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International Journal of Data and Network Science

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Artificial intelligence-based chatbots adoption among higher education institutions by integrating with UTAUT2

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C H R O N I C L E

Article history:
Received: April 3, 2024
Received in revised format: May 28, 2024
Accepted: June 24, 2024
Available online: June 24, 2024

Keywords:
Chatbots
UTAUT2
Hedonic motivation
Habit
Artificial Intelligence

A B S T R A C T

Despite certain advancements, the incorporation of artificial intelligence in universities is still inadequate. The requirement for students will continue for a while, although the development of artificial intelligence-based chatbots in schools has limited the role of students. The research aimed to assess the willingness of Jordanian learners in higher education to use artificial intelligence-powered chatbots for instructional purposes. The present research suggests nine hypotheses derived from the UTAUT2 model to assess students' desire to use artificial intelligence-based chatbots in learning. The pupils' information was gathered and examined using PLS-SEM. The research results showed that nine hypotheses were confirmed. The outcomes indicate that learners are interested in adopting artificial intelligence-based chatbots into their studies. The research's findings will supply administrators at higher education with valuable insights into the effectiveness of artificial intelligence-based chatbots in learning. Moreover, the findings will help developers of artificial intelligence-based chatbots, higher learning administrators, and legislators execute artificial intelligence-based chatbots that fulfil modern educational requirements.

1. Introduction

The significant impacts of advancements in the century continue to shape today's society. Artificial intelligence is aimed at developing computer systems that can learn from their surroundings and demonstrate adaptable behaviors. The evolution of technology has brought about transformations in communication, healthcare practices and information access. In the realm of education there is a growing emphasis on implementing Artificial Intelligence Based Chatbots (AIBC) solutions like learning environments, intelligent tutoring systems and instructional robots driven by AI. These systems strive to emulate the effectiveness of tutoring offering tailored learning experiences to enhance user learning quality and cater to students' social needs. AIBC stands out for its autonomy, flexibility and interactive nature. Through intelligence techniques educational institutions can. Analyze learners behavioral and psychological data linking them with knowledge networks. These approaches enable the adaptation and customization of learning programs based on learners' interactions and feedback rather than rigidly following pre established expert strategies. The future success of AIBC in settings hinges on advancements in technology as well as user reception. Introducing Artificial Intelligence and Blockchain Computing (AIBC) in schools could potentially influence students' learning and personal development over the years according to research, by Sajjad et al. (2023). Higher education institutions need to adjust to the shifting landscape and evolving trends to prepare individuals for success, in this modern era as suggested by Roy et al. (2022). AIBC has the potential to transform education by making substantial changes to the learning process, the responsibilities of educators and researchers, and the entire operations of universities as establishments (Yang et al., 2022). Scholars have shown that despite technical progress, there has been no discernible improvement in present educational practices (Chen et al., 2022). An instructional approach that incorporates various technology tools should be used to improve learners' performance. Learners must be alert to changes and embrace new tools to promote active and collaborative

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

doi: 10.5267/j.ijdns.2024.6.017

learning among student instructors. China's education system has seen significant growth throughout the years. An urgent and significant overhaul is needed in the students, teaching-learning environment, and administrative duties within the higher education system in Jordan. Modern educational environments need several elements to integrate problem-based learning based on real-world intricacies. The artificial intelligence robot business is developing significantly because of the increasing demand for smartphones and the rising use of messaging apps in the era of artificial intelligence (Oliver & Christina, 2021). Nowadays, robot technology has been used in several sectors, such as food delivery, financial services, e-commerce, and others. Utilising AIBC technology might provide significant advantages to the field of education, positioning it as one of the businesses with guaranteed growth. Researchers have contended that creating AIBCs for teaching has several benefits. Intelligent systems may enhance teaching and learning efficiency, increase productivity, improve communication, and reduce ambiguity in interactions. An innovative educational system effectively tackles pressing difficulties in education by using AIBC technology as an interactive tool. Pillai & Sivathanu (2020) said that AIBC in education enhances the student-learning experience. Adam et al. (2020) assumed that using AIBC in the education sector improved human welfare policy, teaching, and research. Al-Sharafi et al. (2022) researched the use of AIBC in higher education. The effective application of AIBC will significantly help authorities promote its use in higher education. Lee et al. (2021) researched 131 elementary pupils to analyse the elements affecting their desire to engage in AIBC learning. The research showed that the primary element influencing students' behavioural intentions is the learning aim of AIBC for social benefit. There are few studies in the available literature that investigate students' willingness to adopt AIBC in the field of education. Understanding the adoption of AIBC from the students' viewpoint is crucial (Mohammed et al., 2023; Yang et al., 2022). The aim of this research is to explore the elements that impact students' adoption of AIBC at higher education institutions in Jordan, focusing on behavioural intention and use behaviour. The paper clarifies the choice of the UTAUT2 model, underpinning our measurement in terms of both constructs and items. We extend it by adding the constructs of perceived trust and personal innovativeness, which are established in the research corpus. We anticipate useful insights into the adoption of AIBC in education by students in the present research. The results of this study should help in advancing AIBC and in aiding the administrators of universities in their efforts to integrate and make use of AIBC in higher education institutions.

2. Literature Review

Adoption of AIBC among university students was explored via the UTAUT2 model in this research. UTAUT2 is known for its strong explanative power as Ma et al. (2017) and Gatzioufa and Saprikis (2022) pointed out making it the popular adoption model. UTAUT2 is an extension of the original UTAUT by Venkatesh, Thong, & Xu (2012); the UTAUT model explains usage behaviors by “performance expectancy, effort expectancy, social influence, and facilitating conditions” (Venkatesh, Thong, & Xu, 2012, p. 20). These four components are valuable for understanding and assessing the purpose of using technology inside organizations, as stated by Venkatesh, Thong, & Xu (2003). Performance expectancy is the confidence in how much technology can improve performance. Effort expectancy assesses the ease of use of technology. Social influence is whether social elements impact technology use. Facilitating circumstances assesses the presence of the resources and support needed to adopt technology (Venkatesh, Thong, & Xu, 2003). UTAUT2 ventured out of an organizational setting by Venkatesh, Thong, & Xu (2012) by adding three additional variables—“hedonic motivation, price value, and habit” to better its explanatory ability. Hedonic motivation is one’s excitement to use the technology out of pleasure gained from it by utilization. Price value is the worth vs. effort one out forth into usage of the technology. As described by Venkatesh et al. (2012) habit is the use of technology. The UTAUT is a good model for an organizational setting; however, the UTAUT2 is not as biased and can be used in many settings (Venkatesh, Thong, & Xu, 2012). UTAUT2 has proven to be more effective than UTAUT in explaining the differences in people’s willingness to use technology as indicated by Dwivedi et al. (2019). This study applied UTAUT2 to identify the factors influencing students’ interest in utilizing AIBC. By focusing on AIBC without considering pricing but emphasizing learning value instead as explored by Chu et al. (2022). The application of UTAUT2 has shed light on how students engage with technologies like e-learning, the metaverse and augmented reality in an environment demonstrating its strong explanatory power. According to studies by Sitar & Mican (2021) and Lin et al. (2023) individuals exhibit behaviors influenced by factors. Personal innovativeness emerges as affecting individual differences in embracing new technologies according to Tewari et al. (2023) and Senali et al. (2023). It is proposed that human innovativeness can moderate the impact of characteristics on AIBC adoption outcomes. Research findings indicate that the accuracy of information significantly influences chatbot usage patterns based on Zhao et al.’s study (2021). Factors such as innovativeness and perceived trust are believed to shape individuals’ motivations for adopting AIBC. The willingness to try out ideas and the level of trust perceived play a role in offsetting the effects of factors that affect the adoption of AIBC.

2.1 Performance Expectancy

The current study defines performance expectations as users' perceptions of how a chatbot can provide answers, according to existing research. Zwain (2019) found that performance expectations have evolved over time. Performance expectations were examined as a factor influencing people’s confidence in using technology to improve their results while engaging with the technology. The authors discovered that performance expectations are tied to users’ emotions when seeking precise answers from a chatbot. Venkatesh initially introduced the concept of performance expectations from the UTAUT2 framework (Chu et al., 2022). The authors validated the idea that performance expectations influence university students’ likelihood of using chatbots. The authors of reference 24 used a UTAUT2 model to determine users' perceptions of chatbot usage in customer relationship management (CRM) adoption within the higher education setting. The study revealed that the performance expectation of the construct had a substantial impact on students' behavioral intention to utilize chatbot technology. The writers of references 24 and 25 agreed that this indicator should center on the user's view of technology adoption throughout the community. Thus, the following theory is proposed:

H$_1$: *Performance expectancy has a significant influence on the use of AIBC in higher education.*

2.2 Effort Expectancy

Effort expectation is the user's desire to use a chatbot easily or the ease of use associated with using a chatbot, as per prior studies. Effort expectations and related hidden factors have been shown in several studies to strongly predict a user's readiness to adopt new technology. According to Zacharis and Nikolopoulou (2022), there is a positive correlation between the level of effort required and university students' propensity to use chatbots in the future. Khoshkam & Mirzaei (2023) defined effort expectation as the user's impression of the ease of use of a technological platform or the anticipated effort needed to utilize it. The research's premise indicated that users' attitudes towards technology are favorably impacted by the technological platform's expectations of effort. This research examines how effort expectation influences students' adoption of a chatbot by assessing predicted performance and effort, which are significant considerations. Thus, the following theory is proposed:

H$_2$: *Effort expectancy has a significant influence on the use of AIBC in higher education.*

2.3 Social Influence

Research has shown that the social influence component affects conduct. Social influence is the extent to which a person believes that influential people think they should utilize technology. Social impact has been identified as a crucial determinant of a user's intention to embrace a certain technology in several studies (Al-Sharafi et al., 2022). Research conducted by Tewari et al. (2023) shows that social influence affects learners' inclination to use chatbots in a favorable manner. This study shows that this case has a clear influence on the learner's inclination to use a chatbot for engaging with university activities. Students who are positively reinforced regarding employing a chatbot demonstrate increased commitment to utilizing it regularly, as shown by the findings. Consistent with the prior research, we propose that social influence motivates the learners to use a chatbot in a favorable manner. Thus, the following theory is proposed:

H$_3$: *Social influence has a significant influence on the use of AIBC in higher education.*

2.4 Facilitating Conditions

Facilitating conditions refer to an individual's perception of the presence of organizational and technological assistance for using a system. The authors of reference 42 said that enabling circumstances pertain to an individual's confidence in the presence of technology and the organizational infrastructure necessary to support the usage of the technology mentioned (Sidorova, 2018). The hypothesis presented by Lai (2017) shows that favorable settings positively influence university students' inclination to utilize chatbots in the future. This research investigates students' beliefs on the presence of infrastructure preparedness while using a chatbot as a student engagement platform in a higher education institution setting. Thus, the following theory is proposed:

H$_4$: *Facilitating conditions has a significant influence on the use of AIBC in higher education.*

2.5 Hedonic Motivation

Hedonic motivation is an individual's belief that motivation has a beneficial impact on technology adoption and utilization. The researchers in reference 43 described hedonic motivation as a sentiment that emerges from using technology, such as pleasure or happiness. Regarding student involvement, internal factors like pleasure and amusement were discovered to significantly influence the student's perception of a new technology (Zwain, 2019). This variable pertains to the enjoyment experienced while interacting with the chatbot, notwithstanding potential performance impacts. Based on prior research by (Laumer et al., 2019), it was shown that this characteristic positively influences the adoption and use of technology by students. Hedonic incentive is seen to be a good factor that encourages pupils to use a chatbot. The following hypothesis is constructed accordingly:

H$_5$: *Hedonic motivation has a significant influence on the use of AIBC in higher education.*

2.6 Price Value

UTAUT 2 (Venkatesh et al. 2012) has an additional element called price value. Unlike in the office, individuals in private settings are responsible for covering the expenses associated with acquiring new items or technologies. Brown and Venkatesh's Model of Adoption of Technology in Households (MATH) focuses on the acceptability of personal computers for home usage. The study reveals that prices have a notable detrimental impact on the anticipated use of PCs. Moreover, Venkatesh et al. (2012) suggest that factor price value complements factor effort expectation by focusing on the time and effort invested in adopting and using new technologies. The pricing value better considers the individual situation. If the benefits of utilizing a product are greater than the financial expenses associated with it, a positive price value is considered. From this, we deduce the following hypothesis:

H$_6$: *Price value has a significant influence on the use of AIBC in higher education.*

2.7 Habit

In the realm of information systems and technology, habit refers to the degree to which individuals do actions (utilize IS) instinctively due to prior experience. The two terms that describe habit are previous behavior and automatic behavior. The writers said that habit may be seen as either a past deed or a recurring pattern. The UTAUT2 paradigm asserts that habit influences the usage of technology both directly and indirectly. Research by [25] showed that university learners' inclination to utilize chatbots is favorably impacted by habit. The present study intends to assess the appropriateness of the habit construct in empirical research on students' chatbot adoption in the higher education institution environment. The following hypothesis is constructed accordingly:

H_7: *Habit has a significant influence on the use of AIBC in higher education.*

2.8 Personal innovativeness

Personal innovativeness (Agarwal & Prasad, 1998) is the extent to which a person is willing to experiment with new information technologies. Innovative people possess curiosity and a thirst for learning about new technology. Innovativeness is positively correlated with the implementation uncertainty of new technology, according to Samsudeen & Mohamed, (2019). These individuals play a role in spreading ideas and hold a regard in the business world (Senali et al., 2023). Those who are innovative are more open to accepting technology with favorable views compared to individuals who are less creative indicating that personal innovativeness influences this connection (Agarwal & Prasad 1998). Creative individuals are more willing to confront the challenges that come with adopting technologies (Wilmer et al., 2017). Therefore, the expectations of performance and effort may have an impact on their decision to embrace technologies (Khazaei & Tareq 2021). According to research studies (Agarwal & Prasad, 1998; Cheng, 2014; Alkawsi et al., 2021) people with more personal innovativeness are less influenced by the opinions of others. Innovators disregard system complexity and resource availability while embracing new technologies to be the first to use them (Jianlin & Qi, 2010;). Integrating new technologies may disrupt people's usual habits (Kabra et al., 2017). Innovators are more inclined to adopt new technologies due to their favorable attitudes towards innovations, despite any disruptions to their usual routines. We offered the following:

H_8: *Personal innovation has a significant influence on the use of AIBC in higher education*.

2.9 Perceived trust

Perceived trust is the consumers' belief in the anticipated dependability and honesty of the chatbot platform. Previous research has shown a clear correlation between perceived trust and behavioral intention. Trust in technology adoption results in increased commitment to engaging in certain activities (Laumer et al.,2019; Al-Sharafi et al., 2016). Prior studies have provided indications about the key components that determine learners' confidence in chatbots. Considering the distinctive properties of chatbots, it is essential to focus on trust in connection with this interactive technology. Perceived trust may encourage learners to consistently use a chatbot in their everyday campus activities (Chen et al., 2022; Adam et al., 2020). Prior experience with chatbots may be associated with sustained use. A negative interaction with a chatbot might result in distrust against utilizing chatbots later. Therefore, we suggest that students are more likely to use a chatbot for learner support if their trust difficulties do not affect their willingness to use chatbot technology. Thus, the following theory is proposed:

H_9: *Perceived trust has a significant influence on the use of AIBC in higher education*.

3. Methodology

3.1 Sample and Sampling Method

The study investigated students enrolled at Jordanian institutions who used chatbots. An example is given to students who are asked to complete a questionnaire about their opinions on the advantages of chatbots in completing their learning assignments. The online survey link was shared on the learning management systems (LMS) of two institutions in Jordan. There were 3344 students enrolled in these institutions. A movie was added at the start of the survey questionnaire to enhance students' comprehension of how chatbots may be used for educational purposes. We requested participants to connect to chatbots using the supplied login URL and input their requests and queries to understand their functionality. The cover letter states that participation in the research is optional and anonymous, and participants have the option to withdraw at any point. Out of 411 replies, 31 were removed from the study due to low variation in their answers. We have 380 relevant data points for our study, which is an effective response rate of 11.36 percent. In the study, we looked at any data points by calculating ratings for each individual case. We didn't find any values within three deviations based on Goodboy and Klines (2017) guidelines. Even if there weren't any standout scores, a case could still be considered an outlier if its pattern significantly diverged from the norm within our sample. We used the Mahalanobis distance method to pinpoint these outliers. To validate our identification process, we conducted a significance test at $p<0.001$. After detecting and removing 31 multivariate outliers, we were left with 380 responses for analysis. We took steps before. After collecting data to minimise response errors, Participants were assured of their anonymity. That their personal details would remain confidential to encourage their engagement. Privacy was a priority to boost participation rates. The survey was carefully designed to be user-friendly and efficient in order to prevent survey fatigue or related non-responses. Post-data collection, we performed a response error assessment to ensure the sample's representativeness. We divided the responses into two categories: early and late. Compared the characteristics of each group using a t test. Our research revealed no distinctions between the groups based on our evaluation criteria, indicating that concerns about response errors were minimal in this study. We explored the presence of Common Method Bias (CMB) in our research due to relying on self-reported surveys for data collection. We employed two approaches to investigate CMB: Harman's single factor. The complete collinearity examination. Harman's analysis demonstrated that the primary factor accounted for 31.4% of the variance, which is less than half. The findings from the collinearity test indicated that all concept variance inflation factors (VIF) remained below the recommended threshold of 3.3.

3.2 Measurement of constructs

The study utilized established measures, from existing research to validate the relevance and accuracy of the variables. Factors such as influence, ease of use, motivation, performance expectations, habit formation, learning value and information reliability were drawn from studies by Zwain (2019) and Dwivedi et al. (2019). Oliver & Christina (2021) respectively. The questions assessing innovativeness and perceived trust were adapted from the studies of Laumer et al. (2019). Senali et al. (2023). We gauged these questions using a Likert scale ranging from 1 (“disagree”) to 5 (“agree”). A pre test was conducted by three experts to assess the questionnaire's clarity and relevance with adjustments made based on their feedback. Subsequently the revised questionnaire underwent evaluation, in a pilot study involving 25 students.

4. Results

4.1 Validity of measurement model

The effectiveness of a measurement framework hinges on its ability to accurately assess the core concept it aims to gauge. It plays a role in research by guaranteeing the trustworthiness and significance of the measurements employed in a study. According to Hair et al. (2021) a measurement model is utilized to appraise variables or composite variables. The accuracy of the measurement model is assessed using three criteria; construct validity, convergent validity and discriminant validity (Hair et al., 2021).

4.1 Convergent validity

Multiple tests were conducted to assess how well the components fit together. These tests involved examining factor loadings, composite reliability (CR), average variance explained (AVE), and reliability (Cronbachs alpha) as outlined by Fornell & Larcker in 1981. Convergent validity is demonstrated when specific criteria are met, ensuring CR values are 0.7 or higher, standardizing factor loadings to 0.5 or above, and confirming AVE values of 0.5 or more, according to Gatzioufa & Saprikis in 2022 and Senali et al. in 2023. The findings presented in Table 1 indicate that the measurement model satisfies the criteria for construct reliability (CR), standardized loading, average variance extracted (AE), and construct reliability (Cronbach's alpha). CR values range from 0.826 to 0.924, signifying the consistency and reliability of the measurement model. Higher CR values suggest that the observable indicators are more reliable in evaluating their structures. The typical loading levels fall between 0.701 and 0.881, representing the strength of the relationship between indicators and their underlying constructs. Higher standardized loadings show a meaningful connection between the factors and the main elements. The AVE figures range from 0.807 to 0.956, indicating the amount of variance observed in factors linked to their components. Greater AE values suggest that the constructs account for a part of the variability in the factor. The Cronbach's alpha values span from 0.821 to 0.928, serving as an indicator of consistency and reliability much like CR does. Cronbach's alpha values signify increased dependability and coherence among the elements of the measurement model.

Table 1
Measurement Model

Factors	Loading	CA	CR	AVE
Performance expectancy		0.913	0.910	0.863
	0.772			
	0.763			
	0.701			
	0.731			
	0.741			
Effort expectancy		0.914	0.854	0.783
	0.851			
	0.872			
	0.812			
	0.852			
Social influence		0.921	0.901	0.903
	0.778			
	0.757			
	0.745			
	0.751			
Facilitating conditions		0.821	0.826	0.814
	0.744			
	0.723			
	0.720			
	0.731			

Table 1
Measurement Model (Continued)

Factors	Loading	CA	CR	AVE
Hedonic motivation		0.891	0.828	0.921
	0.717			
	0.715			
	0.770			
Price value		0.928	0.911	0.809
	0.819			
	0.825			
	0.861			
	0.881			
Habit		0.914	0.924	0.956
	0.725			
	0.763			
	0.722			
Personal innovativeness		0.891	0.854	0.807
	0.809			
	0.819			
	0.830			
Perceived trust		0.892	0.898	0.913
	0.795			
	0.754			
	0.753			
	0.737			
Behavioral intention		0.880	0.891	00.901
	0.812			
	0.821			
	0.817			

4.2 Discriminant validity

The discriminant validity test explores how well a concept is connected to its indicators in the PLS path model (Hair et al., 2017). The Fronell-Larcker criteria are commonly used to assess the validity of measurement models (Dwivedi et al., 2019). As per this criterion, the square root of the variance extracted (AVE) by a construct should exceed its correlation with all constructs (David & Jos'e, 2015; Wu et al., 2023). This approach was selected for its effectiveness in identifying issues with validity (Alzoubi & Alzoubi 2020) using the Heterotrait-Monotrait ratio of the correlation (TMT) method. The HTMT values displayed in Table 2 indicate that the measurement model exhibits validity among the studied constructs. All values are below 0.85, indicating validity across constructs. The correlations between constructs and their respective indicators are lower than those between indicators within the concept, suggesting clear distinctions and minimal overlap between concepts.

Table 2
Discriminant validity

	PE	EE	SI	FC	HM	PV	H	PI	PT	
PE	0.726									
EE	0.710	0.860								
SI	0.720	0.818	0.803							
FC	0.844	0.849	0.802	0.719						
HM	0.832	0.841	0.849	0.736	0.734					
PV	0.739	0.815	0.833	0.748	0.765	0.717				
H	0.831	0.717	0.741	0.712	0.809	0.737	0.801			
PI	0.819	0.711	0.701	0.706	0.855	0.722	0.857	0.761		
PT	0.729	0.818	0.887	0.790	0.707	0.854	0.753	0.704	0.706	
BI	0.830	0.852	0.710	0.814	0.845	0.753	0.864	0.832	0.854	0.789

4.3 Assessment of structural model

We employed Partial Least Squares Structural Equation Modelling (PLS-SEM) to investigate our research ideas. The PLS uses the bootstrapping method to calculate the standard errors. Table 3 displays the route coefficients and p-values for the proposed theoretical model obtained from PLS analysis. We found strong statistical support for hypotheses H1 ($\beta = 0.66$, $t = 3.265$, $p < 0.000$), H2 ($\beta = 0.68$, $t = 3.377$, $p < 0.000$), H3 ($\beta = 0.72$; $t = 4.197$, $p < 0.000$), H4 ($\beta = 0.59$, $t = 5.191$, $p < 0.000$), H5 ($\beta = 0.57$; $t = 5.226$, $p < 0.000$), H6 ($\beta = 0.67$, $t = 6.102$, $p < 0.000$), H7 ($\beta = 0.68$, $t = 4.528$, $p < 0.000$), H8 ($\beta = 0.61$, $t = 6.258$, $p < 0.000$), and H9 ($\beta = 0.78$, $t = 4.404$, $p < 0.000$). The evaluation uses routes R^2 and Q^2 to establish their importance. The R^2 result of 0.633 from the rustle analysis suggests that the independent factors in the model can explain about 63.3% of the variance in the dependent variable. The independent factors together account for 63.3% of the variation observed in the dependent variable, AIBC.

Table 3
Hypothesis results.

Hypotheses	B	T	P	Decision
H1	0.66	3.265	0.000	Supported
H2	0.68	3.377	0.000	Supported
H3	0.72	4.197	0.000	Supported
H4	0.59	5.191	0.000	Supported
H5	0.57	5.226	0.000	Supported
H6	0.67	6.102	0.000	Supported
H7	0.68	4.528	0.000	Supported
H8	0.61	6.258	0.000	Supported
H9	0.78	4.404	0.000	Supported

5. Discussion

The study examined the factors that affect the adoption of AI-based instruction in education using the UTAUT2 model. The results revealed that students' positive expectations of performance significantly influenced their willingness to utilize AI-based instruction. This finding is consistent with studies by Adam et al. (2020) and Alkawsi et al. (2021). Al Sharafi et al. (2022). Chu et al. (2022) also noted an impact of performance expectations on the use of AI-based instruction. Therefore, incorporating a learning approach into education has proven to be beneficial and substantial. The research indicated that students' positive expectations of effort influenced their intention to adopt AI-based instruction, which is supported by studies such as those by Dwivedi et al. (2019) and Laumer et al. (2019). Additionally, it was found that effort expectations significantly influenced the utilization of animation and storytelling techniques, making the teaching and learning process more feasible in a learning environment. Social influence played a role in encouraging students to embrace AI-based instruction, aligning with research findings by Laumer et al. (2019), Cheng (2014), and Zhao et al. (2021). Moreover, Alzoubi & Alzoubi (2020) highlighted the impact of interaction on the use of AI-based instruction. The organization of the university, along with the thoughts of teachers and students, plays a role in shaping the cultural atmosphere at the university. We believe that the cultural environment can impact and inspire students to utilize the AIBC system. The ease of use influenced students' intentions to use AIBC. However, this model did not influence student's actual use of AIBC. Research by Khoshkam and Mirzaei (2023) and Lin et al. (2023) suggested that ease of use did not affect the adoption of AIBC. The technology infrastructure substantially affects students' willingness to adopt AIBC. Students should have access to technology resources such as the internet and robust computers to use the AIBC approach. They should also receive support and training from AIBC. Successful integration of the AIBC system in education necessitates governance and advanced ICT infrastructure strategies. Enjoyable motivation positively influenced students' inclination towards using AIBC, which is consistent with findings by Zwain (2019). Yang, Luo, and Su (2022) discovered a connection between motivation and interest in mobile learning. Positive learning experiences play a role in implementing learning approaches. An accessible environment and electronic material greatly influence the creation of delightful learning experiences. Educational designers should focus on these qualities. The research revealed that pricing value had a notably favorable effect on students' behavioral intention to use AIBC. Based on our research, Jordanian students found affordable access to AIBC resources and internet use to be crucial criteria in accepting AIBC. This outcome aligns with the research conducted by Tewari et al. (2023) on students. Sitar & Mican (2021) researched the acceptability of e-learning among English students. Their research demonstrated that photovoltaic technology did not influence the adoption of e-learning. According to different research, American and Qatari students believed that PV did not influence their acceptance of e-learning. Diverse economic and social factors in industrialized and developing nations influence students' perspectives on this matter. The research found that habits (HT) positively influenced students' inclination to employ e-learning. Furthermore, HT positively impacted the students' practical use of e-learning. This aligns with the findings of Wilmer et al. (2017) and Yang et al. (2022). Mohammad & Muhammad (2023) found that the regular use of a technology has a significant impact on its acceptance. The research demonstrated that the desire to utilize AIBC behaviorally significantly impacted students' actual utilization of mixed learning. Our results aligned with the conclusions of previous investigations (Oliver & Christina, 2021; Roy et al., 2022; Mohammed et al., 2023). The behavioral aim predicts the real-world application of blended learning. The implementation of AIBC was contingent on the students' desire to utilize it. Our research indicated that students were eager to use the AIBC system to enhance the quality of their educational experiences. Students in rich and developing nations have distinct economic, social, and cultural origins. Various circumstances might significantly influence students' inclination to embrace a new learning approach. AIBC is a growing method at Jordanian institutions, which are considered developing. Hence, it is advisable to carry out more research on AIBC. The research has some constraints. A self-reporting measure was used to evaluate the behavioral intention to utilize AIBC. This data-gathering strategy might have influenced the precision of the findings. It is recommended to use qualitative approaches in future investigations. This research examined variables influencing the adoption of AIBC via the UTAUT2 paradigm. Future research should explore the impact of other aspects, including attitude towards AIBC, technological anxiety, experience, self-efficacy, compatibility, and reluctance to change on the intention to utilize AIBC. It is essential to examine the impact of moderator characteristics, including sex, age, experience, and voluntariness, in future research. This research was done on students at a Jordanian university; hence, the results may not be applicable to students from other institutions. Due to the substantial disparities in technical and pedagogical aspects across institutions, we recommend doing this research at different universities. The findings indicate that the design has a favorable impact on perceived trust in adopting AIBC. The concept corroborates the findings of prior studies (Al-Okaily et al., 2020). This indicates that the design of AIBC functionalities has a favorable effect on customers' confidence in selecting

AIBC for customer care. The way an AI-based learning tool is designed can significantly impact how confident users feel about using it. This can address the concerns raised in a study by Conrad et al. (2015) about how a crafted AI learning tool can cater to the needs of students from all age groups, educational backgrounds, and life experiences. The research suggests that design plays a role in encouraging creativity when adopting AI-based learning tools, which aligns with earlier studies by Chen (2022) and Sajjad et al. (2023). Personal creativity is characterized by a sense of curiosity, openness to complexity, and willingness to try things (Pillai & Sivathanu 2020). Those who are innovative may be more inclined to explore emerging technologies like AI-based learning tools because of their practicality, user friendliness, external perceptions, or resource limitations. These factors have an influence on individuals compared to students who are less creative.

6. Conclusion

The research revealed that the model built using UTAUT2 effectively identifies the factors that influence the adoption of AIBC in education. Factors such as performance expectations, ease of effort, social influence, conducive conditions, enjoyment motivation, value for money, and habitual behaviors positively influenced students' readiness to embrace AIBC. The analysis of existing literature confirmed that the study's results aligned with research. This paper serves as a resource for investigations into incorporating artificial intelligence in higher education. The study demonstrated that organizational and social factors within the UTAUT2 model significantly influenced students' willingness to use AIBC. Key components include performance expectations, ease of effort, conducive circumstances, and social influence. Establishing an environment offering organizational support and shifting students' attitudes towards new learning methods are crucial for the successful integration of the AIBC system.

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