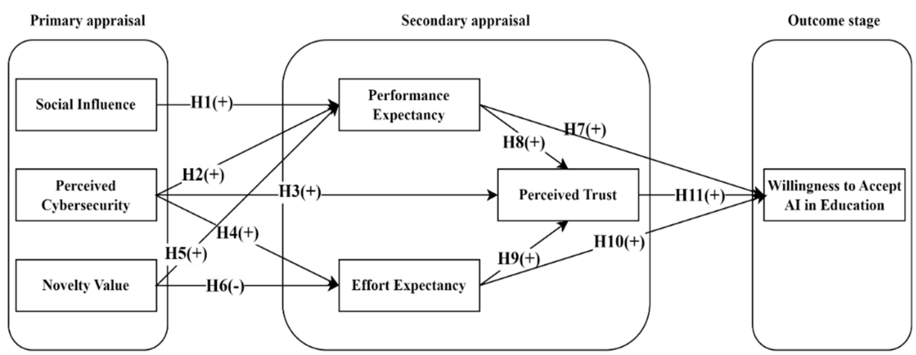

Fig. 6. Research model

2.1 Social Influence

Social influence (SI) is defined as the degree to which individuals believe that important people in their lives think that they should adopt new technology (Venkatesh et al., 2003). Im et al. (2011) found that SI is of great importance in countries characterized by high levels of power distance and collectivist cultural values. In a community known for its collectivist nature and high power distance such as the Jordanian community, people's decisions to accept technology are likely influenced by opinions of others in their close social group.

H$_1$: *Social influence has a positive impact on performance expectancy.*

2.2 Perceived Cybersecurity

Perceived cybersecurity (PC) indicates how the individuals assess effectiveness of the security measures of a website (Shah et al., 2014). It plays a particularly critical role in a country like Jordan, whose community is characterized by high level of uncertainty avoidance (Ala'a & Ramayah, 2023a). Lee and Pan (2023) reported that perceived security has significant positive effects on PE and EE. Furthermore, in communities exhibiting high levels of uncertainty avoidance, trust in the technology is a remarkably crucial factor for its adoption (Ala'a & Ramayah, 2023a). The extent to which the Jordanian students trust the ability of the AI system to perform the tasks accurately and reliably while precluding unanticipated negative outcomes is probably of high importance for their acceptance of technology. The studies of Ala'a and Ramayah (2023a) and Kumar et al. (2022) pinpointed that perceived security reinforces PT directly. On account of this, the following three hypotheses were proposed:

H$_2$: *Perceived cybersecurity has a positive impact on performance expectancy.*

H$_3$: *Perceived cybersecurity has a positive impact on perceived trust.*

H$_4$: *Perceived cybersecurity has a positive impact on effort expectancy.*

2.3 Novelty Value

Recently, the novelty value (NV) has been recognized as an influential factor for adoption of technology (Ma & Huo, 2023). It is a metric that assesses how originality and newness of a product contribute to perceived distinctiveness of it (Im et al., 2015). When the users realize that the technology is novel, they usually find the process of task completion much enjoyable (Adapa et al., 2020), which positively influences enjoyment and the practical utility of using it (Karjaluoto et al., 2019). AI is novel and its use in the educational setting is a novel utilization of its capabilities in new, vital, ever-growing domain. It enables the students to accomplish their learning tasks in an enjoyable way (Luqman et al., 2017). This is quite important owing to that enjoyment can reduce the psychological resistance to the new technologies (Xie et al., 2022). In this respect, Ma and Huo (2023) found that NV does positively affect EE and that it has negative effect on the EE. Hence, the sequent two hypotheses were posited:

H$_5$: *Novelty value (NV) has significant positive effect on the performance expectancy (PE).*

H$_6$: *Novelty value (NV) has significant positive effect on the effort expectancy (EE).*

2.4. Performance Expectancy (PE)

Performance expectancy (PE) may be defined as the extent to which artificial intelligence utilization in the educational context makes a practical benefit for the students (Ala'a, 2023a, 2023b). Willingness the artificial intelligence adoption is linked with PE (Pande & Gupta, 2023; Zhang et al., 2021; Bedaf et al., 2019), which highlights the fundamental role of PE in the user's acceptance of technology. Based on this, the subsequent two hypotheses were formulated:

H$_7$: *Performance expectancy (PE) has a significant positive effect on the perceived trust (PT).*

H$_8$: *Performance expectancy (PE) has a significant positive effect on the willingness to accept AI.*

2.5. Effort Expectancy (EE)

Effort expectancy was defined as the perceived level of the effort which is needed for the technology utilization (Venkatesh et al., 2003; Sharma et al., 2022b). Effort expectancy may be related to the user's perception of ease of interacting with the AI to be used in differing tasks (Ma & Huo, 2023). Pande and Gupta (2023) found no positive effect of EE on PT in AI. Trust has a positive relationship with ease of use (Chang et al. ,2017; Zheng et al.,2012). EE significantly affects the user's willingness to new technologies adoption (Ma & Huo, 2023). Accordingly, the following two hypotheses were proposed:

H$_9$: *Effort expectancy has a positive impact on perceived trust.*

H$_{10}$: *Effort expectancy has a positive impact on willingness to accept AI.*

2.6 Perceived Trust

Perceived trust (PT) has been defined as the user's belief in adoption of new technology (Khazaei, 2020). It is a pivotal theme in technology adoption research. In effect, this trust is focal, both in adoption of the new technology and in overcoming the challenges it presents (Pande & Gupta, 2023). A number of studies in varied fields identified trust as an essential factor in one's acceptance of the AI (Ala'a, 2023a, 2023b). Chi et al. (2021) stressed that the user's trust in robots, which is a subset of the AI technologies, depends significantly upon reliability of their designs and functionality. Many studies (e.g., Pande & Gupta (2023), Seo & Lee (2021), and Weitz et al. (2019)) asserted that trust remains a crucial factor in willingness to accept AI. Bearing these findings in mind, the researcher hypothesized what follows:

H$_{11}$: *Perceived trust has a positive impact on willingness to accept AI.*

3. Method

3.1. Participants

In this cross-sectional, quantitative study, the random sampling method was employed as suggested by Zaman and Bulut (2023). The sample consisted of 680 students in universities in and around the capital, Amman, who agreed to participate in this study. Of the 680 questionnaire forms distributed, exactly 580 filled forms were received. Fifty-four forms of which were found to be unsuitable for statistical analysis and, thereupon, were excluded. Thus, the valid sample comprised 526 students. This number corresponds to a response rate of 77.3%.

Analysis of the demographic profile of the respondents revealed that 40.8% of them were males and 59.2% were females and that 85.2% of sample students were undergraduate students while the rest 14.8% were postgraduates. The majority of the respondents (67.9%) were enrolled in the two faculties of arts and social sciences whereas the remainder 32.1% were students in scientific colleges. Regarding prior experience with AI, this study found that 71.8% of the students had previous exposure to AI, while 28.2% had not experienced AI any earlier. Furthermore, nearly 44.9% of the students reported high levels of technology proficiency whilst 28.9% others reported low levels and 26.2% reported moderate levels of technology proficiency.

3.2 Measures

In this study, the data collection tool was a self-administered questionnaire. Its construction was guided by an extensive literature review. It was initially written in English and then, translated into Arabic to ensure participants' understanding of the questionnaire items and warrant accurate responses. The data collection period extended from September 18 to November 12, 2023. Scoring of respondent's level of agreement on the questionnaire items was based on a five-point Likert scale, extending from 1, which corresponds to strong disagreement, to 5, which denotes strong agreement.

3.3 Analytical Approach

The study initiates with an extensive descriptive analysis, where the investigation of means, standard deviations, and correlations helps establish initial patterns in the dataset (Barrientos-Báez et al., 2022; Pallathadka et al., 2023; Rahamneh et al., 2023).

Table 1
Confirmatory factor analysis of the questionnaire.

Constructs	Factors	Loadings	AVE	MSV	AVE	CR
Social Influence	SI1	0.752	0.538	0.274	0.733	0.777
	SI2	0.711				
	SI3	0.736				
Perceived Cybersecurity	PC1	0.701	0.560	0.311	0.748	0.792
	PC2	0.793				
	PC3	0.748				
Novelty Value	NV1	0.581	0.520	0.309	0.721	0.866
	NV2	0.764				
	NV3	0.670				
	NV4	0.771				
	NV5	0.797				
	NV6	0.722				
Performance Expectancy	PE1	0.803	0.551	0.382	0.742	0.830
	PE2	0.681				
	PE3	0.713				
	PE4	0.766				
Effort Expectancy	EE1	0.781	0.563	0.415	0.750	0.837
	EE2	0.755				
	EE3	0.720				
	EE4	0.743				
Perceived Trust	PT1	0.662	0.554	0.392	0.745	0.832
	PT2	0.814				
	PT3	0.735				
	PT4	0.759				
Willingness to Accept AI	WA1	0.825	0.650	0.503	0.807	0.848
	WA2	0.811				
	WA3	0.783				

The correlation matrix (Table 1) points out significant relations among the research variables, thus supporting the theoretical framework of this study (Fig. 6). Most of the variables have positive mutual associations. Though, some variables, e.g., EE and NV, have negative associations. On the other hand, the coefficients of correlations among the variables were all below 0.90, which is the threshold of multicollinearity (Eleimat et al., 2023; Kim et al., 2009; Kim, 2019; Mohammad et al., 2022). This supports that the study variables do not have the problem of multicollinearity.

Owing to the effectiveness of structural equation modeling (SEM) as a comprehensive statistical method for analyzing interactions between independent and dependent variables (Hoyle, 1995 as cited in Ala'a, 2022), it is employed in this research. Following the guidelines of Kline (2023), SEM, facilitated by AMOS software, is used to explore the relationships between different constructs, with a particular focus on path coefficients and model fit indices.

4. Results

4.1 Measurement Model

In addition to outcomes of correlation analysis, Table 1 gives the means and standard deviations of the main study variables. Students' willingness to accept AI had the highest mean score of 3.81. This indicates their strong inclination towards acceptance of AI in the educational process. This variable was followed by PT, which ranked next with a mean score of 3.75, and PE, which had a mean score of 3.68. These mean scores echo high levels of agreement. On the other hand, the other variables received moderate levels of agreement that decreased in the following order: the PC (M = 3.63), the EE (M = 3.62), the NV (M = 3.57), and SI (M = 3.51). The standard deviations, which ranged from 0.802 to 0.925, are somewhat acceptable, being all less than 1. They reflect consensus among the respondents on these variables.

4.2 Descriptive Statistics

The descriptive statistics in Table 2 present a detailed view of respondents' perceptions regarding various constructs related to AI acceptance. The willingness to accept AI recorded the highest mean score of 3.81, indicating a strong inclination among respondents towards AI acceptance. This is closely followed by perceived trust (M= 3.75) and performance expectancy (M= 3.68), which also show high levels. In contrast, the other variables displayed moderate levels: perceived cybersecurity (M= 3.63) was fourth, then effort expectancy (M= 3.62), novelty value (M= 3.57), and social influence (M= 3.51). The standard deviations, ranging from 0.802 to 0.925, demonstrate a consistent consensus among respondents on these variables, as they are all below 1.

Table 2 provides information on the directions and strengths of the relationships among the latent constructs and their indicators. It was found that the factor loadings fell in the range of 0.581-0.825. These values exceed the minimal acceptable limit of 0.50 (Alshawabkeh et al., 2022; McNeish & Wolf, 2023), hence indicating strong validity. The values of Average Variance Extracted (AVE), which is a fundamental measure of convergent validity, ranged from 0.520 to 0.650. They surpass the standard threshold of 0.5. This suggests that most of the variance in every construct is due to its underlying factors. This finding confirms the convergent validity of the measurement model (Muda et al., 2022; Shamaileh et al., 2023; Sujati et al., 2020). Regarding the discriminant validity, the Square Root of AVE and Maximum Shared Variance (MSV) were analyzed. The values of the MSV lied in the range of 0.274-0.503, which indicates low variance shared between the constructs and confirms the discriminant validity of the model (Bader et al., 2022; Dwijendra et al., 2023; Rönkkö & Cho, 2022). Square root values of AVE come between 0.721 and 0.807 which exceed the coefficients of correlations value which supports distinctiveness of each of these constructs (Afthanorhan et al., 2021; Hijjawi et al., 2023). Lastly, values of the Composite Reliability (CR) ranged from 0.777 to 0.866. They surpass the recommended threshold of 0.7, therefore confirming reliability of this measurement model (Sahoo, 2019).

Table 2
Means, standard deviations, and correlations among variables.

Constructs	M	SD	SI	PC	NV	PE	EE	PT	WA
Social Influence	3.51	0.802	1						
Perceived Cybersecurity	3.63	0.872	0.385**	1					
Novelty Value	3.57	0.825	0.415**	0.502**	1				
Performance Expectancy	3.68	0.915	0.296*	0.312**	0.468**	1			
Effort Expectancy	3.62	0.911	0.362**	0.457**	-0.332**	0.402**	1		
Perceived Trust	3.75	0.903	0.241*	0.256*	0.225*	0.295*	0.395**	1	
Willingness to Accept AI	3.81	0.925	0.462**	0.492**	0.503**	0.241*	0.434**	0.524**	1

Note: * refers to a significant level less than 0.05, ** refers to a significant level less than 0.01.

4.3 Structural Model

As can be seen in Fig. 7, the values of the goodness-of-fit indices support a good model fit. The Cmin/df ratio is 2.845, which indicates a good fit according to the chi-square statistic relative to the degrees of freedom as it is below 3 (Cho et al., 2020). The values of the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) are 0.917 and 0.902, respectively. Both exceed the 0.90 reference value, thus supporting a satisfactory fit compared to a baseline model (Xia & Yang, 2019). Furthermore, the Root Mean Square Error of Approximation (RMSEA) is less than 0.08. This signifies a reasonably good fit for the structural model (Ximénez et al., 2022). Overall, the research model has a good fit as evidenced by the values of these indices.

Table 3 lists the structural equation path coefficients, which shed light on the relationships among the latent constructs in the research model. Performance expectancy was found to be significantly influenced by SI (B = 0.454, *Beta* = 0.438, $p < 0.001$), perceived cybersecurity (B = 0.267, *Beta* = 0.252, $p < 0.01$), and NV (B = 0.233, *Beta* = 0.219, $p < 0.05$). Effort Expectancy is positively impacted by PC (*B* = 0.305, *Beta* = 0.292, $p < 0.001$). On the other hand, the NV has a negative effect on EE (*B* = -0.352, *Beta* = -0.312, $p < 0.001$). Additionally, perceived trust is positively influenced by PC (*B* = 0.411, *Beta* = 0.408, $p < 0.001$), performance expectancy (*B* = 0.340, *Beta* = 0.325, $p < 0.01$), and EE (*B* = 0.255, *Beta* = 0.218, $p < 0.05$). Lastly, the willingness to Accept AI is positively affected by PE (*B* = 0.395, *Beta* = 0.388, $p < 0.001$), effort expectancy (*B* = 0.362, *Beta* = 0.341, $p < 0.001$), and PT (*B* = 0.488, *Beta* = 0.472, $p < 0.001$).

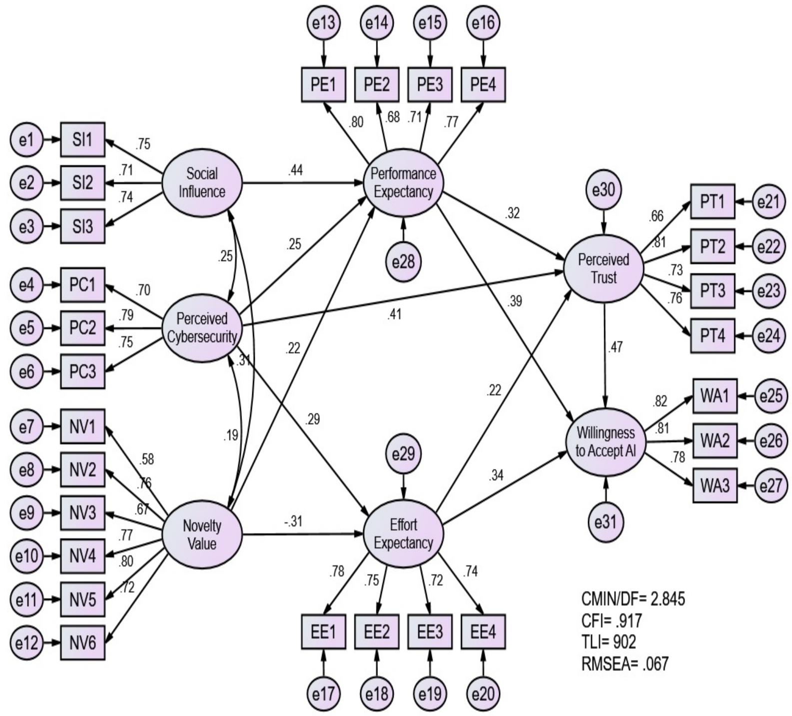

Fig. 7. Full model SEM including goodness of fit indices

Table 3
Structural equation path coefficients among variables.

			Unstandardized	Standardized	S.E.	T
			B	Beta		
Social Influence	→	Performance Expectancy	0.454	0.438	0.066	6.878***
Perceived Cybersecurity	→	Performance Expectancy	0.267	0.252	0.061	4.377**
Novelty Value	→	Performance Expectancy	0.233	0.219	0.068	3.426*
Perceived Cybersecurity	→	Effort Expectancy	0.305	0.292	0.066	4.621**
Novelty Value	→	Effort Expectancy	-0.352	-0.312	0.062	5.677***
Perceived Cybersecurity	→	Perceived Trust	0.411	0.408	0.059	6.966***
Performance Expectancy	→	Perceived Trust	0.340	0.325	0.072	4.722**
Effort Expectancy	→	Perceived Trust	0.255	0.218	0.074	3.445*
Performance Expectancy	→	Willingness to Accept AI	0.395	0.388	0.069	5.724**
Effort Expectancy	→	Willingness to Accept AI	0.362	0.341	0.073	4.958**
Perceived Trust	→	Willingness to Accept AI	0.488	0.472	0.075	6.506***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5. Discussion and Conclusion

5.1 Research Implications

Adapting the AIDUA model of Gursoy et al. (2019) to encompass the constructs of PC, NV, and PT, especially considering the Jordanian cultural characteristics outlined by Hofstede's cultural dimensions, provided compelling theoretical insights. The characteristic strong inclination towards uncertainty avoidance in the Jordanian culture results in preference for security. This underlines the vital roles of the PC and PT in adoption of AI technologies. This finding suggests that a focus on robust cybersecurity measures in the AI devices and applications has high potential to substantially boost technology acceptance and adoption by probable users in Jordan. Furthermore, the NV of integration of AI into education aligns with the Jordanian students' emphasis on achievement and success, which is an emphasis that was spotlighted by Hofstede's dimensions. In a culture that values these traits (that is, achievement and success) like the Jordanian one, innovations and advancements, which are inherent in the AI, are seen as essential tools for enhancement of performance and efficiency. Thus, in the context of the educational setting in Jordan, the novelty value of incorporation of AI into education is not just about the technology itself but also about its potential to embody the traits of achievement and success and promote them. Accordingly, incorporating these elements into the AIDUA framework created a culturally-informed perspective on AI acceptance in Jordan.

5.2 Practical Implications

This study unclosed the key factors that affect students' acceptance of AI in the educational setting in Jordanian universities. Furthermore, the study determined new factors that affect this acceptance, namely, perceived cybersecurity, novelty value, and perceived trust. These three factors proved to be influential in shaping the Jordanian students' willingness to accept AI in their educational institutions. This conclusion was drawn from a survey that engaged 526 university students with diverse educational backgrounds in Jordan. Artificial intelligence developers can utilize these findings to craft AI solutions that are more effectively tailored to higher education institutions. In the educational context, the findings can inform strategic planning which ensures that designs align with the students' needs and perceptions. In addition, the results of this study provide valuable guidance for the administrations of higher education institutions for strategizing successful AI integration in their institutions. In consequence, these results have notable implications, both for the university administrations and their student communities. The results of this investigation suggest that the model presented in this paper will contribute to facilitation of future adoption of AI in education which particularly benefits those users who are quite eager for incorporation of AI into their educational experience.

5.3 Limitations and Future Directions

The researcher underscores a number of limitations that should be tackled in future research. Firstly, this study focused primarily on the university education setting in Jordan. This may limit generalizability of its findings to other cultural and educational contexts. Future studies can widen their scopes to encircle multiple countries or regions. Secondly, even though the AIDUA framework is reasonably comprehensive, it may not fully address factors that are especially relevant for distinct educational environments. Consequently, incorporating other factors into the AIDUA framework (e.g., certain educational policies, infrastructural variables, and pedagogical requirements) can broaden its applicability and increase its effectiveness in evaluation of acceptance of technology, in general, and AI, in specific. Thirdly, while this study acknowledged cultural factors such as achievement orientation and uncertainty avoidance in Jordan, there may be other cultural variables that affect AI adoption which were not covered in this study. Future research can delve into further cultural factors.

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