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Bridging the Gap: Understanding M-Learning Acceptance Among University Students Through Technological and Individual-Social Perspectives

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This study explores the crucial influence of technological and individual-social factors on the willingness of university students to use mobile learning (m-learning). It analyzes the direct, indirect, and overall effects of these factors. Furthermore, it examines how gender and age serve as moderators of the direct impact of each determinant on students' intentions to embrace m-learning. Based on a thorough review of the recent studies in m-learning acceptance, the theoretical model is developed employing two categories, each of which has three factors and two moderating factors. This quantitative cross-sectional study collects the data using self-administered questionnaires delivered to the respondents using google forms. The model is analyzed by the structural equation modeling technique using 687 valid student responses. The results affirm that higher education students prioritize technological aspects when considering the adoption of m-learning, as indicated by the direct effect findings. Moreover, the analysis of total effects highlights that individual-social factors exert the most substantial influence on students' intention to use m-learning. Furthermore, the study presents evidence supporting the role of gender as a moderating factor in the association between perceived enjoyment and behavioral intention. This research addresses the lack of comprehensive theoretical knowledge regarding the adoption of m-learning in Indonesia. It introduces novel theoretical insights concerning direct, indirect, total effects, and moderating effects, which are then utilized to analyze the significant practical implications of the study's findings.

Keywords: mobile learning, technological aspect, individual-social aspect, SEM

INTRODUCTION

The significant growth of mobile technology with internet capability has enabled mobile phones to become essential devices to support daily activities. Meanwhile, the functionality of mobile devices is not limited to communication as an initial purpose only but also to conduct several other tasks such as performing financial transactions, which refers to mobile banking (Nguyen, 2020; Zhou, 2018), to carry out payment transactions which refer to the mobile payment (Lisana, 2021) and to facilitate the learning process which refers to mobile learning (m-learning) (Buabeng-Andoh, 2021). There is no doubt that mobile devices offer users great value and convenience since they can use them without the limitation of time and place.

Recently, m-learning has gained popularity due to the Covid-19 pandemic, which has led students to switch from learning on-site to online learning. Most countries have closed their education institutions due to the COVID-19 pandemic. However, students are still required to study at home. Consequently, online and mobile learning use has increased due to the emergency remote online learning and teaching activities (Zaidi et al., 2021). Various levels of education institutions have implemented m-learning in their learning process (Chavoshi & Hamidi, 2019). This new way of learning is believed to provide students with many benefits (Qashou, 2021). Furthermore, a study by Rehman et al. (2016) indicated that several studies have emphasized that mobile technology could enhance the quality of the learning process. In the education context, Senaratne et al. (2019) clarified five advantages of the usage of m-learning, including individuality, connectivity, context-sensitivity, interactivity, and portability. Additionally, no geographical constraints and efficient communication were also considered valuable benefits of m-learning (Kumar & Chand, 2019).

Globally, the integration of m-learning in the higher education field is becoming more important due to the aforementioned benefits (Buabeng-Andoh, 2021; Chavoshi & Hamidi, 2019). As a developing country, Indonesia has also started to take advantage of m-learning at the higher education level. A study revealed that Indonesia had more mobile internet connections than the total population in 2019 and was estimated to be the third-world-ranked smartphone user by 2025 (Lisana, 2021). Meanwhile, the Directorate General of Higher Education (PD-Dikti, 2020) reported the number of higher education students in Indonesia reached 8.5 million in 2020. Hence, Indonesia has a great opportunity to adopt m-learning as an innovative method in the learning process, especially for higher education students.

However, despite some advantages, Chavoshi & Hamidi (2019) confirmed that most universities failed to implement m-learning due to differences in student's perceptions of m-learning. Another research showed that higher educational institutions are relatively slow in adopting m-learning as a new way of learning, and none of them had fully obtained the capability of m-learning (Kumar & Chand, 2019). Some studies revealed that integrating m-learning into the learning process in higher education is still challenging since it is related to several issues that need to be considered, including cultural, individual, social, and technological issues (Senaratne et al., 2019; Kumar & Chand, 2019; Al-Azawei & Alowayr, 2020).

The current circumstances underscore the necessity of comprehending students' perceptions of m-learning, which could serve as the groundwork for implementing m-learning in higher education. While some research has explored the acceptance of m-learning platforms, particularly in higher education settings, there remains no established theoretical model. Moreover, numerous authors have argued that m-learning research is still in its infancy stage, particularly in developing countries (Kaliisa & Michelle, 2019; Kumar & Chand, 2019; Moya & Camacho, 2021). Recognizing the technological aspect is crucial for increasing the number of students who embrace m-learning (Hao et al., 2017). Additionally, individual and social factors may pose challenges to the development of students' perceptions of m-learning platforms (Kumar & Chand, 2019).

Building on the aforementioned issues, this study seeks to investigate factors influencing students' intentions regarding m-learning adoption in higher education, focusing on two key aspects: individual-social and technological. The technological aspect comprises three constructs—perceived usefulness, perceived ease of use, and facilitating conditions—aligned with the characteristics influencing students' decisions to use or not use m-learning as proposed by Kumar & Chand (2019). Meanwhile, the individual-social aspect encompasses three constructs—perceived enjoyment, social influence, and perceived convenience—following the categorization from Moya & Camacho's systematic review of m-learning research (2021).

Hao et al. (2017) highlighted the scarcity of prior studies examining the impact of individual and social aspects on students' intention to use m-learning. Furthermore, prior research, as noted by Chavoshi & Hamidi (2019), has yet to provide a complete categorization of m-learning adoption. According to a systematic review by Al-Emran et al. (2018), no m-learning adoption research had been conducted in Indonesia from 2006 to early 2018. This study aims to address this gap by exploring the factors influencing m-learning acceptance from various perspectives in a developing country, Indonesia. Its contributions lie in the comprehensive analysis (direct effect, indirect effect, and total effect) among constructs and the inclusion of two moderating factors (age and gender) that could impact the relationship between each construct and behavioral intention. Additionally, the valuable insights gleaned from this study are expected to aid both m-learning developers and higher education organizations in making strategic decisions regarding the implementation of m-learning in the learning process.

LITERATURE REVIEW

The realm of m-learning has seen diverse definitions proposed in existing research, reflecting varied perspectives. Lisana & Suciadi (2021) conceptualized m-learning as the utilization of internet-enabled mobile devices to facilitate learning anytime and anywhere. Buabeng-Andoh (2021) contended that m-learning is a subset of electronic learning (e-learning), wherein students access learning materials via wireless mobile devices, independent of time and location. This mobility aspect distinguishes m-learning from e-learning (Al-Emran et al., 2018). For the purposes of this study, the definition of m-learning within the context of higher education pertains to the attainment of students' cognitive knowledge utilizing mobile devices with internet capabilities through wireless technology, without temporal or spatial constraints. Such mobile devices encompass smartphones, handheld computers, PDAs, laptops, and tablet computers (Sidik & Syafar, 2020).

Numerous recent studies have explored students' intentions to adopt m-learning at higher education levels across various countries, as summarized in Table 1. The Technology Acceptance Model (TAM) proposed by

Davis (1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) have emerged as the predominant theoretical frameworks employed in this area of research. In addition to these models, the Theory of Planned Behaviour (TPB) introduced by Ajzen (1991) has also been widely used to explain technology adoption by emphasizing the roles of attitude, subjective norm, and perceived behavioral control. Some studies have combined TPB with TAM to develop more comprehensive models that better capture the complex factors influencing m-learning adoption. Nevertheless, relatively few studies have incorporated moderating factors into their models, despite the emphasis placed on such factors within the UTAUT framework.

Table 1

Prior studies in m-learning

Author	Field of Study	Theory	Construct	MF	Country
Alturki & Aldraiweesh (2022)	Mobile learning Usage in higher education	TAM	PU, PEU, PI, TTF, ST, BI, AU	-	Saudi Arabia
Alturise et al. (2022)	Mobile learning acceptance in K-12 Education	UTAUT	PE, EE, SI, SQ, HM, SML, BI	Gender	Saudi Arabia
Zaidi et al. (2021)	Mobile learning adoption by university students	TAM	PU, PEU, ME1, AT, ME2, BI	-	India
Buabeng-Andoh (2021)	The intention of university students in using mobile learning	TAM TPB	PEU, PU, SE, SN, AT, BI	-	Ghana
Sitar-Tăut (2021)	Mobile learning adoption in social distancing	UTAUT	EE, PE, FC, SI, BI, HM	-	Romania
Mutambara & Bayaga (2021)	Mobile learning usage for STEM education in rural areas	TAM	PEU, SI, PU, PE, BI, AT, PSR, PR, PPR	-	South Africa
Adanır & Muhametjanova (2021)	The acceptance of mobile learning by University students	TAM TPB	PEU, PU, SN, LA, SE, AT, BI BI, IR, SR, PBC,	-	Turkey and Kyrgyzstan
Qashou (2021)	Factors affecting m-learning usage in higher education	TAM	PEU, PU, PM, ENJ, SE, AT, BI	-	Palestine

Author	Field of Study	Theory	Construct	MF	Country
Welch et al. (2020)	The adoption of mobile learning in the workplace	UTAUT	EE, PE, FC, SI, BI, SML	Age, Gender	UK
Al-Azawei & Alowayr (2020)	The intention to use and hedonic motivation for mobile learning in two middle eastern countries	UTAUT2	EE, PE, PV, SI, TR, HM, BI	-	Iraq dan Saudi Arabia
Chelvarayan et al. (2020)	Student's perceptions on mobile learning	TAM UTAUT	EE, PE, SI, PE, QS, BI	-	Malaysia
Chavoshi & Hamidi (2019)	The impact of individual, Social, Technological and Pedagogical Factors toward Mobile Learning usage in Higher Education	TAM UTAUT	PEU, PU, FC, SI, PI, SE, TR, LCQ, INT, UI, ML, SUP, BI	-	Iran
Pramana (2018)	Mobile learning systems adoption among university students	TAM UTAUT	PU, PEU, SI, SE, PI, LA, FC, PE, PM, BI	Gender, Experience	Indonesia
Hao et al. (2017)	The factors influence mobile learning acceptance	TAM	PU, PEU, FC, PI, SN, VOL, IM, BI	-	China
Rehman et al. (2016)	Mobile learning adoption framework from the learners perspective	TAM UTAUT	PE, EE, ENJ, PM, SI, MR, BI		Pakistan

Notes: AT=Attitude, AU=Actual Use, BI=Behaviour intention, EE=Effort expectancy, FC=Facilitating condition, HM=Hedonic motivation, IM=Image, INT=Interactivity, IR=Instructor readiness, LA=Learning autonomy, LCQ=Learning content quality, ME1=Mobile system efficacy, ME2=Mobile service efficacy, ML=Mobile device limitations, MR=Mobile Readiness, PU=Perceived usefulness, PEU=Perceived ease of use, PE=Performance expectancy, ENJ=Perceived enjoyment, PM=Perceived mobility, PI=Personal Innovativeness, PV=Price Value, PBC=Perceived behavioral control, PSR=Perceived skills readiness, PR=Perceived resources, PPR=Perceived psychological readiness, QS=Quality of service, SML=Self-management of learning, SE=Self efficacy, SI=Social influence, SN=Subjective norm, SQ=System Quality, SR=Student readiness, ST=Satisfaction, SUP=Government Support, TR=Trust, TTF=Task-Technology Fit, UI=User interface, Vol=Voluntariness

DEVELOPMENT OF HYPOTHESES AND THEORETICAL MODEL

Technological aspect

The technological aspect concerns the extent to which the characteristics of a particular technology affect its adoption decision (Cruz-Jesus et al., 2019). In line with this, the technological context also addresses the compatibility of the technology and the trade-off between its potential benefits and the challenges faced during the adoption process (Na et al., 2022). In the context of m-learning, this technological aspect is operationalized through three key factors: perceived usefulness, perceived ease of use, and facilitating conditions, based on the categorization proposed by Kwabena et al. (2021). Perceived usefulness is defined in this study as a student's belief that the m-learning system offers numerous advantages (Al-Azawei & Alowayr, 2020), thereby enabling them to enhance their learning performance (Tao et al., 2022). When students perceive greater benefits from m-learning as an innovative teaching method, they are more likely to develop a stronger intention to use it. Previous studies consistently demonstrate that perceived usefulness significantly influences the intention to adopt new technologies across various service contexts (Balouchi & Samad, 2021), particularly at the higher education level (Alturki & Aldraiweesh, 2022; Sidik & Syafar, 2020; Chelvarayan et al., 2020). Moreover, in prior systematic review studies, perceived usefulness emerged as the most frequently used construct in the adoption of mobile services (Moya & Camacho, 2021). Thus, this study posits the hypothesis:

H1: Perceived usefulness directly influences student's behavior intention toward m-learning

The decision to adopt an innovative technology is undoubtedly influenced by its perceived ease of use. The simpler users perceive the technology to be, the greater their intention to accept it. Perceived ease of use has been recognized as a critical factor in determining user behavior intention across various service domains, including virtual reality devices (Lee et al., 2019; Manis & Choi, 2019), MOOCs (Tao et al., 2022; Al-Rahmi et al., 2019), mobile banking (Zhou, 2018), mobile payment (Lisana, 2021; Lisana, 2022), and automated vehicles (Zhang et al., 2019). In this study, perceived ease of use refers to the level of difficulty experienced by students when using m-learning systems (Lisana & Suciadi, 2021). While some studies have underscored the significance of perceived ease of use as a critical predictor affecting students' intention to adopt m-learning in higher education (Alturki & Aldraiweesh, 2022; Welch et al., 2020; Sidik & Syafar, 2020), others have reported contradictory findings, suggesting that perceived ease of use did not significantly influence behavioral intention toward m-learning (Lisana & Suciadi, 2021; Al-Azawei & Alowayr, 2020; Chelvarayan et al., 2020). Furthermore, while several authors have affirmed the importance of perceived ease of use on students' perceptions of usefulness in m-learning platforms (Lisana & Suciadi, 2021; Rehman et al., 2016), other research across different service domains has yielded contradictory results (Revythi & Tselios, 2019; Tao et al., 2018; Chang et al., 2017). Hence, this study postulates the following hypotheses:

H2: Perceived ease of use directly influences student's behavior intention toward m-learning
H3: Perceived ease of use directly influences student's perceived usefulness toward m-learning

The third factor in the technological aspect is the facilitating condition, defined as the availability of technical and organizational infrastructure to support the students using m-learning systems (Pramana, 2018). This study refers to the facilitating condition of internet access and speed, resources, and student support during the learning process. Several authors believe this factor can be a barrier to adopting various mobile services (Lisana, 2021, Tarhini et al., 2017; Ramírez-Correa et al., 2019). However, research on m-learning adoption in the higher education context confirmed that facilitating condition did not predict the student's switching behavior to use m-learning (Welch et al., 2020; Pratama, 2021). Additionally, Hao et al. (2017) and Pramana (2018) declared that student's perception of usefulness is affected by the availability of those related to facilitating conditions. Thus, the following hypotheses are proposed:

H4: Facilitating condition directly influences student's behavior intention toward m-learning
H5: Facilitating condition directly influences student's perceived usefulness toward m-learning

Individual-Social aspect

The role of individual-social aspects is pivotal for students when determining whether to adopt m-learning or not (Kumar & Chand, 2019). This study employs three factors to gauge individual-social aspects: perceived enjoyment, perceived convenience, and social influence. Perceived enjoyment is recognized as a significant intrinsic motivator for students in educational settings, as discussed by Alalwan et al. (2018). Within the m-learning context, perceived enjoyment refers to students' perception that m-learning systems provide them with a sense of enjoyment (Pramana, 2018). The influence of perceived enjoyment on m-learning adoption at higher education levels has been extensively investigated by several authors, including Chelvarayan et al. (2020), Pramana (2018), and Rehman et al. (2016). The findings indicated that all authors, except Rehman et al. (2016), demonstrated that students' perception of enjoyment leads to their intention to use m-learning. Furthermore, Pramana (2018) and Rehman et al. (2016) identified the impact of perceived enjoyment on both constructs: perceived usefulness and perceived ease of use. This suggests that if students perceive using m-learning as enjoyable, they are more likely to perceive the m-learning system as easy to use and beneficial. Therefore, the following hypotheses are proposed:

H6: Perceived enjoyment directly influences student's behavior intention toward m-learning
H7: Perceived enjoyment directly influences student's perceived usefulness toward m-learning
H8: Perceived enjoyment directly influences student's perceived ease of use toward m-learning

The concept of convenience used in this study refers to the two dimensions, namely time and place. This study defines perceived convenience as the student's ability to access m-learning system without the restriction of time and location (Rehman et al., 2016). If the students have a mobility perspective that m-learning can be used anyplace and anytime, their willingness to accept m-learning will be increased. Perceived convenience has been studied extensively in the acceptance of the following new technology: MOOCs (Al-Adwan, 2020), mobile banking (Bhatiasevi, 2016), online shopping (Raman, 2019), and mobile payment (Teo et al., 2015). However, limited studies explored the impact of perceived convenience on student's intention to adopt m-learning in higher education environments and found that Rehman et al. (2016) appear to be the only one. Moreover, several studies confirmed when students feel that m-learning is accessible anywhere and anytime, they will perceive that m-learning is valuable and free of effort (Al-Adwan, 2020; Teo et al., 2015; Wong et al., 2015). Hence, several hypotheses are proposed:

H9: Perceived convenience directly influences student's behavior intention toward m-learning
H10: Perceived convenience directly influences student's perceived usefulness toward m-learning
H11: Perceived convenience directly influences student's perceived ease of use toward m-learning

Social influence constitutes the third factor in the category of individual-social aspects. In this study, social influence is defined as the persuasion exerted by significant individuals such as friends, supervisors, and lecturers to encourage students to use m-learning (Chelvarayan et al., 2020). Despite numerous studies investigating the effect of social influence on students' intention to use m-learning, the results remain somewhat inconclusive. Some research in higher education contexts has suggested that students' adoption of m-learning is influenced by the opinions of those close to them (Al-Azawei & Alowayr, 2020; Welch et al., 2020). However, Alturise et al. (2022), Hao et al. (2017), and Chelvarayan et al. (2020) reported contradictory findings. Furthermore, the impact of social influence on students' perceptions of the ease of use and usefulness of m-learning remains uncertain (Alturise et al., 2022; Hao et al., 2017; Rehman et al., 2016). This situation leads to the formulation of the following hypotheses:

H12: Social influence directly influences student's behavior intention toward m-learning
H13: Social influence directly influences student's perceived usefulness toward m-learning
H14: Social influence directly influences student's perceived ease of use toward m-learning

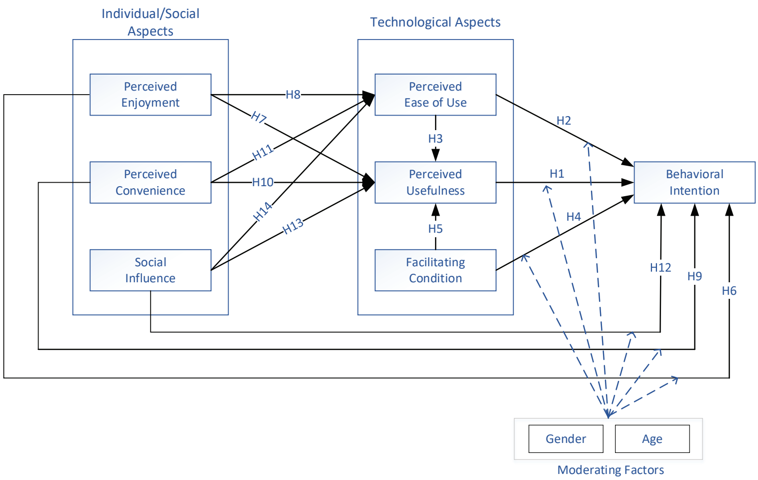
Figure 1 presents the theoretical model developed based on prior studies on m-learning adoption. The model consists of seven constructs and 14 direct effects, corresponding to the 14 hypotheses proposed earlier. In addition, two moderating variables, namely age and gender, are incorporated into the model to examine their influence on the strength of the direct relationships between the independent variables and behavioral intention. The decision to focus only on age and gender as moderating variables was driven by the inconsistent findings reported in previous studies regarding their effects (Welch et al., 2020; Pramana, 2018). Furthermore, prior research indicated that m-learning experience does not exhibit any significant moderating effect on the direct relationships with behavioral intention to adopt m-learning (Pramana, 2018). Thus it was excluded from the present model.

RESEARCH METHODOLOGY

This study has developed its research design following the guidelines outlined by Neuman (2014). It adopts a quantitative cross-sectional approach and collects data using self-administered questionnaires distributed to respondents via Google Forms. The choice of Google Forms as the data collection tool was due to its accessibility on mobile devices and the respondents' familiarity with its use, which facilitated the data collection process. However, familiarity with Google Forms does not imply prior adoption of m-learning, as completing a Google Form is not classified as a m-learning activity.

Figure 1

The theoretical model



The measurement items for the constructs are adapted from previous studies, as detailed in Table 2. Responses are elicited using a 5-point Likert scale to gauge students' opinions on each measurement instrument. Prior to distribution, the initial questionnaire underwent expert review by three individuals with experience in m-learning to ensure content validity. Subsequently, a pilot study was conducted to assess the clarity and appropriateness of all items.

The study utilizes purposive sampling, distributing the final questionnaire to potential respondents residing in various urban cities in Indonesia via Google Forms. The respondents consist of students from both public and private higher education institutions who have experience with m-learning.

To enhance representativeness and reduce sampling bias, the questionnaire was disseminated through multiple online academic networks, student communities, and university mailing lists to reach a diverse pool of respondents across different regions. Furthermore, screening questions were included to ensure the relevance of each participant to the research context. The study aims to gather a minimum of 400 valid responses to meet the recommended sample size for a 95% confidence level with a 5% margin of error, following Israel (2003).

Regarding data preparation, this study employed Confirmatory Factor Analysis (CFA) to assess the validity of all constructs, as recommended by Fornell & Larcker (1981). Additionally, reliability testing was conducted to evaluate the internal consistency of sets of indicators, utilizing Cronbach's alpha coefficients, following the guidelines outlined by George & Mallery (2003). After confirming the measurement model, the final data was analyzed using the Structural Equation Modeling (SEM) technique with Amos software. SEM was chosen due to its ability to simultaneously estimate multiple relationships among latent variables, making it particularly suitable for testing complex models involving direct, indirect, and moderating effects (Pramana, 2018; GC et al., 2024). This approach enables a comprehensive evaluation of both the measurement and structural models, ensuring the robustness of the findings.

Table 2

Items from the measurement

Variable, Reference	Instrument
Perceived Convenience, Wong et al. (2015)	PC1: M-learning enable me to perform learning process anytime
	PC2: M-learning enable me to perform learning process anywhere
	PC3: It is convenient for me to perform learning process using m-learning
	PC4: Compared to traditional learning methods, I believe that m-learning is more convenient
Perceived Enjoyment, Pramana (2018)	PE1: Using m-learning is fun
	PE2: M-learning makes me feel good
	PE3: I think, m-learning is interesting
	PE4: Using m-learning is enjoyable

Variable, Reference	Instrument
Social Influence, Ramírez-Correa et al. (2019)	SI1: People whose opinions I value prefer me to use m-learning
	SI2: People who influence my behavior think that I should use m-learning
	SI3: People who are important to me think that I should use m-learning
	SI4: The top students think that I should use m-learning
Perceived Usefulness, Lisana (2021)	PU 1: M-learning increases my learning productivity
	PU 2: M-learning enables me to perform learning activities more quickly
	PU 3: M-learning is useful in my learning
	PU 4: M-learning will increase my chances to get a better grade
Perceived Ease of Use, Sidik & Syafar (2020)	PEU1: I think it is easy to become skillful at using m-learning
	PEU2: M-learning is flexible and easy to use
	PEU3: I do not require much effort in using m-learning
	PEU4: My interaction with m-learning is clear and understandable
Facilitating Condition, Tarhini et al. (2017)	FC1: I have the knowledge necessary to use m-learning
	FC2: M-learning is compatible with other technologies I use
	FC3: I have the resources necessary to use m-learning
	FC4: I can get help from others when I have difficulties with m-learning
Behavioral Intention, Al-Azawei & Alowayr (2020)	BI1: I plan to use m-learning in the future
	BI2: I will always try to use m-learning in my daily study
	BI3: I intend to use m-learning in the future
	BI4: I will recommend other students to use m-learning

PRELIMINARY ANALYSIS

The study initially collected 758 responses from students across ten universities located in three major cities in Indonesia. However, 71 responses were deemed invalid due to incomplete data, resulting in 687 valid responses retained for analysis. The respondents' demographic profile is summarized in Table 3. Male students represented a slightly higher proportion, accounting for 52.8% of the sample, compared to 47.2% female students. In terms of age distribution, younger students aged between 18 and 21 years dominated the sample, comprising 62.7% of the respondents.

Table 3

Profile of respondent

Characteristic	Item	Frequency	Percentage
Gender	Male	363	52,8
	Female	324	47,2
Age (year)	Younger (18-21 years old)	431	62,7
	Older (22-40 years old)	256	37,3

Prior to conducting SEM analysis, the validity and reliability of the variables in the theoretical model were assessed using Confirmatory Factor Analysis (CFA) and Cronbach alpha coefficients, respectively. Both testing results are summarized in Table 4. The construct validity is deemed satisfactory as indicated by loading factor values exceeding 0.4 for all indicators, as suggested by Straub et al. (2004). Additionally, the values of Average Variance Extracted (AVE) and Composite Reliability (CR) are greater than 0.5 and 0.7, respectively, meeting the criteria recommended by Fornell & Larcker (1981). The validity test results confirm both convergent and divergent validity of the constructs. Furthermore, following George & Mallery's (2003) interpretation, the Cronbach alpha coefficients for all constructs demonstrate satisfactory results. Additionally, the results presented in Table 4 and Table 5 confirm satisfactory discriminant validity, as each construct exhibits a higher AVE value than all correlation coefficients associated with it. All correlations among constructs in the theoretical model are positive and significant at the 0.01 level or less.

Table 4

Result of validity and reliability testing

Latent variable	Indicator	Factor loading	CR	AVE (√AVE)	Cronbach alpha	Interpretation
Perceived Enjoyment	PE3	.808	.852	.590	.885	Good
	PE4	.780		(.768)		
	PE2	.778				
	PE1	.703				

Latent variable	Indicator	Factor loading	CR	AVE (√AVE)	Cronbach alpha	Interpretation
Perceived Usefulness	PU2	.839	.841	.571 (.756)	.870	Good
	PU3	.793				
	PU1	.700				
	PU4	.678				
Behavioral Intention	BI3	.825	.847	.583 (.763)	.852	Good
	BI4	.803				
	BI2	.741				
	BI1	.676				
Perceived Ease of Use	PEU3	.818	.838	.567 (.752)	.844	Good
	PEU4	.783				
	PEU2	.777				
	PEU1	.618				
Social Influence	SI2	.806	.865	.616 (.785)	.829	Good
	SI1	.802				
	SI4	.778				
	SI3	.752				
Perceived Convenience	PC2	.803	.819	.533 (.730)	.782	Acceptable
	PC1	.779				
	PC3	.688				
	PC4	.639				
Facilitating Condition	FC2	.810	.805	.512 (.715)	.757	Acceptable
	FC1	.758				
	FC3	.676				
	FC4	.599				

Table 5

Correlation matrix

Variables	PC	SI	FC	PE	PEU	BI	PU
Perceived Convenience	1						
Social Influence	.301**	1					
Facilitating Condition	.297**	.278**	1				
Perceived Enjoyment	.441**	.324**	.378**	1			
Perceived Ease of Use	.368**	.252**	.486**	.437**	1		
Behavioral Intention	.391**	.296**	.372**	.476**	.448**	1	
Perceived Usefulness	.436**	.313**	.318**	.594**	.456**	.495**	1

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

Meanwhile, the results of the descriptive statistics showed that the mean values of all variables are higher than a neutral value of 3, as shown in Table 6. The skewness and kurtosis magnitudes of all constructs also fulfilled the criteria from Kline (2016).

Table 6

Skewness and kurtosis

Variable/ Indicator	Mean	Std. Dev	Skewness	Kurtosis	Variable/ Indicator	Mean	Std. Dev	Skewness	Kurtosis
AvPC	4.27	.486	-.198	-.824	AvPU	3.90	.618	-.003	-.529
PC1	4.36	.606	-.364	-.665	PU1	4.15	.606	-.085	-.394
PC2	4.37	.626	-.481	-.653	PU2	3.96	.768	-.264	-.507
PC3	4.24	.619	-.215	-.597	PU3	3.84	.750	.056	-.804
PC4	4.13	.650	-.165	-.538	PU4	3.68	.751	.139	-.560
AvSI	3.43	.597	.152	.155	AvPEU	3.85	.555	.130	.037
SI1	3.22	.706	.354	.283	PEU1	3.75	.700	-.073	-.261
SI2	3.30	.730	.242	.007	PEU2	3.78	.679	.015	-.373
SI3	3.32	.792	.059	-.397	PEU3	3.95	.634	-.099	-.113
SI4	3.89	.698	-.179	-.197	PEU4	3.92	.675	-.128	-.237
AvFC	3.76	.500	.228	.079	AvBI	4.05	.577	-.031	-.380
FC1	3.74	.667	.034	-.327	BI1	4.21	.660	-.257	-.756
FC2	3.89	.629	-.128	.028	BI2	3.95	.718	-.138	-.515

Variable/ Indicator	Mean	Std. Dev	Skewness	Kurtosis	Variable/ Indicator	Mean	Std. Dev	Skewness	Kurtosis
FC3	3.72	.650	.057	-.329	BI3	4.02	.682	-.158	-.421
FC4	3.71	.687	.093	-.410	BI4	4.05	.706	-.269	-.369
AvPE	3.86	.618	.201	-.403					
PE1	3.88	.710	-.041	-.535					
PE2	3.94	.692	-.155	-.301					
PE3	3.80	.735	.161	-.808					
PE4	3.84	.724	.027	-.635					

RESULT

Figure 2 depicts the direct effect results among all latent variables in the theoretical model produced by Amos software. All hypotheses, excluding both causal effects facilitating condition toward perceived usefulness (H5) and perceived convenience to behavioral intention (H9), are statistically significant at the level of 0.001 or less. Furthermore, the causal model was examined using the interpretation criteria proposed by Kline (2016), and the fit statistics results are satisfactory, as presented in Table 7.

Figure 2

SEM analysis

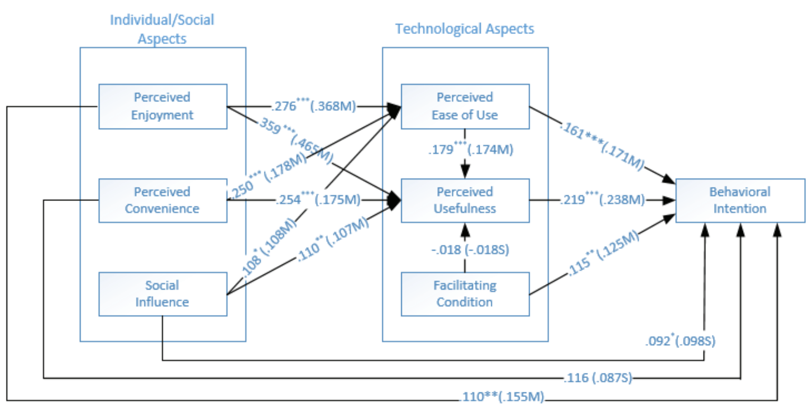


Table 7

Fit statistics

Sample Size	Normed chi-square (NC) = $\chi 2/df$	RMR	GFI	AGFI	NFI	IFI	CFI	RMSEA
687	1038.332/330= 3.146	0.030	0.900	0.877	0.896	0.927	0.926	0.056
	R^2: BI: 0.408; PEU: 0.283; PU: 0.519							

Notes: R2 is the proportion of the variance explained by the variables that affect it

This study investigated both the direct and indirect effects of the factors in two aspects: the individual-social aspect and the technological aspect on the student's intention to use m-learning. The heuristic from Cohen & Cohen (1983) was used to determine the significance of indirect effects. The significance of total effects: direct and indirect, was evaluated using a thousand random samples in a nonparametric bootstrapping feature from Amos software. Table 8 displays the complete analysis results, and the value is presented using the following format. The first number refers to the unstandardized effect. The adjacent symbol of *, **, ***, or ^{ns} refers to the statistical significance level of 0.05, 0.01, 0.001, or not significant. Next, the value of the standardized effect with its magnitude is provided within parentheses. The magnitude symbol follows the interpretation from Cohen & Cohen (1983): S (small), M (medium), or L (large).

Table 8

Direct and indirect analysis

Factor	Effect	Behavioral Intention (BI)	
Perceived Enjoyment (PE)	Direct		0,110**(0,16M)
	Indirect	PE-PEU-BI	0,044***(0,063S)
		PE-PEU-PU-BI	0,011***(0,015S)
		PE-PU-BI	0,079***(0,111M)
	Total Indirect		0,134***(0,189M)
	Total Direct & Indirect		0,244***(0,344M)

Factor	Effect	Behavioral Intention (BI)	
Perceived Convenience (PC)	Direct		0,116^{ns}(0,09S)
	Indirect	PC-PEU-BI	0,040***(0,030S)
		PC-PEU-PU-BI	0,010***(0,007S)
		PC-PU-BI	0,056***(0,042S)
	Total Indirect		0,106***(0,079S)
	Total Direct & Indirect		0,222**(0,166M)
Social Influ-ence (SI)	Direct		0,092*(0,100S)
	Indirect	SI-PEU-BI	0,017*(0,018S)
		SI-PEU-PU-BI	0,004*(0,004S)
		SI-PU-BI	0,024**(0,025S)
	Total Indirect		0,046**(0,048S)
	Total Direct & Indirect		0,138***(0,146M)
Perceived Ease of Use (PEU)	Direct		0,161***(0,17M)
	Indirect	PEU-PU-BI	0,039***(0,041S)
	Total Indirect		0,039*(0,041S)
	Total Direct & Indirect		0,200***(0,212M)
Perceived Usefulness (PU)	Direct		0,219***(0,238M)
	Indirect	None	None
	Total Indirect		None
	Total Direct & Indirect		0,219***(0,238M)
Facilitating Condition (FC)	Direct		0,115**(0,13M)
	Indirect	FC-PU-BI	-0,004^{ns}(-0,004S)
	Total Indirect		-0,004^{ns}(-0,004S)
	Total Direct & Indirect		0,111*(0,121M)

Lastly, this study examined whether gender and age moderate the six relationships between factors in both aspects and behavioral intention, as depicted in Figure 1. For each moderator, two groups were created, as shown in Table 3. The results claimed that gender appeared to be a significant moderator only on the direct effect of perceived enjoyment on the behavioral intention with the difference value of unstandardized effect between group 1 (male) and group 2 (female) of -0.193. However, another finding confirmed that age did not significantly affect any of the six direct effects paths of the theoretical model.

DISCUSSION AND CONTRIBUTION

The analysis results of the direct effects on the theoretical model, as depicted in Figure 2, validate 12 out of 14 hypotheses. The two hypotheses that are not statistically significant are the direct effects of facilitating conditions on perceived usefulness (H5) and perceived convenience on behavioral intention (H9). Among the 14 hypotheses, six pertain to the direct effects of each of the six factors on behavioral intention, and five of them are supported. Notably, the technological aspects, perceived usefulness (H1) and perceived ease of use (H2), emerge as the top two influential factors affecting students' intention to adopt m-learning, while facilitating conditions (H4) rank fourth. This finding suggests that in deciding to use m-learning, students at higher education levels prioritize the system's ability to offer benefits, ease of usage, and reliability of resources, consistent with findings from prior studies (Kwabena et al., 2021; Al-Adwan, 2020; Hao et al., 2017). As an implication, to increase the adoption of m-learning, both institutional organizations and m-learning developers are encouraged to focus on developing more useful and informative content within the system. Additionally, designers should adhere to established standard guidelines when designing the user interface to ensure simplicity and ease of use. Lastly, the m-learning system should provide students with informative guidance and responsive technical support.

Meanwhile, only perceived enjoyment (H6) and social influence (H12) are statistically significant in developing student intention toward m-learning usage in the individual-social aspects. This means that students are willing to use the m-learning platform if it is fun and their friends and families are using it, which is in line with several studies (Sitar-Tăut, 2021, Alturise et al., 2022, Dumpit & Fernandez, 2017). Therefore, this finding leads to recommendations to the m-learning developers and strategic decision-makers in higher education institutions to create the learning materials by taking advantage of multimedia, so the students can perform learning activities with more enjoyment and unstressful using their mobile devices. In the social context, top management in universities should create a strategic plan, especially for the academic community (students, lecturers, and staff), to promote m-learning as a new innovative method in the learning process.

However, it is important to acknowledge that the implementation of m-learning strategies is not without challenges. Institutions may face several barriers, such as unequal access to mobile devices or reliable internet connectivity among students, particularly in less developed areas. Furthermore, varying levels of digital literacy, resistance to pedagogical change among faculty members, lack of institutional support or clear policy frameworks, and difficulties in ensuring student engagement and motivation in m-learning environments may hinder the success of m-learning initiatives. Addressing these challenges requires comprehensive planning, ongoing training for both educators and learners, and sustained institutional commitment to digital transformation in education.

Surprisingly, the only individual-social factor that does not affect student's decisions toward m-learning usage is perceived convenience (H9). This finding indicates that the flexibility offered by m-learning, particularly in terms of time and location, does not significantly influence students' intention to use it. This result is consistent with the study by Teo et al. (2015), which similarly reported that perceived convenience had no significant impact on technology adoption in educational settings. A possible explanation for this outcome is that flexibility in time and place has become a normative expectation among students in urban higher education environments, especially post-pandemic, where digital tools are already widely integrated into academic routines. As such, convenience may no longer be viewed as a differentiating or motivating factor.

In the technological aspect, facilitating condition was found to have no significant influence on perceived usefulness (H5) in the context of m-learning adoption. This result suggests that even when technical and organizational support is available, it does not necessarily enhance students' perception of the usefulness of m-learning platforms. One possible interpretation of this finding is that students may perceive mobile technologies and related infrastructures as already ubiquitous and accessible, thereby diminishing the perceived importance of additional facilitating conditions in shaping their evaluation of m-learning's usefulness.

As mentioned earlier, this study analyzes not only direct effects but also indirect effects. Table 8 presents that only five determinants, excluding perceived usefulness, have indirect effects on behavioral intention, bringing the total indirect effects to 11. Each determinant in the individual-social aspects: perceived enjoyment, perceived convenience, and social influence, has three indirect effects respectively. Meanwhile, in the technological aspects, two determinants: perceived ease of use and facilitating condition, have one indirect effect for each. Regardless of the indirect effect of facilitating condition on behavioral intention, all indirect effects are found positive and significant at the level of 0.05 or less. The results show that all indirect effects have a small magnitude, except for the indirect effect from perceived enjoyment to perceived usefulness and subsequently to behavioral intention, which has a medium magnitude. This result highlights the importance of perceived enjoyment on the development of student's intention toward m-learning usage indirectly through the mediating factor of perceived usefulness.

Another significant finding pertains to the analysis of the total direct and indirect effects of factors within both technological and individual-social aspects, as outlined in Table 8. Notably, within the individual-social aspect, perceived enjoyment exhibits the highest total effect on behavioral intention, followed in descending order by perceived usefulness, perceived ease of use, perceived convenience, social influence, and facilitating conditions. However, the analysis of direct effects reveals a different sequence: perceived usefulness, perceived ease of use, perceived enjoyment, facilitating conditions, and social influence. This discrepancy underscores the importance of examining total effects, particularly for factors within the individual-social aspect, such as perceived convenience and social influence. Despite perceived convenience having a small magnitude and insignificant direct effect on behavioral intention, the total effect is significant at the 0.01 level with a medium magnitude, supporting findings from a study by Rehman et al. (2016). Additionally, while the direct effect of social influence on behavioral intention is small and significant at the 0.05 level, it exhibits a significant total effect at the 0.001 level with medium magnitude. Hence, analyzing both indirect and total effects is crucial for enhancing the insights derived from direct effects, as advocated by Lisana (2021) and Pramana (2018).

Furthermore, this study unveiled the significance of gender as a moderating factor in the relationship between perceived enjoyment and behavioral intention. This finding suggests that female Indonesian students at higher education levels place greater emphasis on the enjoyable aspects of the system when using m-learning. As a significant implication, m-learning developers should prioritize the development of learning materials that offer more enjoyment and pleasure, particularly catering to female students. Interestingly, this result contrasts with the findings of Pramana (2018), who reported no significant moderating effect of gender on the relationship between perceived enjoyment and behavioral intention. It also diverges from Welch et al. (2020), who found gender to be a significant moderator in the relationship between perceived usefulness and behavioral intention. These inconsistencies may be attributed to contextual differences, such as cultural background, sample characteristics, or shifts in user interaction with mobile learning technologies. However, contrary to gender, age does not emerge as a significant moderating factor in any direct effect between each factor and behavioral intention.

CONCLUSION, LIMITATION, AND FUTURE RESEARCH

In conclusion, this study reveals that students at the higher education level, especially in Indonesia, still prioritize technological aspects when deciding to use m-learning, based on the direct effect results. However, upon analyzing the total effect, individual-social aspects emerge as having the most significant impact on student's intention toward m-learning usage. A comprehensive investigation was conducted by analyzing the direct, indirect, and total effects of all factors on students' intentions toward m-learning usage, along with assessing the moderating role of two factors, age, and gender, on the direct effects on behavioral intention. This study is expected to address the gap in limited m-learning adoption research, particularly in the context of Indonesia.

However, the study encounters several limitations. First, the study observed the behavioral intention of Indonesian students in the context of m-learning adoption, and therefore, the findings cannot be generalized to other countries or educational contexts. In addition, as the sample was drawn specifically from urban university students in Indonesia, the generalizability of the results is limited to this demographic group. Caution should be exercised when extending the conclusions to students in rural areas or different cultural and socioeconomic settings within Indonesia or other countries. Second, to examine the significance of the moderating effect of age, the median value divided the respondents into two groups. Meanwhile, using different groups may produce different outcomes. Lastly, the study focused only on the two categories, each of which has three factors that influence student's perception of using m-learning. Adding other constructs in each category may yield different findings. This study opens the door for future research by considering adding other categories to increase the explanatory power of the research model, using different moderating effects (e.g., experience, uncertainty avoidance), and assessing the model with respondents from other countries.

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