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Factors Impacting the Behavioural Intention to Use E- learning at Higher Education amid the Covid-19 Pandemic: UTAUT2 Model

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The purpose of this study is to evaluate the behavioural intention of higher education students to use e-learning during the Covid-19 pandemic. Not many researchers have utilized the UTAUT2 model to study the use of technology during this pandemic in the education setting. Therefore, snowball sampling was carried out and the research population consisted of higher education students (n = 159) who have been using e-learning platforms during the ongoing pandemic. The data was collected using a questionnaire based on the adapted UTAUT2 model. Partial Least Squares-Structural Equation Modelling (PLS-SEM) was used for statistical analysis. Social Influence and Habit significantly influenced Behavioural Intention to use e-learning. However, Performance Expectancy, Effort Expectancy, Facilitating Conditions, Hedonic Motivation and Price Value did not have any influence. Habit was found to be the strongest predictor for Behavioural Intention. The findings of this study will guide higher educations to consider the factors for effective implementation of e-learning in an academic setting and provide directions for future research.

Keywords: behavioural intention, Covid-19, e-learning, UTAUT2, higher education.

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Факторы, влияющие на поведенческое намерение использовать электронное обучение при получении высшего образования в условиях пандемии Covid-19: модель UTAUT2

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Цель данного исследования — оценить поведенческие намерения студентов высших учебных заведений использовать электронное обучение во время пандемии Covid-19. Модель UTAUT2 для изучения использования технологий во время этой пандемии в образовательных учреждениях применяется сегодня в малом числе исследований. В нашем исследовании была проведена выборка «снежный ком»; исследуемая группа состояла из студентов высших учебных заведений (n = 159), которые использовали платформы электронного обучения во время продолжающейся пандемии. Данные были собраны с помощью анкеты на основе адаптированной модели UTAUT2. Для статистического анализа использовалось моделирование структурных уравнений методом частичных наименьших квадратов (PLS-SEM). Исследование показало, что ожидаемые результаты, ожидаемые усилия, благоприятные условия, гедоническая мотивация и материальные затраты не оказали никакого влияния на поведенческое намерение в использовании электронного обучения. Было выявлено, что значительное влияние оказывают социальное влияние и привычка, причем привычка является самым сильным предиктором поведенческого намерения. Результаты этого исследования помогут высшим учебным заведениям в эффективном внедрении электронного обучения в академической среде и зададут направление для будущих исследований.

Ключевые слова: поведенческое намерение, Covid-19, электронное обучение, UTAUT2, высшее образование.

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Introduction

The outbreak of the coronavirus disease 2019 or COVID-19 [26; 53] has brought massive, unprecedented impact to global Higher Educations (HEs) [8; 11; 27]. In response to the World Health Organisation declaration of Covid-19 as a pandemic on March 11, 2020 [55], schools, colleges, and universities in 177 countries were closed, disrupting 98,6 percent of the world's student population [13]. Public and private HEs in Malaysia were ordered to close during the movement control order, which was put in place on March 13, 2020, to break the chain of the Covid-19 infection [11; 13; 14]. Approximately 1 284 876 HE students have been affected in Malaysia and had to turn to many e-learning platforms to continue their studies. Researchers of HEs have debated over the most effective teaching methods, and learning environments with vast coverage [18; 21] and if HEs are prepared for the challenges brought about by digital era of learning [24; 58]. Due to the pandemic, HEs depended entirely on e-learning to disseminate knowledge and continue with teaching. Furthermore, e-learning systems have replaced face-to-face education with digital and online learning worldwide [11; 33; 54]. Not only has e-learning revolutionized educational systems at HEs in developed countries [3; 8; 30], but it has also transformed educations across developing countries [9; 20]. However, the 'new normal' teaching and learning strategy has resulted in significant challenges to HEs in many countries [3; 11; 58]. There have been reports that students in rural areas faced challenges due to the limited access to IInternet bandwidth [6; 50]. Furthermore, countries such as India, Pakistan, and Afghanistan have reported that their HEs are not prepared for remote learning [28].

Since the pandemic outbreak, not many studies have been carried out on the effects of Covid-19 in educational settings [3; 42; 43]. Furthermore, only a few researchers have used the UTAUT2 model to study the use of technology during Covid-19 in the education setting [9]; or before the pandemic [15; 32]. Therefore, this study uses the adapted UTAUT2 model [52] to study the factors impacting behavioural intention to use e-learning amongst students at a HE in Malaysia during the Covid-19 pandemic.

Literature Review

E-learning

E-learning which is also known as "distance education", "internet learning", "online courses" or "learning portal" plays the role of producing technology savvy graduates who could utilize technology to accelerate new technology in advancing e-economies [7]. Moreover, for education and professional development, e-learning can be used to distribute knowledge, information, and communication through web-based learning ecosystems [10].

Unified Theory of Acceptance and Use of Technology

Over the last two decades, significant research has been carried out to examine factors that affect students' behavioural intention to use technology at HEs. The present study integrates the adapted constructs from the UTAUT and UTAUT2 models (namely, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit) in the research framework. Venkatesh, Morris, Davies & Davis [51] measured the direct effect of facilitating conditions on the use of e-learning because they opined that when effort expectancy and performance expectancy existed together, facilitating conditions did not predict behavioural intention to use e-learning significantly.

Performance expectancy

Venkatesh et al. [51] defined performance expectancy (PE) as the extent to which an individual believes that utilizing a system will help to enhance job performance. In the present study, PE refers to students' belief that e-learning will help to carry out daily lessons; enlarge their understanding of studies; help to complete tasks, and increase their academic performance. PE was found to be predictors for Greek students' behavioural intention to use mobile phones [36]; determinant of students' behavioural intention to use animation and storytelling [46], and predictor of students' intentions to use Learning Management Systems [2]. Therefore, this study posits that:

H1: *Performance expectancy (PE) positively influences the students' behavioural intention (BI) to use e-learning.*

Effort expectancy

Effort expectancy (EE) is explained as the level of ease when using innovation to carry out tasks [51]. This variable is researched by examining if learning how to utilize e-learning is effortless; using e-learning platforms is easy to be understood, and e-learning applications can be mastered. Previous research has discovered that EE determines students' behavioural intention to use Google Classroom [25], and the effect of effort expectancy on behavioural intention was significant [52]. Based on this literature, this study proposes:

H2: *Effort expectancy (EE) positively influences the behavioural intention (BI) to use e-learning.*

Social influence

Social influence (SI) is defined as the level at which an individual gives considerable prominence to the opinion of important people when using technology [51]. Ameri, Khajouei, Ameri & Jahani [4] argued that SI positively affected behavioural intention among pharmacy students using mobile-based educational application. Kang, Liew, Lim, H, Jang & Lee [27] posited SI significantly affected behavioural intention to use m-learning amongst Korean HE students. Jakkaew & Hemrungrote [25] discovered that SI determined students' use of Google Classroom. Thus, it can be hypothesized that:

H3: *Social influence (SI) positively impacts on the behavioural intention (BI) to use e-learning.*

Facilitating Conditions

Venkatesh et al. [51] defined facilitating conditions (FC) as an "individual's opinion as to whether the organization provides technology facilities to augment e-learning". This study examined whether students had the following criteria to enable e-learning: technology resources (laptop/Wi-Fi/mobile phone); knowledge; other compatible technologies; support when difficulties while using e-learning. Raman&Don [39] verified the UTAUT2 model and opined that the regression model revealed 29.5% of the variance in students' intentions, and FC were predictors of behavioural intention. Moreover, increased students' adoption of e-learning platforms took place in developing countries such as Qatar but not in the USA [15]. Based on this, the following hypothesis is examined:

H4. *Facilitating conditions (FC) positively influences students' behavioural intention (BI) to use e-learning.*

Hedonic Motivation

Hedonic motivation is defined as the "happiness attained from using technology" [52]. Hedonic motivation (HM) significantly affected students' behavioural intention to use e-learning [31]. Moreover, Kang et al., [27] proved that behavioural intention to use m-learning was determined by hedonic motivation. El-Masri, Tarhini [15] opined that hedonic motivation and habit predicted behavioural intention (BI) to use e-learning platforms by HE students. The hypothesis examined is:

H5. *Hedonic motivation (HM) positively influences students' behavioural intention (BI) to use e-learning.*

Price value

Price value can be referred to as "apparent worth or advantages of using the technology, in comparison to the cost for utilizing them" [52]. Many studies omitted price value because the Internet is available for free to HEs users [2; 5; 29; 45]. However, Wong et al. [56] recommended price value to be used in future studies. Moreover, El-Masri, Tarhini [15] found no relationship between price value and behavioural intention. From this literature, the hypothesis below is formed:

H6. *Price value (PV) positively influences students' behavioural intention (BI) to use e-learning.*

Habit

Habit is explained as the level at which" individual actions can be prompted instinctively" [52]. Habit positively influenced students' Behavioural Intention (BI) to use e-learning during the pandemic, and this finding is in line with Nikolopoulou et al. [36], whose research proved that habit was the strongest predictor for students' behavioural intention (BI) to use mobile phones. Moreover, Moghavvemi et al. [31] opined that habit positively affected students' use of e-learning through Facebook. The hypothesis formed is

H7. *Habit (H) positively influences students' behavioural intention (BI) to use e-learning.*

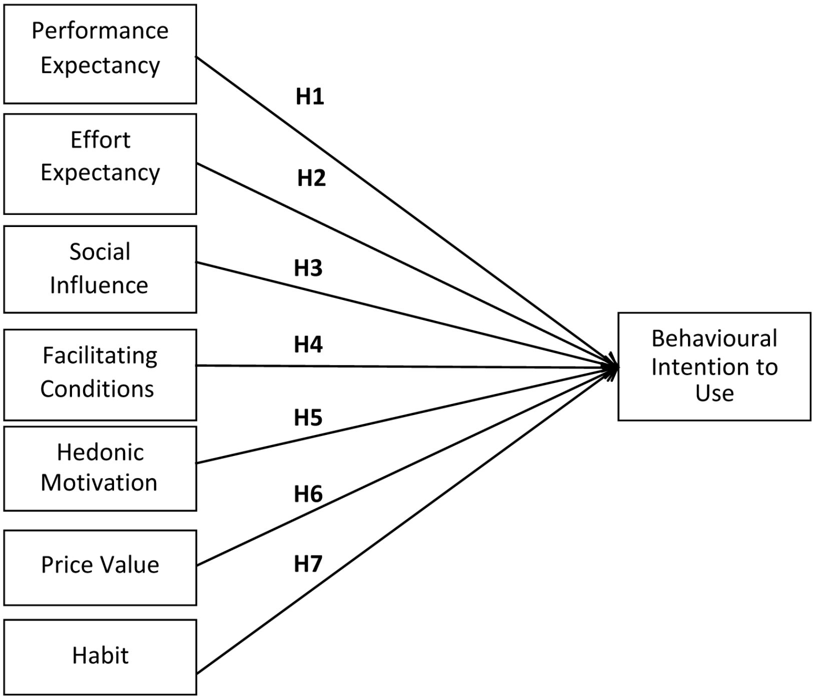

Fig. 1. Conceptual Framework

Method

The current research adapted a quantitative study using the cross-sectional design. Snowballing, a non-probability convenience sampling method was used as it involves samples available to the researcher where existing study subjects recruit other subjects among their acquaintances [34]. Questionnaires were distributed via Google Forms to students of Universiti Utara Malaysia during the pandemic. A total of 159 students, consisting of 68 males (42.8%) and 91 females (57.2%) responded.

The questionnaire, which is adapted from the UTAUT2 [26], consisted of 27 items based on seven constructs: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit. All the items were measured using a five-point Likert scale from ‘strongly disagree’ to ‘strongly agree”. Given the statistical requirements for performing a precise analysis [23], PLS-SEM was considered the best approach for data analysis, and SmartPLS 3 was applied [41].

Results

Assessment of Measurement Model

Individual item reliability, internal consistency reliability, convergent validity, and discriminant validity are determined [23; 19]. Figure 2 demonstrates the measurement model in the current study.

Examining Individual Item Reliability

The measurement model examined the individual item reliability (outer loading) of each construct [12; 19; 23]. For the average variance extracted of more than 0,500, the value of outer loading above 0,708 is essential [23]. All the constructs achieved these values in the current study (Table 1).

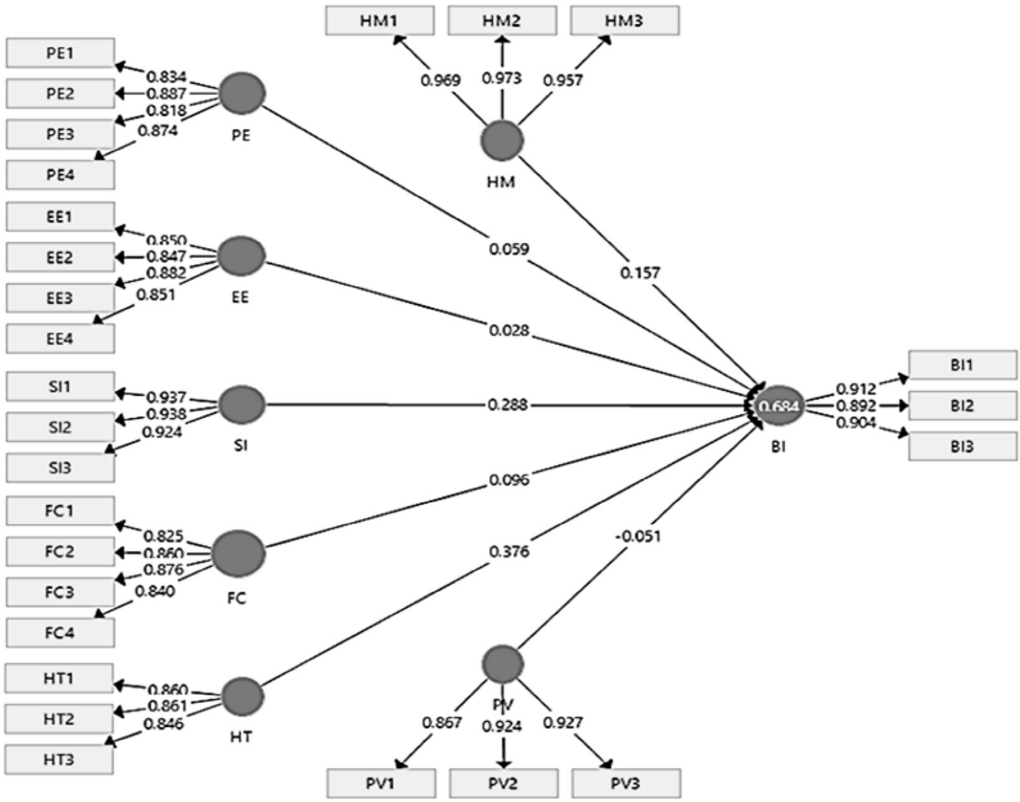

Fig. 2. Measurement Model Evaluation

Ascertaining Internal Consistency Reliability

Internal consistency reliability measurement consists of Cronbach's alpha (which affirms that items are reliable) and composite reliability (which measures the internal consistency reliability) [23]. In this measurement model, the composite values between 0,892 and 0,977, which are more than 0,70 are acceptable for confirmatory research (Table 1) [19; 23].

Ascertaining Convergent Validity

By examining the outer loadings (item loadings) [12; 23] and the Average Variance Extracted (AVE) [17; 23], the convergent validity can be determined. Hair et al. [23], Nunnally and Bernstein [37] suggested that the items with the outer loading of more than 0,50 could be accepted. In this measurement model, the outer loadings are between 0,699 (PV3) to 0,891 (FC4) confirming that all the constructs have met the requirements of composite reliability. In addition, all of the constructs had also met the requirements of AVE, which is above 0,50 [23].

Ascertaining Discriminant Validity

In the present study, the Fornell-Larcker criterion, as suggested by Fornell and Larcker [17], was used to examine discriminant validity. Discriminant validity confirms that a construct is not similar to other constructs and is shown by the value of the square root of the AVE, which should be greater than the correlations among the constructs [23], as shown in Table 2.

Assessment of Structural Model

The standard bootstrapping procedure with 5000 subsamples, one-tailed test type, and a

Table 1

Measurement model reliability and validity results

Constructs	Items	Outer Loadings	Cronbach's alpha	Composite reliability	Average Variance Extracted
Performance Expectancy	PE1	0.780	0.876	0.915	0.669
	PE2	0.852			
	PE3	0.846			
	PE4	0.792			
Effort Expectancy	EE1	0.873	0.880	0.917	0.735
	EE2	0.867			
	EE3	0.879			
	EE4	0.830			
Social Influence	SII	0.890	0.926	0.953	0.870
	SI2	0.874			
	SI3	0.819			
Facilitating Conditions	FC1	0.791			
	FC2	0.878	0.873	0.913	0.724
	FC3	0.866			
	FC4	0.891			
Habit	HT1	0.765	0.818	0.892	0.733
	HT2	0.776			
	HT3	0.844			
Hedonic Motivation	HM1	0.819	0.964	0.977	0.934
	HM2	0.890			
	HM3	0.752			
Price value	PV1	0.884	0.892	0.933	0.822
	PV2	0.883			
	PV3	0.699			
Behavioural Intention	BI1	0.809	0.887	0.930	0.815
	BI2	0.846			
	BI3	0.855			

Table 2

Fornell-Larcker Criterion

	BI	EE	FC	HT	HM	PE	PV	SI
BI	**0.903**							
EE	0.615	**0.858**						
FC	0.629	0.749	**0.851**					
HT	0.764	0.657	0.690	**0.856**				
HM	0.706	0.680	0.614	0.754	**0.966**			
PE	0.633	0.652	0.572	0.629	0.666	**0.854**		
PV	0.588	0.629	0.651	0.650	0.636	0.572	**0.906**	
SI	0.696	0.535	0.540	0.627	0.625	0.654	0.625	**0.933**

Note: BI: Behavioural Intention, EE: Effort Expectancy, FC: Facilitating Conditions, HT: Habit, HM: Hedonic Motivation, PE: Performance Expectancy, PV: Price Value, SI: Social Influence.

0,05 significant level was applied to measure the significance of the path coefficients [23]. Table 3 illustrates the structural model path coefficient (direct effect), which was conducted to test and confirm the hypotheses. The result shows that H1, H2, H4, H5, and H6 were not supported; where else, H3 and H7 were supported. From the path coefficients in Table 3, it can be concluded that Habit (HT) is the strongest predictor for behavioural intention to use e-learning (0,376) followed by Social Influence (SI) (0,288).

Discussion

This study employed the adapted UTAUT2 model [52] to study the factors affecting behavioural intention to use e-learning amongst students at a HE in Malaysia during the Covid-19 pandemic. Interestingly, it was found that Performance expectancy (PE) did not influence students' behavioural intention (BI). Thus, it can be concluded that students could not achieve their learning objectives or expectations as they found that studying through e-learning was difficult and posed challenges to them during the pandemic. This is in line with the findings of Testa & Tawfik [48]; Nandwani & Khan [35]. However, this finding contradicts a number of previous studies [2; 4; 15; 25; 27; 31; 36; 39; 40]. The current study also proved that Effort expectancy (EE) did not significantly influence Behavioural intention (BI). This supports the finding of Nandwani &Khan [35]; Afshan & Sharif [1]; Thongsri et al., [49]. Such results were expected as Malaysian HEs are still facing issues related to security, and privacy, lack of professionalism, and slow Internet [44].

The study also shows that Social influence (SI) positively influenced the Behavioural Intention (BI) to use e-learning. This is consistent with studies by Ameri et al. [4]; Kang et al. [27]; Jakkaew, Hemrungrote [25]; Suki [46]. The students in the study gave prominence to influential people like peers, lecturers, supervisors to continue utilizing e-learning. El-Masri, Tarhini [15] posited that SI increased the adaption of e-learning in developing countries such as Qatar.

Furthermore, the findings of this study suggest that Facilitating cConditions (FC) do not influence students' Behavioural Intention (BI) to use e-learning. This is in line with Zuiderwijk et al. [59] and Pullen et al., [38]. Zuiderwijk et al., [59] stated that facilitating conditions were not predictors of acceptance and use of open data technologies. The present study supports Pullen et al. [38], who posited that pre-service teachers did not consider FC as a determinant of their intent to use e-learning. The students in this research most probably had laptops and mobile phones with Internet data which enabled them to engage in e-learning.

Surprisingly, Hedonic Motivation (HM) was shown to have an insignificant impact on Behavioural Intention (BI) to use e-learning (Table 1). It can be inferred that it is not right to consider that when students enjoyed e-learning, the probability of using it was higher. This finding contradicts Fadzil [16], who opined that HM had the strongest influence on BM to use mobile applications among the University students in Malaysia. Furthermore, Nikolopulou et al. [36] also opined that HM predicted students' BI to use mobile phones for learning.

Table 3

The Path analysis results

Hypothesis	Path	Path Coefficient	p-value	Result
H1	PE→BI	0.059	0.482	Not Supported
H2	EE→BI	0.028	0.776	Not Supported
H3	SI→BI	0.288	0.001	Supported
H4	FC→BI	0.096	0.194	Not Supported
H5	HM→BI	0.157	0.186	Not Supported
H6	PV→BI	-0.051	0.477	Not Supported
H7	HT→BI	0.376	0.000	Supported

Note: BI: Behavioural Intention, EE: Effort Expectancy, FC: Facilitating Conditions, HT: Habit, HM: Hedonic Motivation, PE: Performance Expectancy, PV: Price Value, SI: Social Influence

Another interesting finding was that Price Value (PV) is insignificant towards Behavioural Intention (BI) to use e-learning. This is in line with studies by El-Masri, Tarhini [15] and Tamilmani et al. [47]. The reason for this finding was free access to e-learning technologies such as mobile applications (Google Classroom and Google Meet) and social networking (What's App, We Chat, and Telegram) in organizational and consumer settings. Under the RM250 billion economic stimulus packages, Malaysian students received free data for educational purposes and learning portals until 31 December 2020 [57].

The essential finding in this study is, Social Influence (SI), and Habit (H) influenced Behavioural Intention (BI) to use e-learning, with Habit (H) being the most decisive predictor and Social Influence — the next one. This supports the study of Nikolopoulou et al. [36] that habit was the strongest predictor of Behavioural Intention to use mobile phones for studies. Moreover, Mogavvemi et al. [31] opined that habit positively affected undergraduate students' usage of e-learning through Facebook at the University of Malaya.

Limitations and Recommendations

The current study only examined the UTAUT2 model from the viewpoint of undergraduates. Further studies must investigate the opinions and challenges faced by lecturers at HEs. Furthermore, during the pandemic, almost all students were locked down in their hometowns where they might have faced problems such as slow Internet and lack of functioning Internet devices. Moreover, at the time of the survey, students could also be facing emotional and psychological issues that could have affected the results of this study. It is suggested that further research shall be carried out at post-pandemic period when HEs start using other teaching and learning methods such as Hybrid Learning and Blended Learning when Universities resume in-person learning.

Conclusion

This study set out to critically examine the factors impacting behavioural intention to use e-learning at Higher Education amid the Covid-19 pandemic utilizing the modified UTAUT2 model. Only two constructs which are Social Influence (SI) and Habit (HT), influenced the Behavioural Intention (BI) to use e-learning, while the other five — Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Hedonic Motivation (HM), and Price Value (PV) — did not have any influence.

The proposed model could help the University management and academic administrators to understand the adaptability to e-Learning and consider the factors for the successful implementation of e-learning in an academic setting. This empirical research contributes to the growing body of knowledge in educational technology by examining the validity of UTAUT2 framework in a developing country.

Disclosure statement

The authors reported no potential conflict of interest.

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