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SUSTAINABLE LEARNING ENVIRONMENT AMIDST THE PANDEMIC: AN ADOPTION OF MOBILE LEARNING READINESS AMONG UNDERGRADUATE STUDENTS IN MALAYSIA'S HIGHER INSTITUTIONS

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ABSTRACT

Aim/Purpose	The present study explores the key determinants that influence the intention of public higher education institutions in Malaysia to utilize mobile learning. Furthermore, this study investigates the correlation between these attributes and the components that affect the sustainability viability of mobile learning.
Background	The proliferation of mobile devices and the impact of COVID-19 have both played a role in the exponential growth of mobile learning. Mobile learning has emerged as an essential instrument and principal approach to student education within the higher education system amidst the pandemic. Nevertheless, research concerning the sustainability of mobile learning is still in its nascent phases in the post-pandemic period.

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Methodology	Structural equation modeling is utilized to analyze the gathered data and validate the hypotheses in this study, which comprises an online survey of 280 undergraduate students attending public higher education institutions in Malaysia.
Contribution	This mobile learning research on the sustainability of learning environments during COVID-19 adds to the educational literature. This study reconstructs the antecedent factors of three fundamental constructs of the Theory of Planned Behavior (TPB) to explain the features of mobile learning sustainability. This research provides a theoretical framework for mobile learning sustainability.
Findings	Based on the empirical evidence, the intention to adopt mobile learning in Malaysian higher education institutions is notably and directly influenced by attitude, subjective norms, and perceived behavioral control. Additionally, the core constructs of TPB are significantly impacted by perceived usefulness, instructor readiness, student readiness, perceived self-efficacy, and learning autonomy. Nevertheless, in Malaysian higher education institutions, the intention to adopt mobile learning is not significantly affected by the perceived ease of use.
Recommendations for Practitioners	Mobile learning providers should work on enhancing the performance of this technology to improve content appropriateness and support. Higher education administrators should improve faculty readiness to strengthen the sustainability and efficacy of mobile learning. Improving students' self-discipline in mobile learning and their perceived preparedness and self-efficacy is critical.
Recommendations for Researchers	This study provides future researchers with a comprehensive perspective on mobile learning, which should be studied regarding technology acceptance, self-perception, and external influences, as well as a holistic research framework that combines internal and external aspects to explain mobile learning adoption behavior. Furthermore, future researchers should broaden their study horizons to include other educational institutions and populations and identify disparities to encourage broader use of mobile learning.
Impact on Society	COVID-19 has profoundly impacted educational quality and the achievement of sustainable development goals (SDGs). This study demonstrates how mobile learning gives a unique chance for students to continue their learning journey from the comfort of their homes, lessening the disruption caused by pandemics and contributing to the progress of excellent education globally.
Future Research	Based on the findings, future research should broaden the study's scope to include selecting students (undergraduate and postgraduate) and instructors from multiple universities in various states of Malaysia, collecting data and examining the differences between them, and providing an overall view of mobile learning adoption behaviors (intention to adopt and actual usage) from the perspective of both interactions.

Keywords	sustainability, mobile learning, intention, instructor readiness, student readiness, learning autonomy

INTRODUCTION

Mobile learning is a developing online learning approach (Khalil-Ur-Rehman, 2019). It uses wireless devices like smartphones and tablets to offer learning materials that are neither time-sensitive nor location-sensitive. Mobile learning is learning where students can access material anytime and from any location while engaging in genuine learning activities using mobile technology (Martin & Ertzberger, 2013). Mobile learning is more contextualized and personalized, with more particular and portable material than e-learning (Traxler, 2009). COVID-19 has moved traditional learning and working techniques from in-person to online, owing to the requirement for robust solutions and technology's ability to enable virtual interactions (Dhawan, 2020).

During the pandemic, mobile learning was the predominant method of educating students (Romero-Rodríguez et al., 2020). According to Norbutayevich's (2023) findings, mobile learning is an innovative approach using mobile devices to efficiently complete coursework and access learning resources, regardless of time or space constraints. It is an essential component of making learning simple and adaptable. The pandemic encouraged the implementation of various techniques to prevent interruption in education, including flexible online learning and e-assessment. According to studies by Saikat et al. (2021), Alturki and Aldraiweesh (2022), Almaiah et al. (2022), and Sever Mališ et al. (2022), the pandemic has highlighted the potential of mobile learning. Educational systems across the globe are investigating and integrating its novel functionalities. Mobile learning allows students to access learning resources whenever needed, utilizing mobile phones or tablets and an Internet connection (Lan & Sie, 2010; Yi et al., 2009). Mobile learning encourages students to acquire knowledge and apply their abilities in diverse contexts, fostering the development of their problem-solving capabilities beyond the confines of conventional classroom environments. Furthermore, mobile learning approaches enable instructors to tailor instruction while students self-regulate their learning (Naciri et al., 2020). As a result, engaging in additional activities outside of the classroom might boost children's enthusiasm for learning. Moving ahead to future educational problems, as Norbutayevich's (2023) research highlighted, mobile learning represents the cutting edge of technology in the twenty-first-century digital era, capturing students' eager attention. This development could suggest that mobile learning could potentially serve as an effective educational instrument in the post-pandemic period.

Notably, Malaysian education systems have implemented e-learning as a preventive measure against the pandemic's transmission (Adams, 2021), emphasizing the necessity of digital teaching training for educators (Chang et al., 2021). A survey of Malaysian university students conducted during the pandemic found that the vast majority possessed a mobile device, including tablets and cell phones. It was found that 97.7% believed mobile devices could facilitate their learning process, while 73.8% utilized them for online information retrieval and research (Karim et al., 2020). The policy orientation during the pandemic and the widespread popularity of hardware devices have resulted in the rapid advancement of mobile learning, which appears ready for widespread application. However, apparent readiness does not imply that everything is truly ready (Parkes et al., 2015). The investigation into the sustainability of mobile learning in education is presently in its nascent developmental phases (Medrano et al., 2023). Sustainability is defined as the enduring nature of the perpetual advancement of mobile learning, its ability to accommodate evolving user demands and align with its intended objectives, its capacity to adapt to potential changes, and its likelihood of achieving widespread user acceptance (A. M. Al-Rahmi et al., 2021). Prior to the pandemic, studies revealed that mobile learning might be an effective way of training, possibly superior to traditional face-to-face lectures (Shih et al., 2010). Consequently, additional study is required to investigate the post-pandemic educational sustainability of mobile learning, especially since the majority of higher education institutions have embraced mobile learning as an indispensable pedagogical instrument.

This study demands the development of an explicit empirical feasibility model to analyze sustainability factors in mobile learning thoroughly. Mobile learning is an emerging technology. While investigating its acceptability or intention to use, it is clear to employ technology acceptance theory to explain user behavior. In order to explain whether mobile learning can meet current educational needs, this study incorporates perceived usefulness and perceived ease of use. Furthermore, Cheon et al. (2012) stated that when examining the determinants of mobile learning adoption among college students, it is crucial to commence by assessing their readiness for mobile learning. Ismail et al. (2016) and Mahat et al. (2012) found that Malaysian college students exhibit a moderate readiness for mobile learning. In contrast, instructors perceive a low level of readiness (Ibrahim et al., 2021), indicating that instructors and students in the Malaysian higher education system possess a certain degree of readiness regarding mobile learning. However, no previous studies have empirically examined learning readiness affecting usage behavior. Mobile learning readiness refers to students' preference and readiness to use technology, such as mobile devices, in the learning process (Mahat et al., 2012). However, the learning process is a two-way interactive process with the essential elements being the instructor and the student; thus, this study incorporates the variables of instructor readiness and student readiness into the research framework. Mobile learning places the student in the center of the entire learning activity, and the student-centered learning process allows students to choose when and how often they learn, making student self-directed learning a significant factor influencing mobile learning adoption (Kankok et al., 2020).

Considering all of those mentioned above, by employing the theory of planned behavior (TPB), this study attempts to reconstruct the conceptualization antecedents that explain the characteristics of sustainable mobile learning. The TPB states that individuals' intentions regarding attitudes, subject norms, and perceived behavioral control combine to shape their behavioral intentions and actions (Ajzen, 1991). Subjective norm is the manner in which an individual interprets the social pressures that they encounter. Attitude relates to the positive or negative sentiments that an individual holds regarding a particular behavior, and perceived behavioral control pertains to an individual's subjective assessment of their capability to exert influence over the resources and opportunities necessary to participate in a specific behavior; it is alternatively referred to as the subjective evaluation of the behavior's ease or difficulty to execute. Perceived behavioral control may be separated into two categories: self-efficacy (the perception of one's capacity to conduct behavior) and external resources (the availability of resources to individuals from external sources and obstacles encountered in accessing these resources) (Ajzen, 2002). This study aims to investigate in depth the determinants that impact the adoption of mobile learning in Malaysian higher education institutions, with a particular focus on the disturbing and complex period following the pandemic. To achieve this objective, the study constructs a holistic theoretical framework with comprehensive explanatory power. This framework is founded on the TPB theory and incorporates perceived usefulness and ease of use as antecedent variables of attitude, instructor readiness, and student readiness as antecedent variables of subjective norms and learning autonomy and self-efficacy as antecedent variables of perceived behavioral control.

LITERATURE REVIEW

MOBILE LEARNING IN HIGHER INSTITUTIONS

Mobile learning, as defined by Naismith et al. (2004), is an instructional approach that leverages mobile technology. Furthermore, research by Peters (2007) and Dahri et al. (2023) demonstrated that mobile learning's unique relevance is its adaptation to time and place. The sharing and exchange of information via mobile learning within academic institutions is an emerging subject of discourse (Salhab & Daher, 2023). According to the research by Lavidas et al. (2022), educating students regarding the advantages linked to mobile learning within higher education institutions is of the utmost importance. Advanced mobile devices have improved organizational, administration, and generation capabilities for teaching and learning due to superior hardware (such as cameras and accelerometers) and a multitude of software alternatives (such as applications) (Chen et al., 2008; Keskin & Metcalf, 2011). These capabilities facilitate individualized, contextual, collaborative, and informal learning by allowing students to build technological and communicative skills, communicate, exchange knowledge, and improve learning outcomes. Unquestionably, the proliferation of mobile devices has given rise to mobile learning as a feasible substitute for students desiring to attain fresh proficiencies or update pre-existing ones (Dahri et al., 2023). However, COVID-19 has prompted system adjustments at educational institutions, which raises concerns regarding the quality of education and the prospects of students. During the pandemic, colleges worldwide adopted online education dramatically, and many students study online using cell phones, desktop computers, or laptops (Voicu & Muntean, 2023). At the same time, Usak et al. (2020) and Naciri et al. (2020) discovered that the urgent scenario prompted a number of concerns, including students' futures and a reduction in educational quality.

The research conducted by Siron et al. (2020) in Indonesia amidst COVID-19 unveiled that students' utilization of e-learning was significantly impacted by experience, self-efficacy, perceived enjoyment, and computer fear. Additionally, perceived ease of use and usefulness influenced students' willingness to adopt e-learning. Unlike face-to-face encounters, mobile learning eliminates physical and temporal barriers between instructors and learners while delivering a different perspective through digitalized content. Previous research has established a correlation between learners' perceived enhanced learning efficiency and the willingness to utilize mobile learning (Hao et al., 2017). The study by Wei and Chou (2020) investigated the relationship between students' online learning outcomes and their levels of online readiness and perception. The findings indicated that their satisfaction with online learning was significantly influenced by their self-efficacy with computers and the Internet. Moreover, it was noted that the relationship between course satisfaction and online learning perception was moderated by self-efficacy in utilizing computers and the Internet to facilitate online learning.

Given that knowledge acquisition is the fundamental objective of learning, users' favorable perceptions of learning outcomes are anticipated to impact their attitudes toward the system (Yuan et al., 2021). In light of the circumstances, directing attention toward mobile learning readiness is judicious. This entails assessing students' inclination to adopt or reject mobile learning according to their abilities and discernment in a mobile learning context, particularly considering alternative online platforms. Therefore, based on the TPB, the primary objective of this research is to provide an all-encompassing comprehension of the factors that influence students' intentions concerning the adoption of mobile learning.

Sustainable Mobile Learning

According to Naciri et al. (2020) and Alfalah (2023), mobile learning refers to the pedagogical practice of obtaining knowledge via mobile devices. Mobile learning is among the new millennium's learning techniques. In accordance with the findings of a recent study on the expansion of mobile learning (Alshurideh et al., 2023), educational and information systems scholars have examined approaches to integrate it into pedagogical practices. COVID-19 has increased people's reliance on mobile learning as they seek alternate ways to complete their jobs (Alfalah, 2023). According to Lin et al. (2016), individual readiness is among the most significant determinants impacting the implementation and efficacy of mobile learning. Readiness includes psychomotor, cognitive, social, and emotional components of a person's ability to act (Borotis & Poulymenakou, 2004). Tang et al. (2021) found that students' readiness for live online learning influences their willingness, participation, and quality of online learning. However, in a separate study, Teo (2010) demonstrated that prior experiences with objects and actions have the most significant impact on an individual's readiness. This finding is consistent with Lin et al.'s (2016) research, which found a significant link between these experiences and the execution of actions or the use of objects.

As a result, Parasuraman (2000) emphasized that the technology itself may be the object when discussing adoption readiness. Moreover, the research by Liu et al. (2010) underlined that mobile learning enhances learning experiences by enhancing student-instructor contact and encouraging favorable attitudes towards learning and instructors. However, from a psychological standpoint, mobile learning readiness overlaps with technology acceptance and learning readiness (Lin et al., 2016). Meanwhile, Lin et al. (2016) discovered that mobile learning readiness is an individual's inclination to embrace and utilize mobile technology for educational purposes, including informal and formal learning. Motiwalla (2007) describes mobile learning as the application of mobile technologies in educational activities. Nonetheless, Ahmad (2019) stressed that the efficiency of mobile technology integration into learning would be determined by the readiness, communication, and commitment of teachers and university officials.

RESEARCH FRAMEWORK AND HYPOTHESIS DEVELOPMENT

THEORY OF PLANNED BEHAVIOR

The Theory of Planned Behavior (TPB) (Ajzen, 1991) is a psychological theory that establishes a link between thoughts and actions. TPB is also a well-known theory for predicting and understanding people's intentions and behaviors (Nie et al., 2020). As a result, limited research has employed the TPB model to elucidate the readiness of institutions of higher education for the adoption of mobile learning (Akour et al., 2021; Tagoe & Abakah, 2014) despite the profound impact that the Internet has had on distance education on a global scale. As a result of the platforms' requirement to sustain the learning environment, the worldwide pandemic has impacted online distance learning. The TPB is the paradigm for investigating the elements that impact students' adoption of mobile learning and its consequences. Therefore, this study constructs an extended research framework based on the TPB model as well as the readiness theory, as shown in Figure 1.

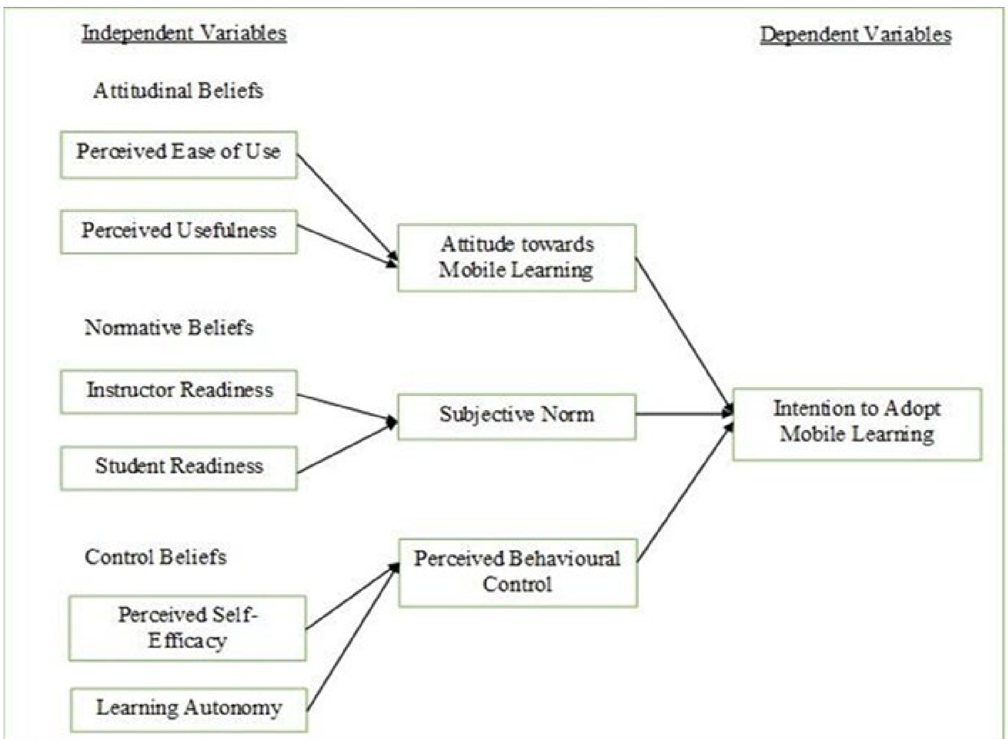

Figure 1. Research Framework

ATTITUDES TOWARDS MOBILE LEARNING

Given the technological limitations of mobile learning at this level and the multiple determinants of user behavior, this study employs two antecedent constructs (perceived ease of use and usefulness) from the technology adoption model to elucidate the attitude variable. Previous studies have also demonstrated significant relationships and high explanatory validity between these two antecedent constructs and attitude variables in various types of mobile applications, such as mobile health (Ramdani et al., 2020), mobile payments (Kavitha & Kannan, 2020), mobile banking (Normalini, 2019), and mobile learning (Cheon et al., 2012). Perceived usefulness relates specifically to the perception that mobile learning increases learners' performance in technological fields (W. M. Al-Rahmi et al., 2018; Davis, 1989). Furthermore, perceived ease of use pertains to an individual's belief that utilizing a specific item is effortless (Davis, 1989). Surveys show that pupils prefer mobile learning when the technology is straightforward. Indeed, as Avci and Askar (2012) showed, perceived usefulness significantly influences the intention to utilize technology applications in various scenarios. Hsu (2012), Joo et al. (2016), and Teo et al. (2019) revealed that students' behavioral intentions to utilize mobile learning management systems are significantly predicted by their perception of the systems' usefulness. Consequently, the subsequent hypotheses are presented:

H1: Perceived usefulness has a positive attitude-changing effect on students' inclination to use mobile learning.

H2: Perceived ease of use positively influences students' attitudes and intentions about mobile learning adoption.

SUBJECTIVE NORMS ON MOBILE LEARNING

Subjective norms are defined as others' perceptions of social effects on conduct (Ajzen, 1991), which reflect teacher and student readiness. This readiness is crucial for adopting mobile learning throughout the pandemic and sustaining the learning environment. After reviewing the studies on the determinants of mobile learning adoption by students worldwide (Cheon et al., 2012; Iqbal & Ahmed Bhatti, 2015; Mahat et al., 2012), it is critical to emphasize that this concept is in a state of constant development, especially in the realm of remote and open education. As a result, Cheon et al. (2012) found that professors and instructors significantly impacted students' decisions to use mobile learning. Furthermore, as emphasized by Alrasheedi et al. (2015), it is vital to assess students' perceptions of the acceptability of mobile learning since its efficacy is intrinsically tied to student technological acceptance. Therefore, teacher readiness for mobile learning adoption and student readiness should be investigated in Malaysian higher education institutions, where online learning has been crucial to the learning environment throughout the pandemic. Instructors are students' primary source of advice; thus, the learning environment should be consistent with low failure risk. Furthermore, students' utilization of mobile learning was significantly impacted by the level of assistance provided by the university administration, according to Almaiah et al. (2022). Hence, these hypotheses are derived:

H3: Instructor readiness influences students' desire to use mobile learning positively.

H4: Student readiness has a favorable subjective norm-changing effect on the intention to adopt mobile learning.

PERCEIVED BEHAVIORAL CONTROL

Aguilera-Hermida's (2020) research defines perceived behavioral control as an individual's competence, effort, and enabling factors that impact their ability to engage with educational technology. Al-Emran et al. (2020) and Azizi and Khatony (2019) discovered a consistent positive link between learners' perceived behavioral control and their inclination to employ mobile learning. However, prior studies have demonstrated that attitude is a dependable indicator of intention. According to Armitage and Conner (2001), a person's desire to participate in an activity increases as their attitude towards it improves. In contrast, Davis' (1989) research highlights that mentality comes before aspirations to use computer technology. The study by Normalini et al. (2018) revealed that attitude is the strongest predictor influencing undergraduate students' intention to use mobile applications in Malaysian public universities. The social cognitive theory by Bandura (1986) supposes that individuals' behavior is significantly impacted by perceived self-efficacy. Afful and Boateng (2023) discovered that students' self-efficacy influences their behaviors when engaging in practical mobile learning activities. Nowadays, most students have the confidence, organizational skills, and action-taking abilities to use mobile learning effectively. Holec (1981) defined learning autonomy as the ability to direct one's own learning, and it refers to the extent to which students are in command and accountable for their own actions while using mobile learning. Nonetheless, autonomy is a crucial predictor of behavioral control in mobile learning. Cheon et al. (2012) revealed that mobile learning requires self-motivated and self-disciplined learners, mobility, and flexibility. Thus, these hypotheses are constructed.

H5: Perceived self-efficacy impacts the perception of behavioral control in favor of the intention to adopt mobile learning.

H6: Learning autonomy has a favorable impact on how behavioral control is viewed and the propensity to use mobile learning.

H7: Attitude influences the intention to use mobile learning positively.

H8: Subjective norm has a favorable impact on the intention to adopt mobile learning.

H9: Perceived behavioral control influences the intention to use mobile learning favorably.

MATERIALS AND METHODS

DATA COLLECTION AND SAMPLING METHOD

The research sample comprises 280 undergraduate students currently enrolled in one of Malaysia's public higher education institutions. The purposive sampling approach was used to implement the non-probability sampling method. Data were collected over four weeks via an online Google Form survey from undergraduate students who used mobile devices for online courses owing to the outbreak. All measurements in this research were derived from prior studies (Cheon et al., 2012) and were assessed using a 7-point Likert scale that ranged from "strongly disagree" to "strongly agree." Three measurements were attached to each construct in this study. The 18th WMA General Assembly in Helsinki, Finland, adopted the ethical principles for this research in June 1964 (World Medical Association, 2013). Even though it may be necessary to communicate with family members or community leaders, it is strictly forbidden to participate in a research project without the voluntary consent of an individual competent to provide informed consent. The present study is conducted in accordance with the Helsinki Protocol.

DATA ANALYSIS AND RESULTS

DEMOGRAPHIC PROFILE AND TECHNOLOGY USAGE

The survey instrument was divided into three discrete stages. Following the collection of demographic information in the first section was a segment pertaining to technology usage. In the third section, the responses of the participants regarding the specific measurement items associated with each construct were extracted. The study used the deliberate sampling approach to target specific groups of people, especially mobile learning users, who best provided the necessary information for the study.

The respondents' technology usage and demographic profile are detailed in Table 1. Most respondents were female (73.5%), with a male proportion of only 26.8%. The age range of males and females who answered the questionnaire was 24-26 years (9.3%), followed by 21-23 years (86.1%), and the lowest was 18-20 years (4.6%). The percentage of individuals falling within the age range of 21-23 years is the highest of all age ranges documented.

Table 1. Profile of Demographic

Demographic	Categories	Frequency	Percentage (%)
Age	18-20	13	4.6
	21-23	241	86.1
	24-26	26	9.3
Gender	Male	75	26.8
	Female	205	73.2
Ethnicity	Malay	90	32.1
	Chinese	141	50.4
	Indian	43	15.4
	Others	6	2.1
School	Arts Course	212	75.7
	Science Course	68	24.3
Year	First Year	20	7.1
	Second Year	111	39.6
	Third Year	121	43.2
	Fourth Year	25	8.9
	Fifth Year	3	1.1
CGPA	3.00-3.50	129	46.1
	3.51-4.00	151	53.9
Smartphone Brand	Apple (iPhone)	88	31.4
	Samsung	47	16.8
	Nokia	1	0.4
	HTC	3	1.1
	Sony Xperia	3	1.1
	LG	3	1.1
	Vivo	40	14.3
	Xiaomi	18	6.4
	Huawei	44	15.7
	Others	33	11.8
Own Tablet PC	Yes	280	100
PC Brand	Apple (Ipad)	33	11.8
	Samsung	26	9.3
	Asus	74	26.4
	Acer	43	15.4
	Microsoft Surface	16	5.7
	Sony	15	5.4
	Lenovo	15	5.4
	HP	34	12.1
	Others	24	8.6
Years Using Internet	1-10	164	58.6
	11-20	114	40.7
	21-30	2	0.7
Hours	Almost Never	1	0.4
	Less than 1 hour	23	8.2
	1-5 hours	48	17.1
	6-10 hours	109	38.9
	11-15 hours	63	22.5
	16-20 hours	29	10.4
	More than 20 hours	7	2.5

Demographic	Categories	Frequency	Percentage (%)
Data Plan	Yes	260	92.9
	No	20	7.1

Most responders were Chinese, accounting for 50.4%, followed by Malays (32.1%). The Arts course cluster, which included social sciences, humanities, education, language, and communication courses, had the most responses (212, 75.7%). The remaining 24.3% comprised 68 Science course cluster students studying chemistry, pharmacy, physics, biology, industrial technology, computer science, and mathematical science. The highest year of study reported was by third-year students, at 43.2%, followed by second-year students at 39.6%. First-year students scored just 7.1%, followed by fourth-year students at 8.9% and fifth-year students at 1.1%. The recorded cumulative grade point average (CGPA) of the 129 students varied from 3.00 to 3.50 (46.1%), with 151 individuals achieving a higher CGPA of 3.51 to 4.00 (53.9%). The Arts course cluster is far more extensively represented than the Science course cluster; nevertheless, variations in optional topics and grade levels do not influence mobile technology use for the Generation Z cohort. Among the 280 respondents, all the students had a smartphone, with 192 using Android (68.6%) and 88 using an iPhone (31.4%). On the other hand, all 280 respondents also have a tablet PC (Apple: 11.8%; Windows PC Operating Systems: 88.2%). This suggests that Malaysian university students are selective about mobile devices during mobile learning and can choose different devices depending on the scenario. Most students prefer Android phones and Windows systems, which may be associated with the compatibility of mobile learning programs. Of the respondents, 164 had used the Internet for ten years, while 114 had used it for up to 20 years. Most respondents (109, 38.9%) spent 6-10 hours daily on the Internet, with the lowest time spent at 0.4%. Most respondents (92.9%) had data subscriptions, while just 7.1% used a free Wi-Fi network.

ANALYSIS

This study's constructed models were analyzed using SmartPLS 3.3.3, a second-generation structural equation modeling software (Ringle et al., 2015). The present study utilized a two-step approach, commencing with an assessment of the measurement model, which was subsequently followed by an examination of the instrument's validity and reliability. Using the structural model, the hypothesis was examined during the second phase of the research.

MEASUREMENT MODEL

This study conforms to the analysis and evaluation by Hair et al. (2020), who employed outer loadings, average variance extracted (AVE), and composite reliability (CR) to assess quality indicators, including convergent validity, discriminant validity, and other external model indicators. The loading, AVE, and CR threshold values specified by Ramayah et al. (2018) are 0.7, 0.5, and 0.7, respectively. According to the results shown in Table 2, all loadings exceeded 0.7, AVE was less than 0.5, and CR exceeded 0.7. The findings indicate that the assessment has convergent validity and can be considered reliable. We then examined the discriminant validity employing the HTMT ratio proposed by Franke and Sarstedt (2019). When the HTMT value is less than 0.90, it indicates that the structures being evaluated are distinct. As seen in Appendix A, all but a few HTMT ratios were less than 0.90. Nonetheless, after doing the HTMT bootstrapping, we noticed that the UL between variables over the proposed threshold was less than 1.0, indicating that respondents were aware that the ten constructs tested were independent.

Table 2. Measurement Model

Construct	Item	Loadings	AVE	CR
Attitude	ATT1	0.896	0.836	0.938
	ATT2	0.921		
	ATT3	0.925		
Intention	INT1	0.949	0.872	0.953
	INT2	0.950		
	INT3	0.902		
Instructor Readiness	IR1	0.899	0.798	0.922
	IR2	0.907		
	IR3	0.874		
Learning Autonomy	LA1	0.957	0.919	0.958
	LA2	0.961		
Perceived Behavioral Control	PBC1	0.945	0.854	0.946
	PBC2	0.899		
	PBC3	0.929		
Perceived Ease of Use	PEOU1	0.829	0.724	0.887
	PEOU2	0.879		
	PEOU3	0.844		
Perceived Self-Efficacy	PSE1	0.963	0.869	0.952
	PSE2	0.925		
	PSE3	0.909		
Perceived Usefulness	PU1	0.865	0.775	0.912
	PU2	0.897		
	PU3	0.880		
Student Readiness	SR1	0.872	0.789	0.918
	SR2	0.888		
	SR3	0.906		
Subjective Norm	SN1	0.931	0.822	0.933
	SN2	0.893		
	SN3	0.895		

Note: LA3 was deleted due to low loadings

MEASUREMENT OF STRUCTURAL MODEL

This study employed 5,000 bootstrap resamples (Hair et al., 2020; Ramayah et al., 2018) to examine the structural model and test the hypotheses formulated. The outcomes of this analysis are presented in the form of confidence intervals, t-values, standard errors, p-values, beta values, and standard errors. According to the final results, the R^2 was 0.458 ($Q^2 = 0.376$) for Attitude, R^2 was 0.7 ($Q^2 = 0.59$) for Perceived Behavioral Control, R^2 was 0.684 ($Q^2 = 0.555$) for Subjective Norm and R^2 was 0.805 ($Q^2 = 0.695$) for Intention. The findings determined that the predictors could explain 45.8% of the variance in Attitude, 70% of the variance in Perceived Behavioral Control, 68.4% of the variance in Subjective Norm, and 80.5% of the variance in Intention. Based on the results of the analysis (see Figure 2), We found a positive correlation between Attitude and Perceived Usefulness ($\beta = 0.676$, $t = 9.674$, $p < 0.01$) but no significant relationship with Perceived Ease of Use ($\beta = 0.002$, $t = 0.027$, $p = 0.489$) when examining the factors influencing Attitude. Secondly, both Student Readiness ($\beta = 0.395$, $t = 6.088$, $p< 0.01$) and Instructor Readiness ($\beta = 0.492$, $t = 7.879$, $p < 0.01$) had a significant and positive impact on Subjective Norms. Moreover, significant positive correlations were observed in this study among Perceived Behavioral Control, Learning Autonomy ($\beta = 0.568$, $t = 7.395$, $p < 0.01$), and Perceived Self-efficacy ($\beta = 0.29$, $t = 3.768$, $p < 0.01$). In conclusion, the findings of this research demonstrated that Intention to Use was significantly and positively influenced by Attitude ($\beta = 0.292$, $t = 4.998$, $p < 0.01$), Subjective Norms ($\beta = 0.281$, $t = 4.944$, $p < 0.01$), and Perceived Behavioral Control ($\beta = 0.416$, $t = 7.510$, $p < 0.01$). Consequently, H2 was not supported in this investigation, while H1, H3, H4, H5, H6, H7, H8, and H9 were supported (see Appendix B).

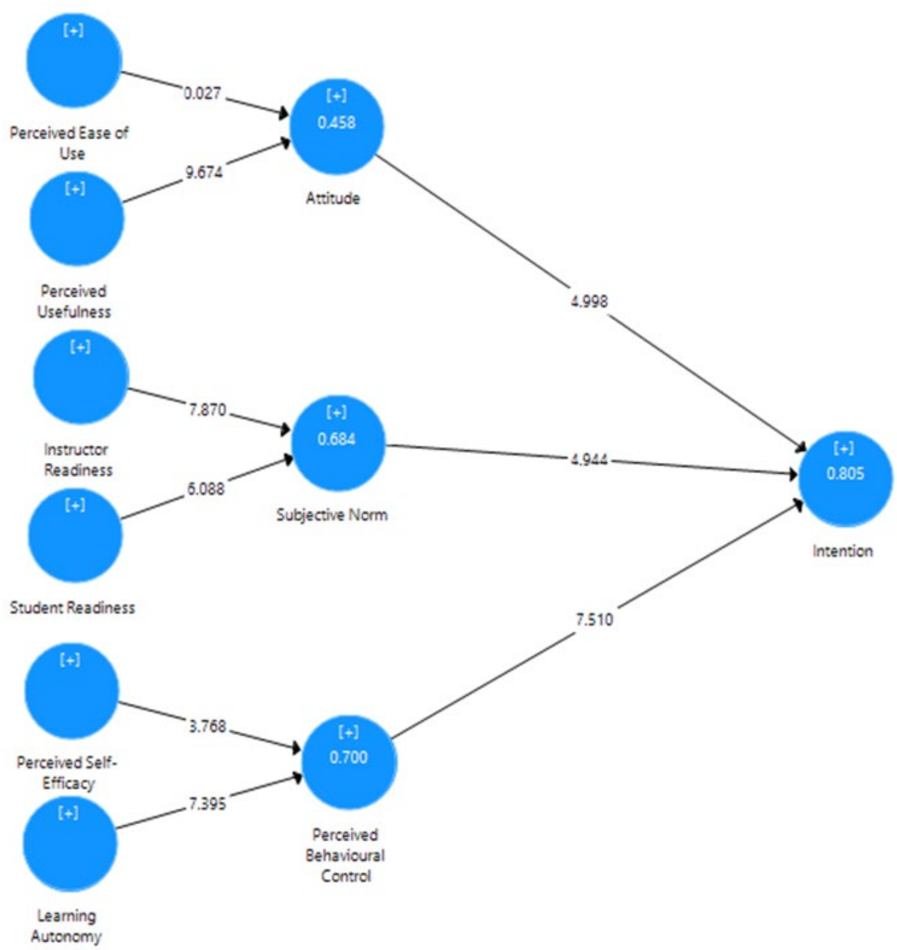

Figure 2. Hypothesis Testing Results

DISCUSSION AND IMPLICATIONS

DISCUSSION

This study employed the TPB theory to examine the determinants that impact the intentions of university students to adopt mobile learning, and the findings presented insightful conclusions about the dynamics of technology adoption in higher education. This study developed predicted beliefs for each of the three essential components of the TPB hypothesis. According to the findings of this study, perceived behavioral control (β = 0.416) had the most substantial influence on the intentions of university students to utilize mobile learning. The abovementioned results corroborated those of Cheon et al. (2012). Meanwhile, two predictive beliefs, learning autonomy and perceived self-efficacy, had the most explanatory power for perceived behavioral control ($R^2 = 0.700$). Perceived behavioral control was more significantly impacted by learning autonomy (β = 0.568) than perceived self-efficacy (β = 0.290). This finding suggested that students' self-regulation responsibility and control of the learning process (Liu, 2008) had a more substantial effect on perceived behavioral control than self-referential judgments of competence for adopting mobile learning. Importantly, this study confirmed that learning autonomy is a prerequisite for mobile learning-related perceived behavioral control. This implies that learners with autonomous and self-directed learning abilities are more inclined to use mobile learning. In contrast, learners with more excellent self-directed learning skills and potential are more effective at using mobile learning.

Attitude (β = 0.292) significantly increased adoption intention. Nevertheless, concerning the two antecedent variables of Attitude, the impact of perceived ease of use on Attitude was insignificant. This nuanced finding suggested that undergraduates' perceptions of the mobile learning platform's ease of use in Malaysian higher education institutions may not substantially influence their intention to use mobile learning. This insight highlighted the present students' growing familiarity with digital technologies, which may reduce perceived obstacles to ease of use. The perceived usefulness (β = 0.676) strongly affected attitudes towards embracing mobile learning. The findings indicated that the better college students viewed mobile learning performance, the more beneficial they thought this technology to be, and the more favorable their attitudes towards adopting mobile learning were, resulting in more excellent mobile learning adoption intentions. In this study, the effect of the two antecedent variables of Attitude on Attitude is consistent with the findings of Normalini and Ramayah (2015).

Subjective norms (β = 0.281) positively and directly influenced adoption intentions, according to this study. The influence of instructor readiness (β = 0.395) on subjective norms was found to be more substantial in comparison to student readiness (β = 0.290). These two variables together explained 68.4% of the variation in perceived norms ($R^2 = 0.684$). This finding indicates that enhancing teacher readiness is likely to increase the propensity of college students to utilize mobile learning. The observed result is in accordance with the conclusions posited in the research conducted by Cheon et al. (2012). The results of this study support previous research that found low teacher readiness in Malaysia's higher education system due to traditional teacher-centered educational philosophy and a lack of holistic understanding of pedagogical integration in mobile learning (Ibrahim et al., 2021). This means that sustained performance attainment and effective deployment of mobile learning in higher education need a thorough understanding of mobile learning's potential, limits, and successes by instructors and students (Azizi & Khatony, 2019).

In conclusion, to confirm the substantial determinants that significantly impact the intention of Malaysian university students to adopt mobile learning and thereby ensure its long-term sustainability and prosperity, an exhaustive investigation was conducted to validate these factors. The finding of this study demonstrated that the combined influence of attitude, subjective norms, and perceived behavioral control explained 80.5% of the variance ($R^2 = 0.805$) of the adoption intention for mobile learning. This finding indicates that the model constructed specifically for this study possesses a greater capacity to explain the intention of undergraduate students in Malaysian higher education institutions to implement mobile learning. Simultaneously, the reconstructed core constructs' antecedent variables provided a transparent empirical sustainability model. These variables effectively interpreted the different components of mobile learning sustainability.

PRACTICAL IMPLICATIONS

This study investigated the factors influencing undergraduates' intention to utilize mobile learning to provide a comprehensive perspective on initiatives to enhance sustainability and support students' intention for mobile learning. Based on the results, we can provide stakeholders in the mobile learning domain with actionable recommendations. First, mobile learning providers must work on increasing the performance of mobile learning technology, which may be accomplished through content, efficiency, and resource integration, in order to support student learning successfully. Higher education administrators may improve faculty readiness for mobile learning by capitalizing on faculty influence and reputation among students, increasing the durability and efficiency of mobile learning readiness. Simultaneously, each educational institution should provide diverse opportunities for training in mobile learning functions to promote students' self-efficacy perspectives. Initially, students should concentrate on improving their self-control and self-discipline when using mobile devices for educational reasons. Based on this assumption, students ought to make an effort to enhance their readiness for learning, proactively acquire proficiency in utilizing mobile learning technologies, and engage in diverse training and guidance offered by tertiary educational establishments to augment their self-efficacy and performance perceptions of mobile learning. Furthermore, COVID-19 has tremendously influenced global progress toward sustainable development objectives and educational excellence. This study illustrates how mobile learning gives students a tough chance to continue their learning journey from the comfort of their homes, alleviating the interruptions caused by the pandemic's early beneficial impacts and helping the growth of excellent education globally.

CONCLUSION

The present study employed the TPB theory as a conceptual model to comprehensively examine the principal determinants impacting mobile learning adoption in Malaysian higher education institutions by reconstructing the antecedent variables of the critical components that explain the attributes of sustainable mobile learning. The study's findings indicated that attitude, subjective norms, and perceived behavioral control significantly influenced the adoption of mobile learning in Malaysian higher education institutions. Nonetheless, perceived usefulness significantly affects the attitude variable, and increasing perceived usefulness aids mobile learning in meeting the sustainability element of responding to current educational needs. Instructor readiness significantly impacts subjective norms more than student readiness, directly affecting the sustainability element of increased user acceptance. Learning autonomy and self-efficacy significantly influence perceived behavioral control and the long-term potential of mobile learning to adapt and develop. The findings effectively aid stakeholders in better understanding the integrated perspective of mobile learning and contribute to developing mobile learning's sustainability in education by bridging the research of pre-pandemic and post-pandemic mobile learning system acceptance factors.

LIMITATIONS AND DIRECTIONS FOR FUTURE STUDIES

This study provides an original viewpoint regarding the sustainable implementation of mobile learning in Malaysian higher education institutions. Nevertheless, this investigation did not examine the practical implementation of mobile learning. Meanwhile, increased data collection will facilitate comparative analyses, reveal differences, and provide a comprehensive understanding of mobile learning adoption behaviors from the perspectives of all stakeholders, both in terms of intentions and actual usage. Given these findings, further research should aim to broaden the scope of this investigation by incorporating academic staff and undergraduate and graduate students from multiple colleges and regions within Malaysia.

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APPENDIX A

Discriminant Validity (HTMT)

	1	2	3	4	5	6	7	8	9	10
1. Attitude										
2. Instructor Readiness	0.896									
3. Intention	0.867	0.790								
4. Learning Autonomy	0.826	0.843	0.892							
5. Perceived Behavioral Control	0.774	0.735	0.899	0.902						
6. Perceived Ease of Use	0.535	0.570	0.511	0.479	0.468					
7. Perceived Self-Efficacy	0.846	0.836	0.895	0.974	0.865	0.503				
8. Perceived Usefulness	0.767	0.817	0.704	0.696	0.654	0.843	0.719			
9. Student Readiness	0.791	0.844	0.812	0.747	0.714	0.459	0.761	0.670		
10. Subjective Norm	0.826	0.885	0.888	0.864	0.822	0.607	0.840	0.759	0.860	

APPENDIX B

Hypothesis Testing

Hypo-thesis		Std. Beta	Std. Error	t-value	P values	f^2	Q^2	VIF	R^2	Decision
H1	Perceived Usefulness → Attitude	0.676	0.070	9.674	0	0.393		2.145	0.458	Supported
H2	Perceived Ease of Use → Attitude	0.002	0.065	0.027	0.489	0	0.376	2.145		Not Supported
H3	Instructor Readiness → Subjective Norm	0.492	0.063	7.870	0	0.352	0.555	2.180	0.684	Supported
H4	Student Readiness → Subjective Norm	0.395	0.065	6.088	0	0.227		2.180		Supported
H5	Perceived Self-Efficacy → Perceived Behavioral Control	0.290	0.077	3.768	0	0.056	0.590	4.979	0.700	Supported
H6	Learning Autonomy → Perceived Behavioral Control	0.568	0.077	7.395	0	0.216		4.979		Supported
H7	Attitude → Intention	0.292	0.058	4.998	0	0.173	0.695	2.531	0.805	Supported
H8	Subjective Norm → Intention	0.281	0.057	4.944	0	0.142		2.890		Supported
H9	Perceived Behavioral Control → Intention	0.416	0.055	7.510	0	0.351		2.521		Supported

AUTHORS

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