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Integrating Teachers' TPACK Levels and Students' Learning Motivation, Technology Innovativeness, and Optimism in an IoT Acceptance Model

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Abstract: The growing use of the Internet of Things (IoT) around the world has encouraged researchers to investigate how and why the IoT is implemented in colleges and universities. Previous studies have focused on individual attitudes rather than the integration of attitudes from two different perspectives. Furthermore, other studies have investigated the use of the IoT in non-educational settings, ignoring the effect of the IoT related to the technology acceptance model (TAM) and technological pedagogical content knowledge (TPACK) model. The present work aims to address this research gap by determining the main factors that influence acceptance of the IoT, leading to increased awareness in collaborative learning, where technology forms the core tool in enhancing the use of the IoT. A questionnaire was used to collect data from teachers and students from colleges and universities in Oman and the United Arab Emirates (UAE). The data were analyzed through the structural equation modeling (SEM) method. The findings indicated that there are two levels of positive effects on the intention to use IoT. The first level is technology features, which are represented by technology optimism and technology innovation; these factors are crucial to using the IoT. The second level is learning motivation, which has a close relationship with teachers' knowledge, and content pedagogy, which has a significant effect on the familiarity with IoT tools and applications. TAM constructs have a positive and direct impact on the intention to use IoT. The practical and managerial implications show that teachers, educators, and students can obtain benefits from these results to help IoT features to suit users' needs.

Keywords: IoT; TAM; teachers' TPACK; innovativeness and technology optimism

1. Introduction

IoT applications are becoming powerful technologies in the educational environment by providing more flexible and quantifiable education systems that enable learners and instructors to work under the same umbrella of technologies [1]. IoT refers to a set of systems that work collaboratively with other devices, such as computers and digital machines, to transfer data. The IoT encompasses the connections between both humans and computers and computers and computers. IoT is quickly developing into a system that embraces the artificial intelligence revolution in the modern-day world [2]. In addition to school, college, and university education, IoT innovation is assuming a significant role in bringing about changes to training at all levels. Everyone can benefit from this innovation, including students, instructors, classrooms, and college grounds. Educators and administrators can gain actionable insights into the IoT by connecting people to relevant devices and data. Despite being a novel technology, the use of the IoT in education has transformed the traditional human-centered educational system into an IoT-based one [3–5].

The IoT transforms the way institutions work and increases learning capabilities at any level and in many directions. University lecturers, students, and assisting officers can successfully implement large platforms through the IoT. Consequently, different types of educational institutions seek to make greater progress in using the IoT. Relevant systems, devices, applications, and services can be developed by learners, thereby turning the educational environment into an undeniably novel concept that has created interest around the globe. Recently, colleges and universities have deployed advanced IoT technologies, positively affecting the development of effective learning tools [6,7]. Our study investigates and examines the acceptance of the IoT among teachers and students in higher education institutions in the Gulf area.

For the sake of comprehensive measurement, the present study integrates the TAM [8] and TPACK [9] models to measure the effectiveness of the IoT as an educational tool on the basis of both teachers' attitudes and students' attitudes. For this purpose, the TAM and TRAPCK models are here considered as measures along with external variables. Recent studies have focused on using a mixed qualitative and quantitative approach to investigate the adoption of the IoT, demonstrating that positive attitudes, usefulness, and satisfaction indirectly affect the adoption of IoT technologies and applications, in addition to affordability, basic knowledge, and security and privacy [10,11]. Apart from motivation and enjoyment, studies have emphasized the effect of training and experience in accepting IoT technology. Moreover, training workshops can increase the user experience in IoT, significantly affecting actual life skills, interactive learning, and problem-solving [12–14].

TAM is a well-known model that expresses the relationships among different variables that are correlated with acceptance and adoption. However, TPACK and TRAPCK can function differently as they focus on pedagogical aspects. The integration of these two models can enhance the obtained results and empower the model itself. The term TRACK refers to Technological Pedagogical Content Knowledge, whereas TRAPCK refers to the knowledge needed to integrate technology into learning. All concerned academics and teachers are well-aware of TPACK, as it has a great influence on pedagogical domains, teaching effectively, and the implementation stages where teachers can actively integrate various learning styles with the appropriate technology [15,16].

2. Literature Review

The literature review used the IoT to determine both theoretical and practical dimensions, proposing a relationship between IoT and other variables such as self-efficacy, technology usage, motivation, security, privacy, training, and other factors [12,14,17–21]. Similarly, studies have tackled the effects of the IoT in association with TPACK and other external factors [22,23].

2.1. Students' Attitudes towards the IoT

IoT applications are becoming increasingly varied and complex, which may deeply affect the learning process. The difficulty lies in the rapid development of IoT technologies and the demand for the acquisition of different skills at one time. The IoT requires a wide range of skills, from the development of IoT applications to the integration of the devices themselves into management systems to allow the processing of data generated by the devices [18,24]. Recent studies investigated the importance of focusing on the difficulties and problems that students may face when dealing with new IoT technologies and applications. One of the possible solutions is to tackle the concept of computational thinking education, which could allow students to find solutions to their problems. Another possible solution is to plan for a suitable design with clear instructions, thereby making it easier to link newly enrolled students to IoT technology and promote professional learning. Another study adopted a different type of solution by offering a workshop that sheds light on the significance of IoT. It was demonstrated that students considered interventions during the workshop to be very satisfactory from the perspectives of learning about IoT, acquiring problem-solving skills, and enjoyment [17–19].

Students' attitudes towards IoT have been investigated in relation to various external factors, including motivation, satisfaction, usability performance, engagement, and enjoyment. The most influential factors that affect students' attitudes are motivation and enjoyment of using the IoT. The level of motivation and perceived enjoyment are significant in increasing the acceptance of IoT technologies among students. On the other hand, factors such as satisfaction and performance have an indirect effect on the use of the IoT. A high level of satisfaction does not necessarily lead to a high level of engagement [20,21].

2.2. Teachers' Attitudes towards IoT

Technological Pedagogical Content Knowledge (TPACK) is considered an efficient model that can determine teachers' competencies in efficiently teaching with technology. This model was designed to suit training programs with learning activities using IoT-based tools. Researchers have proposed that training programs designed by adapting the TPACK model are beneficial at two different levels. First, this model can improve teachers' learning outcomes; second, this model can support positive attitudes toward adopting IoT technologies in the teaching and learning process. IoT technology is highly dependent on teachers' education and readiness to accept the integration of technology as part of their educational tools, in addition to teachers' own beliefs, which can play a critical role in developing practices for technology integration. The adoption of TPACK has a significant effect on technology integration and is closely associated with teachers' motivation and confidence [25,26].

Past studies have shown the many advantages that strengthen the educational environment through the use of IoT technologies. One such benefit is that teachers can gain knowledge of students' performance and level of knowledge. In addition, the quality of teaching can be improved.

Accordingly, the IoT has a great influence on learning environments, which may lead to a more advanced educational environment. IoT will impact how we, as the general public, engage, communicate, and work together, which will further help us navigate our increasingly expanding, interconnected universe [27,28].

Although studies on the IoT have tackled students' attitudes from different perspectives [10,18,24], few studies have explored the importance of using IoT technology from the perspective of teachers' knowledge or the effects of the IoT on the development of pedagogy in the teaching environment. The present study intends to fill this gap by developing a model that integrates students' and teachers' attitudes to investigate IoT effectiveness and efficiency in an educational environment.

3. Theoretical Framework and Hypotheses Development

The research model is illustrated in Figure 1. The model shows the impact of learning motivation, technology optimism, and technology innovativeness on students' attitudes on the basis of the TAM constructs for the perceived ease of use and perceived usefulness of IoT. These hypotheses have not yet been investigated in the context of IoT technologies and applications. Previous studies, however, addressed the effects of these variables on intention to use [29]. Nevertheless, the influence of these two variables has not yet been independently analyzed. Moreover, their effects on students' attitudes toward IoT remain to be seen. This model also explores the effect of TPACK on teachers' attitudes. The three components of TPACK, namely, technology knowledge, content knowledge, and pedagogical knowledge, have a positive effect on the acceptance of the IoT.

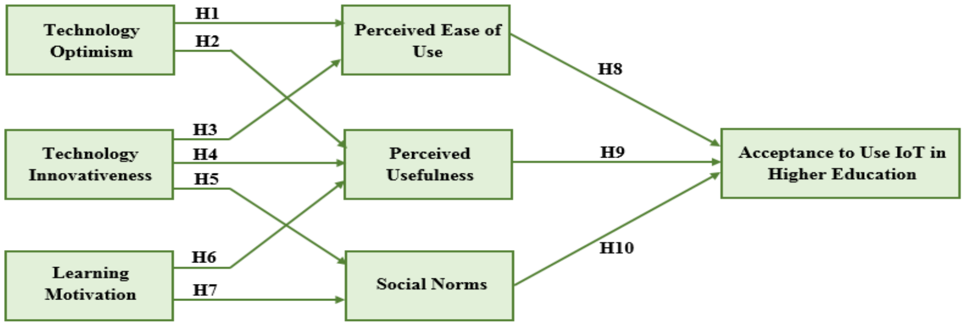

Figure 1. The proposed model.

3.1. Learning Motivation, Technology Innovativeness, and Optimism and TAM

Learning motivation has proven to affect students' attitudes in both traditional and online environments. Learning motivation as an external factor in the proposed framework can be affected by environments, expectations, and social values [30]. Learning motivation, moreover, was shown to have a significant effect on learning achievement [31]. To obtain the proposed learning goals, learners must be motivated to learn [32,33]. As a consequence, learners who are highly motivated to learn can spontaneously and willingly achieve their learning goals. The values of beliefs, expectations, and behaviorism are the focus of social cognitivism.

Researchers are currently investigating whether technological optimism and technology innovativeness can affect student use of the IoT in education. The present study makes use of three theoretical constructs of learning motivation, technology optimism, and technological innovation, which are all considered to be determinants of students' attitudes and behaviors toward the use of technology. The integration of TAM constructs with the previously mentioned variables facilitates the objectives of the current study. The impact of the TAM was previously applied by several researchers to investigate TAM's effectiveness in IoT technology and applications [34]. This model illustrates the reasons behind accepting technology based on attitudes and considers the impacts of certain beliefs on a person's attitude and behavioral intention toward using a technology [35,36]. This model was chosen because it determines the intention to use technology. Evidence from past studies indicates that this is a valid model that can justify the use of technology in various environments and has a close relationship with technology innovation [37,38]. The predictive power of this model stems from the fact that it facilitates the relationship between various context-specific factors that could influence the acceptance of a specific technology, including technology optimism and technology innovativeness [39,40]. The first factor is concerned with users' positive perceptions of technology, as such users may be more reluctant to have greater control over their lives. The second factor refers to users' tendencies to be pioneers of technology and leaders in its use.

The variables of TAM, including perceived ease of use, perceived usefulness, and subjective norms, have a close relationship with technology innovativeness and technology optimism. Previous studies have shown that subjective norms have a positive impact on technology optimism and innovativeness, which are part of students' personal characteristics [41–44]. Technology usage beliefs can also be influenced by academics and classmates in an academic setting. A student will likely develop a positive view of a specific technology if their immediate circle of academics and peers has a positive opinion of it. In the same vein, students will likely perceive themselves positively if they are prepared to use the technology. In the early stages of the technology's adoption, students are willing to be pioneers in the use of advanced technologies. Additionally, an individual's optimism about technology is associated with the degree to which the individual has pioneered the use of the technology [45–48]. Similarly, technology optimism can impact students' attitudes remarkably. Students who are ready to explore new technologies are more willing to accept IoT. New technologies rarely seem complicated or beyond the understanding of technology pioneers. Moreover, users who are denied the opportunity to experiment with new technologies are likely to regret it later [49]. Therefore, the following hypotheses are proposed:

H1: *Learning motivation will significantly affect subjective norms, perceived ease of use, and perceived usefulness;*

H2: *Technology optimism will significantly affect subjective norms, perceived ease of use, and perceived usefulness;*

H3: *Technology innovativeness will significantly affect subjective norms, perceived ease of use, and perceived usefulness;*

H4: *Perceived ease of use will significantly affect the intention to use the IoT;*

H5: *Perceived usefulness will significantly affect the intention to use the IoT;*

H6: *Subjective norms will significantly affect the intention to use the IoT.*

3.2. TPACK

Researchers have previously examined the knowledge development of teachers in content-related fields and contexts in previous TPACK literature reviews. These studies examined the knowledge development of teachers in TPACK in various contexts within educational environments. In the literature, TPACK has been studied in higher education and K-12 schools across various contexts for both in-service and prospective teachers [22,23]. Several obstacles may arise during the process of integrating technology into education. For instance, behaviors, beliefs, knowledge, and skills have been reported frequently in the literature [50]. Taking into consideration the barriers before technology integration, teachers have a considerable role to play in achieving effective technology integration [51,52]. Technology integration can be facilitated by eliminating all the obstacles that emerge as a consequence of the integration of technology in education.

According to previous literature reviews that examined the development of teacher knowledge in TPACK studies, TPACK studies have been conducted in multiple educational environments in various fields and contexts. As noted previously, TPACK has been studied in various contexts within higher education and K-12 for prospective and in-service teacher development [25]. To evaluate the TPACK development of teachers, the authors in [53] argued that methodological and technological tools must be taken into consideration. To establish the current state of affairs, it would be worthwhile to research the relationship between TPACK development and technology usage among teachers.

Many universities in the United States and the European Union have adopted TPACK to redesign their teacher-training programs [54]. Teachers must be able to keep up with the constant advances in information and technology to contribute to a developed society and successful education system. TPACK is a critical skill that teachers need and should develop throughout their professional careers [55–58]. Under this background, the following hypotheses are formed:

H7: *Teachers' technology knowledge will significantly affect their intention to use the IoT;*

H8: *Teachers' content knowledge will significantly affect their intention to use the IoT;*

H9: *Teachers' pedagogical knowledge will significantly affect their intention to use the IoT.*

By reviewing the relationship between TPACK and the related variables, we hope to contribute to the existing literature. It was also suggested that measuring these qualifications and analyzing their relationship to TPACK are important because they will provide important information regarding the effectiveness of the IoT in the educational environment. The literature has also noted that previous studies mostly focused on prospective teachers, meaning that further studies on teachers themselves will strengthen the application dimension of the TPACK model [9,59]. In this study, by working with teachers from different branches, we investigated the relationship between teachers' TPACK levels and their effects on IoT acceptance.

4. Methodology

This research intends to assess the important factors of IoT acceptability in the context of higher education. A quantitative research approach was employed to carry out the investigation, and data were gathered through an online survey.

4.1. Data Collection

Data collection took place from 13 February to 30 April 2020 over the winter semester (2021–2022) at Al Buraimi University College in Oman via online surveys. The research team randomly distributed 800 questionnaires. Of these surveys, 769 questionnaires were answered by the respondents, yielding a 96% response rate. Thirty-one questionnaires were rejected because of some missing values. Consequently, the number of usable questionnaires was 769. On the basis of the work by Krejcie and Morgan [60], these accepted questionnaires reflect an appropriate sample size (i.e., the expected sampling size for 306 respondents/1500 population). There is a great difference, however, between the sample size (769) and the minor requirements. Ultimately, the sample size was deemed appropriate for an evaluation using structural equation modeling [61], which was subsequently used to confirm the hypotheses. It is also worth noting that previous theories (based on the IoT context) formed the foundation of our hypotheses. For the evaluation of the measurement model, structural equation modeling (SEM) (SmartPLS Version 3.2.7) was used by the research group, and advanced treatment was conducted with the help of the final path model.

4.2. Students' Personal Information/Demographic Data

The demographic/personal data were evaluated, as shown in Table 1. Respondents included 47% male students and 53% female students. In total, 57% of respondents were within the age range of 18–29 years, and the rest were above the age of 29. The respondents mostly had university degrees and reflected an academic background. More specifically, the percentages of students with a bachelor's degree, master's degree, and doctoral degree totaled 76%, 22%, and 2%, respectively. Salloum and Shaalan [62] suggested that in cases where the respondents show a willingness to volunteer, a "purposive sampling approach" can be utilized. In the present sample, the students belonged to different universities, age groups, educational programs, and levels. Additionally, IBM SPSS Statistics ver. 23 was used to measure the demographic data.

Table 1. Demographic data for the respondents.

Criteria	Factor	Frequency	Percentage
Gender	Female	410	53%
	Male	359	47%
Age	From 18 to 29	439	57%
	From 30 to 39	264	34%
	From 40 to 49	56	7%
	From 50 to 59	10	2%
Educational qualifications	Bachelor's	584	76%
	Master's	167	22%
	Doctorate	18	2%

4.3. Study Instrument

In this study, a survey instrument was suggested for validating the hypothesis. In order to measure the questionnaire's seven constructs, 21 additional items were added to the survey. Table 2 presents the sources of these constructs. To make the research more applicable, we made amendments to the questions of prior studies.

Table 2. Measurement Items.

Constructs	Items	Definition	Instrument	Sources
Technology Innovativeness	TI1	Technology innovativeness refers to users' beliefs that they are pioneers in using technology. Pioneers rarely consider new technologies as complex or beyond their understanding. Such users are likely to regret losing the opportunity to explore new technologies [49].	I am ready to accept IoT technology in my daily classes.	[49]
	TI2		Among my peers, I am the only one who is ready to experience complex IoT technology.	
	TI3		I plan to experiment with new information technologies.	
Technology Optimism	TO1	Technological optimism refers to the individual's preparedness to use technology [63].	I am prepared to use IoT technology.	[63]
	TO2		I am ready to use the IoT to do my assignments.	
	TO3		My readiness to use the IoT will increase my learning achievements.	
Learning Motivation	LM1	Learning motivation is used as an indicator of behavioral intention to use technology. Motivational learning includes four components of attention, relevance, confidence, and satisfaction. [64,65]	I feel that IoT will increase my focus during daily classes.	[64,65]
	LM2		I feel more confident when I use the IoT in my studies.	
	LM3		I feel satisfied when I use the IoT in my studies.	
Subjective Norm	SN1	Subjective norms refer to the perception of those important to the individual regarding a determined behavior [66].	People around me support my use of new technology.	[66]
	SN2		My classmates think that I can use new technology.	
	SN3		I use new technology because people who I value prefer to use technology.	
Perceived ease of Use	PEOU1	The TAM was developed in [8], which proposed a way of measuring technology effectiveness and acceptance. Perceived ease of use refers to users' perception of the effortless usage of technology [8].	Using IoT technology will improve my skills because it is easy to use.	[8]
	PEOU2		Using IoT technology can increase my learning achievements.	
	PEOU3		I find the IoT effortless.	
Perceived Usefulness	PU1	Perceived usefulness is defined as the level of usefulness that the users of technology may perceive [8].	Using IoT technology will be of great benefit to me.	[8]
	PU2		Using the IoT can improve my learning abilities and skills.	
	PU3		I find the IoT to be of great benefit to my daily classes.	
Intention to use the IoT	BI1	Behavioral intention to use refers to an individual's perception of what others think he or she should do for a determined behavior [66].	I will use the IoT to do my daily homework and assignments.	[66]
	BI2		I will continue using the IoT in my future studies.	
	BI3		I will strongly recommend that other students use IoT technology.	

4.4. Survey Structure

A questionnaire was distributed to the students. This survey had three sections:

1. *The first section focused on the respondents' personal data.*
2. *The second section presented three items representing general questions on the respondents' intention to use the IoT.*
3. *The third section consisted of eighteen items dealing with "Technology Innovativeness, Technology Optimism, Learning Motivation, Subjective Norm, Perceived ease of Use, and Perceived Usefulness".*

To measure these 21 items, a 5-point Likert Scale was used with the following options: strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5).

5. Data Analysis and Results

For this study, data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS V 3.2.7 [67–69]. The collected data were analyzed using a two-step assessment approach that included the measurement model and structural model [70]. PLS-SEM was selected in this research for a number of reasons.

Firstly, if the given research aims to explore a current theory, preference should be given to PLS-SEM [71]. Secondly, PLS-SEM can help with effectively handling exploratory research that has complex models [72]. Thirdly, PLS-SEM can be used to carry out an analysis of the entire model as one unit rather than making subdivisions out of the model [73]. Lastly, PLS-SEM also enables the concurrent analysis of structural and measurement models, through which accurate measurements are generated [74].

5.1. Convergent Validity

For assessing the measurement model, the authors in [70] suggested using construct reliability, which includes Cronbach's alpha (CA), Dijkstra–Henseler rho (pA), and composite reliability (CR), and validity, which includes discriminant and convergent validity. For determining construct reliability, Cronbach's alpha (CA) value was found to be within the range of 0.799 to 0.901 (see Table 3). The threshold value (0.7) was lower than these values [75]. The results shown in Table 3 indicate that the composite reliability (CR) values ranged from 0.809 to 0.891, all of which exceed the threshold value [76]. Instead, researchers should use Dijkstra–Henseler's rho (pA) reliability coefficient for evaluating and reporting construct reliability [77]. As with CA and CR, the reliability coefficient ρA should be at least 0.70 for exploratory research and 0.80 or 0.90 for advanced research stages [75,78,79]. Table 3 also shows that 0.70 is the minimum reliability coefficient ρA for all measurement constructs. These results confirm the construct's reliability, and each construct was ultimately considered free from errors.

To measure convergent validity, it is necessary to test the mean variance extracted (AVE) and factor loading [70]. Additionally, Table 3 suggests that each factor loading value exceeded the threshold value of 0.7. According to the results in Table 3, the AVE values ranged from 0.595 to 0.759, exceeding the 0.5 threshold value. On the basis of these results, it is possible to achieve convergent validity.

5.2. Discriminant Validity

To measure discriminant validity, it was suggested to consider two criteria: the Heterotrait–Monotrait ratio (HTMT) and Fornell–Larcker criterion [70]. The findings in Table 4 suggest that the Fornell–Larker condition confirms the requirements because each AVE and its square roots exceed the value's correlation with other constructs [80].

Table 3. Convergent validity results.

Constructs	Items	Factor Loading	CA	CR	PA	AVE
Technology Innovativeness	TI1	0.893	0.868	0.828	0.891	0.595
	TI2	0.891				
	TI3	0.824				
Technology Optimism	TO1	0.827	0.830	0.875	0.858	0.605
	TO2	0.886				
	TO3	0.889				
Learning Motivation	LM1	0.813	0.809	0.861	0.830	0.604
	LM2	0.713				
	LM3	0.737				
Subjective Norm	SN1	0.891	0.851	0.891	0.874	0.645
	SN2	0.880				
	SN3	0.895				
Perceived Ease of Use	PEOU1	0.886	0.888	0.819	0.801	0.759
	PEOU2	0.809				
	PEOU3	0.910				
Perceived Usefulness	PU1	0.909	0.799	0.809	0.845	0.736
	PU2	0.837				
	PU3	0.844				
Intention to use the IoT	BI1	0.926	0.848	0.849	0.895	0.676
	BI2	0.921				
	BI3	0.919				

Table 4. Fornell–Larcker Scale.

	TI	TO	LM	SN	PEOU	PU	BI
TI	**0.854**						
TO	0.691	**0.861**					
LM	0.624	0.535	**0.896**				
SN	0.208	0.162	0.137	**0.801**			
PEOU	0.646	0.608	0.373	0.692	**0.851**		
PU	0.559	0.386	0.453	0.576	0.413	**0.807**	
BI	0.344	0.202	0.241	0.316	0.304	0.291	**0.821**

Table 5 shows the HTMT ratio findings, which indicate that the value of each construct is lower than the 0.85 threshold [81]. Consequently, the HTMT ratio was found to be present. With the help of these findings, the discriminant validity was calculated. According to the analysis results, there was no issue in assessing the reliability and validity of the measurement model. Consequently, the collected data were further used for evaluating the structural model.

Table 5. Heterotrait–Monotrait Ratio (HTMT).

	TI	TO	LM	SN	PEOU	PU	BI
TI							
TO	0.261						
LM	0.268	0.627					
SN	0.336	0.575	0.467				
PEOU	0.702	0.360	0.529	0.322			
PU	0.342	0.508	0.534	0.404	0.356		
BI	0.473	0.479	0.604	0.531	0.553	0.547	

5.3. Research-Model Testing Using PLS-SEM

To determine whether the structural model's theoretical constructs are interdependent and thus a complete analysis of the proposed hypotheses, we utilized structural equation modelling alongside Smart PLS with maximum likelihood estimation [82–85]. Figure 2 and Table 6 also illustrate the high predictive power of the model [86], showing a 78.4% variance within the intention to use the IoT (BI).

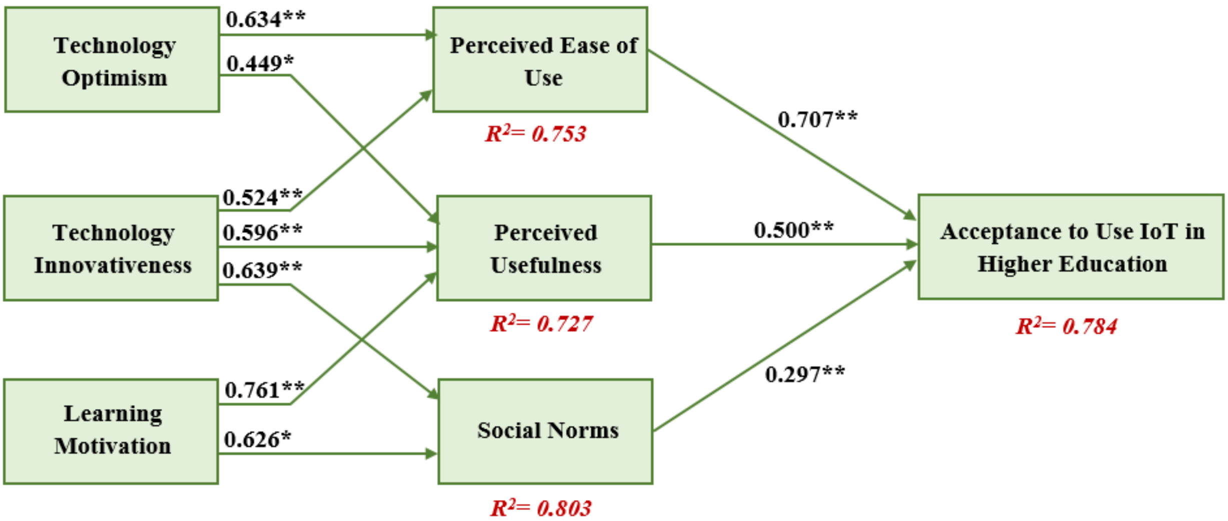

Figure 2. Path coefficient of the model (significant at p ** < = 0.01, p * < 0.05).

Table 6. R^2 of the endogenous latent variables.

Construct	R^2	Results
PEOU	0.753	High
PU	0.727	High
SN	0.803	High
BI	0.784	High

In Table 7, the beta (β) values, t-values, and p-values for all of the developed hypotheses are described on the basis of the produced findings with the help of the PLS-SEM technique. The results supported each hypothesis. Taking into consideration the data analysis hypotheses, the empirical data indicate support for H1, H2, H3, H4, H5, H6, H7, H8, H9, and H10. Technology optimism (TO) and technology innovativeness (TI) had significant effects on perceived ease of use (PEOU), with (β = 0.634, $p < 0.001$) and (β = 0.524, $p < 0.001$), respectively. Thus, H1 and H3 are supported. The results also indicate that perceived usefulness (PU) significantly influenced perceived technology optimism (TO) (β = 0.449, $p < 0.05$), technology innovativeness (TI) (β = 0.596, $p < 0.001$), and learning motivation (LM) (β = 0.761, $p < 0.001$), thereby supporting the hypotheses H2, H4, and H6, respectively. The relationships between technology innovativeness (TI) and learning motivation (LM) was found to have significant effects on subjective norm (SN), with (β = 0.639, $p < 0.001$) and (β = 0.626, $p < 0.05$), respectively. Hence, H5 and H7 are supported. Finally, the relationships between perceived ease of use (PEOU), perceived usefulness (PU), and subjective norm (SN) were found to have significant effects on intention to use the IoT (BI) (β = 0.707, $p < 0.001$), (β = 0.500, $p < 0.001$), and (β = 0.297, $p < 0.001$), respectively. Hence, H8, H9, and H10 are supported.

Table 7. Hypotheses testing of the research model (significant at p ** < = 0.01, p * < 0.05).

H	Relationship	Path	*t*-Value	*p*-Value	Direction	Decision
H1	TO -> PEOU	0.634	12.649	0.001	Positive	Supported **
H2	TO -> PU	0.449	6.579	0.012	Positive	Supported *
H3	TI -> PEOU	0.524	13.066	0.000	Positive	Supported **
H4	TI -> PU	0.596	16.241	0.000	Positive	Supported **
H5	TI -> SN	0.639	14.321	0.000	Positive	Supported **
H6	LM -> PU	0.761	10.364	0.000	Positive	Supported **
H7	LM -> SN	0.626	4.102	0.040	Positive	Supported *
H8	PEOU -> BI	0.707	15.984	0.000	Positive	Supported **
H9	PU -> BI	0.500	11.411	0.000	Positive	Supported **
H10	SN -> BI	0.297	11.015	0.000	Positive	Supported **

6. Discussion and Implications

The results of data analysis indicate that technology features serve as the foundations from which users build their own perceived ease of use and usefulness for IoT tools and applications. Technology optimism and technology innovation, moreover, had a significantly positive effect on all model variables. Technology features were found to significantly affect perceived ease of use, perceived usefulness, and subjective norm, suggesting that excellent technology features can enhance IoT acceptance.

The Impacts of perceived ease of use, perceived usefulness, and social norms were reflected in a significant effect on the intention to use the IoT. The findings of the present study are supported by the fact that the availability of the TAM construct can provide a friendly operational experience, meet users' value demands, and invoke users' pleasure. Furthermore, technology features have a significantly positive influence on technology optimism. In this way, users were more willing to use IoT-related technology if they believed that the system was of high quality and would facilitate the adoption of relevant technology. Additionally, the social aspect was directly related to the intention to use the IoT, especially when users of the IoT were affected by the familiarity of this technology among clients. In this case, IoT features would be familiar to users based on their cognition and operation, thereby reducing their operational difficulties. Technology innovation was found to have a significant impact on perceived ease of use and perceived usefulness, showing that innovative tools and applications can speak for themselves. During the user experience process, excellent innovative features were perceived, and a sense of trust emerged naturally. Consequently, Hypotheses H1-H3 were confirmed. Previous studies also agree with the present findings. Confirmation of these results strengthens the proposed conceptual model and proposed hypotheses [87–89].

It can be seen that, although IoT users have overcome the difficulties in the process of rapid growth during the last few years, they are still willing to proceed with the use of the IoT tools and applications; as such, users can develop their knowledge whenever their teachers' content, knowledge, and pedagogy improves. Early adopters had an improved experience when their teachers' content, knowledge, and pedagogy were well-built due to the use of IoT tools in their daily classes. Students were satisfied with the given information and less distrustful because the gap between them and their teachers decreased, and their expectations were met. More interestingly, the influence of familiarity may be an additional factor that affects TPACK components and leads to a better teaching–learning environment. Hence, hypotheses H4-H9 are supported. The existing literature supports the findings of the current study [11,90,91]. Although the present study focused on variables that enhance the use of the IoT, other studies have proposed findings that are not in agreement with the current study (e.g., adding factors that may negatively affect one's intention to use the IoT). Teachers and others in educational settings believe that a lack of sufficient security and privacy are among the main challenges that could hinder the deployment of the IoT in education [11,90]. To reduce the obstacles observed in previous research and sustain this technology's effective use, future efforts related to implementing the IoT in education must take these factors into account. However, this technology is still not widely adopted in developing countries.

Managerial implications are related to the type of IoT application in the teaching environment. Intention to use the IoT was also correlated with high competency in using IoT technology by teachers in the classroom, including the competent use of computers, technology pedagogy, and applications in teaching. Developers and educators should ensure that their academic staff has sufficient training in the use of IoT applications. In addition, TPACK, which includes technology content, technology, and pedagogy, will facilitate the use of IoT tools and applications in educational environments. A teacher's knowledge of TPACK can be expressed through the integration of different components, such as professional capacity, computer technology, and teaching techniques. Thus, managers should add more features that can improve teachers' TPACK knowledge, thereby paving the way toward self-learning and integrated training.

Furthermore, the present research has implications that could affect both teachers and students. Teachers will gain benefits from the integration of IoT tools to lessen the burden on their shoulders and find the best solution to pedagogical issues that required excessive time and effort in the past. Similarly, students from different regions could make use of these benefits, especially those in rural areas that have a very high interest in using online learning applications.

Limitations of the Study and Future Studies

This study mainly explored the TAM construct with a group of independent variables in a conceptual model to assess IoT acceptance by a group of users. The current model is focused on two conceptual levels. The first level is related to the social attitudes of the users because it incorporates the motivation to learn as an independent variable. The second level is related to the users' preferences and experiences with IoT because it examines the influence of individual characteristics on technology optimism and technology innovation. In the future, the influence of personality traits on learning motivation will be further discussed and may include users' gender, age, education level, occupation, monthly income, family status, technology experience, etc., thus enabling user types to be analyzed. Additionally, it is hypothesized that technology optimism and technology innovation could significantly affect TAM constructs. Hence, future studies may focus on other features of technology that affect the adoption of the IoT. Both individual traits and features of technology could directly or indirectly affect the intention to use the IoT in future models. Adding the mediating roles between individual traits and technology features could also enrich future analyses. In future studies, we would also like to explore further the assumption of mediating variables in a conceptual model that measures the significance of the IoT. Finally, while the present study is focused on the IoT, future studies could utilize the same conceptual model and apply it to innovative features such as artificial intelligence and the metaverse.

7. Conclusions

IoT technology has changed the world of technology and industry. The IoT has become the infrastructure of future smart cities and is an essential driving force of economic and social transformation. Recently, this particular technology has experienced rapid development and unprecedented growth. The establishment of perceived ease of use, perceived usefulness, and social norms is the basis for users' adoption of this technology. The present study established the perceived ease of use and perceived usefulness model for Arab consumers through path analysis and structural equation modeling based on the responses of a group of users. These variables were connected to other independent variables, including technology optimism, technology innovation, and learning motivation, to investigate the extent to which these variables are influenced by TAM constructs. The findings showed that these variables have a one-to-one relationship with TAM constructs. The three variables in the model, namely technology optimism, technology innovation, and learning motivation, were found to have a significant effect on perceived ease of use, perceived usefulness, and social norms, respectively. Among them, technology optimism and technology innovation were found to be essential and fundamental variables that affect one's intention to use the IoT. Indeed, as confirmed in the existing literature, TAM constructs affect our intention to use. However, the present study showed that these constructs might also be affected by other external variables related to social factors, such as learning motivation.

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