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# UNDERSTANDING UNIVERSITY STUDENTS' E-LEARNING ADOPTION IN THE MIDDLE EAST: AN APPLICATION OF THE UTAUT MODEL

**Rebean Al-Silefanee** (Corresponding Author, Email: [r.alsilefanee@gmail.com](mailto:r.alsilefanee@gmail.com))

Department of Economics, College of Administration and Economics, University of Duhok, Iraq

ORCID ID: 0000-0002-3251-3674

**Ramazan Uctu**

Department of Business Administration, American University of Iraq-Sulaimani (AUIS), Iraq and

Department of Economics, Stellenbosch University, South Africa

ORCID ID: 0000-0001-5189-5762

**Sinbl Hawro Yakoob**

PhD Candidate, International Entrepreneurship and Innovation Department, Horizons University, Paris, France

ORCID ID: 0009-0006-5553-7202

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## ABSTRACT

In many developing contexts, including the Middle East, the adoption of e-learning remains limited compared to developed countries. This study explores the factors influencing students' behavioral intentions to use e-learning systems at two American universities in the Kurdistan Region of Iraq (KRI), using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. A total of 463 student responses were collected and analyzed using Structural Equation Modeling (SEM) to evaluate the impact of four core constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC).

The results indicate that PE and FC significantly and positively affect Behavioral Intention (BI) ( $p < 0.001$ ), suggesting that perceived academic benefits and available technical support are critical drivers of adoption. In contrast, EE ( $p = 0.055$ ) and SI ( $p = 0.529$ ) did not show significant effects, pointing to challenges in user interface design and limited peer influence. The model explained 82.6% of the variance in BI ( $R^2 = 0.826$ ), demonstrating strong predictive power.

These findings highlight the need for institutions to prioritize infrastructure, usability, and communication of e-learning benefits. The study also underscores the value of contextualized digital readiness strategies, particularly in regions with infrastructural and language diversity.

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## KEYWORDS

E-learning Adoption, UTAUT, Behavioral Intention, Higher Education, Middle East

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## CITATION

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## 1- Introduction

The expansion of the Internet has profoundly transformed sectors across the globe, with education being no exception. As of April 2024, over 5.44 billion people were using the Internet worldwide, including approximately 184 million users in the Middle East (Abbad, 2021; Statista Research Department, 2024). This widespread access, combined with rapid advances in Information and Communication Technologies (ICT), has accelerated the integration of e-learning systems (ELS) into higher education institutions (HEIs) throughout the region. E-learning provides flexibility, real-time communication, access to diverse content formats, and the ability to swiftly update learning materials positioning it as a critical component of modern higher education (Abdou & Jasimuddin, 2020).

Despite its potential, the adoption of ELS -particularly in developing regions like Iraq- remains uneven. Challenges such as poor infrastructure, low digital readiness, motivational barriers, and student isolation persist (Akbar, 2021). The COVID-19 pandemic acted as a turning point, triggering a rapid transition from face-to-face instruction to online platforms, with global e-learning adoption reportedly rising by over 200% (Peck, 2024). In the Kurdistan Region of Iraq (KRI), the shift revealed disparities in preparedness and highlighted the urgent need to understand factors that affect the successful implementation of ELS.

To address this gap, the current study focuses on two American-style universities in KRI, the American University of Iraq, Sulaimani (AUIS) and the American University of Kurdistan (AUK). The main research question guiding this work is:

What are the key factors influencing the adoption and use of e-learning systems in KRI based on the UTAUT model?

This question is essential to uncovering the behavioral and contextual elements shaping students' interaction with ELS in the region. By applying the Unified Theory of Acceptance and Use of Technology (UTAUT) model, this study analyzes how constructs such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) impact students' Behavioral Intention (BI) to adopt e-learning tools.

While numerous studies have applied UTAUT to explore technology adoption in education (e.g., Cheon et al., 2012; Venkatesh et al., 2003; Zandi et al., 2022), limited empirical research has investigated its applicability in the context of higher education within the KRI. This study adopts the original UTAUT model without extensions, aiming to assess its explanatory power in a region characterized by unique structural, linguistic, and institutional challenges. By doing so, it contributes context-specific insights into behavioral intention toward e-learning adoption an area that remains underexplored in the existing literature.

Although no new constructs are added to the original UTAUT model, applying it in the distinct context of American universities in the Kurdistan Region provides theoretical value. The region's post-conflict setting, multilingual education environment, and emerging digital infrastructure represent underexplored variables that may influence technology acceptance differently than in other regions. Testing the model's robustness in this environment helps evaluate its cross-cultural applicability and generalizability, contributing to both theory and practice.

The study offers practical implications for stakeholders, including policymakers, institutional leaders, and digital learning platform providers. Understanding what drives or hinders adoption can support more inclusive, user-friendly, and accessible online learning environments in Kurdistan and similar developing regions.

The structure of the paper is as follows: Section 2 presents a review of the literature and empirical studies using the UTAUT model. Section 3 outlines the research design, methodology, and data collection process. Section 4 discusses the findings and compares them to existing literature. Finally, Section 5 provides theoretical and practical implications, acknowledges limitations, and offers suggestions for future research.

## 2- Literature Review

The integration of digital technologies into higher education has evolved significantly in the past two decades, with ELS becoming central to modern educational delivery. These platforms help institutions overcome barriers of time, location, and physical infrastructure, offering flexible, scalable, and cost-effective learning options. E-learning is associated with improvements in academic performance, time management, and learner engagement, particularly when platforms are easy to access and user-friendly (Abbad, 2021; Mani, 2023; Peck, 2024). With platforms such as Moodle and Microsoft Teams gaining global popularity, the user base for online learning is projected to surpass 57 million learners by 2027 (Peck, 2024).

The COVID-19 pandemic dramatically accelerated the adoption of online learning, revealing both opportunities and persistent challenges, especially in developing and post-conflict regions (UNESCO, 2023). While many institutions in high-income countries transitioned relatively smoothly due to mature digital ecosystems, universities in countries such as Iraq faced significant barriers. These included poor internet infrastructure, limited digital skills among faculty and students, and the absence of standardized learning platforms and pedagogical training (Camara, 2022; Ferri *et al.*, 2020).

In the KRI, these challenges were compounded by frequent electricity outages, limited access to affordable high-speed internet, and the widespread use of English as the medium of instruction in American-style universities. These conditions created additional barriers to equitable participation in online learning (Mpatheni *et al.*, 2024). The rural-urban digital divide further amplified disparities in access to educational technology, with students in remote areas reporting lower access to devices and weaker internet connectivity (Awhrahman *et al.*, 2023; Kareem, 2017). Such structural disparities have significant implications for equity in higher education and for the long-term sustainability of e-learning initiatives in the region.

Several studies specific to KRI have consistently emphasized these structural and linguistic challenges. For instance, Awhrahman *et al.* (2023) highlight the limited access to ICT infrastructure, including electricity, and the ineffective use of informal communication tools such as WhatsApp for educational purposes. Kareem (2017) similarly notes the technological constraints in rural areas, while Ahmed & Allawi (2020) emphasize how these limitations affect cloud-based learning and the overall adoption of digital education models. Fadhil & Al-Ameen (2016) found that infrastructural issues affect the capacity of private universities to fully implement e-learning systems, particularly in English-language programs. Moreover, Faraj & Hassan (2017) suggest that information technology has the potential to reduce educational inequality but stress the need for better policy frameworks to bridge the urban-rural gap.

Despite these challenges, e-learning still holds strong potential to improve access, reduce costs, and enhance academic quality in higher education. To realize this potential, institutions must invest in targeted interventions to reduce digital inequities, improve infrastructure, and address linguistic and technical barriers. However, beyond technical solutions, the successful implementation of e-learning depends heavily on students' attitudes, perceptions, and behavioral intentions. This highlights the need to examine not just access but also the acceptance and usage of these systems (Ahmad *et al.*, 2023; Hasan *et al.*, 2023).

One of the most widely used models to explore technology acceptance in education is the UTAUT, developed by Venkatesh *et al.* (2003). The model identifies four key constructs PE, EE, SI, and FC as predictors of BI and actual system use. UTAUT has been extensively applied in educational research, particularly to examine students' attitudes and behaviors toward adopting e-learning tools (Batucan *et al.*, 2022; Salloum & Shaalan, 2018). These constructs allow researchers to systematically analyze both the psychological and contextual factors that drive or inhibit e-learning engagement.

Recent empirical studies confirm UTAUT's relevance in diverse educational contexts. For example, Abbad (2021) and Shah *et al.* (2025) found PE and SI to be strong predictors of BI. However, results regarding EE and FC remain mixed -significant in some studies and not in others- highlighting the importance of local context in shaping technology adoption. While moderating variables such as gender and prior education were often found to have limited influence (Dečman, 2015; Shah *et al.*, 2025), UTAUT remains a robust and adaptable framework, particularly useful in studying digital transitions in developing regions, post-crisis settings, and multilingual environments.

In summary, the literature suggests that while digital platforms and ELS offer substantial benefits in higher education, their success is influenced not only by infrastructure and access but also by users' behavioral intentions and contextual challenges. The UTAUT model offers a robust framework to examine these dynamics, particularly in regions like the KRI, where structural and sociolinguistic barriers complicate technology adoption.

Table 1 provides an overview of key empirical studies that have applied the UTAUT or extended UTAUT frameworks in higher education. These studies reflect diverse educational settings, sample characteristics, and findings, offering comparative insight into how core UTAUT constructs perform across countries. The table highlights consistent support for PE and SI as strong predictors of behavioral intention, while also identifying context-specific variations in the effects of EE and FC. This synthesis reinforces the utility of UTAUT in guiding future research and interventions targeting e-learning adoption.

Across most studies, Performance Expectancy emerged as the dominant predictor of students' intention to use digital learning tools, reinforcing the importance of perceived usefulness in technology acceptance. Effort Expectancy and Social Influence also featured prominently, although their significance varied

depending on the local educational and cultural context. For instance, studies from Jordan, India, Ghana, and the Philippines consistently emphasized the role of peer and institutional influence in shaping students' adoption behavior. Meanwhile, Facilitating Conditions were often found to have a mixed effect, suggesting that infrastructure alone may not be sufficient without adequate support systems and training.

The table also underscores the increasing attention given to contextual and moderating factors, such as personal innovativeness, perceived security, and even financial cost especially in developing and crisis-affected countries. Studies from Iraq, Bangladesh, and Ethiopia specifically illustrate how infrastructural and socioeconomic barriers intersect with psychological readiness to influence digital learning outcomes.

By reviewing these studies collectively, it becomes evident that the UTAUT model provides a versatile and comprehensive lens to understand e-learning acceptance. It also validates the importance of tailoring digital education policies and interventions to the specific challenges, expectations, and behaviors of learners in various national and institutional contexts particularly in regions like the KRI, where structural and sociolinguistic obstacles are especially pronounced.

**Table 1.** Summary of Empirical Studies Using the UTAUT Model to Investigate E-Learning Adoption in Higher Education in Developing Countries

#	Author(s)	Title	Sample / Country	Key Findings
1	(Abbad, 2021)	Using the UTAUT model to understand students' usage of e-learning systems in developing countries.	370 students Jordan	Performance expectancy and effort expectancy were found to significantly influence students' intentions to use Moodle, an e-learning system at Hashemite University in Jordan.
2	(Shah et al., 2025)	Investigation of e-learning adoption in higher education based on the unified theory of acceptance and use of technology model	410 students India	The study found that performance expectancy, effort expectancy, and social influence positively support behavioral intention to adopt E-learning, indicating that students are likely to engage with E-learning platforms if they believe it will enhance their performance, if they find it easy to use, and if they are influenced by their peers or social environment.
3	(Nabila et al., 2024)	Exploring the Factors Affecting the Student's Acceptance of Using IAIN Ponorogo E-Learning through the UTAUT Model	400 students Indonesia	The study found that facilitating condition factors have a positive but insignificant effect on students' behavior, indicated by a parameter coefficient value of 0
4	(Tewari et al., 2023)	A modified UTAUT framework to predict students' intention to adopt online learning: moderating role of openness to change	424 students India	The study found that performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FS), and perceived security (PS) significantly impact students' intention to adopt online learning in India
5	(Arthur et al., 2023)	Digital paradigm shift: Unraveling students' intentions to embrace Tablet-based Learning through an extended UTAUT2 model	409 students Ghana	The study found that perceived learning opportunities, trust, effort expectancy, hedonic motivation, social influence, and facilitating conditions significantly positively influenced students' intention to use Tablet-based Learning, indicating that these factors are crucial for encouraging the adoption of TBL among students
6	(Haron et al., 2021)	Implementation of the UTAUT Model to Understand the Technology Adoption of MOOC at Public Universities	400 students Malaysia	The study found that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influenced the respondents' intention to use MOOC technology in their learning at Universiti Kebangsaan Malaysia (UKM)

7	(Rudhumbu, 2022)	Applying the UTAUT2 to predict the acceptance of blended learning by university students	432 students Zimbabwe	The study found that five out of the seven factors of the UTAUT2 model, performance expectancy, effort expectancy, social influences, facilitating conditions, and hedonic motivation significantly and positively influenced the behavioral intentions of university students to accept blended learning.
8	(Yakubu & Dasuki, 2019)	Factors affecting the adoption of e-learning technologies among higher education students in Nigeria: A structural equation modelling approach	286 students Nigeria	The study found that performance expectancy and effort expectancy significantly influence the adoption and use of educational technology among higher education students in Nigeria, with a p-value of less than 0.
9	(Kamalasena & Sirisena, 2021)(Kamalaseena & Sirisena, 2021)	Factors Influencing the Adoption of E-Learning by University Students in Sri Lanka: Application of UTAUT-3 Model During Covid-19 Pandemic	191 students Sri Lanka	The study identified several positive factors influencing the adoption of e-learning among Sri Lankan university students, including performance expectancy, facilitating conditions, habit, price-value, and personal innovativeness in IT
10	(Maphosa, 2021)	Factors Influencing Student's Perceptions Towards E-Learning Adoption During COVID-19 Pandemic: A Developing Country Context	600 students Malaysian	The study found that performance expectancy, effort expectancy, and facilitating conditions positively influenced students' behavioral intentions to use Moodle for online learning
11	(Batucan et al., 2022)	An Extended UTAUT Model to Explain Factors Affecting Online Learning System Amidst COVID-19 Pandemic: The Case of a Developing Economy	1238 students Philippines	The study empirically tested the extended UTAUT model, incorporating factors such as enjoyment, interactivity, flexibility, and quality, which significantly influenced students' intentions to use online learning systems during the COVID-19 pandemic
12	(Arif et al., 2018)	Factors affecting student use of Web-based services: Application of UTAUT in the Pakistani context	318 students Pakistani	The study found that performance expectancy, effort expectancy, and social influence are significant predictors of students' behavioral intention to use university Web-based services
13	(Chumo & Kessio, 2015)	Use of UTAUT model to assess ICT adoption in Kenyan public Universities	414 students Kenya	The study found that performance expectancy significantly affects students' use of web-based information systems, as students believe that these systems facilitate easy and convenient access to university services
14	(Ameen et al., 2019)	Towards the successful integration of e-learning systems in higher education in Iraq: A student perspective	300 students Iraq	The study found that perceived usefulness (PU), perceived ease of use (PEOU), subjective norms (SNs), information quality (IQ), system quality (SQ), technical support (TS), and self-efficacy (SE) significantly affect students' behavioral intention (BI) to use e-learning systems in Iraq.
15	(Attuquayefio & Addo, 2014)	Using the UTAUT model to analyze students' ICT adoption	400 students Ghana	Effort Expectancy (EE) significantly predicted Behavioural Intention (BI) to use ICT, while Social Influence (SI) and Performance Expectancy (PE) were statistically insignificant in predicting BI.

16	(Liebenberg et al., 2018)	Acceptance of ICT: Applicability of the Unified Theory of Acceptance and Use of Technology (UTAUT) to South African Students	738 students South African	The study found that Performance Expectancy (PE <sub>x</sub> ) had the highest practically significant relationship with Behavioral Intention (BI), explaining 64% of the variance.
17	(Thomas et al., 2013)	The utility of the UTAUT model in explaining mobile learning adoption in higher education in Guyana	322 students Guyana	The study confirms several relationships in the UTAUT model, particularly that performance expectancy significantly influences attitude towards mobile learning technologies, followed by effort expectancy and facilitating conditions.
18	(Twum et al., 2021)	Using UTAUT, personal innovativeness and perceived financial cost to examine student's intention to use E-learning	617 students Ghana	The study found that personal innovativeness in information technology, perceived financial cost, performance expectancy, hedonic motivation, and social influence significantly affect the intention to use E-learning among university students during the COVID-19 pandemic.
19	(Salloum & Shaalan, 2018)	Factors Affecting Students' Acceptance of E-Learning System in Higher Education Using UTAUT and Structural Equation Modeling Approaches	280 students Egypt	The study found that the UTAUT model was strongly supported in predicting students' intention to use E-learning systems, with significant factors influencing this intention identified as social influence, performance expectancy, and facilitating conditions.
20	(belshoska et al., 2022)	Understanding students' online learning behavior using utaut model – the case of north macedonia	120 students Macedonia	The research identifies critical factors influencing students' behavior towards online learning, including performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and usage behavior, as outlined in the UTAUT model.
21	sodiq onaolapo, Olawale Oyewole (2018.0)	Performance Expectancy, Effort Expectancy, and Facilitating Conditions as Factors Influencing Smart Phones Use for Mobile Learning by Postgraduate Students of the University of Ibadan, Nigeria.	217 students Nigeria	The study found a significant positive relationship between Performance Expectancy (PE), Effort Expectancy (EE), and Facilitating Conditions (FC) with the use of smart phones for mobile learning among postgraduate students, with PE being the strongest predictor.
22	(Teo et al., 2014)	Exploring E-Learning Acceptance among University Students in Thailand: A National Survey:	1981 students Thailand	The study found that tutor quality, perceived usefulness, and facilitating conditions were significant predictors of e-learning acceptance among university students in Thailand.
23	(Boustani & Sayegh, 2021)	E-learning: Factors Affecting Students Online Learning During COVID-19 Quarantine in a Developing Country	458 students Lebanon	The study found no significant gender differences in the intention to use e-learning, indicating that both male and female students had similar attitudes towards online learning during the COVID-19 quarantine.

24	(Alam et al., 2023)	e-Learning as a Doubled-Edge Sword for Academic Achievements of University Students in Developing Countries: Insights from Bangladesh	275 students Bangladesh	The study found that a significant portion of university students in Bangladesh faced challenges with e-Learning due to limited access to technological devices and internet connectivity.
25	(Hagos & Negash, 2014)	The adoption of e-learning systems in low-income countries: the case of Ethiopia	255 students Ethiopia	The study found that both perceived usefulness and perceived ease of use significantly influence the behavioral intention of distance learners in Ethiopia to use e-learning systems.

## 2.1 UTAUT and Its Extensions

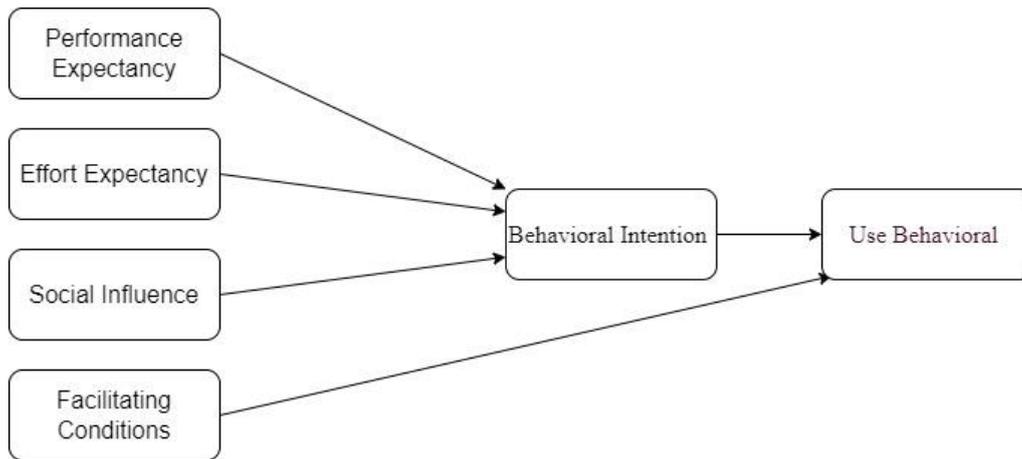
The UTAUT Model and the Technology Acceptance Model (TAM) are two of the theoretical models that have been established to explain the adoption and usage of technology. Within the spectrum of TAM, an individual's propensity to use technology and, subsequently, their actual use is influenced by two critical factors: perceived usefulness and perceived ease of use (Abdou & Jasimuddin, 2020). As factors of behavioral intention and use behavior, UTAUT expands on TAM by incorporating constructs from eight behavioral models (Akbar, 2021; Ali & Arshad, 2016; Batucan *et al.*, 2022).

When applied to different e-learning platforms, such as virtual learning environments, web-based platforms, and interactive whiteboards, the UTAUT model has demonstrated efficacy in anticipating technology adoption, particularly in educational contexts (Batucan *et al.*, 2022). The model's explanatory power has been further enhanced by several expansions, such as UTAUT-2 and UTAUT-3, which contain additional components such as hedonic motivation, price value, habit, and personal innovativeness (Akbar, 2021; Batucan *et al.*, 2022).

The incorporation of supplementary dimensions, namely self-efficacy, enjoyment, and satisfaction has enhanced the application of UTAUT. This is particularly applicable in comprehending the adoption behaviors of e-learning among scholars and students (Izkair & Lakulu, 2023). Subsequently, a more thorough understanding of technology acceptability and use in educational contexts has been made possible by these extensions.

Research has classified multiple key factors that influence e-learning adoption. Pettersson, (2023) identifies that gender, age, and experience are just a few of the moderating elements that have been found to shape how these dimensions alter the adoption of e-learning. To the same extent, Venkatesh *et al.* (2016) demonstrate that experience can moderate the links between effort expectancy, social influence, and enabling conditions, whereas gender can affect the relationships between performance expectancy, social influence, and effort expectancy.

Venkatesh *et al.* (2003) utilized the UTAUT model to explore acceptance behaviors across various disciplines. This study adopts the model, encompassing constructs such as Performance Expectancy (PE), which reflects individuals' beliefs about the system's benefits for job performance; Effort Expectancy (EE), indicating perceptions of system usability; Social Influence (SI), measuring the impact of significant others on system adoption beliefs; and Facilitating Conditions (FC), assessing organizational and technical support for system use. In the UTAUT framework (Figure 1), PE, EE, and SI directly influence Behavioral Intentions (BI), while FC relates to actual system usage (Behavior). This study specifically focuses on examining how these constructs influence intention rather than actual behavioral outcomes.



*Fig. 1. UTAUT model*

### 3- Research Methodology

#### 3.1 Research Framework

This study adopts the original UTAUT model developed by Venkatesh *et al.* (2003) to examine the factors influencing students' behavioral intention to adopt E-learning Systems (ELS) in Iraqi higher education institutions, with a specific focus on American-style universities in the KRI. The model includes four core constructs - PE, EE, SI, and FC- which are hypothesized to significantly influence BI.

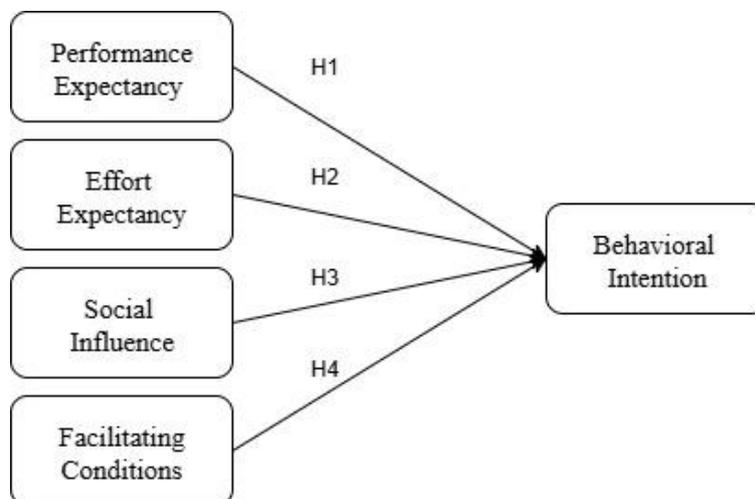
The conceptual framework is presented in Figure 2, outlining the proposed relationships among these constructs. The hypotheses guiding this study are:

H1: Performance expectancy has a positive effect on behavioral intention.

H2: Effort expectancy has a positive effect on behavioral intention.

H3: Social influence has a positive effect on behavioral intention.

H4: Facilitating conditions have a positive effect on behavioral intention.



*Fig. 2. Hypotheses of the study*

#### 3.2 Measurement Instruments

The questionnaire used in this study was developed based on the original UTAUT model and adapted from previously validated instruments, particularly from Abbad (2021). To ensure the content was relevant to the local context, minor adjustments were made to the wording of several items. These changes were guided by the cultural and institutional environment of American-style universities in the Kurdistan Region of Iraq. The questionnaire was reviewed by two academic experts in educational technology to confirm its clarity and appropriateness before distribution.

The survey consisted of two main parts. The first part collected basic demographic information such as age, gender, level of study, and department. The second part included 20 items that measured the five UTAUT constructs used in this study: PE, EE, SI, FC, and BI.

All items were rated using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). This scale allowed respondents to express varying levels of agreement with each statement and helped to capture their perceptions and intentions in a quantifiable way.

Each construct was measured using four specific items, as follows:

**Performance Expectancy (PE):** These items asked students whether they believed that using e-learning systems would help them improve their academic performance. Examples include whether e-learning helps complete learning tasks more efficiently and improves grades.

**Effort Expectancy (EE):** This section assessed how easy students found it to use e-learning platforms. Questions focused on ease of navigation, learning to use the system, and overall user-friendliness.

**Social Influence (SI):** These items explored how much students felt encouraged or supported by others (e.g., teachers, classmates, or university policies) to use e-learning systems. It included perceptions of influence from people important to the student's academic journey.

**Facilitating Conditions (FC):** This construct captured the availability of resources and support necessary for successful e-learning use. Students were asked whether they had access to the required technology, reliable internet, and technical help.

**Behavioral Intention (BI):** These items measured the likelihood that students would continue using e-learning systems in the future and whether they would recommend them to others.

The final version of the questionnaire was distributed electronically, and no personal data were collected. A copy of the full survey and how each question is linked to its related construct is included in Appendix 1.

### 3.3 Sample and Data Collection

This study used a convenience sampling method targeting students at the American University of Iraq, Sulaimani (AUIS) and the American University of Kurdistan (AUK). The online survey was distributed across 12 departments with assistance from faculty members during 2024.

A total of 470 responses were collected, of which 463 valid responses remained after screening for incomplete or outlier entries. According to Hair *et al.* (2007), a sample size of 15-20 responses per variable is acceptable. With five variables under study, the sample was sufficient for meaningful analysis.

### 3.4 Ethical Considerations

Ethical approval was secured from the relevant institutional review board from AUIS. The study upheld stringent ethical standards in data handling and respondent anonymity, ensuring that the data collected were used solely for academic purposes and that participants could respond without any coercion.

## 4- Results and Data Analysis

The study utilized structural equation modeling (SEM) to test the hypothesis. The SEM was estimated in two steps: initially the measurement model and subsequently the structural model, following the methodologies proposed by Hair Jr *et al.* (2014) and Rahi (2017). The analysis began with descriptive statistics, followed by SEM estimation.

### 4.1 Descriptive Statistics

The final dataset comprised 463 valid responses from undergraduate students after data cleaning processes removed outliers from the initial pool. The sample distribution between the two universities was weighted with 65.9% (305 respondents) from the AUIS and 34.1% (158 respondents) from the AUK. This diverse sample from different academic environments enhances the robustness and applicability of the study findings.

The sample demographics included 58.3% male and 41.7% female participants. Participants primarily studied in fields of business, engineering, and information technology, making up 36.5%, 36.1%, and 13.8% of the sample, respectively.

The distribution of students across academic years was diverse: 4.5% in the Academic Preparatory Program, 25.9% in the first undergraduate year, 21.2% in the second, 15.8% in the third, and 32.6% in the fourth year (see Table 2). This distribution aids in understanding different perspectives on e-learning adoption among students at various stages of their education.

Regarding e-learning platform usage, there were notable trends across demographic groups. Female students were more likely to use Moodle (56%), Microsoft Teams (66%), and Zoom (59%) compared to male students, with Google Classroom usage being more evenly distributed. The age group 20-30 was the most active in using all platforms, comprising 46% of Moodle users, 51% of Microsoft Teams, and 51% of Zoom. Students in their final year (UG 4) showed the highest usage rates, particularly for Moodle (37%) and Zoom (56%), underscoring their increased need for resources and support as they near graduation.

**Table 2.** Demographic characteristics of the samples

Variable		Frequency	Percent
<b>Gender</b>	Male	270	58.3%
	Female	193	41.7%
	<b>Total</b>	<b>463</b>	<b>100%</b>
<b>Age</b>	18-20 years	146	31.5%
	21-23 years	217	46.9%
	Above 23 years	100	21.6%
	<b>Total</b>	<b>463</b>	<b>100%</b>
<b>University</b>	American University of Iraq-Sulaimani	305	65.9%
	American University of Kurdistan	158	34.1%
	<b>Total</b>	<b>463</b>	<b>100%</b>
<b>College/department</b>	Academic Preparatory Program (English Learning Program)	20	4.320%
	College of Arts and Sciences	8	1.728%
	College of Business / Department of Business Administration	169	36.503%
	College of Engineering / Department of Engineering	167	36.07%
	College of Nursing	1	0.216%
	College of Pharmacy	3	0.648%
	Department of English	2	0.432%
	Department of Information Technology	64	13.823%
	Department of Medical & Health Sciences	17	3.672%
	Department of Social Sciences and Law	12	2.592%
	<b>Total</b>	<b>463</b>	<b>100%</b>
<b>Year of Study</b>	Academic Preparatory Program	20	4.3%
	UG 1	121	26.1%
	UG 2	98	21.2%
	UG 3	73	15.8%
	UG 4	151	32.6%
	<b>Total</b>	<b>463</b>	<b>100%</b>

Source: Authors' own construction

Note: The College of Arts and Sciences, College of Business, College of Engineering, College of Nursing, and the English Learning Program belong to the AUK. All other listed departments and colleges belong to the AUIS.

#### 4.2 Measurement Model (Confirmatory Factor Analysis)

The Structural Equation Modeling (SEM) process begins with an assessment of the measurement model, focusing on construct reliability, indicator reliability, convergent validity, and discriminant validity of the specified constructs (Kline, 2011).

Initially, a two-step SEM approach (Kline, 2011) was implemented. The first step involved Confirmatory Factor Analysis (CFA) to verify the fidelity of the intended constructs. In this stage the modification indices suggested that model fit could be enhanced by removing highly correlated indicators (EE3, SI4, FC1, BI4), resulting in enhanced model fit.

Evaluation of the priori measurement model, detailed in Table 3, revealed satisfactory fit indices. Notably, the model demonstrated good fit based on critical indices: Comparative Fit Index (CFI) and Tucker-Lewis Index

(TLI) exceeding 0.90, Root Mean Square Error of Approximation (RMSEA) below 0.08, and Standardized Root Mean Square Residual (SRMR) under 0.08 (Browne, 1993; Hu *et al.*, 1995; Kline, 2011; McDonald, 2013). These findings indicated robust support for the adequacy of the measurement model (see Table 3).

**Table 3.** CFA Fit Statistics and Measures

Model	$\chi^2$	df	$\chi^2/df$	CFI	TLI	RMSEA	SRMR
Criteria			$1 < \chi^2/df < 3$	$\geq 0.90$	$\geq 0.90$	$\leq 0.80 < 0.1$	$\leq 0.80 < 0.1$
Obtained	203	90	2.255	0.969	0.962	0.0522	0.0259

Source: Authors' own construction

Post-fit assessment involved computing Construct Reliability (CR) for convergent validity and Average Variance Extracted (AVE) for discriminant validity (Kline, 2011). Results affirmed that all factors within the measurement model met stringent thresholds for factor loadings ( $>0.5$ ), AVEs ( $>0.5$ ), and internal consistency measures such as Cronbach's Alpha (CA) ( $>0.70$ ) and Composite Reliability (CR) ( $>0.70$ ) (Hair *et al.*, 2010; Raykov, 1998).

To ensure a comprehensive reliability assessment, McDonald's Omega ( $\omega$ ) was computed, aligning with current methodological recommendations (Hayes & Coutts, 2020). Table 3 presents detailed statistics, including factor loadings, standardized estimates, CR, and AVE for each construct. Factor loadings were uniformly significant ( $p < 0.001$ ), underscoring the substantial contribution of each indicator to its respective construct (Hair *et al.*, 2010).

The high values of Cronbach's Alpha and McDonald's Omega across all constructs underscored strong internal consistency and reliability of the measurement scales (see Table 4).

In conclusion, the comprehensive analysis confirmed the robust validity and reliability of the measurement model, providing a solid foundation for subsequent structural assessments in this study.

**Table 4.** Results for the Measurement Model

Factor	Indicator	Mean	SD	Stand. Estimate	CR $\geq 0.70$	AVE $\geq 0.50$	Cronbach's $\alpha \geq 0.70$	McDonald's $\omega \geq 0.70$
Performance Expectancy	PE1	4.09	0.772	0.735	0.871	0.628	0.876	0.877
	PE2			0.789				
	PE3			0.830				
	PE4			0.808				
Effort Expectancy	EE1	4.04	0.729	0.717	0.785	0.550	0.784	0.786
	EE2			0.712				
	EE4			0.793				
Social Influence	SI1	3.79	0.793	0.684	0.761	0.516	0.790	0.794
	SI2			0.745				
	SI3			0.724				
Facilitating Conditions	FC2	4.08	0.731	0.802	0.822	0.608	0.815	0.822
	FC3			0.816				
	FC4			0.717				
Behavioral Intention	BI1	4.09	0.859	0.893	0.924	0.802	0.927	0.927
	BI2			0.903				
	BI3			0.891				

Source: Authors' own construction  
 Note: Deleted indicators (EE3, SI4, FC1, BI4)

**4.3 Structural Model (SEM)**

Following the validation of the measurement model through Confirmatory Factor Analysis (CFA), the study advanced to analyzing the structural relationships among the variables using Structural Equation Modeling (SEM). SEM provides a comprehensive statistical tool to evaluate complex interrelations between observed and latent variables, which is particularly crucial in testing theoretical constructs such as those proposed in the UTAUT model.

The assessment of model fit was conducted using the Chi-square test, which demonstrated that the user model significantly outperformed the baseline model, suggesting a superior fit to the collected data (Hooper *et al.*, 2012). Additionally, the model achieved commendable fit indices, with the Standardized Root Mean Square Residual (SRMR) being below 0.08 and the Root Mean Square Error of Approximation (RMSEA) falling below 0.06. These metrics indicate a satisfactory model fit, which is further confirmed by a high RMSEA p-value. This evidence supports the structural model's adequacy in representing the data accurately, as shown in Table 5.

**Table 5.** Overall Tests

Model tests				
	X <sup>2</sup>	df	p	
	124	105	0.099	
Fit indices				
	95% Confidence Intervals			
<b>SRMR</b>	<b>RMSEA</b>	<b>Lower</b>	<b>Upper</b>	<b>RMSEA p</b>
<b>0.026</b>	0.020	0.000	0.032	1.000

Source: Authors' own construction

Further, table 6 presents detailed estimates, standard errors, confidence intervals, standardized regression coefficients ( $\beta$ ), Z-values, and p-values for the relationships between constructs. The structural model analysis (see Figure 4) offers insights into the factors influencing BI regarding e-learning tool adoption among university students in the Kurdistan region. PE and FC emerged as significant positive predictors of BI ( $p < 0.001$ ), indicating that students are more likely to intend to use e-learning tools when they perceive them as useful and when there are adequate resources and support available. This aligns with the UTAUT model, which posits that perceived usefulness and external support are crucial determinants of technology adoption.

EE did not demonstrate a significant impact on BI at the 0.05 level ( $p = 0.055$ ); however, the sign was negative. This finding underscores the importance of user-friendly interfaces and intuitive designs in enhancing the acceptance and use of educational technologies among students.

In contrast, SI did not significantly influence BI ( $p = 0.529$ ), indicating that peer and social pressures may not strongly affect students' decisions to adopt e-learning tools in this context. This finding highlights the predominant role of perceived utility and usability over social factors in shaping students' intentions regarding technology adoption.

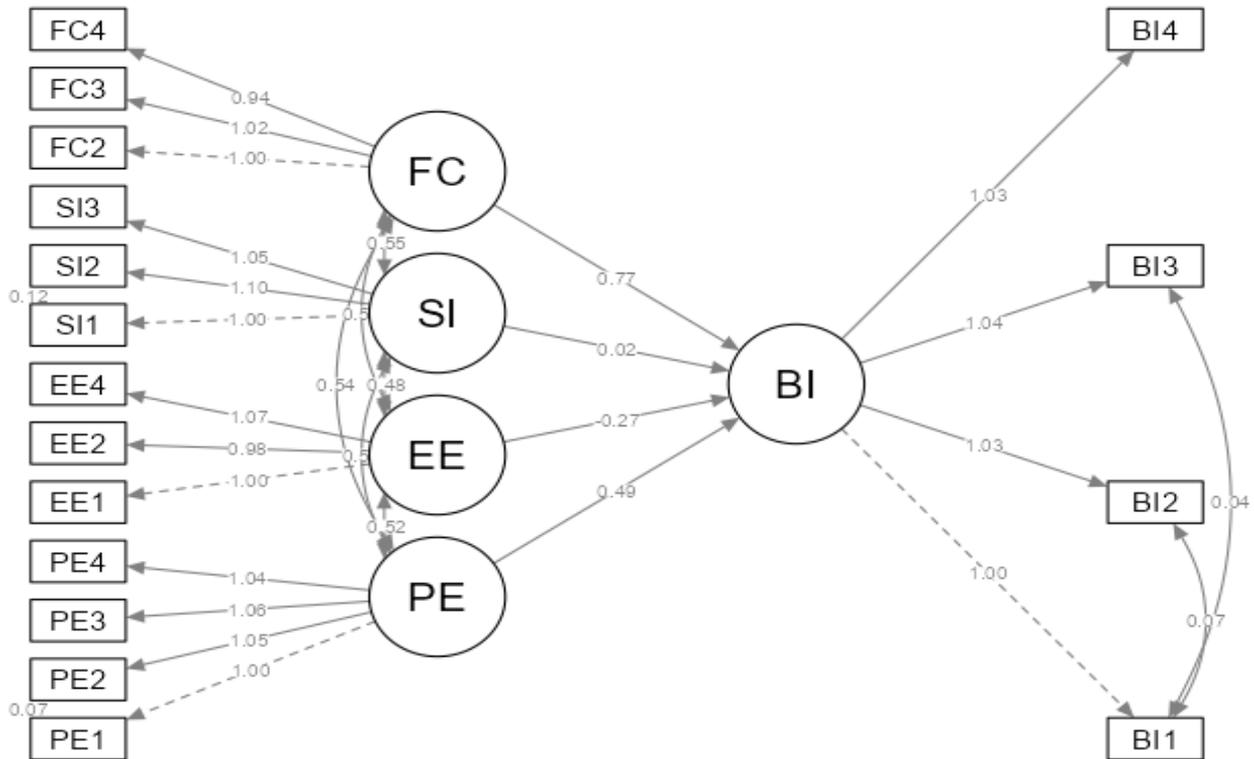
Overall, the high coefficient of determination ( $R^2 = 0.826$ ) indicates that the model explains a substantial portion of the variance in BI, emphasizing its robustness in predicting students' behavioral intentions towards e-learning tools. These insights provide valuable implications for educators and policymakers aiming to enhance technology integration in higher education settings, emphasizing the need for user-centered design and supportive infrastructures to promote e-learning tool adoption effectively.

**Table 6.** Structural model for hypothesis testing results.

Hypothesis	Path		Estimate	SE	$\beta$	z	p	Result
H1	PE	→ BI	0.4937	0.0976	0.4555	5.060	< .001	Supported
H2	EE	→ BI	-0.2706	0.1411	-0.2392	-1.918	0.055	Not Supported
H3	SI	→ BI	0.0182	0.1762	0.0150	0.103	0.918	Not Supported
H4	FC	→ BI	0.7655	0.1615	0.7305	4.739	< .001	Supported

Source: Authors' own construction

Note:  $R^2 = 0.854$



**Fig. 4.** SEM

**5- Discussion and Conclusion**

Universities in the Kurdistan Region of Iraq (KRI) play a vital role in equipping young people with the skills needed for the future, yet the region’s higher education system continues to face substantial challenges. Uctu & Al-Silefanee (2024) identify education and training as the weakest components within the regional educational ecosystem, citing outdated practices and limited digital transformation. Although there are currently 18 public and 17 private universities operating under the Ministry of Higher Education and Scientific Research in KRI, digital readiness remains uneven across institutions.

While many universities offer access to formal e-learning platforms such as Moodle, Microsoft Teams, Zoom, and Google Classroom, students do not consistently engage with these systems. Instead, informal tools like WhatsApp and Viber are often preferred for communication and sharing materials, largely due to their ease of use and familiarity (Awrahman *et al.*, 2023). This inconsistent usage reflects broader issues related to digital literacy, platform usability, and lack of structured e-learning policies.

The COVID-19 pandemic exposed these weaknesses, resulting in varied institutional responses. Some universities, particularly public ones with limited infrastructure, extended closures or faced delays in adopting digital tools. This lack of preparedness not only disrupted academic continuity but also led to student dissatisfaction and even protests against online learning in certain institutions. In contrast, universities like the American University of Iraq, Sulaimani (AUIS), acted swiftly by introducing training programs for both

faculty and students. Their proactive approach facilitated a smoother transition to digital learning and served as a model for other institutions in the region, fostering public-private collaboration in e-learning adoption (Mpatheni *et al.*, 2024).

Amid the challenges posed by the COVID-19 pandemic, some universities in the KRI demonstrated strong institutional readiness and adaptive capacity. For instance, the AUIS responded quickly by providing training to both faculty and students and adopting online platforms like Zoom and Moodle. This proactive approach contrasts with institutions that lacked structured preparation and experienced operational difficulties.

A notable example of collaboration between institutions emerged in Sulaimaniyah, where a private and a public university partnered to conduct a needs assessment for online education using the Community of Inquiry (CoI) framework. Findings from this initiative emphasized several priorities: ensuring accessibility of learning materials, mitigating barriers such as unreliable electricity and internet connectivity, and increasing the frequency of synchronous (real-time) learning sessions to enhance student engagement (Mpatheni *et al.*, 2024). Findings from this collaboration stressed the critical importance of stable internet access and adaptive learning materials, especially given regional electricity shortages and digital inequities (Awrahman *et al.*, 2023; Kareem, 2017).

This case highlights how institutional leadership and inter-university cooperation can improve e-learning implementation, offering valuable lessons for post-conflict, multilingual contexts like KRI (Uctu & Al-Silefanee, 2024).

The results of this study confirm that Performance Expectancy (PE) significantly influences students' Behavioral Intention to adopt E-learning Systems (ELS). This aligns with numerous studies indicating that students are more likely to use digital platforms when they believe these systems enhance their academic performance, save time, and improve communication efficiency (Jebri, 2021; Koceska & Koceski, 2020; Violaine & Hwang, 2019; Zandi *et al.*, 2022). This is consistent with the UTAUT model's foundational principle that perceived usefulness is a key determinant of technology acceptance (Venkatesh *et al.*, 2003). Within the context of KRI, where higher education institutions are actively integrating digital platforms, this finding suggests that clear communication of performance benefits is vital to encouraging adoption.

Facilitating Conditions (FC) also had a significant and positive impact on students' intentions, underscoring the importance of reliable internet, digital infrastructure, and available technical support in enabling e-learning adoption. This supports findings from Alblooshi & Abdul Hamid (2021), Saleh *et al.*, (2014), and Vinodh & Mathew (2012), and aligns with Budur *et al.*, (2021), who emphasized that resource readiness and IT infrastructure are central to a university's preparedness for online education. In the KRI context, where inconsistent electricity and limited digital access persist, facilitating conditions remain a critical enabler. These results reinforce the argument by Abbad (2021) that the mere presence of digital tools is insufficient without institutional support and student access to necessary resources.

In contrast, Effort Expectancy (EE) did not show a significant effect on Behavioral Intention in this study. While this appears to contradict earlier UTAUT studies (e.g., Cheon *et al.*, 2012; Venkatesh *et al.*, 2003), it aligns with more recent regional findings by Aboki *et al.*, (2022), who also observed a weak or negative relationship between ease of use and intention to adopt e-learning. This suggests that in digitally maturing environments like KRI, perceived usefulness and available support may outweigh concerns about system complexity, especially among students already exposed to basic digital platforms through hybrid or emergency remote learning.

Social Influence (SI) similarly did not emerge as a significant predictor. While SI has been found relevant in other cultural contexts (Cruz *et al.*, 2014; Handoko & Prianto, 2020; Zandi *et al.*, 2022), this finding supports Abbad (2021) and Budur *et al.*, (2021), who suggest that students in the KRI are more self-directed in their adoption of technology, relying more on personal needs and system performance than peer or instructor pressure. This may be particularly true in private and international universities where digital literacy is comparatively higher, and institutional norms already assume e-learning participation.

Together, these findings highlight that in the KRI, successful adoption of e-learning depends more on functional performance and institutional readiness than on usability concerns or social persuasion. This suggests a strategic focus for university administrators: improving infrastructure, highlighting tangible academic benefits, and reducing systemic barriers may be more effective than relying on peer-driven promotion or interface improvements alone.

The findings of this study present key recommendations for university leaders and policymakers in the KRI. First, the significant role of Performance Expectancy and Facilitating Conditions indicates that institutions must prioritize infrastructure development, including reliable internet access, technical support

services, and functional learning management systems. As Budur *et al.*, (2021) emphasize, organizational readiness (especially IT infrastructure and resource availability) is essential for ensuring effective online education delivery.

Moreover, institutions should focus on enhancing system usability and accessibility through user-friendly platforms and multilingual interfaces, particularly in a context where both English and Kurdish/Arabic are used in instruction. While Effort Expectancy was not a strong determinant in this study, earlier research (e.g., Cheon *et al.*, 2012; Martin *et al.*, 2019) highlights that usability still contributes to long-term student satisfaction and engagement.

Given the low influence of Social Influence, universities should not rely solely on peer or faculty encouragement, but instead ensure practical, individualized support and clear communication of academic benefits. This includes onboarding programs, digital skills training, and guidance for both students and instructors. As Abbad (2021) and Budur *et al.*, (2021) both stress, continuous training and motivation-building among faculty and students is critical for digital transformation in education.

Finally, higher education authorities should integrate these insights into strategic planning and quality assurance frameworks, ensuring that digital readiness is not just a temporary emergency measure but a permanent component of educational policy. Institutionalizing digital education policy -along with regular assessments of readiness and student feedback- can enhance both equity and effectiveness in higher education across the region.

This study focused on students from two private American universities in the KRI, which limits the generalizability of the findings to broader populations, especially those studying in public institutions or under different instructional models. As Budur *et al.*, (2021) highlight, significant differences exist between public and private universities in terms of infrastructure, faculty readiness, and strategic orientation, which may influence students' perceptions of e-learning tools.

Moreover, while the study applied the UTAUT framework, it did not incorporate contextual variables such as cultural attitudes, socioeconomic status, or language proficiency, all of which have been identified in previous literature as important determinants of e-learning adoption (Cheon *et al.*, 2012; Olafsen *et al.*, 2021). In particular, the dominance of English-language platforms in private universities may pose a challenge to wider adoption across institutions where Arabic and Kurdish are the primary languages of instruction.

Given the rapid evolution of digital education and ongoing infrastructure development in KRI, future research should expand sampling to include a diverse set of universities, particularly public institutions, and consider longitudinal designs to capture shifting user behavior and technological adaptation over time (Venkatesh *et al.*, 2016). Researchers are also encouraged to explore the impact of language localization, economic disparities, and institutional support models on students' behavioral intentions.

Finally, future studies may benefit from incorporating qualitative approaches to better understand the lived experiences and challenges faced by both students and faculty, offering richer insights into how to make e-learning more inclusive, accessible, and effective in the region.

#### **Author Contributions**

- Rebean Al-Silefanee: Conceptualized and designed the survey; conducted data collection, data analysis, and prepared the introduction section.
- Ramazan Uctu: Contributed to the survey design, results interpretation, conclusion writing, and participated in data collection.
- Sinbl Hawro Yakoob: Conducted the literature review, contributed to the introduction, and assisted in data collection.

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#### **Declarations**

The authors declare that they have no conflict of interest. All procedures performed in this study involving human participants were conducted in accordance with institutional ethical standards, and informed consent was obtained from all participants.

### Data Availability and Sharing Policy

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request. Data were collected anonymously and are used solely for academic and research purposes.

### Author Notes

The opinions expressed in this article are those of the authors and do not necessarily reflect the official views of their affiliated institutions.

### REFERENCES

1. Abbad, M. M. M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. *Education and Information Technologies*, 26(6), 7205–7224.
2. Abdou, D., & Jasimuddin, S. M. (2020). The use of the UTAUT model in the adoption of e-learning technologies: An empirical study in France based banks. *Journal of Global Information Management (JGIM)*, 28(4), 38–51.
3. Aboki, P. Z., Olatokun, W., Apuru, J. I., & Lakan, L. E. (2022). Acceptance of E-Learning by Students of Federal University of WUKARI, Nigeria Using Unified Theory of Acceptance and Use of Technology. *IOSR J. Comput. Eng*, 24(2), 45–54.
4. Ahmad, S., Mohd Noor, A. S., Alwan, A. A., Gulzar, Y., Khan, W. Z., & Reegu, F. A. (2023). eLearning acceptance and adoption challenges in higher education. *Sustainability*, 15(7), 6190.
5. Ahmed, A. M., & Allawi, O. W. (2020). A review study on the adoption of cloud computing for higher education in kurdistan region-iraq. *UHD Journal of Science and Technology*, 4(1), 59–70.
6. Akbar, M. (2021). Investigating the Intentions to Adopt E-Learning using UTAUT-3 model: A Perspective of COVID-19. *Proceedings of the AUBH E-Learning Conference*.
7. Alam, M. F., Ogawa, K., & Islam, S. R. Bin. (2023). e-Learning as a Doubled-Edge Sword for Academic Achievements of University Students in Developing Countries: Insights from Bangladesh. *Sustainability*, 15(9), 7282. <https://doi.org/10.3390/su15097282>
8. Alblooshi, S., & Abdul Hamid, N. A. B. (2021). The role of unified theory of acceptance and use of technology in e-learning adoption in higher education institutions in the UAE. *IBIMA Business Review*, 1(26), 1–22.
9. Ali, R. A., & Arshad, M. R. M. (2016). Perspectives of students' behavior towards mobile learning (M-learning) in Egypt: an extension of the UTAUT model. *Engineering, Technology & Applied Science Research*, 6(4), 1109–1114.
10. Ameen, N., Willis, R., Abdullah, M. N., & Shah, M. H. (2019). Towards the successful integration of e-learning systems in higher education in Iraq: A student perspective. *British Journal of Educational Technology*, 50(3), 1434–1446. <https://doi.org/10.1111/BJET.12651>
11. Arif, M., Ameen, K., & Rafiq, M. (2018). Factors affecting student use of Web-based services: Application of UTAUT in the Pakistani context. *The Electronic Library*, 36(3), 518–534. <https://doi.org/10.1108/EL-06-2016-0129>
12. Arthur, F., Arkorful, V., Salifu, I., & Nortey, S. A. (2023). Digital paradigm shift: Unraveling students' intentions to embrace Tablet-based Learning through an extended UTAUT2 model. *Cogent Social Sciences*. <https://doi.org/10.1080/23311886.2023.2277340>
13. Attuquayefio, S. N., & Addo, H. (2014). Using the UTAUT model to analyze students' ICT adoption. *International Journal of Education and Development Using Information and Communication Technology*, 10(3), 75–86. <https://files.eric.ed.gov/fulltext/EJ1059042.pdf>
14. Awrahman, B. J., Aziz, C. F., & Said, K. W. (2023). Challenges and opportunities in integrating ICT into teaching and learning: A study of higher educational institutions in Iraqi Kurdistan. *Indonesian Journal of Curriculum and Educational Technology Studies*, 11(1), 18–27.
15. Batucan, G. B., Gonzales, G. G., Balbuena, M. G., Pasaol, K. R. B., Seno, D. N., & Gonzales, R. R. (2022). An extended UTAUT model to explain factors affecting online learning system amidst COVID-19 pandemic: The case of a developing economy. *Frontiers in Artificial Intelligence*, 5, 768831.
16. belshoska, M. M., Blagoeva, K. T., & Trpkova-nestorovska, M. (2022). Understanding students' online learning behavior using utaut model – the case of north macedonia. *Proceedings of the International Conference "Economic and Business Trends Shaping the Future."* <https://doi.org/10.47063/ebtsf.2022.0028>
17. Boustani, N. M., & Sayegh, M. M. (2021). *E-learning: Factors Affecting Students Online Learning During COVID-19 Quarantine in a Developing Country* (pp. 17–28). Springer, Cham. [https://doi.org/10.1007/978-3-030-85977-0\\_2](https://doi.org/10.1007/978-3-030-85977-0_2)
18. Budur, T., Demir, A., & Cura, F. (2021). University readiness to online education during Covid-19 pandemic. *International Journal of Social Sciences & Educational Studies*, 8(1), 180–200.
19. Camara, J. S. (2022). *The Ecosystem of Online Learning in the Philippine Setting: A Case of Pangasinan State University*.
20. Cheon, J., Lee, S., Crooks, S. M., & Song, J. (2012). An investigation of mobile learning readiness in higher education based on the theory of planned behavior. *Computers & Education*, 59(3), 1054–1064.

21. Chumo, K. P., & Kessio, D. K. (2015). Use of UTAUT model to assess ICT adoption in Kenyan public Universities. *Information and Knowledge Management*, 5(12), 79–83. [http://ir.mu.ac.ke:8080/jspui/bitstream/123456789/5377/1/Kiyeng and David.pdf](http://ir.mu.ac.ke:8080/jspui/bitstream/123456789/5377/1/Kiyeng%20and%20David.pdf)
22. Cruz, Y., Boughzala, I., & Assar, S. (2014). *Technology acceptance and actual use with mobile learning: First stage for studying the influence of learning styles on the behavioral intention*.
23. Dečman, M. (2015). Understanding technology acceptance of government information systems from employees' perspective. *International Journal of Electronic Government Research (IJEGR)*, 11(4), 69–88.
24. Fadhil, A., & Al-Ameen, Z. (2016). E-Learning at private universities in Kurdistan region: A comparative field study. *International Journal of Modern Education and Computer Science*, 8(9), 35–42.
25. Faraj, H. A., & Hassan, K. M. (2017). Survey Study about the Importance of e-Learning in Kurdistan, Iraq. *Journal of Kufa for Mathematics and Computer*, 4(2), 1–10.
26. Ferri, F., Grifoni, P., & Guzzo, T. (2020). Online learning and emergency remote teaching: Opportunities and challenges in emergency situations. *Societies*, 10(4), 86.
27. Hagos, Y., & Negash, S. (2014). The adoption of e-learning systems in low income countries: the case of Ethiopia. *International Journal for Innovation Education and Research*, 2(10), 79–84. <https://doi.org/10.31686/IJIER.VOL2.ISS10.249>
28. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate Data Analysis*. Prentice-Hall.
29. Hair, J. F., Money, A. H., Samouel, P., & Page, M. (2007). Research methods for business. *Education+ Training*, 49(4), 336–337.
30. Hair Jr, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, 26(2), 106–121.
31. Handoko, B. L., & Prianto, J. A. (2020). The influence of UTAUT on ERP systems in start-up business. *International Journal of Management*, 11(4).
32. Haron, H., Hussin, S., Yusof, A. R. M., Samad, H., & Yusof, H. (2021). *Implementation of the UTAUT Model to Understand the Technology Adoption of MOOC at Public Universities*. 1062(1), 12025. <https://doi.org/10.1088/1757-899X/1062/1/012025>
33. Hasan, A., Habib, S., Khan, M. A., & Hamadneh, N. N. (2023). Student adoption of E-learning in higher education institutions in Saudi Arabia: opportunities and challenges. *International Journal of Information and Communication Technology Education (IJICTE)*, 19(1), 1–21.
34. Hayes, A. F., & Coutts, J. J. (2020). Use omega rather than Cronbach's alpha for estimating reliability. *But... Communication Methods and Measures*, 14(1), 1–24.
35. Hooper, D. U., Adair, E. C., Cardinale, B. J., Byrnes, J. E. K., Hungate, B. A., Matulich, K. L., Gonzalez, A., Duffy, J. E., Gamfeldt, L., & O'Connor, M. I. (2012). A global synthesis reveals biodiversity loss as a major driver of ecosystem change. *Nature*, 486(7401), 105–108.
36. Izkair, A. S., & Lakulu, M. M. (2023). Model of Intention and Actual Use Mobile Learning in Higher Education Institutions in Iraq. *Indonesian Journal of Electrical Engineering and Computer Science*, 30(2), 1250–1258.
37. Jebiril, H. (2021). Investigating online learning satisfaction in Jordan schools during the COVID-19 outbreak: The student perspective. *Asian Journal of Education and Social Studies*, 23(4), 46–57.
38. Kamalaseena, B. D. T. M., & Sirisena, A. B. (2021). *Factors Influencing the Adoption of E-Learning by University Students in Sri Lanka: Application of UTAUT-3 Model During Covid-19 Pandemic*. 12(2), 99–124. <https://doi.org/10.4038/wjm.v12i2.7533>
39. Kareem, N. N. (2017). *The importance of using information communication technology for learning and teaching the English language in Kurdistan of Iraq*.
40. Kline, R. (2011). *Principles and Practice of Structural Equation Modeling, 3rd edn Guilford Press*.
41. Koceska, N., & Koceski, S. (2020). *Measuring the impact of online learning on students' satisfaction and student outcomes using integrated model*.
42. Liebenberg, J., Benadé, T., & Ellis, S. (2018). *Acceptance of ICT: Applicability of the Unified Theory of Acceptance and Use of Technology (UTAUT) to South African Students*. 10(3), 1. <https://digitalcommons.kennesaw.edu/cgi/viewcontent.cgi?article=1499&context=ajis>
43. Mani, B. (2023). *100+ Incredible Online Learning Statistics in 2024*. <https://sellcoursesonline.com/online-learning-statistics>
44. Maphosa, V. (2021). *Factors Influencing Student's Perceptions Towards E-Learning Adoption During COVID-19 Pandemic: A Developing Country Context*. 2(2). <https://doi.org/10.30935/EJIMED/11000>
45. Martin, F., Budhrani, K., & Wang, C. (2019). Examining faculty perception of their readiness to teach online. *Online Learning*, 23(3), 97–119.
46. Mpatheni, Z., Sur, S. H., Tahir, F. J., Courtney, D., & Peszek, M. (2024). Fostering Community of Inquiry in Public-Private English Language University Settings in Kurdistan (Iraq). *Online Submission*, 3(1), 42–58.
47. Nabila, R., Priyanto, P., & Shiddiq, J. (2024). Exploring the Factors Affecting the Student's Acceptance of Using IAIN Ponorogo E-Learning through the UTAUT Model. *Elinvo (Electronics, Informatics, and Vocational Education)*, 9(1), 90–102.

48. Olafsen, A. H., Nilsen, E. R., Smedsrud, S., & Kamaric, D. (2021). Sustainable development through commitment to organizational change: the implications of organizational culture and individual readiness for change. *Journal of Workplace Learning*, 33(3), 180–196.
49. Peck, D. (2024). *Online Learning Statistics: The Ultimate List in 2024*. <https://www.devlinpeck.com/content/online-learning-statistics>
50. Pettersson, D. (2023). *E-learning acceptance in higher education: A quantitative study comparing pre-and post-COVID-19 students' views on e-learning using the UTAUT model*.
51. Rahi, S. (2017). Research design and methods: A systematic review of research paradigms, sampling issues and instruments development. *International Journal of Economics & Management Sciences*, 6(2), 1–5.
52. Raykov, T. (1998). Coefficient alpha and composite reliability with interrelated nonhomogeneous items. *Applied Psychological Measurement*, 22(4), 375–385.
53. Rudhumbu, N. (2022). Applying the UTAUT2 to predict the acceptance of blended learning by university students. *Asian Association of Open Universities Journal*, 17(1), 15–36. <https://doi.org/10.1108/aaouj-08-2021-0084>
54. Saleh, A. M., Haris, A. Bin, & Bint Ahmad, N. (2014). Towards a UTAUT-based model for the intention to use solar water heaters by Libyan households. *International Journal of Energy Economics and Policy*, 4(1), 26–31.
55. Salloum, S. A., & Shaalan, K. (2018). Factors affecting students' acceptance of e-learning system in higher education using UTAUT and structural equation modeling approaches. *International Conference on Advanced Intelligent Systems and Informatics*, 469–480.
56. Shah, S., Mehta, N., & Sunil, A. (2025). Investigation of e-learning adoption in higher education based on the unified theory of acceptance and use of technology model. *E-Learning and Digital Media*, 22(2), 171–192.
57. Statista Research Department. (2024). *Digital population worldwide from 2014 to 2025*. <https://www.statista.com/statistics/617136/digital-population-worldwide/>
58. Teo, T., Ruangrit, N., Khlaisang, J., Thammatar, T., & Sunphakitjumnong, K. (2014). Exploring E-Learning Acceptance among University Students in Thailand: A National Survey. *Journal of Educational Computing Research*, 50(4), 489–506. <https://doi.org/10.2190/EC.50.4.C>
59. Tewari, A., Singh, R. S., Mathur, S., & Pande, S. (2023). A modified UTAUT framework to predict students' intention to adopt online learning: moderating role of openness to change. *Campus-Wide Information Systems*, 40(2), 130–147. <https://doi.org/10.1108/ijilt-04-2022-0093>
60. Thomas, T., Singh, L., & Gaffar, K. (2013). The utility of the UTAUT model in explaining mobile learning adoption in higher education in Guyana. *International Journal of Education and Development Using Information and Communication Technology*, 9(3), 71–87. <https://files.eric.ed.gov/fulltext/EJ1071379.pdf>
61. Twum, K. K., Ofori, D., Keney, G., & Korang-Yeboah, B. (2021). *Using the UTAUT, personal innovativeness and perceived financial cost to examine student's intention to use E-learning*. <https://doi.org/10.1108/JSTPM-12-2020-0168>
62. Uctu, R., & Al-Silefane, R. (2024). Understanding Entrepreneurial Ecosystem in the Middle East: Insights from Isenberg's Model. *International Journal of Entrepreneurial Knowledge*, 12(1), 1–24.
63. UNESCO. (2023). *Global Education Monitoring Report 2023: Technology in education-A tool on whose terms*. <https://doi.org/10.54676/UZQV8501>.
64. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425–478.
65. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, 17(5), 328–376.
66. Vinodh, K., & Mathew, S. K. (2012). Web personalization in technology acceptance. *2012 4th International Conference on Intelligent Human Computer Interaction (IHCI)*, 1–6.
67. Violaine, A., & Hwang, G.-H. (2019). Key Factors Affecting Students' Satisfaction and Intention to Use e-Learning in Rwanda's Higher Education. *Journal of Digital Convergence*, 17(5).
68. Yakubu, M. N., & Dasuki, S. I. (2019). Factors affecting the adoption of e-learning technologies among higher education students in Nigeria: A structural equation modelling approach. *Information Development*, 35(3), 492–502. <https://doi.org/10.1177/0266666918765907>
69. Zandi, G., Lahrash, H. A. E., & Shakhim, F. R. (2022). Factors effecting the adoption of E-learning: An empirical study of Libyan universities. *Journal of Information Technology Management*, 14(4), 95–117.

**Appendixes**  
Appendix 1: Scale Items

Items	Description of items	Source
PE1	E-learning has a positive impact on my educational performance (i.e., I achieve better grades and learn more effectively with e-learning).	Venkatesh et al. (2011)
PE2	E-learning enables me to accomplish learning tasks more quickly than traditional methods.	Al-Shahrani (2016)
PE3	E-learning enhances my learning productivity by allowing me to manage my study time more efficiently.	Al-Qeisi et al. (2015)
PE4	Using e-learning significantly increases my chances of achieving higher marks in my courses.	Al-Qeisi et al. (2015)
EE1	E-learning platforms are clear and easy to understand.	Venkatesh et al. (2011)
EE2	I am skilled at navigating and utilizing e-learning platforms effectively.	Al-Shahrani (2016)
EE3	Learning to use the e-learning platform is straightforward for me.	Al-Qeisi et al. (2015)
EE4	I find it easy to make the e-learning system do what I need it to do.	Al-Qeisi et al. (2015)
SI1	People who influence my behavior (like family, friends, and peers) think that I should use e-learning.	Venkatesh et al. (2011)
SI2	Influential figures in my educational journey advocate for the use of e-learning.	Al-Shahrani (2016)
SI3	Seniors and experienced students at my university are supportive and helpful regarding the use of e-learning.	Al-Qeisi et al. (2015)
SI4	The university actively promotes and supports the use of e-learning.	Al-Qeisi et al. (2015)
FC1	I have all the resources (e.g., technological, internet access) necessary to use e-learning effectively.	Venkatesh et al. (2011)
FC2	I possess the necessary knowledge and skills to utilize e-learning platforms.	Al-Qeisi et al. (2015)
FC3	The e-learning platform is compatible with other systems I use for my studies.	Al-Qeisi et al. (2015)
FC4	There is a designated person or group available to assist with any difficulties I encounter using the e-learning platform.	Al-Qeisi et al. (2015)
B11	I intend to use e-learning systems in my future studies.	Davis (1986)
B12	I anticipate that I will use e-learning systems in any future educational endeavors.	Venkatesh et al. (2011)
B13	I plan to incorporate e-learning systems into my higher education experience going forward.	Al-Shahrani, H. (2016)
B14	I would recommend using e-learning systems to my peers and colleagues in academia.	Al-Qeisi et al. (2015)