Students' perspectives on the adoption and use of AI tutoring systems in higher education using UTAUT2

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Abstract: *The integration of AI in education has led to the emergence of AI tutoring systems. These systems aim to create personalized learning experiences through the utilization of machine feedback. Despite their increasing prevalence, doubts remain regarding the efficacy, adaptability, and student receptiveness of AI tutoring systems. This necessitates further investigation into AI tutoring systems from the learner's perspective. Moreover, there is insufficient study regarding students' perceptions and responses to AI tutoring systems. This study aimed to quantitatively examine students' perceptions and experiences about AI tutoring systems utilizing UTAUT2. After collecting survey responses from 220 undergraduates, we analyzed the data using SPSS statistical software. The results indicated the presence of favorable correlations among the elements included in the framework. The PE, FC, HT, and HM exert a considerable influence on the BI, as indicated by multiple linear regression analysis. Behavioral Intention (BI) has a big effect on AI tutoring systems' Use Behavior (UB), but Effort Expectancy (EE), Social Influence (SI), and Price Value (PV) have almost no effect on BI. Academic professionals and learners might anticipate the study's findings to be useful for future research.*

Keywords: AI Tutoring Systems, UTAUT2, Students' Perspectives.

1. Introduction

The rapid development of artificial intelligence (AI) has significantly contributed to the massive shift occurring in the Higher Education (HE) sector. Research in that field has led to the development of several learning systems that use AI. These systems include learning analytics and tutor systems (TS). Computer-based educational solutions that use advanced artificial intelligence (AI) to provide students with personalized instruction and support are known as AI tutoring systems (AITS). Obviously, there is enormous promise that AITS will revolutionize the education process. We can tailor the instructional approach to each student's needs. Tailoring lessons to the needs and learning styles of each learner (Rızvı, 2023) helps improve educational outcomes.

Student seeks to assist tutors in various ways. In essence, AITS tailor education to accommodate students' requirements, interests, and learning tempo.

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By providing students with personalized feedback and recommendations, such technologies have facilitated more efficient learning in HE. Students in HE relies on AITS for academic support. It emerged as the educational alternative with the highest potential and appeal (Mounkoro et al., 2024).

AITS such as ChatGPT, Khan Academy, Quizlet, and Duolingo possess the ability to markedly enhance the quality and efficiency of educational activities, including the creation of tailored content, assistance with assignments, and provision of feedback to students. Numerous pupils currently benefit from these initiatives. Approximately two-thirds of AITS users successfully finish all their homework, assignments, and essays (Nipun et al., 2023). Due to their significant utility in the educational process, higher education students have become fully reliant on, or even addicted to, AI tutoring systems. In the long term, these tools may either benefit or detriment students. Therefore, researchers should continuously assess AI tutoring systems (AITS) to ensure their outputs align with student expectations. Furthermore, previous studies necessitate additional investigation into the adoption of AITS (Habibi et al., 2023; Keshtkar et al., 2024).

The current study examines the AITS within the UTAUT2 framework. UTAUT2 has been widely employed in the educational sector to examine the adoption of new technologies by both students (Cabero-Almenara et al., 2024) and educators (Ateş & Gündüzalp, 2025). The implementation and adoption of AITS systems in higher education rely on several factors, including students' behavioral intention (BI) and use behavior of AITS during learning. The Unified Theory of Acceptance and Use of Technology (UTAUT2) could serve as an assessment tool. UTAUT2 is ideally suited for higher education, capable of identifying barriers to adoption and predicting future utilization. UTAUT2 exceeds earlier models by incorporating an increased number of characteristics that affect users' propensity to embrace and maintain technology usage. The model incorporates factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions. The factors include hedonic motivation, habit, price value, behavior intention, and use behavior (Slepankova, 2021). The study investigates students' intentions to utilize AITS by analyzing the primary components of UTAUT2, which encompass performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), habit (HT), price value (PV), behavior intention (BI), and use behavior (UB) of AITS. Educators and developers aiming to implement efficient AI-tutoring systems would significantly benefit from the findings.

2. Material and methods

The research sought to comprehend students' perspectives of AITS through a quantitative methodology. An online questionnaire was conducted to collect data. The study included a sample of 220 out of 242 undergraduates, encompassing a diverse age range. Researchers selected participants for the study from nine distinct

Iraqi universities based on their approachability and accessibility. The form was segmented into three sections. Section One's demographic data includes inquiries regarding age, gender, and university. Table 1 presents a comprehensive analysis of the student's demographics.

Table 1. Demographic information of students

Students' Characteristics		Frequency	Percent
Gender	Male	136	61.8
	Female	84	38.2
Age	18–20	55	25.0
	21–23	121	55.0
	24–26	34	15.5
	27 and above	10	4.5
University	Tishk International University	127	57.7
	Soran University	8	3.6
	Salahaddin University	12	5.5
	University of Sulaimani	11	5.0
	University of Raparin	22	10.0
	Cihan University	19	8.6
	Lebanese French University	12	5.5
	Garmian university	3	1.4
	Koya university	6	2.7
	Total	220	100.0

The second sectione inquires about the utilization of AITS, including the frequency of student usage, their objectives for using, and any encountered difficulties. Table 2 displays the frequency and percentage of inquiries from Section 2.

Table 2. AI Tutoring Systems Usage

AI Tutoring Systems Usage		Frequency	Percent
The most AITS students use	ChatGPT	208	94.5
	Khan Academy	7	3.2
	Duolingo	26	11.8
	Socratic by Google	8	3.6
	Quizlet	9	4.1
Frequency of using AITS	Daily	113	51.4
	Several times a week	72	32.7
	Once a week	21	9.5
	Rarely	14	6.4
Purpose of using AITS	Solving academic assignments	121	27.5%
	Exam preparation	97	22.0%
	Learning new concepts	120	27.3%
	Research assistance	102	23.2%
challenges while using AITS	Lack of accuracy in responses	67	23.2%
	Difficulty in understanding complex topics	84	29.1%
	Limited availability (e.g., server issues)	93	32.2%
	Ethical concerns (e.g., plagiarism)	45	15.6%

Section three inquires about Students' Perspectives on AI Tutoring Systems (ITAS) and encompasses the following elements: PE, EE, FC, PV, HM, HT, BI, and UB of AITS.

The research model was designed to meet research purposes by utilizing nine specific constructs. Behavioral intention (BI) and the use of behavioral artificial intelligent tutoring systems (BU of AITS) were the two constructs that were employed as affected variables in the study. Performance expectancy (PE), effort expectancy (EE), social influence (SI), hedonic motivation (HM), facilitating conditions (FC), price value (PV), and habit (HT) are seven constructs that function as independent variables. Researchers select these constructs as they facilitate the assessment of the technology in adoption and utilization (Habibi et al., 2023). The model was constructed based on eight relationships derived from the literature (Kim, 2013; Venkatesh, Thong & Xu, 2012). Figure 1 shows the relationships between the constructs and the hypotheses.

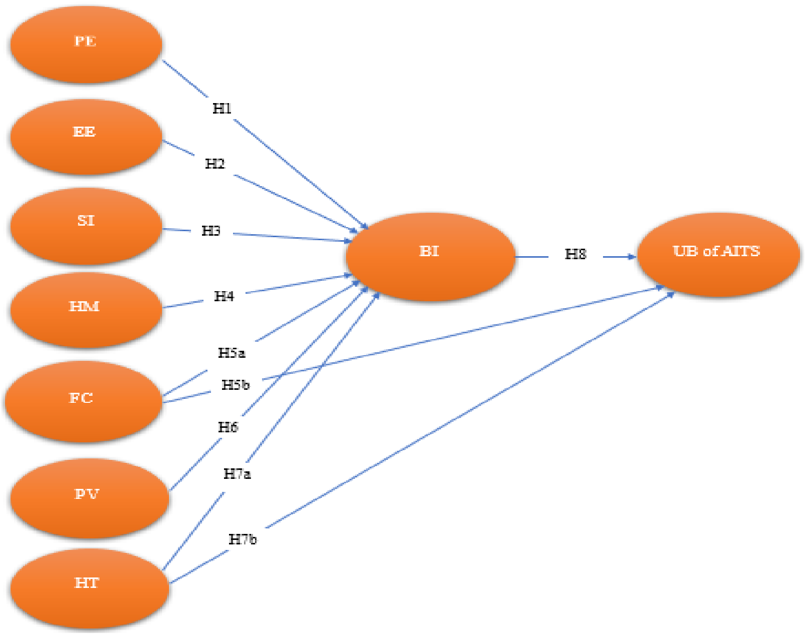

Figure 1. Adopted research model

The hypothesis proposed in the current study stated below:

HI. Performance expectancy significantly influences the behavioral intention to use AITS.

H2. Effort expectancy significantly influences the behavioral intention to use AITS. H3. Social influence significantly influences the behavioral intention to use AITS. H4. Hedonic motivation significantly influences the behavioral intention to use AITS.

H5a. Facilitating conditions significantly influence the behavioral intention.

H5b. Facilitating conditions significantly influence the use behavioral of AITS.

H6. Price value will significantly predict the use behavior of AITS.

H7a. Habit will significantly predict behavioral intention to use AITS.

H7b.Habit will significantly predict the use behavioral of AITS.

H8. Behavioral Intention significantly influences affects use behavioral of AITS during learning.

The scale was adopted from (Venkatesh, et al., 2012), consisting of nine dimensions, each containing distinct items rated on a 5-point Likert scale (estimated from 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree). Upon receiving 220 responses, the researchers downloaded all of them into an Excel spreadsheet. The subsequent phase was converting category data into numerical data. The SPSS application facilitates the analysis of data when it is converted into numerical format. Next, preprocessing data by rejecting two responses because of incomplete data in the dataset, and twenty were eliminated because students did not use AITS at all after classifying the students by inquiring whether they utilized the software or not. Then, Data was analyzed using SPSS, and descriptive statistics; analysis of variance (ANOVA).

Normality of data distribution, reliability and validity, multiple linear regression and correlation analysis tests for the scale were used. To test the normality of data distribution. The kurtosis and skewness test are used to analyse the characteristic shape of the data distribution. Skewness values span from -2 to +2, whereas kurtosis values extend from -7 to +7 (Kim, 2013). The skewness value of PE is -.239 and the kurtosis value is -.918, and for FC -.001, -.646 respectively and so on for the other factors. which means the study data shows a normal distribution since the absolute values of skewness and kurtosis fall within the absolute value of each. Then, parametric analysis can be performed on the date. Cronbach's Alpha is employed to assess the internal consistency of the scale, yielding a value of .975 for 36 items, which indicates an excellent percentage of internal consistency. Verifying internal consistency enhances the trustworthiness of study results and guarantees that the data collection instrument is reliable and consistent (Bujang, Omar & Baharum, 2018). Multiple linear regression used to facilitate the evaluation of the relationship between a dependent variable and several independent factors, enhancing comprehension of the influence exerted by two or more independent variables on the dependent variable. also, it generates coefficients that quantify the relationship between each independent and dependent variable. Moreover, it enables researcher to discern the influence of each predictor, even while considering other variables (Alita et al., 2021). To ascertain the strength and direction of the relationship between two factors. Researchers utilize Correlation analysis tests to enhance the understanding of the interconnections among various factors.

3. Result

3.1 Person correlation

The relationship between the research model's factors is shown in Table 3, which displays the person correlation matrix. Bivariate analysis was used to find the correlation matrix. nine factors were found to be significantly related to each other based on the correlation result. which can take on values between -1 and 1, where 1 denotes a very strong positive correlation (as one variable rises, the other rise). A value of -1 denotes a very negative correlation, where one element goes up while the other goes down, while a value of 0 shows the exact opposite. Lack of association. Therefore, EE has a strong positive correlation with PE, r=.807, also, BI has a strong positive correlation with (PE, EE, SI, FC, HM, PV, PV, HT) as the r value for each was (0.744,0.739, 0.677, 0.74, 0.765, 0.696, 0.786) respectively.

Table 3. Pearson Correlation among factors

Factors	Mean	Std. Devia-tion	PE	EE	SI	FC	HM	PV	HT	BI	UB
PE	3.299	1.115	1								
EE	3.193	1.145	0.807	1							
SI	3.023	0.946	0.713	0.707	1						
FC	3.135	1.013	0.71	0.751	0.712	1					
HM	3.089	1.043	0.707	0.724	0.703	0.728	1				
PV	2.943	1.036	0.66	0.701	0.635	0.666	0.701	1			
HT	2.927	1.044	0.698	0.734	0.664	0.712	0.716	0.744	1		
BI	3.085	1.069	0.744	0.739	0.677	0.74	0.765	0.696	0.786	1	
UB	3.082	1.050	0.757	0.742	0.679	0.676	0.742	0.709	0.784	0.785	1

3.2 Multiple regression analysis

The study employed multiple linear regression analysis to assess the relationship between the dependent variable and other independent variables. The study also looked at the hypothesis to see if it supported or rejected the model and calculated coefficients to measure the relationship between an independent variable and a dependent variable. Researchers specifically examined the impact of each independent variable on the dependent variable through multiple linear regression analysis. The researchers employed a significance level of 0.05 to assess the p-values of the predictors. Variables with p-values of 0.000, 0.019, and 0.005 ($p < 0.05$) were very statistically significant and had a big effect on the dependent variable (Alita et al., 2021). The data supported this conclusion. Conversely, all variables with p-values exceeding 0.05, specifically 0.774, 0.553, 0.864, 0.480, and 0.116, did not significantly contribute to the model as they lacked statistical significance. This signifies H1, H4, H5a, H7a, H7b, and H8 support the model. Similarly, to has a significant influence on UB, the same with HM, FC, HT, and BI. However, the model was not significantly supported by H2, H3, H7b, or H6. EE, SI, PV, FC No statistically significant association exists between the dependent variable and these independent factors. Their p-values pass the 0.05 significance threshold, although their beta values remain minimal. The value for HT (H7b) is 0.405, indicating the highest standardized Beta coefficient. The dependent variable BI is most strongly impacted by variable HT, as shown in Table 4.

Table 4. Multiple regression analasis

			Unstandardized Coefficients		Standardized Coefficients	t-statistical	p-Value
Hypothesis	Dependent Variable	Independent Variable	B	Std. Error	Beta (β)		
H1	Behavioral Intention (BI)	Performance Expectance (PE)	0.178	0.062	0.186	2.859	0.005
H2		Efforts Expectance (EE)	0.039	0.065	0.041	0.594	0.553
H3		Social Influence (SI)	0.011	0.065	0.010	0.171	0.864

H4		Hedonic Motivation (HM)	0.241	0.063	0.235	3.828	0.000
H5a		Facilitating Conditions (FC)	0.154	0.065	0.146	2.366	0.019
H6		Price Value (PV)	0.042	0.060	0.041	0.708	0.480
H7a		Habit (HT)	0.324	0.064	0.316	5.092	0.000
H5b	UB of AITS	Facilitating Conditions (FC)	0.097	0.061	0.093	1.579	0.116
H7b		Habit (HT)	0.408	0.065	0.405	6.307	0.000
H8		Behavioral Intention (BI)	0.390	0.066	0.397	5.920	0.000

4. Discussions and conclusions

This is the first study to examine the determinant factors of AITS in learning by using the UTAUT2 framework. The study quantitatively investigates undergraduates' perspectives by using modified UTAUT. Among the assessed AITSs, ChatGPT emerged as the most favored. The majority of surveyed students reported utilizing AITS daily, predominantly for academic purposes. They experienced server downtime and additional issues due to AITS's unavailability. Based on the data we already have, the person correlation shows that behavioral intention (BI) is strongly linked to performance expectation (PE), effort expectation (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), and habit (HT). The analysis also considered data from consistent with prior studies (Habibi et al., 2023). Analysis of ChatGPT. Additionally, a strong positive correlation exists between EE and PE. Furthermore, the multiple regression analysis indicates that undergraduates in HE achieves superior learning outcomes and academic performance while utilizing AITS. AITS assists students in comprehending intricate concepts and achieving their educational goals. However, effort expectancy (EE) does not influence BI. Influence the Behavioral Intention (BI) to utilizeEE) does not determine BI to use AITS. Numerous researchers were not successful in demonstrating that EE had any influence in the UTAUT investigation (Andrews et al., 2021; Moorthy et al., 2019; Shivdas et al., 2020). Similarly, Social Influence (SI) and Price Value (PV). Furthermore, the facilitation conditions (FC) do not determine the behavioral use of the AI tutoring system (AITS) of BU. This is in contrast to the findings of previous research (Habibi et al., 2023). Habit HT serves as a robust predictor of the propensity to engage with AITS. As well as, habit HT will serve as a significant predictor of how undergraduates would utilize AITS. This explains the rate at which students utilize the AI-driven educational platform, as well as their familiarity with using AITS during learning. It is also imperative to notice that behavioral intention (BI) is a powerful factor that impacts how undergraduates use AITS while they are learning. Future researchers examining subjects akin to AITS may find this technique beneficial. The study's practical implication is the advancement of AITS. The report provides education stakeholders with guidance on enhancing the enabling conditions, which are the primary determinants of BI.

Therefore, educators must consistently highlight the importance of incorporating AI into their students' regular coursework. The current study has certain limitations that must be considered. This study relied exclusively on a survey, suggesting that alternative methods such as comprehensive interviews or group discussions could have produced comparable outcomes. Should the interviews prove to be more reliable, it will represent a significant advancement for academics engaged in this domain moving forward. The study's limitations were the reliance on one theoretical framework, quantitative approaches, universities from one region, sample size, and the fact that it only included the student perspective. Therefore, this study recommended that further research is necessary to empirically examine the factors influencing the adoption and utilization of AITS in higher education. This study focuses solely on UTAUT2, despite the potential advantages of incorporating additional frameworks such as TAM. Multiple frameworks may be employed for this type of investigation. Mixed research methodologies may yield a higher level of information. Such an approach would facilitate the comparison and enhancement of the results. In other terms, further research is necessary to validate this. The study encompassed both public and private universities in a developing country such as Iraq; incorporating universities from developed countries could enhance the sample and elucidate the rate of technology adoption. Conclusions can be derived from the current sample size; however, a bigger sample would yield results more generalizable to a wider population. Furthermore, to achieve a comprehensive understanding, the study recommended expanding students' perspectives to include teachers' perspectives too.

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