Behavioral Intentions Towards Learning Artificial Intelligence in K-12 School

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Abstract: Artificial intelligence learning in schools and its adoption is a recent trend in schools, thus, this research aims to highlight the factors influencing behavioral intention and actual learning of AI in K-12 schools. The data for the research were gathered from students, and it was analyzed by Smart pls. The results highlighted that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, and price value do not influence behavioral intentions toward learning artificial intelligence in K-12 schools. Whereas habit significantly influences behavioral intentions. Moreover, habit and behavioral intention can influence the actual AI learning artificial intelligence in K-12 schools. These results can help the leaders, or administrators of K-12 schools. The scope of research is limited to K-12 schools, and future studies can expand it by evaluating the UTAUT 2 model in the context of AI learning in higher educational institutions.

Keywords: AI, UTAUT 2, Behavioral Intentions, Actual AI Learning.

النوايا السلوكية تجاه تعلم الذكاء الاصطناعي في المدرسة من الروضة إلى الصف الثاني عشر

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المستخلص: يشكل تعلم الذكاء الاصطناعي واعتماده في المدارس اتجاهاً حديثاً في مجال التعليم. لذلك يهدف هذا البحث إلى تسليط الضوء على العوامل المؤثرة على النية السلوكية والتعلم الفعلي للذكاء الاصطناعي في مدارس الروضة وحتى الصف الثاني عشر. تم جمع بيانات البحث من الطلاب، وتم تحليلها بواسطة Smart pls. أبرزت النتائج أن الأداء المتوقع، الجهد المتوقع، التأثير الاجتماعي، تسهيل الظروف، دوافع المتعة، وقيمة التكلفة والعائد لا تؤثر على النوايا السلوكية تجاه تعلم الذكاء الاصطناعي في مدارس الروضة وحتى الصف الثاني عشر. في حين أن العادة تؤثر بشكل كبير على النوايا السلوكية. علاوة على ذلك، يمكن أن تؤثر العادة والنية السلوكية على الذكاء الاصطناعي الذي يتعلمه الطلاب في مدارس الروضة حتى الصف الثاني عشر. يمكن أن تساعد هذه النتائج قادة أو مديري مدارس الروضة حتى الصف الثاني عشر. يقتصر نطاق البحث على مدارس الروضة وحتى الصف الثاني عشر، ويمكن للدراسات المستقبلية توسيعه من خلال تقييم نموذج UTAUT 2في سياق تعلم الذكاء الاصطناعي في مؤسسات التعليم العالي.

الكلمات المفتاحية: الذكاء الاصطناعي، النظرية الموحدة لقبول واستخدام التقنية، النوايا السلوكية، الأداء الفعلي.

Introduction

The development of Artificial intelligence (AI) is transforming our way of living (Gansser and Reich, 2021), learning, and working and it has diverse applications for society and future generations. Therefore, the notion of artificial intelligence has become more than a branch of academic and professional research, and thus, the adoption of AI in education has shifted from professional to mainstream (Chiu et al., 2021). The inculcation of AI in education can lead to a positive impact on the lives of young people and even children (Leaton Gray, 2020). Moreover, artificial intelligence education at the K-12 level can help students develop an understanding of emerging technologies and their applications, and besides this, it can also inspire future artificial intelligence users, researchers, academicians, software developers, and ethical designers (Pedró et al., 2019).

In K-12 education, the students' diversity, particularly their abilities, needs, and interests is wider within and between schools because every school has different visions, and resources (for example, artificial learning tools and platforms) and mostly importantly the teachers at every school have different qualifications (i.e., capacity to teach artificial intelligence). Some schools teach basic ethics while others teach about the creation of artificial intelligence applications by using cloud computing. Moreover, some schools develop activities for the facilitation of student's artificial intelligence learning from local perspectives whereas, others can increase the global understanding of students (Chiu et al., 2021). Many studies have highlighted the educational impacts of information technologies and particularly their adoption, such as computers (Jacobsen, 1998; Brusilovsky et al., 2014), internet availability/ access (Livingstone and Bober, 2004), computer-aided instructions (Chmielewska & Gilanyi, 2015), LMS (Fearnley & Amora, 2020) and mobile devices (Sung et al., 2016) but now the researchers are keen to highlight the behavioral intentions towards learning artificial intelligence in K-12 schools. Previously artificial intelligence topics were covered only in higher education but now they are making their way toward K-12 classrooms (Pedró et al., 2019) intending to educate the future generation (Chiu, 2021) but it is important to analyze the behavioral intention of K-12 school students towards learning via artificial intelligence.

The user intention toward technology adoption has been studied by using several theories including the "Theory of Reasoned Actions (TRA)" (Fishbein & Ajzen, 1975), the "Technology Acceptance Model (TAM)" (Davis, 1989), "Theory of Planned Behavior (TPB)" (Ajzen, 1991), but these theories have not highlighted all the antecedents of behavioral intention towards technology adoption, therefore, Venkatesh et al., (2003) presented the theory that revealed all the possible factors leading to behavioral intention and this theory is known as "Unified Theory of Acceptance and Use of Technology (UTAUT)". In the context of education/learning, this theory has been studied by researchers who focused on prediction of behavioral intention of students towards using e-learning platforms (Zacharis & Nikolopoulou, 2022), google classrooms (Jakkaew & Hemrungrote, 2017), or adoption of augmented reality technology in education (Faqih & Jaradat, 2021), but there is paucity of literature explaining the user's intention to learn artificial intelligence (Gansser & Reich, 2021) in K-12 schools. Therefore, this intention should be examined by focusing on any specific theory/model, that can depict all the possible factors influencing behavioral intention toward learning artificial intelligence.

The Unified Theory of Acceptance and Use of Technology is a stable model that shows that the variance of use of technology and behavioral intention is 40 % and 56 % respectively (Chu et al., 2022). Venkatesh et al., (2012) presented the extended version of UTAUT, which is known as Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2). This model is more stable than UTAUT as it shows a 74 % variance for behavioral intention and 52 % for the use of technology (Duarte & Pinho, 2019). This research has adjusted the original assumption of UTAUT 2 in such a way that the model works for learning artificial intelligence in K-12 schools. The five factors explained in Unified Theory of Acceptance and Use of Technology 2 are used to determine the behavioral intention of K-12 school students in learning artificial intelligence. These factors include performance expectancy, effort expectancy, social influence, facilitating conditions, and habit. All these factors can influence the behavioral intentions of students towards learning artificial intelligence in K-12 schools.

The extensive literature-based investigation and research highlighted a research gap in accessing how the UTAUT 2 elements, including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, price value, and habit, can enhance the behavioral intention towards learning artificial intelligence in K-12 schools. Thus, this study is an attempt to bridge this gap by developing the relationships between the variables mentioned above. Moreover, the study has answered the following research question.

Q1: Which factors can influence the behavioral intentions of students towards learning artificial intelligence in K-12 schools?

Literature Review

Chiu et al., (2021) conducted a thematic analysis to propose a holistic approach for designing curriculum artificial intelligence curriculum in K-12 and indicated that it depends upon the teacher-student communication, the impact of artificial intelligence, artificial intelligence processes, artificial intelligence knowledge, and student relevance. There is a paucity of literature explaining the behavioral intentions toward learning artificial intelligence in K-12 schools, thus, this research has utilized the UTAUT 2 model which has different factors including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, price value, and habit which can influence the behavioral intention (Venkatesh et al., 2012). UTAUT 2 model is an extension of UTAUT developed by (Venkatesh et al., 2012) with the addition of three important factors including motivation, price value, and habit behavior. These factors were not part of UTAUT. Therefore, current research has also considered all the elements of the UTAUT framework to determine students' behavioral intentions toward learning artificial intelligence in K-12 schools. The literature relevant to each element is given below:

PE&BI of Learning AI

Performance expectancy (PE) is linked to technology usefulness (Zhou et al., 2022); thus, besides UTAUT and UTAUT 2, this concept has been used by many theories/models. Venkatesh et al. (2012, p. 447) defined performance expectancy as "the degree to which the use of a technology will provide benefits to consumers in carrying out certain activities". In the context of current research, performance expectancy is the extent to which students believe that the performance of AI learning tools, applications, and instruments will influence their behavior in learning artificial intelligence. Performance expectancy is the biggest predictor of behavioral intention (BI) (Taiwo & Downe, 2013) for adopting technology (Venkatesh et al., 2003). Similarly, Chu et al. (2022) highlighted it as an important factor affecting the behavioral intention toward adoption of new technologies. However, García de Blanes Sebastián et al. (2022) found an insignificant relationship between performance expectancy and behavioral intention of learning artificial intelligence. To find the influence of performance expectancy on the behavioral intention of learning AI, the following hypothesis is developed.

H1: Performance expectancy significantly influences the behavioral intention in students towards learning artificial intelligence in K-12 schools.

EE & BI of Learning AI

Effort expectancy (EE) is similar to the concept "ease of use" presented in the diffusion of innovation theory (DOI) (Alhwaiti, 2023). Similarly, in the technology adoption model 2 theory (TAM 2) by (Venkatesh and Davis, 2000) and the technology adoption model (TAM) by (Davis, 1989), effort expectancy was conceptualized as perceived ease of use. In the UTAUT 2 model, technology adoption strongly depends upon effort expectancy (Alhwaiti, 2023) which is defined by Venkatesh et al. (2003, p. 450) as "the degree of ease associated with using the system". Many studies have explained the positive relationship between effort expectancy and behavioral intention (BI) (Chopra, 2019; Moriuchi et al., 2021; Schmitz et al., 2022; Ragheb et al., 2022), but there is a paucity of literature focusing on the behavioral intention of learning AI; thus, we hypothesized that:

H2: Effort expectancy significantly influences the behavioral intention in students towards learning artificial intelligence in K-12 schools.

SI & BI of Learning AI

Social influence (SI) was not directly presented in the technology adoption model (TAM), technology adoption model 2 (TAM 2), or theory of planned behavior (TBP), as they focused on subjective norms that are similar to social influence. Venkatesh et al., (2003) defined social influence as "the person's perceptions that group of people who are important to him think he should or should not perform the behavior in question". According to Sun et al., (2013), social influence is the extent to which the technology acceptance by one person is influenced by his or her social environment. The literature has provided empirical evidence relating social influence on the use of technology in different contexts (Moriuchi, 2021; Alhwaiti, 2023; Faqih et al., 2021), but García de Blanes Sebastián et al., (2022) found an insignificant relationship between social influence and users' behavioral intention towards technology. Therefore, to highlight the influence of social influence on the behavioral intention of learning AI, the following hypothesis is developed:

H3: Social influence significantly influences the behavioral intention in students towards learning artificial intelligence in K-12 schools.

Facilitating Conditions and Behavioral Intention of Learning Artificial Intelligence

The theory of planned Behavior (TBP) emphasizes perceived behavioral control which relates to the concept of "facilitating conditions" presented in UTAUT. Venkatesh et al. (2003, p. 453) defined it as "consumers' perceptions of the resources and support available to perform a behavior". According to Chatterjee and Bhattacharjee (2020) facilitating conditions influence the users' behavior towards artificial intelligence in educational systems. Many studies have explained that facilitating conditions lead to behavioral intention towards technology acceptance, such as Alhwaiti (2023) found that these conditions can influence the behavioral intention of teachers towards using artificial intelligence, but several studies have found insignificant relationship between facilitating conditions and behavioral intention towards technology acceptance (i.e., Madigan et al., 2017; Chu et al., 2022; García de Blanes Sebastián et al., 2022; Madigan et al., 2016).

Therefore, it's important to investigate the actual relationship between facilitating conditions and behavioral intention (Mohd Nizar et al., 2018); thus, it is hypothesized that:

H4: Facilitating conditions significantly influences the behavioural intention in students towards learning artificial intelligence in K-12 schools.

HM & BI of Learning AI

Hedonic motivation (HM) is an important factor that can influence consumer behavior (Holbrook and Hirschman, 1982), and it is defined by Venkatesh et al. (2012, p. 157–178) as “the fun element, joy, or pleasure derived from the use of a particular technology without any specific additional benefit”. Brown and Venkatesh (2005) indicated hedonic motivation as an important factor to be used for consideration of technology acceptance and usage. A high level of this motivation for new technology such as artificial intelligence can lead to higher users’ behavioral intention (Gansser and Reich, 2021), thus we hypothesize that:

H5: Hedonic motivation significantly influences the behavioural intention in students towards learning artificial intelligence in K-12 schools.

Price Value and Behavioral Intention of Learning Artificial Intelligence

Zeithaml (1998) defined price value in an educational context as “being the individuals’ assessment of benefits acquired against costs incurred in the adoption of augmented reality in educational settings”. Whereas, in the context of behavioral intention towards technology, it is defined by Venkatesh et al., (2012, pp. 157–178) as “consumers’ cognitive trade-off between the perceived benefits of apps and the cost of using them”. In the context of current research, price value is the net benefit that students will attain for learning AI. Many researchers have found a positive relationship between price value and behavioral intention towards technology (i.e., Merhi et al., 2019; Lee et al., 2019; Alhwaiti, 2023), but there is a paucity of research in the context of learning AI. Thus, to highlight the influence of price value and students’ behavioral intention toward learning AI, the following hypothesis is formulated:

H6: Price value significantly influences the behavioural intention in students towards learning artificial intelligence in K-12 schools.

HBT, BIabit, AU of Learning AI

Venkatesh et al. (2012, p. 157-178) defined habit as “the extent to which individuals tend to perform behaviors automatically due to learning” (Venkatesh et al., 2012, p. 157–178). Many studies have highlighted that habit significantly influences behavioral intention (Ramı´rez-Correa et al., 2019; Abu Gharrah and Aljaafreh, 2021; Alhwaiti, 2023) and actual system usage. Therefore, the following hypotheses are developed:

H7: Habit significantly influences the behavioural intention in students towards learning artificial intelligence in K-12 schools.

H8: Habit significantly influences the actual use of learning AI

Behavioral Intention, and Actual Use of Learning Artificial Intelligence

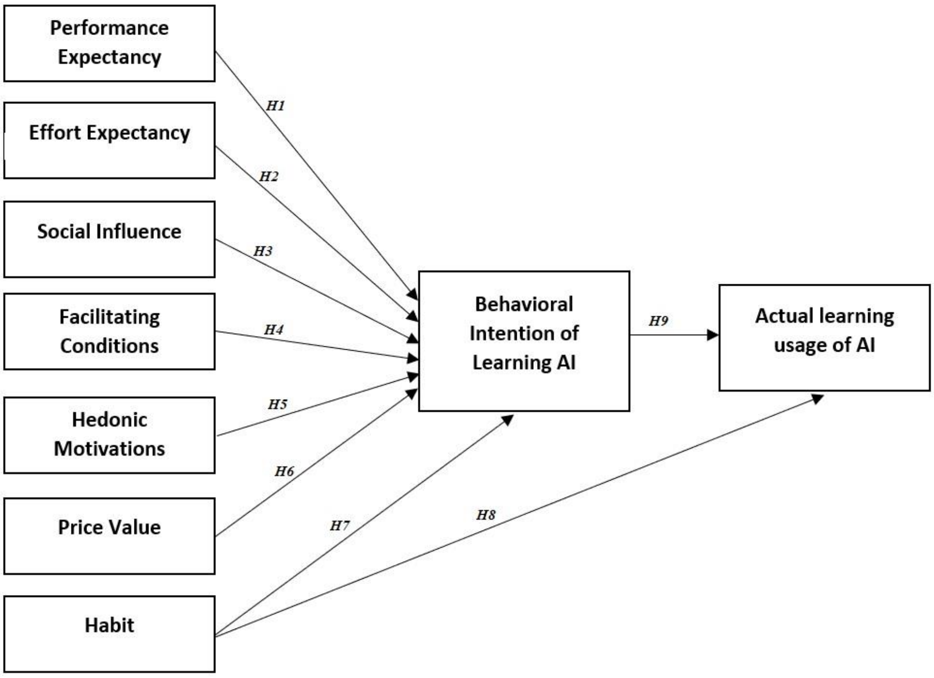
Behavioral intention is an important factor that can lead to the usage intention of technology (Venkatesh et al., 2003). Many studies based on TAM, UTAUT, and UTAUT 2 examined the usage intention of the system, but still, there is limited literature on the context of AI learning. Therefore, to examine the relationship between behavioral intention and actual use of learning artificial intelligence, the following hypothesis is formulated:

H9: Behavioral intention significantly influences the actual use of learning AI.

The conceptual model based on the literature given above is presented in the figure given below: (See figure 1)

Figure 1

UTAUT 2 model for AI Learning in K-12 schools



Methodology

The user intention toward technology adoption has been studied by using several theories including TAM, TAM 2, UTAUT, and UTAUT 2 but there is a paucity of literature explaining the user's intention to learn artificial intelligence in K-12 schools. Therefore, this research has identified the behavioral intentions of students toward learning artificial intelligence in K-12 schools by using the UTAUT 2 model.

This study has utilized an exploratory research design, and the data is collected using a questionnaire survey. The questionnaire was initially designed in the English language, and later it was converted into Arabic language for ease of respondents. The target population of the study was students of K-12 schools. The questionnaire was not only shared online but also it was distributed among respondents. In total 70 responses were gathered, but there was some missing data in the response of one respondent, thus, it was removed, and finally, 69 respondents were considered for final analysis, which shows a 98 % response rate.

Performance expectancy was measured with 4 items adopted from Marchewka et al. (2007), and Venkatesh et al. (2012). 4 items-based scale of effort expectancy was adopted from Venkatesh et al., (2012). 4 items-based scale of social influence and 3 items-based scale of facilitating conditions were also adopted from the research of Venkatesh et al. (2012). Moreover, a 3 items-based scale of hedonic motivation and price value was adopted by Venkatesh et al., (2012). Habit was examined with a scale based on four items, and it was adopted from Venkatesh et al. (2012). 3 items-based scale of behavioral intention was adapted from Venkatesh et al. (2012) and Maldonado et al. (2011). In addition, 4 items-based scale of actual learning of AI was adapted from Chen (2010) and Islam (2013). Every item of variable was analyzed on the five-point Likert scale i.e., “1 (strongly disagree) to 5 (strongly agree) scale”.

Data gathered from research was analyzed by using SPSS, and smart Pls. In SPSS, information about demographics was examined, whereas by using smart pls, covariance-based structural equational modeling (CB-SEM) was done for statistical analysis.

Results and Findings

The research aimed to highlight factors affecting behavioral intention and actual use behavior towards learning artificial intelligence in K-12 schools by using the UTAUT 2 framework that includes performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, price value, and habit. SPSS was used for determining information about demographics, and data analysis was done by using Smart Pls. The results of demographics are given in Table 1.

Table 1

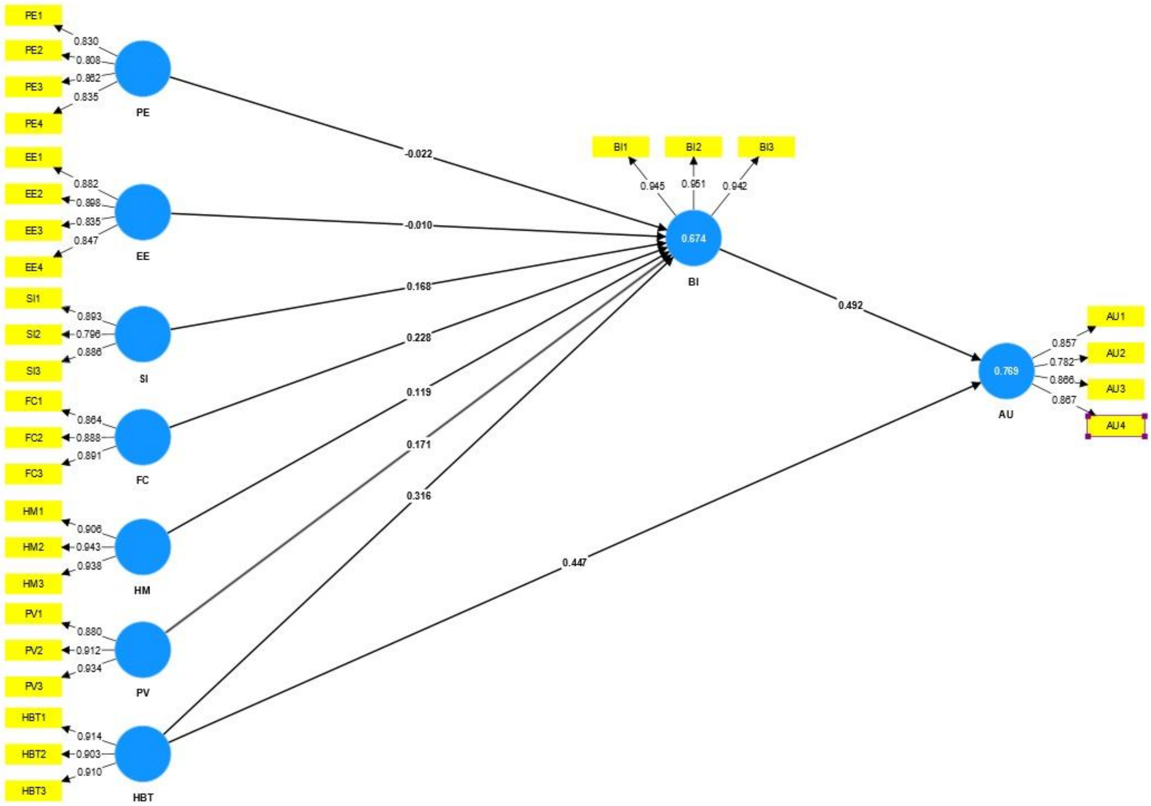
Demographic Information

Gender		
Male	***Female***	
25 (37 %)	43 (63 %)	
Levels of K-12 School		
Primary Education	***Secondary Education***	***High School Education***
24 (35.3%)	24 (35.3%)	20 (29.4%)
School Type		
National School	***International School***	
32 (47%)	36 (53%)	

After determining the demographic information, Smart Pls was used to investigate convergent validity, for which a measurement model was tested that showed loadings for each factor, composite reliability, and average variance extract (Hair et al., 2006). The results highlighted that loadings of every factor were more than 0.7 which is considered a good indicator (Hair et al., 2010; Ramayah et al., 2018; Wijaya, 2023), thus, no factor was dropped during analysis. The values of loadings are shown in figure 02.

Figure 2

Pls Algorithm (Showing loadings)



The results of the Pls Algorithm also revealed the composite reliability, which is explained by Hair et al. (2006) as the extent to which the indicators of constructs show the latent construct, and its cut-off value should be a minimum of 0.7. Besides this reliability, Average Extracted Variance (AVE) is examined to show the total and exact variance between the indicators accounted for by the latent construct, its minimum value should be 0.5. The results of the current study demonstrated that the values of CR and AVE are within the cut-off criteria. Further, the Cronbach's alpha was measured, and its values were more than 0.7. Table 2, given below shows the loadings of each factor, Cronbach's alpha composite reliability, and Average Extracted Variance.

Table 2

Values of AVE, CR, Factor Loadings, Items

Constructs	Items	Loadings
Performance Expectancy	I find artificial intelligence learning useful in my studies	0.830
AVE= 0.696	Using artificial intelligence learning increases my chances of achieving things that are important to me	0.808
Cronbach's Alpha= 0.856	Using artificial intelligence learning helps me accomplish various activities, related to my studies, more quickly	0.862
Composite Reliability= 0.901	Using artificial intelligence learning increases my productivity in my studies	0.835
Effort Expectancy	Learning how to use artificial intelligence is easy for me	0.882
AVE= 0.750	My interaction with artificial intelligence is clear and understandable	0.898
Cronbach's Alpha= 0.889	I find artificial intelligence learning easy to use	0.835

Constructs	Items	Loadings
Composite Reliability= 0.923	It is easy for me to become skillful at learning artificial intelligence	0.847
Social Influence	People who are important to me think that I should use artificial intelligence (and) in my studies and learn it	0.893
AVE= 0.738		
Cronbach's Alpha= 0.823	People who influence my behavior think that I should use artificial intelligence in my studies and learn it	0.796
Composite Reliability= 0.842	People whose opinions I value prefer that I use artificial intelligence (and) in my studies and learn it	0.886
Facilitating Conditions	I have the resources necessary to use artificial intelligence learning	0.864
AVE= 0.797		
Cronbach's Alpha= 0.857	I have the knowledge necessary to use artificial intelligence	0.888
Composite Reliability= 0.870	I can get help from others when I have difficulties in learning artificial intelligence	0.891
Hedonic Motivation	Using artificial intelligence learning in my studies is fun	0.906
AVE= 0.776	Using artificial intelligence learning in my studies is enjoyable	0.943
Cronbach's Alpha= 0.917		
Composite Reliability= 0.912	Using artificial intelligence learning in my studies is very entertaining	0.938
Price Value	Artificial intelligence learning has a reasonable price	0.880
AVE= 0.821	The cost of the services that I have access to through artificial intelligence is worth their money	0.912
Cronbach's Alpha= 0.895		
Composite Reliability= 0.934	At the current price, artificial intelligence learning provides a good value	0.934
Habit	The learning of artificial intelligence has become a habit for me	0.914
AVE= 0.826		
Cronbach's Alpha= 0.911	I am addicted to learn artificial intelligence	0.903
Composite Reliability= 0.944	I must learn artificial intelligence	0.910
Behavioral Intention of Learning Artificial Intelligence	I intend to continue artificial intelligence learning in the future, in my studies	0.945
AVE= 0.895	I will always try to use artificial intelligence learning in my studies	0.951
Cronbach's Alpha= 0.941	I plan to continue to use artificial intelligence learning frequently, in my studies	0.942
Composite Reliability= 0.962		
Actual Learning of Artificial Intelligence	I regularly use artificial intelligence in my studies and learn it	0.857
AVE= 0.712	Artificial intelligence learning is a pleasant experience	0.782
Cronbach's Alpha= 0.864	I currently learn artificial intelligence as it's a supporting tool in my studies	0.866
Composite Reliability= 0.908	I spend a lot of time on learning artificial intelligence in my studies	0.867

In second step of data analysis, discriminant validity was investigated. Discriminant validity is explained by Ramayah, Yeap, & Igatius, (2013) as "the extent to which the measures are not a reflection of some other variables" (p.142). The discriminant validity was ensured with Fornell-Larcker Criterion and its values are given in Table 3.

Table 3

Discriminant Validity

	AU	BI	EE	FC	HBT	HM	PE	PV	SI
AU	0.844								
BI	0.824	0.946							
EE	0.729	0.634	0.866						
FC	0.717	0.620	0.695	0.881					
HBT	0.813	0.744	0.665	0.555	0.909				
HM	0.606	0.653	0.639	0.520	0.632	0.929			
PE	0.611	0.605	0.649	0.651	0.589	0.717	0.834		
PV	0.701	0.701	0.592	0.461	0.756	0.667	0.555	0.909	
SI	0.714	0.712	0.668	0.578	0.696	0.740	0.710	0.743	0.859

Note: AU (Actual Learning of AI), BI (Behavioural Intention of learning AI), EE (Effort Expectancy), FC (Facilitating Conditions), PV (Price Value), SI (Social Influence), HBT (Habit), HM (Hedonic Motivation), PE (Perceived Expectancy).

The goodness fit model tests that the structural models can meet the value of R square, and its values are given in Table 4.

Table 4

R-Square Values

	R Square	R Square Adjusted
Actual Learning of AI	0.769	0.762
Behavioral Intention of AI	0.674	0.636

The table given above shows that the R Square of the behavioral intention of learning artificial Intelligence towards Actual Learning of Artificial Intelligence is 0.674, and it highlights that 67 % of the behavioral intention of learning artificial intelligence can explain the Actual Learning of Artificial Intelligence. To determine the results of the hypothesis, bootstrapping was done, and its graphical representation is given in Figure 3. Table 5 shows the values of hypotheses testing.

Figure 3

Bootstrapping Result

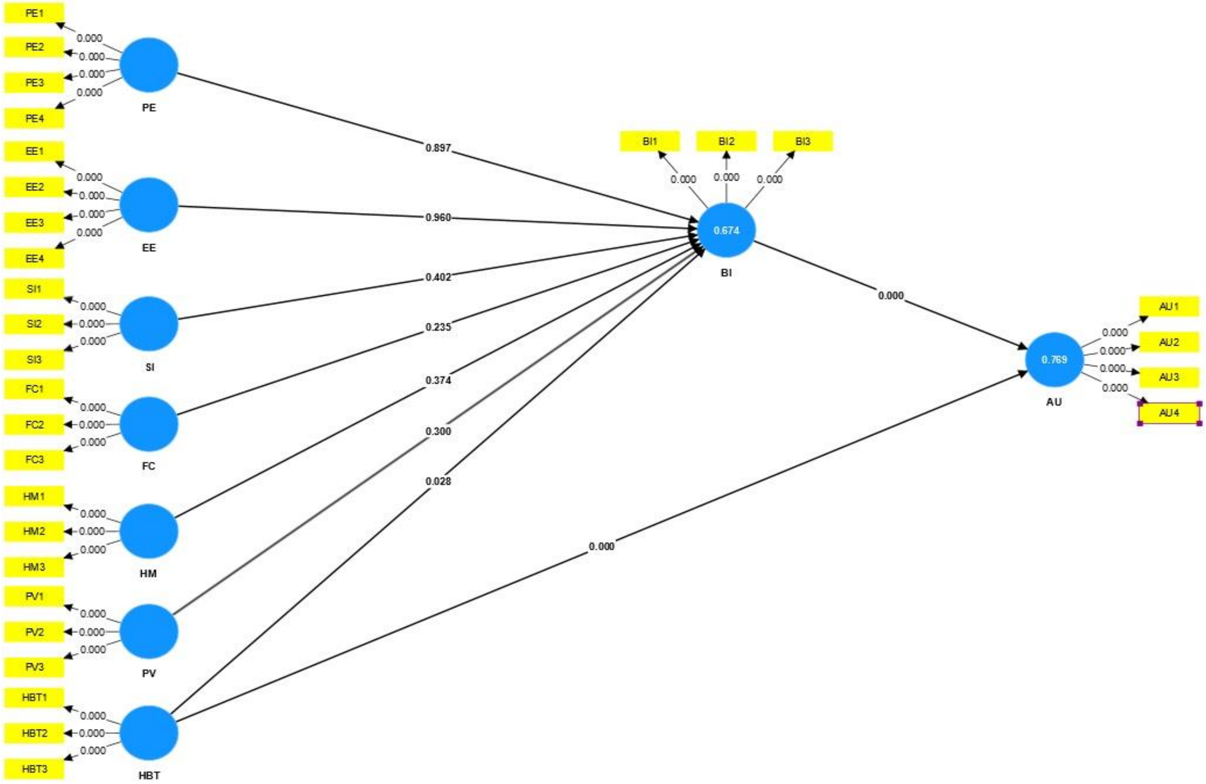


Table 5

Hypotheses testing

Hypothesis	Indication	T-Statistics	P-Values	Results
PE -> BI	H1	0.129	0.897	Rejected
EE -> BI	H2	0.050	0.960	Rejected
SI -> BI	H3	0.837	0.402	Rejected
FC -> BI	H4	1.188	0.235	Rejected
HM -> BI	H5	0.889	0.374	Rejected
PV -> BI	H6	1.037	0.300	Rejected
HBT -> BI	H7	2.201	0.028	Accepted
HBT -> AU	H8	4.570	0.000	Accepted
BI -> AU	H9	4.789	0.000	Accepted

Note: AU (Actual Learning of AI), BI (Behavioural Intention of learning AI), EE (Effort Expectancy), FC (Facilitating Conditions), PV (Price Value), SI (Social Influence), HBT (Habit), HM (Hedonic Motivation), PE (Perceived Expectancy)

The results of hypotheses testing demonstrated that H1, H2, H3, H4, H5, H6, H7 are rejected, and H8, and H9 are accepted. The findings showed that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and price value do not influence the behavioral intention of learning artificial intelligence, but it is only influenced by habit. Moreover, the behavioral intention of learning artificial intelligence can influence the actual learning of artificial intelligence. Therefore, the study claimed that behavioral intention towards learning artificial intelligence in K-12 schools is linked to only one factor of UTAUT 2, which is a habit, and it can influence actual learning of artificial intelligence.

Discussion

UTAUT 2 framework has been studied by many researchers aiming to examine the behavioral intention and use of different technologies or technological platforms, but still, this model has not been used to investigate behavioral intentions towards learning artificial intelligence in K-12 schools and actual learning usage of AI. Therefore, this study has used all the elements of the UTAUT 2 framework, including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, price value, and habit to determine behavioral intentions toward learning artificial intelligence in K-12 schools and actual learning usage of AI. The first hypothesis of the research was designed to investigate the relationship between performance expectancy and behavioral intentions toward learning artificial intelligence. The results revealed an insignificant relationship between performance expectancy and behavioral intentions toward learning artificial intelligence, and these findings are also supported by García de Blanes Sebastián et al. (2022) who found an insignificant relationship between performance expectancy and behavioral intention.

The second hypothesis (i.e., H2) was developed to analyze the influence of effort expectancy on behavioral intentions toward learning artificial intelligence in K-12 schools. The findings revealed that alike performance expectancy, effort expectancy does not influence the behavioral intention of students toward learning AI. Therefore, H2 was rejected. The third and fourth hypotheses were designed to investigate the effect of social influence and facilitating conditions on behavioral intention. The results highlighted that both elements of UTAUT 2 do not influence the behavioral intention of students towards learning AI in K-12 schools, thus, H3 and H4 are rejected. These results are supported by García de Blanes Sebastián et al. (2022), but many studies found a significant relationship between social influence and facilitating conditions with behavioral intention such as Yeop et al. (2019) evaluated the moderation of teachers' workload in between implementation of ICT policies and behavioral intention, they found that facilitating conditions and social influence, both significantly influence behavioral intention. Similarly, Md Yunus et al. (2021) focused on the behavioral intention of online learning and found that it is positively influenced by facilitating conditions and social influence. Moreover, there are many studies explaining the significant relationship between social influence and facilitating conditions on behavioral intention, but in the case of current research, the results are different because they emphasize artificial intelligence in K-12 schools. H5 and H6 were developed to investigate the effect of hedonic motivation, and price value respectively on behavioral intention toward learning artificial intelligence in K-12 schools. All these hypotheses are rejected, as there is an insignificant relation between these UTAUT 2 elements and behavioral intention. Further, H7 was developed to determine the influence of habit on behavioral intention toward learning artificial intelligence in K-12 schools. The results revealed that habit is the only factor among UTAUT 2 elements that can significantly influence the behavioral intention toward learning artificial intelligence in K-12 schools. Therefore, H7 was supported.

The second last hypothesis (i.e., H8) was developed to highlight the influence of habit on the actual use of learning artificial intelligence. The results highlighted that the habit of a student could lead to his or her behavioral intention of learning artificial intelligence. Therefore, this hypothesis was accepted, and these findings align with the study by Nikolopoulou et al. (2021) who also claimed a significant relationship between habit and actual use. The last hypothesis was designed to identify the positive relationship between the behavioral intention of learning artificial intelligence and the actual use of learning AI or AI learning. The results supported the hypothesis by claiming that behavioral intention of learning artificial intelligence in K-12 students can significantly influence their actual use of learning AI or AI learning.

Implications

In the context of education and learning, many studies have used UTAUT 2 theory, and this research has also used this theory to identify the behavioral intention of learning artificial intelligence in K-12 students and the actual use of learning AI or AI learning. Therefore, it has provided several theoretical and practical implications. In terms of theoretical implications, this research has extended the limited understanding of UTAUT 2 theory in the context of learning AI. Moreover, it has used the UTAUT 2 theory model in the context of AI learning. This research is significantly different from prior studies as they either focused on customer adoption of AI (Chu et al., 2022) or emphasized AI adoption by teachers (Alhwaiti, 2023). In the context of practical implications, the findings of this research can act as guidelines for teachers, administrators, principals, or leaders of K-12 schools.

Conclusion

All the elements of UTAUT 2, including performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, price value, and habit, do not influence behavioral intentions towards learning artificial intelligence in K-12 schools, but only habit can influence the actual learning usage of AI. Moreover, the behavioral intentions toward learning artificial intelligence in K-12 schools can lead to actual learning usage of AI.

Limitations and Recommendation

The study has adopted the UTAUT 2 theory model in the context of AI learning in K-12 schools, but still, it has several limitations that future studies can consider. First, the data were gathered from a limited number of students, and future studies can generalize the results by collecting more from diverse students. Secondly, the study has followed the complete UTAUT 2 theory model except moderation of demographics; thus, future studies can fully follow the model.

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APPENDIX I

(Questionnaire)

Section I: Demographics

Q1: What is your gender?

1- Male
2- Female

Q2: What is your level of K-12?

1- Primary Education
2- Secondary Education
3- High School

Q3: What is the type of your school?

1- National School
2- International School

Section II: Questions about UTAUT II

Variables & Items	5	4	3	2	1
Performance Expectancy					
Adopted					
Source: Marchewka et al. (2007), Venkatesh et al. (2012)					
I find artificial intelligence learning useful in my studies					
Using artificial intelligence learning increases my chances of achieving things that are important to me					
Using artificial intelligence learning helps me accomplish various activities, related to my studies, more quickly					
Using artificial intelligence learning increases my productivity in my studies					
Effort Expectancy					
Adopted					
Source: Venkatesh et al. (2012)					
Learning how to use artificial intelligence is easy for me					
My interaction with artificial intelligence is clear and understandable					
I find artificial intelligence learning easy to use					
It is easy for me to become skilful at learning artificial intelligence					
Social Influence					
Adopted					
Source: Venkatesh et al. (2012)					
People who are important to me think that I should use artificial intelligence (and) in my studies and learn it					

People who influence my behavior think that I should use artificial intelligence in my studies and learn it

People whose opinions I value prefer that I use artificial intelligence (and) in my studies and learn it

Facilitating Conditions

Adopted

Source: Venkatesh et al. (2012)

I have the resources necessary to use artificial intelligence learning

I have the knowledge necessary to use artificial intelligence

I can get help from others when I have difficulties in learning artificial intelligence

Hedonic Motivations

Adopted

Source: Venkatesh et al. (2012)

Using artificial intelligence learning in my studies is fun

Using artificial intelligence learning in my studies is enjoyable

Using artificial intelligence learning in my studies is very entertaining

Price Value (PV)

Adopted

Source: Venkatesh et al. (2012)

Artificial intelligence learning has reasonable price

The cost of the services that I have access to through artificial intelligence is worth their money

At the current price, artificial intelligence learning provides a good value

Habit

Adopted

Source: Venkatesh et al. (2012)

The learning of artificial intelligence has become a habit for me

I am addicted to learn artificial intelligence

I must learn artificial intelligence

artificial intelligence learning has become natural to me

Behavioral Intentions of Learning AI

Adopted

Source: Venkatesh et al. (2012), Maldonado et al. (2011) I intend to continue artificial intelligence learning in the future, in my studies I will always try to use artificial intelligence learning in my studies I plan to continue to use artificial intelligence learning frequently, in my studies	
Actual learning usage of AI	
Adopted Source: Chen (2010), Islam (2013) I regularly use artificial intelligence in my studies and learn it Artificial intelligence learning is a pleasant experience I currently learn artificial intelligence as it's a supporting tool in my studies I spend a lot of time on learning artificial intelligence in my studies	