Journal of Theoretical and Applied Information Technology
28th February 2023. Vol.101. No 4

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ACADEMICS' BEHAVIORAL INTENTION AND USAGE OF IOT IN E-LEARNING: MODERATION OF GENDER AND EXPERIENCE

FAIQ AZIZ [1,*], AZIZI SAFIAI [2], NOR WAHIZA ABDUL WAHAT [3], SITI RABA'AH HAMZAH [4], SEYEDALI AHRARI [5], NOMAHAZA MAHADI [6]

[1,2,3,4,5] Faculty of Educational Studies, Universiti Putra Malaysia, Serdang, 43400, Malaysia
[6]Azman Hashim International Business School, Universiti Teknologi Malaysia, 54100, Kuala Lumpur, Malaysia
E-mail: [1] mohdfaiq@upm.edu.my, [2] azizis1128@gmail.com, [3] wahiza@upm.edu.my, [4] srh@upm.edu.my, [5] seyedaliahrari@upm.edu.my , [6] nomahaza.kl@utm.my

ABSTRACT

As the world shifts to e-learning, IoT is becoming increasingly important in the learning and teaching environment. The key concerns are the elements that influence academics' behavioral intention to adopt IoT, and how the whole operation affects their performance. However, there is a research gap in past studies that have not addressed this issue sufficiently. As a result, this study employed the Unified Theory of Acceptance and Use of Technology (UTAUT) as a guideline to examine the factors that influence academics' behavioral intentions to use IoT. Furthermore, the moderating effects of both gender and level of experience on this relationship were inspected. The structural models were validated, and the predefined hypotheses were presented (n = 321). The results from the Structural Equation Modeling approach using Amos 26 indicate that performance expectancy, social influence, and effort expectancy directly influenced behavioral intentions to utilize IoT. The findings also showed that facilitating conditions were the most important determinant of academics' actual usage of IoT. The structural model was further investigated according to the experiences of the male and female academic groups. The findings revealed a different pattern of strength and significant relationships between groups with the overall model, implying that gender and experience act as moderators. This study provides a wealth of antecedents from which to construct a thorough theory of IoT adoption. The theory explores the elements that influence academics' willingness to utilize IoT from the standpoints of the technology itself, social context, and individual user characteristics. By employing the proposed approach, Universities can modify their EL strategies to make the most of their resources and in turn improve efficiency.

Keywords: *IoT adoption; UTAUT; Academics; E-Learning; Gender; Experience*

1. INTRODUCTION

The traditional face-to-face learning approach is no longer enough in today's quickly evolving information society of web-based e-learning (EL) environments [1]. With EL, learners may develop their knowledge, strategize their learning routes and tactics, and access a wide range of information and self-directed learning experiences [2]. The COVID-19 pandemic, which forced the closure of all academic institutions, further highlighted EL's technological importance and its many advantages [3]. However, EL relies heavily on the internet as its information gateway and uses various cutting-edge technologies to access online educational programs [4].

The internet has recently become a vital, omnipresent communication network that connects billions of people across several platforms. EL can not only allow learners to access educational information on the internet but can also extend its services through EL help and community knowledge-sharing networks [5]. EL materials may be transferred through the internet swiftly and efficiently. Significant advancement has further improved the internet's ubiquity in ICT, namely by the effortless linking of common devices to a ubiquitous information network known as the Internet of Things (IoT) [6]. The phrase "IoT" was invented by Ashton [7]. IoT extends the benefits of the ordinary digital internet to physical items, with the primary objective of linking everything [8].

Currently, IoT connects over 25 billion devices worldwide. Despite its novelty, the possibility of applying IoT in the education sector piqued the curiosity of many academics [9]. The current era is characterized by smart learning, which combines EL and IoT [10]. The arrival of IoT has impacted earlier models of EL, allowing EL to adopt a more participatory approach [11]. According to Mathivanan et al. [12], most universities will adopt IoT to boost EL. However, studies have shown that IoT integration continues to be challenging for most users, particularly academics [13]. Scholars have discovered the factors that affect academics' adoption of technology-based learning [14]. However, there has been a lack of thorough studies to validate their usage of IoT. Most previous studies have concentrated on technology concerns around IoT, with little focus on its actual adoption.

There haven't been many attempts up to now to look at factors connected to the real adoption of IoT. Additionally, there haven't been any studies done on academics' behavioral intents to use IoT. In order to give higher education (HE) administrators more information regarding the acceptance of and effects of this technology on academics, researchers should do further empirical study. To provide them with guidelines on how to use IoT in EL for HE, this study sought to answer that question. Guidelines were determined based on the empirical evidence on psychological factors that may impact academic intention and use, as shown by the UTAUT [15].

1.1 Study Context

It is thought that EL would provide an answer to the growing need for HE in many developing countries. HEIs from these nations are thus urged to participate, promote, and coordinate high-quality learning, teaching, and research [16]. Nonetheless, studies demonstrate that IoT usage for EL at HEIs is still in its infancy [17]. The Malaysian government has made an effort to advance IoT in many areas. The Malaysian Ministry of Science, Technology, and Innovation (MOSTI) predict IoT will significantly influence Malaysia's economy in the coming years [18].

The ICT sector in Malaysia has to be improved to increase the nation's output. MOSTI, a pioneer in Malaysia's IT industry, unveiled the National IoT Strategic Plan in 2015 [18]. By 2025, it is anticipated that Malaysia's IoT industry will reach $42.5 billion [19]. The current problems and challenges encountered in the supply chain concerning implementing Industry 4.0 (IR4) have also been highlighted by Malaysia's Ministry of International Trade and Industry. This was done to further promote the necessity for an IoT curriculum. Except for a few private colleges with specialized engineering disciplines, none of the Malaysian research universities (MRUs) have used IoT for EL systematically. The IoT-heavy programs that they do have are isolated, unconnected, and disconnected.

2. LITERATURE REVIEW

EL is determined by three factors: first, it is networked, enabling it to share training or information; second, conventional internet technologies are used to deliver it to the computer user; and third, it focuses on the most comprehensive understanding of learning that goes beyond the typical training paradigms [20]. The demands for flexible modalities of educational curriculum delivery in HE from the standpoint of EL have steadily risen [21]. Several elements are at play now that encourage an increase in academics participating in EL [22].

HEIs recognize the value of a student's ongoing education that is flexible to their own time, creating the convenience needed for learning without taking away from working time [23]. Moreover, IoT can be useful in universities because it increases learners' interaction with digital resources, combines autonomous control and higher infrastructure reliability, and enables open access to anything without requiring a particular path or service. Today, the adoption of technology tools by academics is crucial to EL's success [24]. IoT is a pervasive technological phenomenon that fosters invention in various disciplines, EL being one of them. For instance, Vharkute and Wagh (2015) discovered that combining several EL apps with the aid of the IoT is associated with students' pleasure. It ensures that student and instructor interaction is enhanced while offering a cost-effective education. IoT is regarded as the primary supplier of the smart agent for EL contexts [25]. The IoT application's scope permits switching from an EL model of knowledge transmission to a collaborative kind that advances knowledge transmission [26]. Animations, online lessons, virtual classroom study materials, video tutorials, and many more resources can be misused as part of an EL method. IoT allows academics to use various educational approaches, including personal, active, and participatory models [27]. IoT is evolving to become a key component of modern EL. By building the right infrastructure and using it to its full potential, institutions may reap the rewards of IoT-based EL models [28].

2.1 Conceptual Model and Hypothesis Development

Based on ideas of human behavior, researchers have tried to explain why users adopt new technologies. However, there are certain limitations to these technology adoption models in determining how open individuals are to embracing new technologies [29]. The UTAUT uses the fundamental components based on eight standard technology acceptance models to solve these constraints [15]. This study used this model to explore the potential factors of academics' behavioral intention (BI) and IoT adoption in EL.

2.1.1 Performance Expectancy and Academics' Intention to Use IoT

Performance expectancy (PE) refers to the notion that using technology would improve a person's ability to execute his job [15]. The PE idea, which foresees academics' BI to use emerging technologies, is frequently included in the UTAUT [30]. For instance, Sung et al. [31] used the UTAUT to examine mobile learning in the South Korean setting and concluded that PE is strongly related to BI. IoT can speed up academic work, shorten wait times, and improve customer impressions of service quality. Numerous researchers have employed the UTAUT, and there is evidence of a relationship between PE and the BI use technology [32]. Studies have also shown that PE significantly affects a person's long-term motivation to use EL [33]. As a result, the present study formulated the following hypothesis:

H_1: PE is positively associated with academics' BI to use IoT in EL.

2.1.2 Social Influence and Academics' Intention to Use IoT

The social influence (SI) component of the UTAUT measures how important adopting a new technological instrument is to a person [15]. Studies have examined the impact of SI, such as the influences of close acquaintances, on people's adoption behavior [34]. SI includes the users' assessment of whether those who are significant to them believe they should engage in the action [15]. For instance, Jain and Jain [35] claimed that teachers who interact with students have a stronger BI to adopt new technology in the classroom. Additionally, SI has impacted the adoption of IoT [36]. As a result, Hypothesis 2 suggests:

H_2: SI is positively linked to academics' BI to use IoT for EL.

2.1.3 Effort Expectancy and Academics' Intention to Use IoT

The formal definition of effort expectancy (EE) is the degree of comfort associated with using technology instruments. The main use of EE, a crucial component of the UTAUT, is to gauge users' intent to use technological tools [37]. Jang and Koh [38] have highlighted the impact of EE in determining the acceptability of learning technologies. Researchers like Kaliisa et al. [39] have highlighted an association between EE and BI in contemporary technology. Other studies that have used the UTAUT have also found EE and BI to be related [40]. Consequently, Hypothesis 3 was proposed as follows:

H_3: EE is positively related to academics' BI to use IoT for EL.

2.1.4 Facilitating Conditions and Academics' IoT Usage Behavior

Facilitating circumstances (FC) are the idea that there are sufficient administrative and technical infrastructures in place to make the system simpler to utilize [15]. It is believed that having access to training and support will make it easier for businesses to embrace new technologies. In this study, FC was evaluated based on academics' perceptions about their capacity to obtain the tools and help they need to utilize IoT. FCs have a favorable impact on individuals' inclinations to utilize technology [41]. As a result, the present study suggested that:

H_4: FCs are positively related to academics' IoT UB in EL.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2.1.5 Behavioral Intention and Academics' IoT Usage Behavior

A person's level of dedication to a certain action may be a sign of BI [14]. As a result, the degree of academics' dedication to accepting and implementing IoT to achieve their educational objectives may indicate their BI toward IoT usage in EL [27]. Therefore, Hypothesis 5 implies:

H_5: Behavioral intention is positively related to academics' IoT usage behavior.

2.1.6 Moderating of Gender and Experience

Learner characteristics are a crucial factor for effective EL settings [42]. Understanding the intended audience is essential while building EL. Kwiek and Roszka [43] estimate that almost half of all academics worldwide are women. However, there hasn't been abundant research on how gender variations impact academics' attitudes towards the usage of IoT in EL. The trend of technology adoption and usage is skewed toward one gender over the other [44].

Furthermore, it has been discovered that people who use technology but are inexperienced prefer minimum effort. They are more likely to be swayed by the attitudes of people in their social circle and are also less concerned with FC [15]. Given that the academic participants of this research used IoT voluntarily, the moderating effects of gender and IoT experience were also added to the research framework to improve the model's predictive validity. It is hypothesized that experience with IoT leads to altered perspectives of PE, EE, SI, and FC, which thus impact differently upon the BI to use EL. Henceforth, the subsequent hypotheses were formulated:

H_6. Gender moderates the relationships between (a) PE, (b) EE, and (c) SI and academic' BI to use IoT in EL.

H_7. Academics' level of experience with IoT moderates the relationships between (a) PE, (b) EE, and (c) SI and their BI to use IoT in EL.

3. METHODOLOGY

3.1 Participants and Procedure

Academics from five Malaysian research institutions (MRUs), namely UPM, UKM, UM, USM, and UTM, were included in the study's sample. The scale for data collection was created using elements from the accessible literature. The factors were assessed using 44 questions collected from earlier investigations [15,45]. A sample size of 50 is deemed inadequate for factor analysis, 300 is tolerable, and 500 is very good, while 1000 is excellent [46]. The present study got 321 replies from 350 dispersed questionnaires (91.71% response rate). The questionnaire had two primary elements to assess the theoretical model: (1) demographics of respondents and (2) development measures of the model. For this research, all components of the original UTAUT were integrated and changed. A 5-point Likert scale was defined, ranging from 1 (strongly disagree) to 5 (strongly agree).

3.2 Measures

EE stands for the degree of comfort associated with using technology. In line with this, the initial seven items covered perceptions of difficulty and usefulness in using IOT during EL [15]. A sample item is as follows: '*I find this technology to be simple to use, and IoT in EL would be easy for me to understand*' ($\alpha = 0.808$). Furthermore, a six-item scale that evaluated PE, work fit, extrinsic motivation, relative benefit, and technology-predicted output was used to measure PE [47]. A sample item is '*Using IoT for EL helps me to do tasks quickly*' ($\alpha = 0.808$). Moreover, SI was measured using Venkatesh et al.'s [15] ten-item scale. An example of an item is as follows: '*IoT is something that individuals significant to me would advise me to use*' ($\alpha = 0.867$). Next, eight items measured FC [15]. A sample item is '*I have the necessary resources to implement IoT in education*' ($\alpha = 0.702$). The BI component was further measured using five items [48]. A sample item is '*I aim to adopt IoT technologies during EL during the next few months*' ($\alpha = 0.857$). Finally, UB, defined as the actual frequency of the usage of a particular technology, was measured using eight items [15]. A sample item is '*I intend to use IoT service in the future*' ($\alpha = 0.814$).

3.3 Questionnaire Development

With the assistance of three language specialists, the questionnaire was translated into Malay to evaluate the face and content validity and to guarantee their adaptation to the regional cultural environment. A pilot study was then carried out on 30 academics to assess the

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

reliability of the instruments (SI, α= .76; EE, α = .75; PE, α =.74, FC, α =.79, BI, α = .76, UB, α = .78). Based on participant feedback, the questionnaire was then further improved to increase its face validity. The primary sample of the study did not include any academics who took part in the pilot study.

3.4 Demographics

The respondents who participated in the study had an average age of 41 years (SD=2.87), with the majority being males (N = 179, 56%). A fraction of the respondents (71.02%) reported having less than five years of experience in the online teaching field. Moreover, most of the respondents (N = 299, 93.2%) have Ph.D. degrees. A fair amount of them (47.6%) were also senior lecturers (see Table 1).

Table 1: Responders' backgrounds.

Sample Chrematistics	Frequency	(%)	Mean	SD
Age			41	2.87
Gender				
Male	179	56		
Female	142	44		
Online teaching experience				
<5 years	228	71.02		
>5 years	93	28.9		
Background in education				
PhD	299	93.2		
Master	22	6.8		
Position in education				
Professors	42	13.1		
Associate professors	107	33.5		
Senior lecturers	152	47.6		
lecturers	18	5.8		

In addition to acceptable levels of reliability, the reliability test further revealed considerable composite reliability for all construct items. The loading for the PE build was less than 0.5. The lowest loading can be eliminated if the extracted average variance (AVE) is lower than the threshold level [49]. Therefore, PE Item PE4 was removed. Each scale has a Cronbach's α score between 0.652 and 0.902, which indicates satisfactory reliability for each construct. The lowest loading can be deleted if the AVE is less than the normal level [50].

4. DATA ANALYSIS

The kurtosis and skew values, which are between ±2, which reflect the bounds of normality, validated the data's normal distribution in SPSS v.26. SEM analysis was used in the investigation. SEM includes the exploration of complex models such as moderation and mediation. Moreover, using the AVE and construct reliability, reiterates the high validity and construct reliability (CR).

4.1 Descriptive statistics of constructs

Table 2 displays the means and standard deviations for the study constructs. The results reveal that FC is significantly above average for the respondents, while EE appears to be a little higher. On average, it is perceived that SI to use of IoT among academics is above average compared to PE.

Table 2: Descriptive statistics of latent constructs.

Constructs	Mean	SD
PE	3.654	0.567
SI	3.783	0.585
EE	4.06	0.569
FC	3.816	0.67
BI	3.75	0.671
UB	3.873	0.528

Note. PE= Performance Expectancy, SI = Social influence, FC = Facilitating condition, EE= Effort Expectancy, BI = Behavioral intention, UB= Usage behavior.

4.2 Data preparation

The measurement model was validated by a reliable approach to demonstrate that certain items replicate the unobserved constructs [51]. The outcomes of the CFA showed that the measurement model was acceptable with strong factor loadings for all of the items on the predictable factors and commonality of each item over 0.50. The results show that all the constructs achieved convergent concept validity. The number of items for each construct is listed in Table 3 as follows: PE (5 items), SI (7 items), FC (4 items), EE (4 items), BI (5 items), and UB (3 items); altogether there are a total of 28 items. The present study used AMOS 26 software to examine the data. Convergent validity is concluded for all constructs when the AVE is more than 0.50 and the CRs for all scales are better than 0.80.

Table 3. AVE and construct reliability of study instruments.

Construct	Initial item	Final No. of items	AVE	CR
PE	6	5	0.657	0.905
SI	10	7	0.538	0.890
EE	7	4	0.597	0.855
FC	8	4	0.607	0.860
BI	5	5	0.642	0.899
UB	8	3	0.576	0.800

Note. PE= Performance Expectancy, SI = Social influence, FC = Facilitating condition, EE= Effort Expectancy, BI = Behavioral intention, UE= Usage behavior.

Kline (2016) suggested using model fit indices such as the χ^2/degree of freedom ratio (CMIN/DF), the comparative fit index (CFI), the Tucker–Lewis index (TLI), the goodness-of-fit index (GFI), Incremental Fit Index (IFI), and Normed Fit Index (NFI). The fit indices' values equal to or greater than 0.90 are considered satisfactory [52]. Moreover, the model is considered adequate if the root means squared error of approximation, (RMSEA) is between 0.03 and 0.08. The model of the current study had high fit indices: CMIN/DF = 2.028, $p < 0.01$, CFI = 0.956, GFI = 0.903, IFI = 0.957, TLI = 0.950, NFI = 0.918, RMSEA = 0.049.
The correlations between constructs varied from 0.293 to 0.657, as shown in Table 4. When R^2 is smaller than AVE, discriminant validity is declared. (Henseler et al., 2015). Every AVE value exceeded the values of R^2, demonstrating the excellent discriminant validity of the constructs.

Table 4: AVE and R^2 for study instruments

No.	Construct	1	2	3	4	5	6
1	PE	0.657					
2	SI	0.398	0.538				
3	EE	0.293	0.405	0.607			
4	FC	0.454	0.452	0.407	0.597		
5	BI	0.521	0.533	0.436	0.544	0.642	
6	UB	0.341	0.462	0.344	0.381	0.459	0.576

Note. PE= Performance Expectancy, SI = Social influence, FC = Facilitating condition, EE = Effort Expectancy, BI = Behavioral intention, UB= Usage behavior.

5. RESULT AND DISCUSSION

5.1 Structural Model

PE, SI, FC, EE, and BI are exogenous variables in this model, whereas BI and UB are endogenous variables. As seen in Figure 1, PE had a significant association with BI ($\beta = 0.324$, p-value = 0.000). Thus, H_1 was supported. This outcome is consistent with earlier research [53], in which PE was discovered to significantly impact the intention to use new technologies by academics. Therefore, this finding suggests that academics who anticipate adopting IoT as a helpful EL tool are more likely to have the intention to utilize IoT.

This study also found that SI had a major impact on BI among Malaysian academics ($\beta = 0.497$, p = 0.000). Hence, H_2 was supported. In particular, the results of this research are in line with the idea that academics from the Southeast Asian context are more influenced by the SI factor in their intention to use IoT, unlike other counterparts [54]. Their decision to use IoT may be readily influenced by peer or media pressure. Hence, IoT service providers need to consider the SI factor to encourage the adoption of IoT. The findings further support the UTAUT [15], in which SI is positioned as a key factor. This finding can be attributed to the comparatively significant effect of close co-workers and acquaintances in educational environments. Furthermore, Zhao et al. [55] found that people's opinions mattered when selecting whether to embrace new technologies in the collectivist cultures of Asian countries.

Furthermore, the findings showed that EE is a significant predictor of BI in adopting EL (β = 0.192, p = 0.000), supporting the conclusions of prior research, such as that of Alammary et al. [56] on academics from Saudi Arabia. Therefore, H_3 was accepted. Additionally, the results of the path coefficient show that the FC (β = 0.233, t=2.939, p = 0.000) is significantly related to UE, thus, supporting H_4. The findings align with other studies, such as that of Paul et al. [57] on Ugandan academics. Paul et al. [57] demonstrated that FC improves the UB to adopt modern technologies for EL. Additionally, the results of this study also confirmed the association between BI and UB among academics adopting IoT for EL (β = 0.451, p = 0.000), which supports Venkatesh et al.'s [15] UTAUT. Finally, the exogenous constructs explained 76.3% of the variance in BI, and BI was responsible for 51% of the variance in UB (Table 5 and Figure 1).

Table 5: Unstandardized and standardized regression weights in the hypothesized path model.

Hypothesis	Relationship	β	S. E	*Beta*	C.R	*p*	Decision
H_1	BI ← PE	0.324	0.050	0.316	6.537	***	SU
H_2	BI ←SI	0.497	0.057	0.500	8.675	***	SU
H_3	BI ←EE	0.192	0.050	0.184	3.885	***	SU
H_4	UE ← FC	0.233	0.057	0.288	4.113	***	SU
H_5	UE ←BI	0.451	0.068	0.486	6.671	***	SY

Note. PE= Performance Expectancy, SI = Social influence, FC = Facilitating condition, EE= Effort Expectancy, BI = Behavioral intention, UE= Usage of e-learning, SU= Supported.

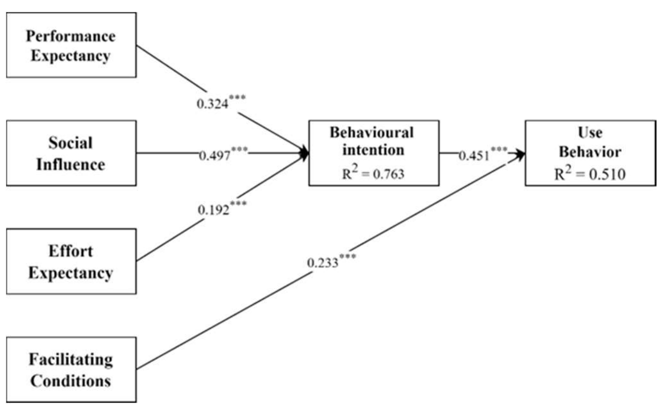

Figure 1. Study's structural model

Further investigation on the moderating role of gender on the intention to use IoT and its relations with the four factors of the model (as indicated in H_6) was performed. Findings revealed that PE, as proposed in H6a was significantly different between males (β = 0.440, p< 0.05) and females (β = 0.250, p< 0.05). This finding is consistent with that of Venkatesh et al. [15] and contrary to that of Gupta et al. [58]. However, the results also revealed that gender did not moderate the relation between the other two factors (SI and EE) and BI. Thus, H_{6b} and H_{6c} were rejected.

Moreover, the results showed that experience moderated the relation between the factors (PE, SI, and EE) and BI. Thus, H_{7a}, H_{7b}, and H_{7c} were supported. Thus, in line with other studies [59], academics' previous experience using IoT technologies will help them. This is because IoT provides greater performance, is easy to use, is welcomed by their colleagues, and previously enabled their creative abilities to be unleashed. IoT is relatively new in Malaysia, so users' experience with IoT would play a critical role.

Table 6: Moderating effects of gender and experience level.

Hypothesized paths	Gender		t	p	Experience		t	p
	Male (n = 179)	Female (n = 142)			5> (n = 228)	5< (n = 93)		
BI ← PE	0.440*	0.250*	2.093	0.037	0.237*	0.616*	2.157	0.032
BI ←SI	0.243	0.175	0.619	0.536	0.692*	0.168*	2.837	0.005
BI ←EE	0.354	0.555	1.666	0.096	0.469*	0.055*	2.200	0.028

Note. PE= Performance Expectancy, SI = Social influence, FC = Facilitating condition, EE= Effort Expectancy, BI = Behavioral intention. *$p < 0.05$.

6. CONCLUSIONS

This study, which was directed by the UTAUT, provides a thorough knowledge of the variables influencing IoT adoption in EL among academics. Practitioners and academics will find it useful to use the verified adoption model to investigate how widely used technology is becoming to permeate daily life. In this study, the importance of IoT was discussed, along with a particular emphasis on EL. SI was found to be the most significant predictor among the antecedents of the BI toward IoT technologies. Furthermore, to fill a clear gap in the literature, this study evaluated the effects of gender and experience on the factors influencing academics' BI toward IoT. Findings showed that the PE's influence on BI varied significantly depending on participants' gender. Moreover, experience had a moderating effect on all other factors influencing BI.

We expect that this study can help HEIs get more scientific understanding of EL utilizing IoT. The fact of IoT adoption for digital learners should be acknowledged by educators and curriculum writers in the twenty-first century. For the purpose of enhancing the academic staff's knowledge and skills, HEIs are required to provide lectures and courses. Thus, users' perceptions of EE to use IoT can be improved, which may evoke their intention to use IoT. Although FC has no direct effect on the usage of IoT, its intention should not be ignored. Academics anticipate an IoT application that is helpful and simple to use. Thus IoT service providers are recommended to supply consumers with this kind of application and other related services. By creating a user-friendly and reliable IoT interface and platform, IoT can deliver more efficient and effective services. Additionally, HEIs should consider the SI factor's impact on academics' embrace of IoT. Even if HEIs cannot alter it, reference groups may be inferred as crucial to the spread of IoT. Therefore, HEIs must find early adopters and encourage their use of IoT services so that they may act as a model for future efforts to promote broad dissemination. Additionally, universities in Malaysia must integrate IoT into one or more current courses, such as programming, networking, ubiquitous computing, data mining and acquisition, computer security, embedded systems, databases, and others to meet industrial demands and close the gap.

7. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

There are some limitations with this study. The recommended approach, at start, did not account for real user behavior. However, a large body of empirical evidence backs up the causal link between BI and UB. A longitudinal study design provides more information than a cross-sectional research strategy, researchers should mention in their second point. Thirdly, although the present study intended to investigate the academic acceptability of IoT in EL, Malaysia was the only country of interest. Future research should widen its focus to analyze IoT acceptability in other developing nations. This will ensure further validation of the model proposed in this study. This is because diverse societal attitudes, governmental restrictions, and conventions may influence the model differently. Furthermore, future research should replicate the present study using various IoT product categories to increase the research model's generalizability. Qualitative research is also suggested for future studies to better understand customers' attitudes towards IoT.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

REFERENCES

[1] Gerasimova VG, Melamud MR, Tutaeva DR, Romanova YD, Zhenova NA. The adoption of e-learning technology at the faculty of distance learning of plekhanov russian university of economics. Journal of Social Studies Education Research 2018;9:172–188.

[2] Theng Y-L, Ei Tun E, Zaw MMH, Cho SYY, Miao C, Kan M-Y, et al. An empirical study of students' perceptions on e-learning systems. Proceedings of the 2nd International Convention on Rehabilitation Engineering & Assistive Technology, 2008, p. 245–249.

[3] Torrisi G, Davis G. Online learning as a catalyst for reshaping practice–the experiences of some academics developing online learning materials. International Journal for Academic Development 2000;5:166–176.

[4] Meskhi B, Ponomareva S, Ugnich E. E-learning in higher inclusive education: needs, opportunities and limitations. International Journal of Educational Management 2019;33:424–37.

[5] Yilmaz R. Knowledge sharing behaviors in e-learning community: Exploring the role of academic self-efficacy and sense of community. Computers in Human Behavior 2016;63:373–382.

[6] Kim KJ. Interacting socially with the Internet of Things (IoT): effects of source attribution and specialization in human–IoT interaction. Journal of Computer-Mediated Communication 2016;21:420–435.

[7] Ashton K. That 'internet of things' thing. RFID Journal 2009;22:97–114.

[8] Khanna A, Kaur S. Internet of things (IoT), applications and challenges: a comprehensive review. Wireless Personal Communications 2020;114:1687–1762.

[9] Rafique W, Qi L, Yaqoob I, Imran M, Rasool RU, Dou W. Complementing IoT services through software defined networking and edge computing: A comprehensive survey. IEEE Communications Surveys & Tutorials 2020;22:1761–1804.

[10] Madni SHH, Ali J, Husnain HA, Masum MH, Mustafa S, Shuja J, et al. Factors Influencing the Adoption of IoT for E-Learning in Higher Educational Institutes in Developing Countries. Frontiers in Psychology 2022;13:3415.

[11] Rahmani AM, Ali Naqvi R, Hussain Malik M, Malik TS, Sadrishojaei M, Hosseinzadeh M, et al. E-Learning Development Based on Internet of Things and Blockchain Technology during COVID-19 Pandemic. Mathematics 2021;9:3151.

[12] Mathivanan SK, Jayagopal P, Ahmed S, Manivannan SS, Kumar PJ, Raja KT, et al. Adoption of e-learning during lockdown in India. International Journal of System Assurance Engineering and Management 2021:1–10.

[13] Leong Y-M, Letchumanan C. Effective learning in higher education in Malaysia by implementing internet of things related tools in teaching and introducing IoT courses in curriculum. 2019 1st International Conference on Artificial Intelligence and Data Sciences (AiDAS), Ipoh, Malaysia: IEEE; 2019, p. 152–157.

[14] Aziz F, Rasdi RM, Rami AAM, Razali F, Ahrari S. Factors Determining Academics' Behavioral Intention and Usage Behavior towards Online Teaching Technologies During Covid-19: An Extension of the UTAUT. International Journal of Emerging Technologies in Learning 2022;17.

[15] Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. MIS Quarterly 2003;27:425–478.

[16] Kenno S, Lau M, Sainty B, Boles B. Budgeting, strategic planning and institutional diversity in higher education. Studies in Higher Education 2021;46:1919–1933.

[17] Sani N, Mostafavi Z, Keykhah A, Ebeadi R. Explanation of retention rates based on the types of student interaction in the e-learning context. Information and Communication Technology in Educational Sciences 2019;10:27–48.

[18] Gerdeman D. Internet of Things in healthcare keeps patients healthy, safe 2016. http://internetofthingsagenda.techtarget.com/feature/Internet-of-Things-in-healthcarekeeps-patients-healthy-safe (accessed August 27, 2021).

[19] Sivakumar D, Jusman MFB, Mastan A. A case study review: Future of Internet of Things (IoT) in Malaysia. ASCENT International Conference Proceedings–

Information Systems and Engineering, Tam Ky City, Vietnam: 2017, p. 23–24.

[20] Rosenberg MJ. E-learning: Strategies for Delivering Knowledge in the Digital. New York, NY: McGraw-Hill; 2001.

[21] Maatuk AM, Elberkawi EK, Aljawarneh S, Rashaideh H, Alharbi H. The COVID-19 pandemic and E-learning: challenges and opportunities from the perspective of students and instructors. Journal of Computing in Higher Education 2022;34:21–38.

[22] Long KC. E-learning, information technology, and student success in higher education. Oxford Research Encyclopedia of Business and Management 2017.

[23] Mohan A. Application and usefulness of internet of things in information technology. International Journal of Engineering and Management Research (IJEMR) 2018;8:57–61.

[24] Ab Jalil H, Rajakumar M, Zaremohzzabieh Z. Teachers' Acceptance of Technologies for 4IR Adoption: Implementation of the UTAUT Model. International Journal of Learning, Teaching and Educational Research 2022;21:18–32.

[25] Şoavă G, Sitnikov C, Dănciulescu D. Optimizing quality of a system based on intelligent agents for e-learning. Procedia Economics and Finance 2014;16:47–55.

[26] Zanella A, Bui N, Castellani A, Vangelista L, Zorzi M. Internet of things for smart cities. IEEE Internet of Things Journal 2014;1:22–32.

[27] Bayani M, Leiton K, Loaiza M. Internet of things (IoT) advantages on e-learning in the smart cities. International Journal of Development Research 2017;7:17747–17753.

[28] Zahedi MH, Dehghan Z. Effective E-learning utilizing Internet of Things. 2019 13th Iranian and 7th National Conference on e-Learning and e-Teaching (ICeLeT), IEEE; 2019, p. 1–6.

[29] Elshafey A, Saar CC, Aminudin EB, Gheisari M, Usmani A. Technology acceptance model for Augmented Reality and Building Information Modeling integration in the construction industry. Journal of Information Technology in Construction 2020;25:161–172. https://doi.org/10.36680/j.itcon.2020.010.

[30] Francisco K, Swanson D. The supply chain has no clothes: Technology adoption of blockchain for supply chain transparency. Logistics 2018;2:1–13. https://doi.org/10.3390/logistics2010002.

[31] Sung H-N, Jeong D-Y, Jeong Y-S, Shin J-I. The relationship among self-efficacy, social influence, performance expectancy, effort expectancy, and behavioral intention in mobile learning service. International Journal of U-and e-Service, Science and Technology 2015;8:197–206.

[32] Almaiah MA, Al Mulhem A. Analysis of the essential factors affecting of intention to use of mobile learning applications: A comparison between universities adopters and non-adopters. Education and Information Technologies 2019;24:1433–1468.

[33] Al-Emran M, Arpaci I, Salloum SA. An empirical examination of continuous intention to use m-learning: An integrated model. Education and Information Technologies 2020;25:2899–2918.

[34] Lu L, Yuan Y, Chen X, Li Z. A Hybrid Recommendation Method Integrating the Social Trust Network and Local Social Influence of Users. Electronics 2020;9:1–27.

[35] Jain V, Jain P. From Industry 4.0 to Education 4.0: acceptance and use of videoconferencing applications in higher education of Oman. Journal of Applied Research in Higher Education 2021;ahead-of-print:1–20. https://doi.org/10.1108/JARHE-10-2020-0378.

[36] Gao L, Bai X. A unified perspective on the factors influencing consumer acceptance of internet of things technology. Asia Pacific Journal of Marketing and Logistics 2014;26:211–31.

[37] Venkatesh V, Thong JY, Xu X. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Quarterly 2012;36:157–178.

[38] Jang H, Koh J. The Influence of the Perceived Value of the Elderly on the Intention of Smart Device Internet Usage: A Lifelong Learning Perspective for the Elderly. Journal of Practical Engineering Education 2019;11:87–103.

[39] Kaliisa R, Palmer E, Miller J. Mobile learning in higher education: A comparative analysis of developed and developing country contexts. British Journal of Educational Technology 2019;50:546–561.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[40] Oke A, Fernandes FAP. Innovations in teaching and learning: Exploring the perceptions of the education sector on the 4th industrial revolution (4IR). Journal of Open Innovation: Technology, Market, and Complexity 2020;6:1–22.

[41] Amadin FI, Obienu AC, Osaseri RO. Main barriers and possible enablers of Google apps for education adoption among university staff members. Nigerian Journal of Technology 2018;37:432–439.

[42] Liaw SY, Tan KK, Wu LT, Tan SC, Choo H, Yap J, et al. Finding the right blend of technologically enhanced learning environments: randomized controlled study of the effect of instructional sequences on interprofessional learning. Journal of Medical Internet Research 2019;21:1–10. https://doi.org/10.2196/12537.

[43] Kwiek M, Roszka W. Gender disparities in international research collaboration: A study of 25,000 university professors. Journal of Economic Surveys 2021;35:1344–1380.

[44] Ameen N, Tarhini A, Shah MH, Madichie NO. Employees' behavioural intention to smartphone security: A gender-based, cross-national study. Computers in Human Behavior 2020;104:106184.

[45] Garone A, Pynoo B, Tondeur J, Cocquyt C, Vanslambrouck S, Bruggeman B, et al. Clustering university teaching staff through UTAUT: Implications for the acceptance of a new learning management system. British Journal of Educational Technology 2019;50:2466–2483.

[46] Goretzko D, Pham TTH, Bühner M. Exploratory factor analysis: Current use, methodological developments and recommendations for good practice. Current Psychology 2021;40:3510–3521.

[47] Zhang Z, Cao T, Shu J, Liu H. Identifying key factors affecting college students' adoption of the e-learning system in mandatory blended learning environments. Interactive Learning Environments 2020:1–14.

[48] Rahi S, Ghani M, Ngah A. A structural equation model for evaluating user's intention to adopt internet banking and intention to recommend technology. Accounting 2018;4:139–152.

[49] Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science 2015;43:115–135.

[50] Hair JF, Gabriel M, Patel V. AMOS covariance-based structural equation modeling (CB-SEM): Guidelines on its application as a marketing research tool. Brazilian Journal of Marketing 2014;13:44–55.

[51] Hair J, Black W, Babin B, Anderson R. Multivariate data analysis. Englewood Cliffs, NJ: Prentice Hall; 2010.

[52] Kline RB. Principles and practice of structural equation modeling. 4rd ed. New York, NY: Guilford publications; 2016.

[53] Pham T, Dang L, Le T. Factors affecting teachers' behavioral intention of using information technology in lecturing-economic universities. Management Science Letters 2020;10:2665–2672.

[54] Lin C-Y, Huang C-K, Ko C-J. The impact of perceived enjoyment on team effectiveness and individual learning in a blended learning business course: The mediating effect of knowledge sharing. Australasian Journal of Educational Technology 2020;36:126–141.

[55] Zhao J, Ye B, Yu L. Peer Phubbing and Chinese College Students' Smartphone Addiction During COVID-19 Pandemic: The Mediating Role of Boredom Proneness and the Moderating Role of Refusal Self-Efficacy. Psychology Research and Behavior Management 2021;14:1725.

[56] Alammary A, Alshaikh M, Alhogail A. The impact of the COVID-19 pandemic on the adoption of e-learning among academics in Saudi Arabia. Behaviour & Information Technology 2021:1–23.

[57] Paul KJ, Musa M, Nansubuga AK. Facilitating condition for E-learning adoption—Case of Ugandan universities. Journal of Communication and Computer 2015;12:244–249.

[58] Gupta B, Dasgupta S, Gupta A. Adoption of ICT in a government organization in a developing country: An empirical study. The Journal of Strategic Information Systems 2008;17:140–154.

[59] Suki NM, Suki NM. Determining students' behavioural intention to use animation and storytelling applying the UTAUT model: The moderating roles of gender and experience level. The International Journal of Management Education 2017;15:528–538.