



Factors Influencing IoT Acceptance among University Students in Iraq: An Application of the Extended UTAUT Model

Fatores que influenciam a aceitação da Internet das Coisas entre estudantes universitários no Iraque: Uma aplicação do modelo UTAUT estendido

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ABSTRACT

This study investigates the factors influencing the acceptance and use of Internet of Things technologies among students enrolled in private universities in Iraq. The Unified Theory of Acceptance and Use of Technology model is employed as the theoretical framework for this research. The study examines six primary factors including: performance expectancy, effort expectancy, social influence, facilitating conditions, perceived privacy, and trust. A total of 386 students from six private universities in Baghdad, Iraq were included in the data collection. Smart PLS conducted to test the hypotheses. The findings revealed that perceived privacy, performance expectancy, and social influence are the most significant predictors of both behavioral intention and actual use of IoT. Conversely, factors such as effort expectancy, facilitating conditions, and trust showed no significant impact, indicating that once basic privacy concerns are addressed and the perceived usefulness of IoT is clear, students are less influenced by ease of use or institutional support. The findings suggest that university officials should give priority to these areas which has the potential to enhance educational outcomes through the use of intelligent and interconnected technologies.



Keywords: internet of things, UTAUT, behavior intention, performance expectancy, effort expectancy, facilitating conditions, trust

RESUMO

Este estudo investiga os fatores que influenciam a aceitação e o uso das tecnologias da Internet das Coisas (IoT) entre estudantes matriculados em universidades privadas no Iraque. O modelo da Teoria Unificada de Aceitação e Uso da Tecnologia (UTAUT) é utilizado como estrutura teórica para esta pesquisa. O estudo examina seis fatores principais, incluindo: expectativa de desempenho, expectativa de esforço, influência social, condições facilitadoras, privacidade percebida e confiança. Um total de 386 estudantes de seis universidades privadas em Bagdá, Iraque, participaram da coleta de dados. O software Smart PLS foi utilizado para testar as hipóteses. Os resultados revelaram que a privacidade percebida, a expectativa de desempenho e a influência social são os preditores mais significativos tanto da intenção comportamental quanto do uso real da IoT. Por outro lado, fatores como expectativa de esforço, condições facilitadoras e confiança não apresentaram impacto significativo, indicando que, uma vez que as preocupações básicas com a privacidade sejam abordadas e a utilidade percebida da IoT esteja clara, os estudantes são menos influenciados pela facilidade de uso ou pelo suporte institucional. Os resultados sugerem que as autoridades universitárias devem priorizar essas áreas, que têm o potencial de aprimorar os resultados educacionais por meio do uso de tecnologias inteligentes e interconectadas.

Palavras-chave: internet das coisas, UTAUT, intenção comportamental, expectativa de desempenho, expectativa de esforço, condições facilitadoras, confiança



1 INTRODUCTION

The Internet of Things (IoT) is revolutionizing educational settings by enhancing learning experiences, streamlining administrative processes, and optimizing campus activities (Glazer, 2023). Despite extensive research on IoT adoption in educational institutions, limited studies have explored its implementation in private universities in Iraq. By early 2024, Iraq is projected to have 36.22 million internet users (78.7% of the population), including 31.95 million regular social media users (Data Reportal, 2024). These statistics underscore the timeliness and significance of examining IoT adoption in higher education.

This study focuses on the factors influencing students at a private university in Iraq to accept IoT. The authors applied the Unified Theory of Acceptance and Use of Technology (UTAUT) model to assess perceptions of privacy and trust. As technology continues to reshape learning environments, it is essential for universities to integrate IoT into their strategies to prepare students for success in an AI-driven, technologically advanced world.

IoT offers numerous benefits to higher education. Okoye et al. (2024) highlight that IoT devices facilitate personalized and engaging learning experiences by providing real-time feedback and fostering collaboration, thereby enhancing student engagement and satisfaction. Additionally, IoT improves campus efficiency by reducing waste, enhancing safety, and simplifying administrative tasks (Fitria & Simbolon, 2023). These tools are indispensable for remote learning, particularly during disruptions like the COVID-19 pandemic, ensuring continuity of classes and laboratory sessions. Furthermore, IoT systems enable data-driven decision-making, allowing universities to analyze student behavior, predict academic performance, and optimize course planning.

This study investigates how IoT acceptance impacts private colleges in Iraq using the UTAUT model, with a focus on perceived privacy and trust as key determinants. The findings aim to assist educators and technology professionals in fostering IoT adoption in educational institutions, thereby improving classroom management and overall educational systems. Privacy and trust perceptions vary significantly depending on the educational setting. For instance, in regions with stringent data protection regulations or higher privacy awareness, concerns over privacy may hinder IoT adoption. Students' willingness to engage with IoT applications depends on their trust in the technology, the institution, and the security of their data (Cheryl & Ng, 2022).



The primary goal of this study is to identify and evaluate the factors affecting university students' acceptance of IoT in Iraq. Specifically, it aims to determine the most significant factors and understand how performance expectations, effort expectations, social influence, facilitating conditions, perceived privacy, and trust influence the adoption process (Zeebaree et al., 2022). Insights from this research can guide university administrators and policymakers in devising strategies to promote IoT adoption, ultimately leading to improved educational outcomes.

The study's findings will contribute to the effective integration of IoT solutions in Iraq's higher education system, enhancing teaching methods and overall learning experiences. By providing valuable insights into the determinants of technological acceptance in higher education, this research serves as a foundation for future initiatives and studies in this field.

2 LITERATURE REVIEW

2.1 Internet of Things (IoT)

The Internet of Things (IoT) recognized as a company capable of improving education that makes integrated projectors and smartboards along with interactive digital textbooks. Learner data can be processed to develop individualized learning paths that provide learner-specific feedback while also supporting classroom management using the IoT. It is enabling long-distance partnership and cooperation, thereby enhancing the efficiency of community educational assets (Kusmulyono et al., 2023). If Iraqi institutions implemented IoT technology, they could also improve education and help solve intractable social problems. It can enhance the educational process, bridge the gap, and prepare for an ever-evolving digital workforce. Also, it can improve the number of students who receive truly personalized remote learning and, therefore, blended learning.

According to Papadopoulos et al. (2024) using IoT devices at a university can make campus life and the experience of being a student much better. Smart classrooms with IoT-enabled sensors, smart surveillance systems for better safety, and energy-efficient smart lighting are all tools that help make the setting more comfortable and useful. Smart waste systems and predictive maintenance are other ways that IoT helps with facility management. Services for students, like smart parking and indoor navigation, make daily chores easier. IoT can also help with health



monitoring and personalized learning, which will make it easier for people to accept by showing how it can improve convenience, safety, and the general look of the campus.

2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) constructed a model explaining behavioral intention. Performance and effort expectations, social impact, and facilitating conditions of behavior are features in this model that affect users' intentions to use technology. Performance expectancy and effort efficacy are two components of TAM that answer a lot about human behavior when using technology. One of the top models for understanding how individuals decide to accept or reject technology is the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT is based on eight theories and comprises four main factors: effort expectancy, performance expectancy, social influence, and facilitating conditions (Fedorko et al., 2021). The performance promise represents a definitive metric to investigate the extent students believe that the application of academic IoT technology could promote their learning and academic performance (Maki, 2023). The level of effort required is what makes IoT devices so easy to use. Their uses of IoT can be likely to be affected and shaped by fellow students, teachers, and a wider education community. It is known as "social influence." Facilitating circumstances are the resources required to make it more convenient for behavior, such as technical assistance and infrastructure. These are the major foundations that ought to be laid for installing IoT in Iraq's private universities.

2.3 Hypothesis Development

2.3.1 Behavioral Intention and Actual use of IoT

In their study, Massoudi & Fatah (2024) declared that a person's behavioral intention is how willing or ready they are to do a certain behavior. Behavioral intention often comes before real usage behavior. Many research on how people accept new technology has shown that behavior and actual use of IOT is related in a good way (Arfi et al., 2021; Tsourela & Nerantzaki, 2020; Türkeş et al., 2020). Study by Zhang & Lee (2023) concluded that behavioral Intention has significant effect on actual use of IoT. Schukat & Heise (2021) showed that behavioral intention has major influence on the actual use of smart products among German farmers. On the other hand,

a study by Virmani et al. (2023) didn't show relationship between behavior intention and the adoption of industry 4.0. from the above discussion, the authors postulate the following hypothesis:

H1: Behavioral Intention has significant effect on Actual Use of IoT

2.3.2 Effort Expectancy

An important factor that influences both behavioral intention (BI) and the actual use of IoT technologies is effort expectation (EE). Studies have shown that people are more likely to use technology if they think it is simple to use (Adwan et al 2023; Camilleri, 2024). This means that more people will accept it. Aytekin et al. (2022) assumed that effort expectancy is the level to which a person thinks that using a certain technology will be simple and not require any work. According to Lin et al. (2022) when talking about IoT, effort expectancy refers to how much students think that using IoT devices in their schoolwork will be easy and straightforward, which will make them more interested and improve their learning. If IoT technologies like smart gadgets, automated systems, and interactive platforms are simple for students and teachers to understand and use, they are more likely to want to use them in the future (Saeed et al., 2021). When used in schools, EE is a positive indicator of both BI and real IoT use. Study by Al-Muhrami et al. (2021) showed positive relationship between performance expectancy and behavior intention. On the other hand, Almetere et al. (2020) showed EE has positive effect on actual use of IoT in public universities. Therefore, the authors proposed the following hypotheses:

H2: Effort expectancy can influence behavioral intention.

H3: Effort expectancy has a positive effect on actual use of IoT.

2.3.3 Facilitating Conditions

Numerous studies have shown that the conditions that make students want to use IoT rely a lot on facilitating conditions (Aziz et al., 2023; Madni et al., 2022, Ming et al., 2022). However, the students' initial intentions are more affected by things like their performance and effort expectations (Bargmann et al., 2022). According to Faqih (2022) facilitating conditions are how certain a person is that the right technical and organizational framework is in place to support the use of a technology. The result of Zaidan & Massoudi (2025) showed that factors that make it



easier to use technology have a big effect on how it is actually used in different situations. For example, important resources like rapid internet, reliable hardware, and simple integration with current systems are key factors that make people more open to and comfortable with using technology, especially in school settings. From the above, the authors postulated the following two hypotheses:

H4: *Facilitating Conditions have an effect on Behavioral Intention*

H5: *Facilitating Conditions have a positive effect on Actual Use of*

2.3.4 Perceived Privacy

Perceived privacy is a big reason why people don't use or adopt IoT devices, especially in places like universities (Schuster & Habibipour, 2024). Concerns about data privacy and security have a big effect on students' desire to use IoT technologies. According to Jaspers & Pearson (2022), concerns about privacy can make students less likely to adopt because they think their information could be used wrongly. Also, Chatterjee (2022) believed that smart devices with easy-to-use privacy controls can raise the expectation of effort, which can have a good effect on behavior intentions. Students are likely to use IoT apps if they have strong privacy rules and are influenced by their friends. This can make learning safer. Taking care of privacy issues at private universities in Iraq can create smart learning spaces, build trust and engagement, and make sure that rules and standards are followed. By focusing on students' worries about privacy, colleges can get students more involved in their learning. This claim is backed up by Ronaghi & Forouharfar (2020) which shows that while PP has a big effect on the actual adoption of IoTs, it is not a good predictor of BI. Instead, users choose to buy technological goods based on factors like how simple and useful they think they will be. So, this study could test the following two hypotheses:

H6: *Perceived privacy has a positive effect on behavioral intention*

H7: *Perceived privacy has positive effect on actual use of IoT*

2.3.5 Performance Expectancy

Performance expectancy (PE) is the extent to which a technology benefits the user in a particular activity (Shatta & Shayo, 2021). It is achievement of goals through recurring activities

by public or private organizations (Massoudi, 2023). In order to investigate the use performance by using UTAUT. A study by Ayaz & Yanartaş (2020) showed that performance expectancy is associated with behavioral intention. The same trend was found in Al-Rahmi et al. (2020). Also, Almetere et al. (2020) indicated that behavioral intention is a mediating variable between the actual usage of IoT and the independent variables which are performance expectancy. On the contrary, a study by Arfi et al. (2021) showed performance expectancy has no impact on intention to use the IoT. Consequently, it is hypothesized that:

H8: Performance expectancy has positive effect on behavioral intention as a mediator

H9: Performance expectancy has positive effect on actual Use of IoT

2.3.6 Social Influence

According to Zhang et al. (2020), social influence is how much people think they should use a certain technology. When it comes to IoT, social influence refers to how much students feel pressured or encouraged by their friends, teachers, or university policies to adopt and use IoT technologies in their schoolwork (Simpson, 2022). This can have a big effect on their decision to use these tools. Different things, such as performance expectations and effort expectations, may be more important in getting students to use technology. Trivedi et al. (2022) and Nassar et al. (2019) found that social influence has the greatest impact on behavioral intention. In addition, Nazemi Bidgoli et al. (2023) and Almazroi (2023) concluded that social influence can influence the behavioral intention to use IoT. From the above, the authors postulate the following hypotheses:

H10: Social influence affecting behavioral intention

H11: Social influence affecting actual use of IoT

2.3.7 Trust

Credibility and trust have an essential role in getting people to use and accept IoT technologies, especially in colleges and universities. The UTAUT model helps figure out how students choose to use IoT devices. Trust, which is affected by how private someone thinks they are, affects behavior plans for using IoT. People who trust others are more likely to want to use IoT technologies because they feel less unsure and risky. Learners need to trust IoT in order to



have confidence in its purity, security, and functionality. For IoT to work in online private colleges, users must trust network providers. This will improve students' learning experiences and help them do better in university. A study by Madni et al. (2022) found that trust has a positive effect on both BI and actual usage when IoT systems used in schools to access e-learning services. In the same way, a study by Mubarak & Petraite (2020) showed that trust is the best indicator of how well people will adopt new technologies and how valuable they see it. This includes both the desire to use them initially and how they will continue to do so over time (Massoudi & Fatah, 2024). From the above, the authors proposed the following hypotheses:

H12: *Trust has positive effect on behavioral Intention*

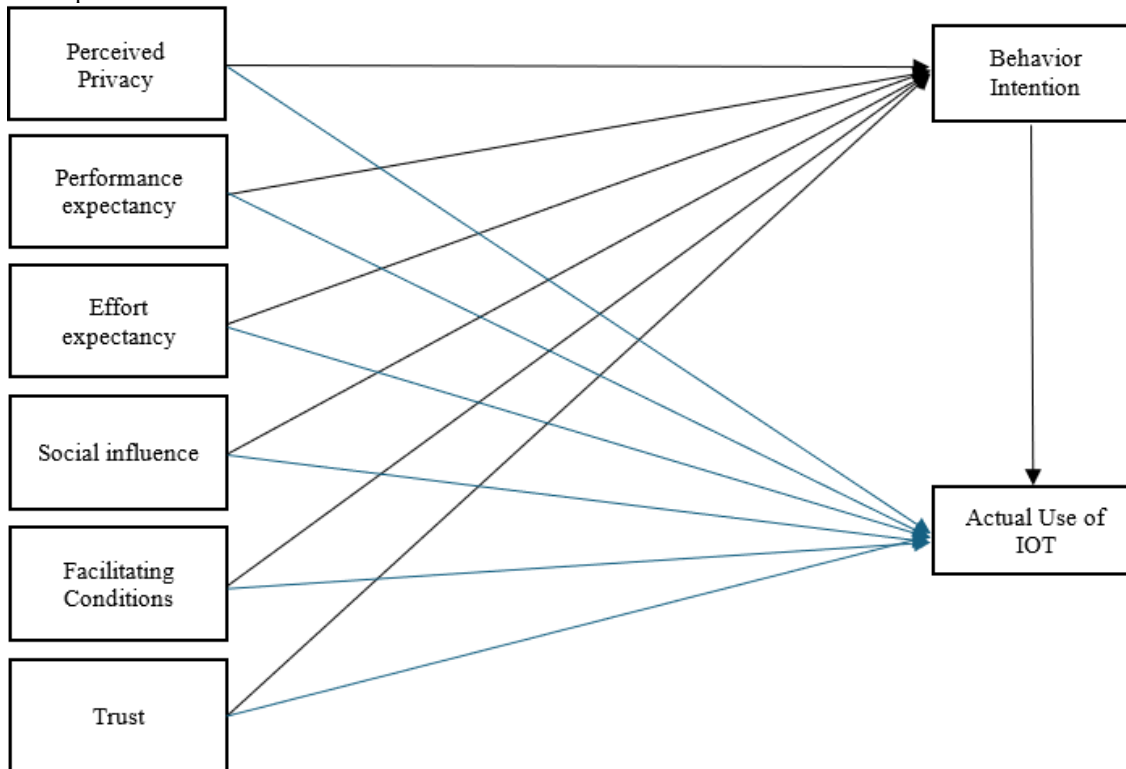
H13: *Trust has positive effect on actual Use of IoT*

2.4 Research Model

The conceptual model used is presented below in Figure 1:

Figure 1

Conceptual Model





3 METHODOLOGY

3.1 Sampling Criteria

This study employed a quantitative research design to examine the factors influencing students' acceptance and use of Internet of Things (IoT) technologies across six private universities in Iraq. The Unified Theory of Acceptance and Use of Technology (UTAUT) model was adopted as the theoretical framework, incorporating six original constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) as independent variables. In addition, Perceived Privacy (PP) and Trust (T) were introduced as contextual extensions to better capture students' behavioral intentions (BI) and the actual use (AU) of IoT technologies in higher education settings.

Participants were undergraduate students enrolled in various faculties (Engineering, Computer Science, Business Administration, and Education) at six accredited private universities located in Baghdad, Iraq. These universities were selected using purposive sampling, as they represent institutions with ongoing IoT-based educational initiatives and digital learning environments. Eligibility criteria required that respondents (a) be actively enrolled as full-time students during the 2024–2025 academic year, and (b) have experience using IoT-based or smart educational technologies (e.g., smart classrooms, IoT-enabled labs, or connected learning platforms).

3.2 Data collection procedures

Data were collected between March and May 2025 through both online and paper-based questionnaires to maximize accessibility and response rates. A total of 450 questionnaires were distributed, 250 electronically via institutional email and 200 in person on campus. After screening for missing or inconsistent responses, 64 questionnaires were excluded, resulting in 386 valid responses, corresponding to an effective response rate of 86%. The survey instrument consisted of 8 latent variables measured using validated multi-item scales adapted from prior studies: UTAUT constructs (PE, EE, SI, FC) from Vidal-Silva et al. (2024). Behavioral Intention (BI) and Actual



Use (AU) from Alyoussef & Al-Rahmi (2022). Trust (T) and Perceived Privacy (PP) from Azeez et al. (2023)

All items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The final dataset was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0 to test the hypothesized relationships among constructs.

3.3 Controls for Common Method Bias

To minimize common method bias (CMB) and enhance the validity of the results, Respondents were assured of the anonymity and confidentiality of their answers to reduce evaluation apprehension and social desirability bias. To assess potential multicollinearity and common method bias, Variance Inflation Factor (VIF) values were examined in SmartPLS 4, following the recommendations of Hair et al. (2024) and Kock (2015). The VIF values ranged from 3.16 to 3.29. Since all values were below the threshold of 3.3 (Kock, 2015), multicollinearity was not a major concern. These are inner VIF values, they show how much each predictor construct (e.g., Behavior Intention, Effort Expectancy, etc.) is correlated with others when predicting another construct (e.g., Actual Use of IoT). Table 1 shows the results confirming that common method bias was not a significant issue in the model:

Table 1

Variance Inflation Factor

Dependent Variable	Predictors (VIFs)	Interpretation
Actual Use of IoT	N/A	N/A
Behavior Intention	3.162 Slightly near 3.3	No issue
Perceived Privacy	3.299 near 3.3	No issue
Others (EE, FC, PE, SI, Trust)	All ≤ 2.4 Within acceptable range	No issue

3.4 Demographic Profile

The final sample of 386 respondents represented a balanced distribution across key demographic variables, including gender, academic year, faculty affiliation, age group, and types



and frequency of IoT technology use. This distribution ensures that the data adequately reflect the diversity of students' experiences and exposure to IoT technologies within Iraq's private higher education sector. Table 2 illustrates the demographic variables

Table 2
Statistical Data of Demographic Questions

Category	Target Number	Frequency (%)
Academic Year		
Freshmen	102	26.4%
Sophomore	96	24.9%
Junior	91	23.6%
Senior	97	25.1%
Gender		
Male	210	63.1%
Female	123	36.9%
Faculty		
Science	68	17.8%
Engineering	79	20.7%
Humanities	83	21.7%
Business	76	19.9%
Other	81	20.9%
Age Group		
<20	89	23.1%
20-22	108	28.0%
23-25	100	25.9%
>25	88	22.8%
Types of Technology Used		
Smartphones	245	63.6%
Tablets	59	15.3%
Laptops/Desktops	81	21.0%
Frequency of Use		
Multiple times a day	252	65.4%
Once a day	67	17.4%
Several times a week	39	10.1%
Once a week	19	4.9%
Less	9	2.3%

4 RESULT AND ANALYSIS

4.1 Reliability and Validity

Before carrying out basic analysis, the research instrument was confirmed using a reliability test. The Cronbach's Alpha test evaluates the reliability between items in the same construct. Sabol et al. (2023) proposed that Cronbach's Alpha should be greater than 0.7 (>0.7) to be considered very reliable. Table 2 shows that the Cronbach's Alpha values for all variables are greater than 0.7, except Social Influence value score of 0.609 which is considered satisfactory in some previous studies. Thus, the research instrument is considered reliable.

The validity of the constructs was evaluated for convergent validity and discriminant validity. For the convergent validity, the results in table 2 show that the average variance extracted (AVE) was higher than 0.5. Hair et al. (2020) state that a degree of variance greater than 0.5 is considered acceptable. The square root of the AVE was used to correlate the latent components for the discriminant validity analysis. This means that the entire loading factors are not insignificant and pass the value of 0.50, thereby satisfying the presented correlations.

The displayed structural equation model (SEM) illustrates numerous latent variables, each assessed by several indicators, with pathways leading to behavioral intention and actual use of IoT. According to Hair, (2020), indication reliability to be good when the outer loadings surpass 0.7. The loads in this model mostly meet the specified criteria. The values range from 0.836 to 0.876 for perceived privacy, 0.849 to 0.930 for performance expectancy, 0.858 to 0.899 for effort Expectancy, 0.807 to 0.878 for social influence, 0.825 to 0.853 for facilitating conditions, 0.835 to 0.926 for trust, 0.884 to 0.892 for behavioral intention, and 0.857 to 0.903 for actual use of IoT. The inner model demonstrates substantial connections between perceived privacy, performance expectation, effort expectancy, social influence, facilitating conditions, and trust with behavioral intention. Furthermore, the path coefficients indicate a strong association between behavioral intention and the actual use of IoT as showing in table 3 and figure 1 below.

**Table 3**

Construct Reliability and Validity

Construct	Indicators	Loadings	α	ρ_A	CR	AVE
Actual Use of IOT	IOT1	0.866	0.895	0.896	0.927	0.760
	IOT2	0.879				
	IOT3	0.857				
	IOT4	0.885				
Behavioral Intention	BI1	0.903	0.821	0.866	0.883	0.660
	BI2	0.857				
	BI3	0.869				
	BI4	0.875				
Effort Expectancy	EE1	0.885	0.856	0.859	0.912	0.776
	EE2	0.858				
	EE3	0.899				
Facilitating Conditions	FC1	0.845	0.794	0.794	0.879	0.708
	FC2	0.853				
	FC3	0.825				
Perceived Privacy	PP1	0.836	0.909	0.910	0.932	0.733
	PP2	0.861				
	PP3	0.876				
	PP4	0.848				
	PP5	0.860				
Performance Expectancy	PE1	0.849	0.884	0.895	0.928	0.812
	PE2	0.930				
	PE3	0.922				
Social Influence	SI1	0.807	0.609	0.665	0.799	0.582
	SI2	0.878				
	SI3	0.847				
Trust	T2	0.926	0.918	0.933	0.942	0.803
	T2	0.911				
	T3	0.835				
	T4	0.910				

Note. α = Cronbach's Alpha; ρ_A = internal consistency; CR = Composite Reliability; AVE = Average Variance Extracted.

All AVE values > 0.50 and CR > 0.70, indicating acceptable convergent validity.

4.2 Discriminant validity

Table 4 displays HTMT statistics for IoT concepts, demonstrating robust discriminant validity. All value less than 0.850, which falls below the threshold. According to Hair et al. (2024) certain constructs may not be empirically distinct, redundant or overlapping items should be



removed. In this model no relationship exceeded the threshold of 0.850 therefore no signal of multicollinearity and this finding ensures that each construct captures a unique aspect of the theoretical framework.

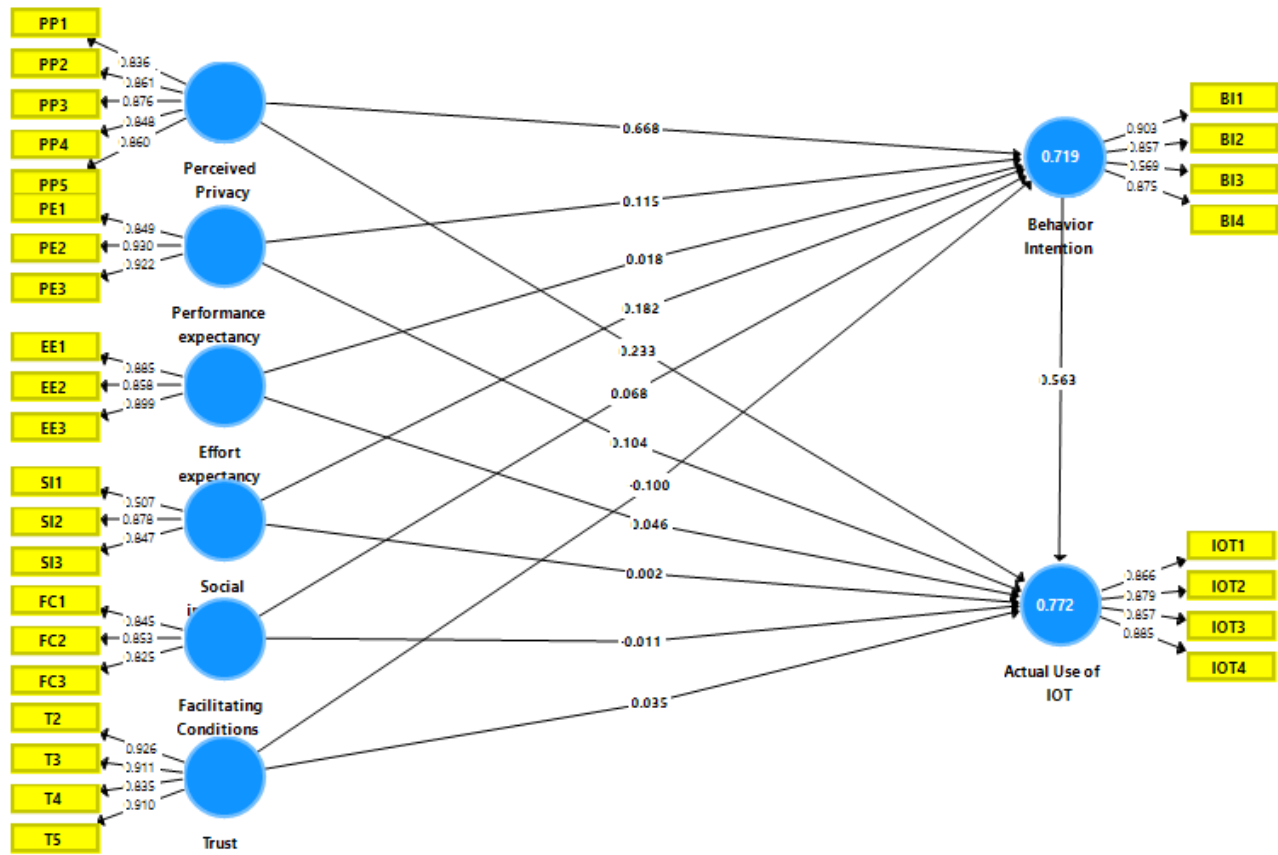
Table 4

HTMT

	Actual Use of IOT	Behavioral Intention	Effort Expectancy	Facilitating Conditions	Perceived Privacy	Performance Expectancy	Social Influence	Trust
Actual Use of IOT	—							
Behavioral Intention	0.845	—						
Effort Expectancy	0.600	0.617	—					
Facilitating Conditions	0.571	0.649	0.507	—				
Perceived Privacy	0.842	0.839	0.590	0.605	—			
Performance Expectancy	0.701	0.720	0.597	0.483	0.674	—		
Social Influence	0.748	0.846	0.832	0.829	0.684	0.779	—	
Trust	0.563	0.570	0.505	0.779	0.614	0.562	0.809	—

Figure 2.

The Pls Model R-Square, Outer loading and Path Coefficients



4.3 The structure model

According to Hair & Alamer (2022) a bootstrapping with 5000 subsamples is proposed. Bootstrapping is applied to compute the estimations' standard errors to test the hypothesis of the proposed model. To do so, the coefficient of determination (R^2) is evaluated. R^2 refers to the measurement of the variance of endogenous to exogenous. Hair et al. (2024) stated that if the R^2 ranges are less than 0.19 it should be rejected. If the ranges between 0.19 to 0.33 it will be considered weak. If it ranged from 0.33 to 0.67 it will be considered moderate. Finally, if R^2 ranges above 0.67 it is considered high. As shown in Table 4, the R^2 value for Actual Use of IoT is 0.772 (adjusted $R^2 = 0.765$), which indicates a considerable level of predictive accuracy and suggests that approximately 77% of the variance in actual usage behavior is explained by its antecedent constructs. Similarly, the R^2 value for Behavioral Intention is 0.719 (adjusted $R^2 = 0.712$), also



reflecting a substantial explanatory power, meaning that 72% of the variance in behavioral intention is accounted for by the predictor variables. These findings validate that the proposed model holds strong predictive capability and theoretical robustness, consistent with the thresholds established by Hair et al. (2024). R-Squared Values is illustrated in table 5 and in figure 2.

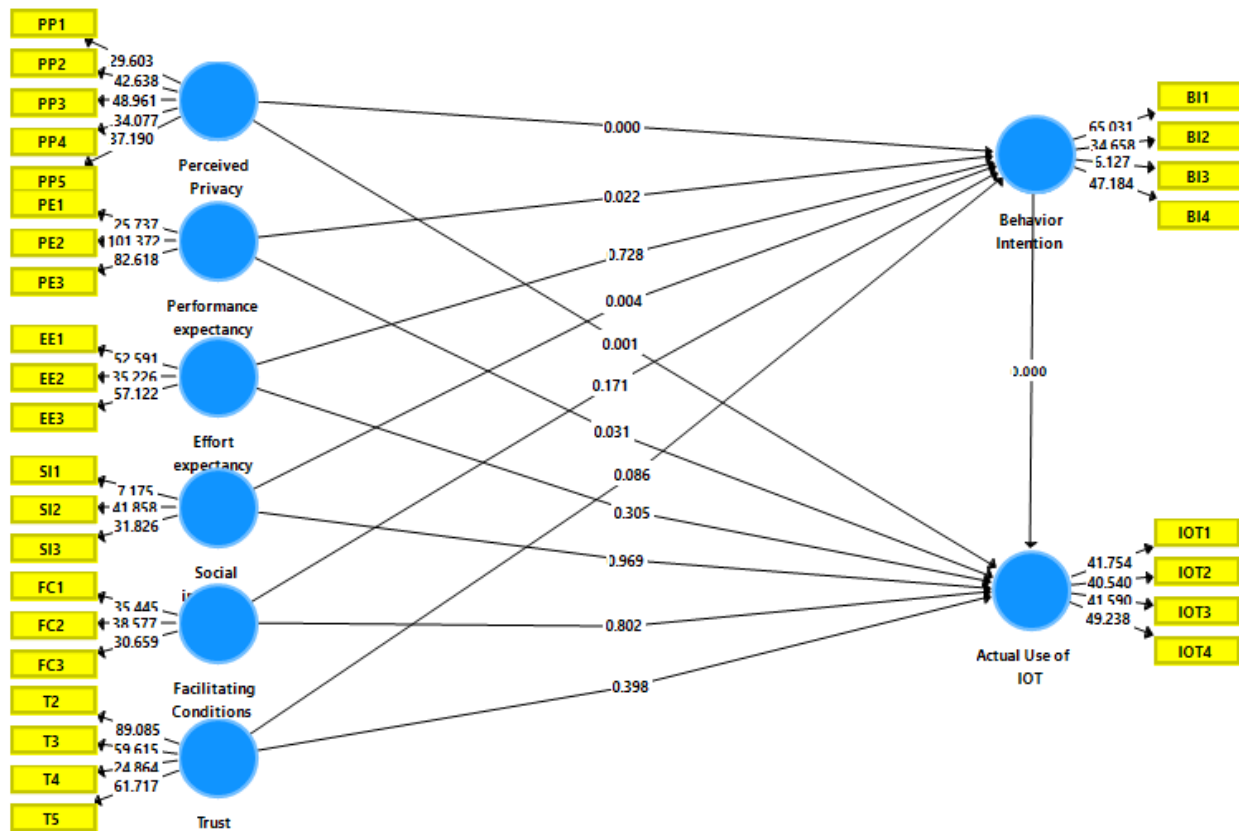
Table 5

R-Squared Values

Variable	R ²	R-Squared Adjusted
Behavioral Intention	0.719	0.712
Actual Use of IoT	0.772	0.765

Figure 3

Model Showing Path Coefficient With P-Values



4.4 Hypothesis Testing

The study reveals key factors influencing IoT adoption in college education in Iraq. Partial Least Squares (PLS) is used in structural equation modelling (SEM) to test how two factors are related. The Original Sample, Sample Mean, Standard Deviation, T Statistics, P Values, and Hypothesis Supported show how strong the relationship as recommended, a path is considered statistically significant when $t \geq 1.96$ and $p \leq 0.05$ at a 5% significance level. Higher values mean the relationship is more significant, while lower values mean it's just a coincidence. Tabel 4 displays the statistical relationships between several variables and their impacts on behavioral intention and actual use of IoT, as reported by Hair & Alamer (2022).

The study found that there is significant relationship between behavioral intention and actual use of IoT ($\beta = 0.563$, $p = 0.000$), suggesting that there is evidence to support this relationship. Thus, H1 is supported. The variable effort expectancy has a negative impact on the variable behavioral Intention, with a coefficient of 0.057 a t-value of 1.029, and a p-value of 0.304. Thus, H2 is rejected. H3 effort expectancy \rightarrow behavioral intention is also rejected ($\beta = 0.563$, $t = 0.348$, $p = 0.728$). H4 facilitating conditions \rightarrow actual use of IoT is also rejected ($\beta = 0.028$, $t = 0.515$, $p = 0.607$). H5 facilitating conditions \rightarrow behavioral intention is also rejected ($\beta = 0.068$, $t = 1.370$, $p = 0.171$). H6 perceived privacy \rightarrow actual use of IoT is confirmed ($\beta = 0.609$, $t = 10.074$, $p = 0.000$). H7 perceived privacy \rightarrow behavioral intention is also confirmed ($\beta = 0.668$, $t = 13.596$, $p = 0.000$). H8 Performance Expectancy \rightarrow Actual Use of IoT is supported ($\beta = 0.169$, $t = 2.970$, $p = 0.003$). H9 Performance Expectancy \rightarrow Behavioral Intention is supported ($\beta = 0.115$, $t = 2.304$, $p = 0.022$). H10 social influence \rightarrow actual use of IoT is rejected ($\beta = 0.105$, $t = 1.791$, $p = 0.074$). H11 Social Influence \rightarrow Behavioral Intention is confirmed ($\beta = 0.182$, $t = 2.887$, $p = 0.004$). The supported hypotheses in table 6 collectively confirm that individuals' perceptions of privacy, expected performance, and social influence significantly contribute to their behavioral intention and actual use of IoT technologies in the Iraqi context.

H12 trust \rightarrow actual use of IoT is rejected ($\beta = -0.021$, $t = 0.402$, $p = 0.688$). Finally, H13 Trust \rightarrow behavioral intention is also rejected ($\beta = -0.100$, $t = 1.720$, $p = 0.086$) implying that trust does not play a decisive role in shaping behavioral intentions or actual usage when users already perceive high utility and privacy assurance in IoT systems. A summary of the results illustrated in table 6.

**Table 6**

Summary of The Results

	Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values	Hypothesis Supported
H1	Behavioral Intention -> Actual Use of IOT	0.563	0.567	0.068	8.256	0.000	Yes
H2	Effort Expectancy -> Actual Use of IOT	0.057	0.062	0.055	1.029	0.304	No
H3	Effort Expectancy -> Behavioral Intention	0.018	0.021	0.052	0.348	0.728	No
H4	Facilitating Conditions -> Actual Use of IOT	0.028	0.027	0.054	0.515	0.607	No
H5	Facilitating Conditions -> Behavioral Intention	0.068	0.067	0.050	1.370	0.171	No
H6	Perceived Privacy -> Actual Use of IOT	0.609	0.602	0.060	10.074	0.000	Yes
H7	Perceived Privacy -> Behavioral Intention	0.668	0.666	0.049	13.596	0.000	Yes
H8	Performance Expectancy -> Actual Use of IOT	0.169	0.171	0.057	2.970	0.003	Yes
H9	Performance Expectancy -> Behavioral Intention	0.115	0.113	0.050	2.304	0.022	Yes
H10	Social Influence -> Actual Use of IOT	0.105	0.105	0.058	1.791	0.074	No
H11	Social Influence -> Behavioral Intention	0.182	0.181	0.063	2.887	0.004	Yes
H12	Trust -> Actual Use of IOT	-0.021	-0.018	0.052	0.402	0.688	No
H13	Trust -> Behavioral Intention	-0.100	-0.097	0.058	1.720	0.086	No

Note. Critical values for significance were determined using the two-tailed test: $t \geq 1.96$ ($p \leq 0.05$). Paths marked as Yes indicate statistically supported relationships.

4.5 Discussion

The aim of this study was to explore the factors influencing the acceptance and use of IoT among students enrolled in private universities in Iraq with the application of the extended UTAUT Model. Behavioral Intention \rightarrow Use of IoT (H1): Results of the analysis indicate a significant positive relationship between behavioral intention and actual use of IoT, such that students' intended behavior is an important predictor of their usage in reality. This result is consistent with the original UTAUT assumption (Venkatesh et al., 2003) and recent pattern of technology adoption research. For example, Almaiah & Al-Khasawneh (2022) noted intention to use was the most

significant factor of IoT and e-learning technology adoption in Middle Eastern university students. Likewise, Hair & Alamer (2022) establish that in the context of educational institutions, behavioral intention is the single best predictor for actual technological use. This means that in Iraqi higher education sector, when students' willingness/motivation towards using IoT increase, it simply reverberates to practice as well.

Perceived Ease of Use → Behavioral Intention (H2, H3): Both hypotheses on effort expectancy were not supported, showing that the ease of use does not significantly affect students' behavioral intentions to adopt IoT. This is in contrary with classic UTAUT but consistent with recent work on mature technologies. Alamri et al. (2023) concluded that in a technologically literate student groups, ease of use may not be most critical as students are already familiar with digital interfaces and system. Salloum & Shaalan (2022) observed that when users believe a system is highly useful in an organization, the effort of learning a system as barrier diminishes. Consequently, as students in Iraqi universities have begun to use digital platforms more extensively, effort expectancy may have been somewhat less pronounced as a determinant.

Facilitating Conditions → Use and Intention (H4, H5): Both facilitating condition paths were also nonsignificant, meaning available infrastructure and the support of institutions barely affect IoT use and intention. This finding might mirror the situational constraints faced by Iraqi universities where infrastructural resources are limited or imbalanced. Al-Kaabi et al. (2023) recorded similar results in Iraq and Jordan stating that just having the resources does not ensure adoption but having sound policy frameworks and training programs. It highlights that universities should not just supply IoT resources, but also create a caring environment by way of training support, curriculum update and infrastructure maintenance.

Perceived Privacy → Actual Use of IOT and Behavioral Intention (H6, H7): Perceived privacy had the strongest effect among them on both actual use and behavioral intention. These findings highlight the privacy assurance as an essential issue for Iraqi students in acceptance IoT technologies. This result is consistent with the results of Shin (2022) and Islam et al. (2023) who exposed that the concerns of privacy and data protection is essential in an environment of poor regulatory trust. Because of Iraq's emerging digital infrastructure and potential cybersecurity related threats, the willingness of students to interact with IoT systems depends on their trust in data privacy and security. This stresses the importance of embedding privacy-by-design principles in academic IoT platforms (Zidan & Massoudi, 2025).



Performance Expectancy → Use and Intention (H8, H9): Both hypotheses were supported, students engaged IoT technologies will improve learning performance and efficiency. According to Venkatesh et al. (2012), performance expectancy is considered as a founding UTAUT driver and it has been further supported in the context of higher education in Iraq practice. An empirical study by Al-Emran & Granić (2022) showed that perceived usefulness, especially in enhancing academic performance continues to be a significant determinant for technology use in developing countries. For this reason, deploying IoT in Iraqi universities could be improved by emphasizing the concrete educational advantages such as real-time access to data, interactive learning and automation.

Social Influence → Use and Intention (H10, H11): Social influence has significant positive effects on behavioral intention. This reveals that whilst peer or lecturer encouragement influences students' views towards IoT usage in education, it may not necessarily motivate continuous use behavior. This trend is in line with Karahanna et al. (2022) and Cheng & Yuen (2023), who found that social influence might only act as an intermediate cause, especially in collectivistic societies where peer norms carry over the initial beliefs but not commitment. In Iraq, cultural and normative elements may initiate formation of an attitude for students, but these elements erode as they form their individual experience of the matter and perceptions about its value.

Trust → Behavior and Intention-to-Use (H12, H13): Both trust hypotheses were not confirmed. Despite that trust is commonly identified as a predictor of technology acceptance, these findings imply students' choices are more driven by concerns over privacy and performance than over perceived institutional trust. According to Zhou et al. (2023), if the systems provide privacy and reliability perspective, trust is no longer necessary as users will observe working rather than institutional reputation. This result demonstrates a practical, outcome-based perspective in Iraqi students where the user confidence and trust are minimized as compared to system utilities traits.

In sum, the underpinning hypotheses (H1, H6, H7, H8, H9, H11) confirm that perceived privacy, performance expectancy and social influence are among the major determinants which shape IoT's acceptance within Iraqi higher educational institutions. The findings identify an interesting trend: security and usefulness are rated higher than ease of use and institutional support by the students, demonstrating a maturing digital literacy and technology experience for Iraqi university communities.



5 CONCLUSION

This study investigated the factors influencing the acceptance and use of IoT technologies among university students in Iraq, utilizing the Extended UTAUT model. By applying Partial Least Squares Structural Equation Modeling (PLS-SEM), the study provided valuable insights into the behavioral patterns of students and the factors that drive or hinder IoT adoption in higher education contexts.

The findings indicate that perceived privacy, performance expectancy, and social influence are the most significant predictors of both behavioral intention and actual use of IoT. This highlights the importance of privacy assurance, perceived usefulness, and the influence of peers or faculty in shaping students' adoption behaviors. Privacy emerged as a particularly strong determinant, suggesting that students in Iraq are highly sensitive to data protection concerns, likely due to the developing state of digital infrastructure and a general mistrust in data security.

Conversely, factors such as effort expectancy, facilitating conditions, and trust showed no significant impact, indicating that once basic privacy concerns are addressed and the perceived usefulness of IoT is clear, students are less influenced by ease of use or institutional support. In the Iraqi context, privacy and functionality outweigh institutional or technological trust as primary drivers of IoT adoption.

The rejection of some hypotheses especially those related to effort expectancy and facilitating conditions suggests that university students in Iraq, already familiar with digital tools, may not view IoT as significantly more difficult to use than other technologies, and that simple access to resources is insufficient for encouraging widespread adoption. This underscores the importance of integrating IoT into educational curricula and ensuring that privacy and performance benefits are clearly communicated to the students.

5.1 Implications for Policy and Practice

The study's findings emphasize the need for targeted strategies to enhance the adoption of IoT technologies within higher education. These strategies should prioritize ensuring that IoT systems comply with stringent data protection regulations and providing clear communication



regarding privacy policies is crucial to addressing student concerns. Also, IoT technologies should be marketed and integrated into academic settings with a focus on how they can improve learning outcomes, student productivity, and administrative efficiency. In addition, encouraging faculty and peer adoption of IoT systems could further motivate students to engage with the technology. Although ease of use was not found to be a major barrier, continuous training programs should be implemented to build confidence in using IoT systems, ensuring students fully understand their utility. Finally, since perceived privacy was found to be one of the most significant factors influencing both behavioral intention and actual use of IoT, universities must prioritize data privacy and security in their IoT systems. This includes adopting robust data protection measures, ensuring that students' personal information is secured, and complying with international privacy standards. By establishing transparent privacy policies that outline how student data is collected, stored, and used will foster trust and alleviate students' concerns regarding potential misuse of their personal information.

5.2 Limitation and Future Direction

While this study offers valuable insights, it is important to acknowledge its limitations. The research was conducted in a single country (Iraq) and within a specific cultural and educational context. Future studies could expand the scope to include other regions or compare findings across different cultures to enhance the generalizability of the results. Additionally, further research could explore longitudinal changes in IoT adoption and investigate how IoT use evolves over time in response to shifting technological, institutional, and socio-political landscapes.

Moreover, future studies could incorporate other models, such as the Technology Acceptance Model (TAM) or Innovation Diffusion Theory (IDT), to compare the explanatory power of different frameworks in predicting IoT adoption. Examining the role of IoT in the classroom, its impact on student engagement, learning outcomes, and teaching methods would also provide deeper insights into how IoT can be optimized for educational purposes.

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