Behavioral Intentions of Higher Education Students toward Using Gadgets for Mobile Learning

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Abstract
This study explores the factors influencing higher education students' behavioral intentions to adopt mobile learning (M-learning) at UNITAR International University, Malaysia. Using a cross-sectional approach with 364 respondents, the research examines the relationship between behavioral intention (BI) and four factors: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The results reveal significant positive relationships between all four factors and students' BI toward M-learning, suggesting that improving these factors can enhance M-learning adoption. The findings emphasize the need for educational institutions to provide user-friendly platforms, socio-cultural support, and technological resources like high-speed internet. The study contributes to the understanding of M-learning adoption, offering insights for educators, policymakers, and developers to foster a more conducive digital learning environment in higher education.
Keywords: Mobile Learning, Behavioural Intention, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions.

Introduction
Social media has grown to be a staple for many individuals worldwide since its inception. According to the most recent data, 5.48 billion people use mobile devices worldwide, with smartphones making up about four out of five active mobile devices. At this time last year, there were an additional 170 million mobile users worldwide, and 68.6% of all persons on Earth now use a mobile phone (Kemp, 2022). In Kemp's report, Malaysia's residents spent an average of eight hours and 24 minutes using gadgets per day. The success of social media in permeating practically every area of our daily lives through mobile devices is credited with its widespread use (Balakrishnan et al., 2016). Currently, a lot of people use social media such as Google Search Engine, WhatsApp, Microsoft Teams, or YouTube for schooling and learning. Mobile learning is what this is known as, and it has several advantages, including convenience, flexibility, and so on (Giannakos et al., 2021).

Mobile learning, commonly referred to as M-learning, can be defined as the process of learning through discussions among individuals in various circumstances using personal interactive gadgets (Sharples et al., 2007). It is a new method of leveraging mobile devices to access educational content (Priscila, 2020). Besides, M-learning is learning that can proceed anywhere and at any time, since there are mobile devices that learners utilize to access content (Kolinski, 2022). There are many convenient portable devices such as a tablet, smartphones and laptops that enable learners to proceed with M-learning. In nations including South Korea, Japan, the United Kingdom, and the United States, M-Learning has proved successful. This is evident in the way that students share notes on their mobile devices (Abd Samad et al., 2019).

According to Praveen Kumar et al (2019), mobile devices or gadgets make learning materials accessible to a wider audience, cater to underserved social groups, save time, reduce printing and pollution, increase interactivity, and support preferred modes of interaction. Other advantages of M-Learning are catering to interests outside of those covered in class, providing immediate feedback on learning performance, and providing psychological support for those at risk of dropping out (Ganesan et al., 2019). These benefits are caused by a variety of functions of mobile Apps in different areas such as communication, games, multimedia, productivity, travel, and utilities.

Learners can use different functions of the mobile device to proceed with M-learning. Users of the Short Messaging Service (SMS) can send and receive messages between mobile phones that are up to 160 characters long. The same functionality as SMS is provided by Multimedia Messaging Service (MMS), and graphics can also be included. Next, users use their Wireless Application Protocol (WAP) which enables mobile phones to access the internet. Personal Digital Assistants (PDAs) also have developed into micro-PCs that use the Palm OS or MS Pocket PC operating system to do many of the fundamental tasks of a bigger Computer. We also have Bluetooth to achieve wireless connection with a short range. Thus, PDAs may now send and receive messages to and from other mobile devices through Bluetooth. MPEG-1 Layer 3 (MP3) is an audio file format, and MPEG-4 Part 14 (MP4) is a video file format that effectively compresses data and makes it possible to share it with others. Camera Angle Management System (CAMs) which the video cameras are now built into PDAs and mobile phones (Hashemi et al., 2011).

Mobile learning become the mainstream of learning in this 21-century especially when technology advances day by day. Since then, Malaysia Education Development Plan 2015-2025 for Higher Education (*PPPM (PT) - Pelan Pembangunan Pendidikan Malaysia 2015-2025 (Pendidikan Tinggi)*), outlined ten leaps to continue Malaysian Higher Education's empowerment (*Dasar e-Pembelajaran Negara 2.0*). Realizing the importance of technology-based education and Malaysia's position in online course development, PPPM(PT) encapsulates Leap 9, which is Globalized Online Learning (GOL), which focuses on expanding access to education, improving the quality of teaching and learning, and allowing learning to be adapted according to the current needs of students. GOL is a tool to expand access to courses offered by higher education institutions. It also aims to liberalize higher education, thereby making higher education more accessible to all segments of society (Dasar e-Pembelajaran Negara 2.0).

However, M-learning is challenging to provide content for everyone because of small screens, restricted storage options, a lack of a standard operating system, and a lack of hardware platforms (Hashemi et al., 2011). On the other hand, students can communicate with one another at any time and check their friends' posts on the same platform that they are using for their studies because of the pervasive social character of mobile social media. As a result, the social component of learning has been more fully integrated, which could distract students (Gupta et al., 2016). Also, some teachers do classes on weekends and holidays and offer a tonne of extracurricular materials for their pupils to use social media to learn. (Loh et al., 2022).

This study is particularly important in the development of higher education within the digital era, researching the factors that influence students to adopt mobile learning. It emphasizes how mobile learning increases flexibility, accessibility, and inclusiveness of education and how it is responsive to modern-day requirements. Focusing on performance expectancy and facilitating conditions, this research therefore provides input that is useful for educators and policymakers in improving digital learning strategies. These results are beneficial to students, institutions, and policymakers in the development of user-friendly platforms, resource allocations, and development of educational policies and contribute to the general literature relating to technology adoption for education.

Problem Statement

The epidemic's long-term effects have led to a non-face-to-face culture throughout the world (Xu et al., 2022). According to Jeon (2021), digital technology has made cultural dissemination feasible in order to get around the constraints of time and geography. Online learning styles are growing more and more popular as a result of the enormous number of students and teachers that have been impacted by the pandemic (Sukendro et al., 2020). There are around ten times as many university students taking at least one online course (Smith et al., 2008). After the COVID-19 epidemic, it might be able to mix regular schooling with online learning (Borukova et al., 2020).

One of the most recent studies on M-Learning in Malaysia, done by Moorthy et al (2019), used solely public universities as examples, namely University Malaya (UM), University Kebangsaan Malaysia (UKM), University Teknologi MARA (UiTM), and University Putra Malaysia (UPM). There have been no similar studies undertaken among Malaysian private university students. Thus, the researcher intends to explore factors influencing Behavioural Intention (BI) in mobile learning among private university students.

Theoretical Foundation

The primary theory is mentioned repeatedly in the research to support the conclusions reached in our general discussion. To provide a more accurate and well-supported collection, these theories are connected to every assertion and analysis from our data collection. Following is the theory that the researcher refers to for this study.

The Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al (2003), was initially composed of four variables that have a direct impact on people's BIs, which then have an impact on how they use things. Effort Expectancy (EE), Social Influence (SI), Performance Expectancy (PE), and Facilitating Conditions (FC). These four dimensions

make up UTAUT. The UTAUT outperformed the earlier theories and empirically demonstrated its efficacy. UTAUT accounts for 70% of behavioural variety, compared to the preceding theories' (27–40%) explanations (Venkatesh et al., 2003).

UTAUT has been used by different researchers. For example, to predict the variables that influence students' BI to use mobile learning (Chao, 2019), to comprehend how students in developing nations use e-learning systems (Abbad, 2021), or to create a new model and perform confirmatory factor analysis to learn more about how students use M-learning in higher education (Alyoussef, 2021). Additionally, UTAUT also helps to investigate students' BI to use tablets for learning (Hamzah et al., (2020).

In short, The UTAUT model is the most recent powerful model that explains the use and adoption of various technologies due to its greater explanatory power of behavioural technology use, which is broadly applicable in various contexts and capabilities. Thus, the researcher chose UTAUT to create a conceptual model for this study to establish a reliable foundation for illuminating students' acceptance or rejection of mobile learning systems.

Literature Review
Performance Expectancy (PE) and Behavioural Intention (BI)
Based on a recent study, the researcher found that Behavioural Intention (BI) was positively impacted by Performance Expectancy (PE) (Ameri et al., 2019). Moreover, Chao (2019), states that PE had positive relationships and favourably influenced BI. In the same year, a research result also showed that Performance Expectancy (PE), Facilitating Conditions (FC)., Learning Value, Hedonic Motivation, Habit, Technological Innovation, and Information Quality were factors that influenced student acceptance of mobile learning (Zwain, 2019). In the same year, other findings revealed that BI's use of a mobile learning system is significantly influenced by PE (Almaiah et al., 2019).

PE has the most significant impact on continued use intention (Cheng et al., 2020). Another research result, confirms that PE plays a significant role in driving users' intentions to continue using news applications, and it offers an integrated framework for evaluating the moderating impact of personalization on technology acceptance (Cheng et al., 2020). The students' BI to employ blended learning was significantly positively impacted by PE, which was found to be a factor (Azizi et al., 2020). The significant influence of PE on BI demonstrates that students are more likely to use mobile gadgets to learn mathematics if they believe doing so will improve their proficiency in the subject (Açıkgül et al., 2021).

This study shows that the inexpensive cost of internet access and mobile technology (primarily state-founded Tablet PCs in this case) utilised in mathematics learning have a beneficial impact on BI (Açıkgül et al., 2021). Besides, the findings demonstrated that PE affects how frequently students in Jordanian institutions use Social Networks Sites (SNS) for educational objectives. The findings showed that at the significance level (=0.015), students believe that employing SNS in education will be more beneficial when there is a greater advantage (Gharrah et al., 2021). Expectations about performance had a big impact on students' BI to use Modular Object-Oriented Dynamic Learning Environment (Moodle) and then students' use of the e-learning system (Moodle) was considerably influenced by the facilitative settings

and BI (Abbad, 2021). It was discovered that PE significantly and favourably influenced users' intentions to use the eLearning platform (Prasetyo et al., 2021).

PE had a substantial impact on university students' BI to use eLearning sites, indicating that doing so will help them do better in their coursework (Zacharis & Nikolopoulou, 2022). Additionally, students' BI to adopt blended learning in universities was significantly and positively influenced by PE (Rudhumbu, 2022). On the other hand, teachers' BI to adopt Massive Open Online Courses (MOOC) was aided by PE. (Tseng et al., 2022). A 2023 study in Saudi Arabia showed that PE had a significant positive effect on BI usage (Alfalah, 2023).

Effort Expectancy (EE) and Behavioural Intention (BI)
According to Chao (2019), Satisfaction, Trust, PE, and EE significantly and favourably influenced BI (Chao, 2019). According to the findings, PE, EE, and FC all contribute to student adoption of mobile learning systems (Almaiah et al., 2019). Moreover, the students' BI to adopt blended learning was significantly positively impacted by EE (Azizi et al., 2020). PE, EE, SI, and FC are all significant predictors of behavioural intention to use m-Learning (Welch et al., 2020). Students' behavioural intention to use mobile learning management systems (m-LMSs) is positively and substantially influenced by EE, as well as SI and FC (Ikhsan et al., 2021).

The study also shows EE has a favourable effect on students' actual use of SNS when the students have a solid understanding of how to utilize SNS because they use them frequently. Regression analysis's significant finding at the significance level (=0.015) showed that students believe employing SNS in their education is simply because doing so doesn't involve a lot of training or effort (Gharrah et al., 2021). EE also had an impact on BI's use of Moodle. The outcomes also supported the notion that students' use of Moodle is directly impacted by their BI and the environment that facilitates their use (Abbad, 2021). In the same year, another study also discovered that EE is an important positive predictor of BI (Açıkgül et al., 2021).

Another research finding confirmed that perceived enjoyment and EE affected attitudes towards using M-learning (Alyoussef, 2021). Besides, a study's findings revealed that EE is an important predictor of BI into use of virtual classrooms (Alshammari, 2021). A study in 2022 showed one of the favourable impacts of MOOC uptake on EE (Meet et al., 2022). Additionally, students' BI to adopt blended learning in universities was significantly and positively influenced by EE (Rudhumbu, 2022). Moreover, the EE has a positive impact on the intention to use m-learning technology (Faqih, 2022). According to a 2023 study in Saudi Arabia, EE has a significant positive effect on BI (Alfalah, 2023).

Social Influence (SI) and Behavioural Intention (BI)
A recent study discovered that Social Influence (SI) had a positive and significant impact on BI. This finding demonstrates that students think their classmates', parents', and teachers' attitudes can influence whether or not they use a mobile learning system (Moorthy et al., 2019). SI was one of the factors that influenced faculty acceptance and student acceptance (Zwain, 2019). In short, BI was positively impacted by SI (Ameri et al., 2019). In 2019, a study showed a significant value of the coefficient is 0.000, indicating that there is a substantial relationship between SI and BI. Therefore, SI influences and maintains the desire of students to use mobile learning for their studies. That study also showed the Standard Coefficient was 0.408, which had the greatest impact on students' use of mobile learning (Israel & Velu, 2019).

There is a substantial connection between SI and BI was discovered (Açıkgül et al., 2021). SI significantly influenced students' BI to use blended learning in a good way (Azizi et al., 2020). The findings also demonstrated that SI characteristics have a positive influence on students' real use of SNS for academic purposes in Jordanian universities. The significance level for each was (=0.00) (Gharrah et al., 2021).

According to a study's findings, college students think that their classmates', parents', or tutors' opinions may affect how they use e-learning platforms. The impact of SI on BI has also been demonstrated in several nations, including Malaysia (Zacharis & Nikolopoulou, 2022). Students' BI to adopt blended learning in universities was significantly and positively influenced by SI (Rudhumbu, 2022). The present findings showed the importance of SI in positively influencing behavioural intention to adopt a mobile learning system (Faqih, 2022).

Facilitating Conditions (FC) and Behavioural Intention (BI)
Facilitating Conditions (FC) will influence faculty acceptance and student acceptance (Zwain, 2019). According to previous research, FC and BI's use of mobile learning tools are closely related. Thus, research suggests that Jordanian universities are on the correct track, as they are presently investing large sums of money in ICT infrastructure (Almaiah et al., 2019). Besides, there was a substantial correlation between the students' BI to employ blended learning and the FC (Azizi et al., 2020).

FC also has a significant impact on continued use intention (FC) (Cheng et al., 2020). As a result, recent research confirms that FC plays a significant role in driving users' intentions to continue using news applications, and it offers an integrated framework for evaluating the moderating impact of personalization on technology acceptance (Cheng et al., 2020).

FC has a large predictive impact on BI (Açıkgül et al., 2021). Students' use of Moodle was considerably influenced by the FC and BI (Abbad, 2021). Students' BI to adopt blended learning in universities was significantly and positively influenced by FC (Rudhumbu, 2022). One of the positive impacts of MOOC uptake is FC (Meet et al., 2022). On the other hand, teachers' BI to adopt MOOCs was aided by FC. Additionally, instructors' uptake of MOOCs was influenced by FC and BI (Tseng et al., 2022). In 2022, a study offered empirical evidence that facilitating conditions have a direct impact on Jordanians' willingness to adopt m-learning (Faqih, 2022).

Research Questions
This study aims to answer the following questions:
1. What is the relationship between Performance Expectancy (PE) and Behavioural Intention (BI) in the usage of mobile learning?
2. What is the relationship between Effort Expectancy (EE) and Behavioural Intention (BI) in the usage of mobile learning?
3. What is the relationship between Social Influence (SI) and Behavioural Intention (BI) in the usage of mobile learning?
4. What is the relationship between Facilitating Conditions (FC) and Behavioural Intention (BI) in the usage of mobile learning?

Hypothesis of Study
H1: There is a significant relationship between Performance Expectancy (PE) and
   Behavioural Intention (BI) in the usage of mobile learning.
H2: There is a significant relationship between Effort Expectancy (EE) and Behavioural
   Intention (BI) in the usage of mobile learning.
H3: There is a significant relationship between Social Influence (SI) and Behavioural
   Intention (BI) in the usage of mobile learning.
H4: There is a significant relationship between Facilitating Conditions (FC) and Behavioural
   Intention (BI) in the usage of mobile learning.

Methodology
The present research employed snowball sampling, a non-probability sampling technique whereby existing participants assist in recruiting subsequent respondents. This method is particularly advantageous for accessing specific populations and was utilized to gather data from students at UNITAR International University, situated in Klang Valley, Malaysia.

Through snowball sampling, the researcher effectively expanded the sample size while ensuring that participants fulfilled the study's criteria, notably prior experience with mobile learning. A total of 364 students were selected as respondents based on the Krejcie and Morgan table, drawn from a larger population of 7,000 students at UNITAR International University. This sample size was considered adequate to represent the broader population in examining behavioral intentions towards mobile learning.

The research was conducted at UNITAR International University, recognized one of the leading institutions in virtual education within Malaysia. The selection of UNITAR was predicated on its status as one of Southeast Asia's pioneering virtual universities, thereby providing an optimal context for investigating mobile learning behaviors among higher education students.

Data collection was facilitated through a Google Forms questionnaire, which was systematically structured into several sections. The initial section collected demographic data, including gender, age, and race. Subsequent sections evaluated critical variables such as Behavioral Intention (BI), Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Participants responded using a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree." The resultant data were analyzed utilizing SPSS Statistics, enabling an exploration of the relationships among various factors influencing students' adoption of mobile learning.

Results
Socio-demographic Information
The study was conducted among undergraduate and postgraduate students enrolled at UNITAR International University. A snowball sampling method was utilized to gather participants. Table 1 presented a total of 364 respondents, comprising students from undergraduate programs (i.e., Degree and Diploma) and graduate programs (i.e., Master's and Ph.D.), participated in the research.

In this study, male respondents constituted a slightly higher proportion, with 194 respondents (53.3%) compared to 156 female respondents (42.9%). Additionally, 14 respondents (3.8%)

preferred not to disclose their gender. These findings suggest that male participants were marginally more active in completing the questionnaire than female participants.

The majority of respondents in this study fell within the 20-24 age range, comprising 176 individuals (48.4%). The second largest group consisted of respondents aged 25-29 years, totaling 97 individuals (26.6%). This was followed by 37 respondents (10.2%) in the 30-34 age category, 33 respondents (9.1%) below the age of 19, and 21 respondents (5.8%) aged 35 years and above. These results indicate that respondents aged 20-24 years were the most engaged in the survey compared to other age groups.

A significant portion of the respondents identified as Malay, with 177 respondents (48.6%) belonging to this ethnic group. This was followed by 100 Indian respondents (27.5%) and 73 Chinese respondents (20.1%). Additionally, a small number of participants from other ethnic groups participated, including Dusun (1.4%), Bumiputera (0.5%), Bajau (0.3%), Bumiputera Sabah (Bugis) (0.3%), Sarawak (0.3%), Siamese (0.3%), and Sino-Kadazan (0.3%). The lowest number of participants came from foreign students, with 0.3% each from African and Ethiopian backgrounds.

Among the 364 respondents, 55.8% (203) held a bachelor's degree, while 33.8% (123) had completed a foundation, diploma, or equivalent professional certification. A smaller proportion of respondents, 8.2% (30), possessed a master's degree, and 2.2% (8) held a Ph.D.

Table 1
Demographic Table of Respondents

Variables	Category	n, (N=364)	Percentage (%)
Gender	Male	194	53.3
	Female	156	42.9
	Prefer not to say	14	3.8
Age	Below 19 years old	33	9.1
	20 - 24 years old	176	48.4
	25 - 29 years old	97	26.6
	30 - 34 years old	37	10.2
	Above 35 years old	21	5.8
Race	African	1	0.3
	Bajau	1	0.3
	Bumiputera	2	0.5
	Bumiputera Sabah - Bugis	1	0.3
	Chinese	73	20.1
	Dusun	5	1.4
	Ethiopian	1	0.3
	Indian	100	27.5
	Malay	177	48.6
	Sarawak	1	0.3
	Siamese	1	0.3
	Sino-Kadazan	1	0.3
Level of Education	Degree	203	55.8
	Foundation, diploma or same	123	33.8
	level	30	8.2
	Master	8	2.2
	PhD		

Relationship between Performance Expectancy (PE) and Behavioural Intention (BI) in the usage of mobile learning

Based on the results presented in Table 2, there is a significant relationship between Performance Expectancy (PE) and Behavioural Intention (BI). Pearson product correlation of PE and BI was found to be strongly positive and statistically significant ($r = 0.716$, $p < 0.001$). Hence, H1 was supported. This shows that an increase in PE would lead to a higher BI in mobile learning.

Table 2
Correlation analysis between PE and BI

		Behavioural Intention
Performance Expectancy	Correlation Coefficient	0.716**
	Sig. (2-tailed)	0.000
	N	364

**Correlation is significant at the 0.01 level (2-tailed)

Relationship between Effort Expectancy (EE) and Behavioural Intention (BI) in the usage of mobile learning?

Table 3 presents the correlation analysis between Effort Expectancy (EE) and Behavioural Intention (BI), which resulted into a significant relationship between EE and BI. It was found to be strongly positive with $r = 0.\,670$, $p < .001$. Hence, H2 was supported. This shows that an increase in EE would lead to a higher BI in mobile learning.

Table 3
Correlation analysis between EE and BI

		Behavioural Intention
Effort Expectancy	Correlation Coefficient	0.670**
	Sig. (2-tailed)	0.000
	N	364

**Correlation is significant at the 0.01 level (2-tailed)

Relationship between Social Influence (SI) and Behavioural Intention (BI) in the usage of mobile learning

Table 4 tabulaed a significant relationship between Social Influence (SI) and Behavioural Intention (BI). Pearson product correlation of SI and BI was found to be strongly positive and statistically significant ($r = 0.\,555$, $p < .001$). Hence, H3 was supported. This shows that an increase in SI would lead to a higher BI in mobile learning.

Table 4
Correlation analysis between SI and BI

		Behavioural Intention
Social Influence	Correlation Coefficient	0.555**
	Sig. (2-tailed)	0.000
	N	364

**Correlation is significant at the 0.01 level (2-tailed)

Relationship Between Facilitating Conditions and Behavioural Intention in the Usage of Mobile Learning
Relationship results for Facilitating Conditions (FC) and Behavioural Intention (BI) also appeared to be significant (Table 5). The Pearson product correlation of FC and BI was found to be strongly positive and statistically significant ($r = 0.709$, $p < .001$). Hence, H4 was supported. This shows that an increase in FC would lead to a higher BI in mobile learning.

Table 5
Pearson correlation analysis between FC and BI

		Behavioural Intention
Facilitating Conditions	Correlation Coefficient	0.709**
	Sig. (2-tailed)	0.000
	N	364

**Correlation is significant at the 0.01 level (2-tailed)

Overall, there are significant relationships between Behavioural Intention (BI) and Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) among 364 students in UNITAR International University. These hypotheses' results are proof of the correlation between the collected data. The Pearson correlation table showed that the BI and PE r value is 0.716, BI with EE r value is 0.670, the BI and SI r value is 0.555, and the r value for BI and FC is 0.709. All of the relationships are $p < 0.001$ and show significant relationships between the BI and PE, BI and EE, BI and SI, and BI with FC. Then, hypotheses 1, 2, 3, and 4 are accepted. Thus, PE, EE, SI, and FC have a strong, positive, and significant relationship with BI. Overall, the increase of PE, EE, SI, and FC will increase the BI of UNITAR International University students to use mobile learning.

The four research questions with the proposed hypotheses and results are summarised in Table 6.

Table 6
Summary of Pearson correlation analysis between PE, EE, SI, FC with BI

Research Questions	Alternative Hypotheses	Results
What is the relationship between Performance Expectancy (PE) and Behavioural Intention (BI) in the usage of mobile learning?	There is a significant relationship between Performance Expectancy (PE) and Behavioural Intention (BI) in the usage of mobile learning.	Accepted (r = 0.716, p < 0.001).
What is the relationship between Effort Expectancy (EE) and Behavioural Intention (BI) in the usage of mobile learning?	There is a significant relationship between Effort Expectancy (EE) and Behavioural Intention (BI) in the usage of mobile learning.	Accepted (r = 0. 670, p < 0.001).
What is the relationship between Social Influence (SI) and Behavioural Intention (BI) in the usage of mobile learning?	There is a significant relationship between Social Influence (SI) and Behavioural Intention (BI) in the usage of mobile learning.	Accepted (r = 0. 555, p < 0.001).
What is the relationship between Facilitating Conditions (FC) and Behavioural Intention (BI) in the usage of mobile learning?	There is a significant relationship between Facilitating Conditions (FC) and Behavioural Intention (BI) in the usage of mobile learning.	Accepted (r = 0. 709, p < 0.001).

Discussion

The current study complements previous research and advances the literature by showing the positive and significant relationship between PE and BI (r = 0.716, p < 0.001), EE and BI (r = 0. 670, p < 0.001), SI and BI (r = 0. 555, p < 0.001) and FC and BI (r = 0. 709, p < 0.001).

In this study, PE and BI have a strong, positive and significant relationship, as is in line with a study from Chao (2019), which states that PE had positive relationships and favourably influenced BI. In the 2020 year, Azizi and his friend also found that students' BI to employ blended learning was significantly positively impacted by PE, which was found to be a factor (Azizi et al., 2020). Additionally, the result was also the same as the study in 2021 which discovered that PE significantly and favourably influenced users' intentions to use the eLearning platform (Prasetyo et al., 2021).

The current results show that EE will influence students' BI to use mobile learning. According to Almaiah et al. (2019) PE, EE, and FC contributed to student adoption of mobile learning systems and predictors of behavioural intention to use m-Learning (Welch et al., 2020). A result from 2021 also reported that students' behavioural intention to use mobile learning management systems (m-LMSs) is positively and substantially influenced by EE (Ikhsan et al., 2021). Faqih (2022) stated EE has a positive impact on the intention to use m-learning

technology (Faqih, 2022). In short, students agree that EE will affect their BI for the usage of mobile learning.

In terms of social influence, SI strongly and positively influences students' behavioural intention to use mobile learning. Zwain (2019) reported that SI was one of the factors that influenced faculty acceptance and student acceptance (Zwain, 2019). In 2021, Açıkgül et al. also found that there is a substantial connection between SI and BI was discovered (Açıkgül et al., 2021). Students' BI to adopt blended learning in universities was significantly and positively influenced by SI (Rudhumbu, 2022). Thus, the increasing SI helps student to have higher BI to using mobile learning.

The current research also found that there is a strong positive and significant relationship between FC and BI. The result was in line with previous research in 2019, which reported FC and BI's use of mobile learning tools are closely related (Almaiah et al., 2019). Besides, Cheng and colleagues showed that FC also has a significant impact on continued use intention (FC) (Cheng et al., 2020).

Comparing the result of this research to the UTAUT model shows that the UTAUT model is still eligible and reliable to be used in future research. This is because the findings had shown PE, EE, SI and FC is a factors and have a significant relationship with students' BI for the usage of mobile learning which in line with the founder of the UTAUT model, Venkatesh et al (2003). However, many researchers also expanded this model such as Venkatesh et al (2012), expanded four factors to eight factors to BI and named UTAUT 2, Cheng (2019) included hedonic motivation, price value, and habit as factors to BI, and Yip et al. (2018) had added self-efficacy as factor influence BI. Therefore, future researchers can choose either to remain or expand the UTAUT model based on the purpose of the study.

Based on this research, the most important component is the FC. This is because it showed the highest engagement with BI through Pearson correlation analysis. Therefore, educational institutions should encourage students to use mobile devices in their learning by providing essential facilities such as free and speed Wi-Fi in universities and encouraging students to use mobile devices in their learning period classes, revision or assignment. Besides, the university also should provide good-condition computers in the knowledge management centre or provide a mobile device rental service which also encourages students' BI to use mobile learning.

Furthermore, in this study, PE was revealed to be the second most significant factor of m-learning retention intention. M-learning designers should guarantee that the m-learning system is designed with adequate functionalities that can meet the expectations and needs of students, which contributes to students' tenacity in their m-learning efforts. Furthermore, the public should be made aware of the benefits and utility of mobile learning using a variety of offline channels such as flyers, physical talk shows, and education camping or online channels such as TikTok, YouTube, and Instagram. This can raise public awareness of the importance of m-learning, boosting the likelihood of recurrent usage.

According to the findings, EE is the third-factor influencing students' BI to continue m-learning at UNITAR International University. As a result, to promote m-learning among students, m-

learning system developers in this university should prioritise convenience and ease of use in the development of m-learning tools and try to provide the highest level of flexibility.

Last but not least, SI also shows a significant relationship with BI. The results conclude that a socio-cultural environment can help to support and encourage students to use mobile learning. The university management structure, as well as the attitudes of staff and students, are among the variables that shape the institution's social and cultural atmosphere. Thus, staff, lecturers and peers at UNITAR International University are encouraged to support the students such as tutoring them to access mobile learning in order to increase their BI in using mobile learning.

Conclusion

In conclusion, the study demonstrates that higher education students at UNITAR International University have a strong Behavioral Intention (BI) to adopt mobile learning (M-learning), influenced significantly by Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). The positive relationships among these factors suggest that enhancing the learning environment through user-friendly platforms, socio-cultural support, and improved technological resources will further promote M-learning adoption. By focusing on these elements, educational institutions can foster a more conducive environment for mobile learning, ensuring that students continue to benefit from the flexibility and accessibility of technology in education.

As this study was cross-sectional and was completed in a short period of time. Students' attitudes towards m-learning in terms of EE, PE, SI, FC, and BI might shift over time as they gain new knowledge and experiences (Chao, 2019). Future research could use a longitudinal strategy to gain more precise results from a specific cohort (Chao, 2019). A more accurate assessment would be to investigate users' usage in longitudinal research while controlling for real system utilisation (Abbad, 2021). For example, a future researcher in UNITAR International University can carry out a study from 2024 to 2028 with the same group of students to investigate how changes in PE, EE, SI, and FC influence BI.

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