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Factors affecting university students switching intention to mobile learning: a push-pull-mooring theory perspective

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Abstract

Adopting technology by its intended users is one of the most important contributors to that technology's success. Therefore, the success of mobile learning (ML) depends on the students' acceptance of the method. Regarding this point, this quantitative research aims to identify factors that affect switching intention to adopt ML among university students in Indonesia based on migration theory, Push-Pull-Mooring (PPM) framework. A theoretical model was developed to examine the determinants that affect students' decision to use ML platforms. This study used an online survey questionnaire to obtain 616 valid responses. A comprehensive analysis of the influence factors of users switching behavior, including the moderating factors, was conducted using Structural Equation Modeling (SEM) and Amos software. The results confirmed that the push factor (learning convenience), pull factors (learning autonomy and enjoyment), and mooring factor (student innovativeness) are perceived as significant factors for accepting ML. Concerning the moderating factor, this study also revealed the significance of moderating factor experience in two causal effects of enjoyment and student innovativeness on the students' intention to switch using ML. Furthermore, based on the findings, several recommendations were suggested for the university policy-makers to develop effective strategic plans to get a competitive advantage.

Keywords Push-pull-mooring · Mobile learning · Switching intention · Moderating factor

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1 Introduction

Many people today heavily depend on mobile devices to support their daily activities. In the educational system, notably in higher education institutions (HEIs), the rapid growth of mobile technologies has impacted the students in increasing their cognitive knowledge by using their portable devices known as mobile learning (ML). ML can be defined as the use of mobile devices, including smartphones, notebooks, laptops, personal digital assistants, and tablets, to perform learning activities anytime and anywhere through wireless communication technologies, which is adapted from Pramana (2018). This promising learning method offers some advantages for the students in terms of convenience and flexibility matters (Chavoshi and Hamidi, 2019). Students may access the resources and conduct the learning process at their own pace via mobile devices without limitation of place and study time. Several studies provided evidence of how ML may enhance students' learning achievements and increase their level of knowledge in HEIs (Oyelere et al., 2018; Kaliisa et al., 2019; Troussas et al., 2020). Additionally, university students of this generation appear to be primed for ML, as they are predominantly composed of generation Z who grow up in a technology-savvy environment (Yeap et al., 2016; Lisana & Suciadi, 2021).

As a developing country and the fourth most populous country, Indonesia's population has reached 273.5 million people in 2020 (Worldometer, 2021). Another survey from Statista (2021a, 2021b) reported that 67% of those populations (183.7 million) are mobile phone users. In addition, 345.3 million mobile internet connections were available in 2020, exceeding the total population (Lisana, 2021; Datareportal, 2021). According to the Indonesian Central Bureau of Statistics, generation Z dominated the Indonesian people in 2020, counting 27.94% of the total population (Triyasni, 2021). This condition provides evidence that the implementation of ML in Indonesia is still promising. However, some studies revealed that the adoption of ML is still low and at the infancy stage, especially in developing countries (Magsayo, 2021; Kaliisa et al., 2019; Moya & Camacho, 2021). Thus, a study is needed to explore the key drivers of ML adoption, particularly in Indonesia, one of the largest developing countries.

The extant studies in the ML context have explored several factors that may impact students' intention in HEIs to accept ML in various countries using some prominent technology adoption models, such as the technology acceptance model (TAM) (Qashou, 2021; Adanır & Muhametjanova, 2021; Mutambara & Bayaga, 2021) and the unified theory of acceptance and use of technology (UTAUT) (Hu et al., 2020; Hoi, 2020; Chao, 2019). However, all these studies are only concerned with the students' direct intention to adopt ML. None of the authors examined the influencing factors toward the ML platform based on switching behavior perspectives, specifically in HEIs.

Push-Pull-Mooring (PPM) is a theory that provides an understanding of the factors that drive individuals to switch from the original platform to the new one (Lin et al., 2021b). PPM recognizes that three effects influence individual migration: push effect as a negative effect, pull effect as a positive effect, and mooring effect. While the push effect forces individuals to leave the current platform, the pull effect drives individuals to the new one (Yoon & Lim, 2021). The mooring effect refers to interpersonal and individual cultures that may facilitate or prevent an individual's decision to migrate

(Chen et al., 2020). Lin et al., (2021b) argued that individual willingness to switch could be captured using this complete three-dimensional framework. Meanwhile, PPM theory has been widely used to explore the individual's switching behavior on various platforms and countries, such as mobile payment in Taiwan (Lu & Wung, 2021), online learning in China (Lin et al., 2021a), internet banking services in Korea (Yoon & Lim, 2021), and mobile game in China (Liu & Lee, 2020). However, in the ML context, to the best of my knowledge, none of the empirical ML research adapted PPM theory in their proposed research models, especially in Indonesia.

This study aims to fill the gap in the literature by proposing a theoretical model that utilizes the PPM framework to examine the factors that affect an individual's decision to use ML, derived from prior ML adoption studies. According to Lin et al., (2021a), the factors influencing individuals' switching intention may vary. The proposed theoretical model employs learning convenience as the foremost push effect factor, while learning autonomy and perceived satisfaction as the essential two pull effect factors. With regard to mooring factors, the study intends to explore the impact of student innovativeness and network externalities on behavior intention to switch using ML. In addition, this study investigates the influence of two moderating effects: gender and experience, on the relationship between PPM factors and students' behavior intention. Hence, this study addresses the following two research questions: (1) What PPM factors affect the students' intention to use ML?; (2) How do gender and experience moderate the effect of PPM factors on intention to adopt ML? Furthermore, the study's findings theoretically contribute to the existing literature on the key factors that drive university students to accept ML using a switching behavior perspective, more specifically in Indonesia, which is still less attention. In practice, the findings are intended to be used as strategic guidelines by top management in HEIs to produce effective policies to encourage more students to use ML.

2 Theoretical background

This section provides a rigorous literature review of the recent studies on ML adoption and the PPM framework usage to capture an individual's switching behavior.

2.1 ML adoption research

Recently, research in the ML adoption context has gained popularity. A systematic review conducted by Kumar & Chand (2019) confirmed that the number of published articles related to the acceptance of ML had increased significantly. They also found that TAM was the most used adoption model, followed by UTAUT. Meanwhile, in the higher education context, some authors have investigated what motivates students to use ML in several countries, as summarized in Table 1. It can be seen that most of those research mainly employed TAM and UTAUT as a base theory when developing their theoretical model, which strengthened the finding of Kumar & Chand (2019). However, none of the studies in ML usage focused on switching behavior perspectives. Moreover, only a few studies explored the moderating factors' role on students' intention toward ML adoption.

Table 1 Previous ML adoption studies in HEIs

Focus of Study	Variable	MF	Country	Reference
ML Adoption Studies Based on TAM				
Influencing factors in m-learning adoption in higher education	PU, PEU, PM, ENJ, SE, AT, BI	-	Palestine	Qashou (2021)
University students' acceptance of mobile learning	PU, PEU, SN, SE, LA, PBC, AT, BI, Instructor and Student readiness	-	Turkey and Kyrgyzstan	Adanır & Muhamet-janova (2021)
Determinants of mobile learning acceptance for STEM education in rural areas	PU, PEU, SI, PE, AT, BI, Perceived skills readiness, resources, psychological readiness	-	South Africa	Mutam-bara & Bayaga (2021)
Adoption of mobile technology for mobile learning by university students during COVID-19	PU, PEU, AT, BI, Mobile system and mobile service efficacy	-	India	Zaidi et al., (2021)
The acceptance of 3D simulation android app for learning physics	PU, PEU, ENJ, BI	-	Indonesia	Lisana & Suciadi (2021)
Exploring university students' intention to use mobile learning	PU, PEU, SN, SE, AT, BI	-	Ghana	Buabeng-Andoh (2021)
Factors that influence adoption of mobile learning in higher education	PU, PEU, Personal and Social integrative gratification, Cognitive and Hedonic gratification	-	Jordan	Aburub & Alnawas (2019)
University students' intention to use mobile learning management systems	PU, PEU, PM, AT, BI, Academic Relevance, Univ Management Support	-	Sweden	Saroia and Gao (2019)
Factors affecting the intention to adopt m-learning	PU, PEU, Mobile system efficacy, System quality, Intrinsic motivation	-	Srilanka	Senaratne et al., (2019)
ML Adoption Studies Based on UTAUT				
Mobile learning acceptance in social distancing during the COVID-19 outbreak	PE, EE, SI, FC, HM, BI	-	Romania	Sitar-Tăut (2021)
Factors affecting academics' adoption of emerging mobile technologies	PE, EE, SI, FC, HM, PV, HT, BI	Gender, age, experience, discipline	China	Hu et al., (2020)
Higher education learners' acceptance and use of mobile devices for language learning	PE, EE, SI, FC, AT, BI	-	Vietnam	Hoi (2020)
Factors affecting mobile learning adoption in the science museum	PE, EE, SI, FC, BI, Self-directed learning	Age, gender	UK	Welch et al., (2020)

Table 1 (continued)

Focus of Study	Variable	MF	Country	Reference
Factors determining the behavioral intention to use mobile learning	PE, EE, ENJ, SE, Trust, BI, Satisfaction	Perceived risk	Taiwan	Chao (2019)
Habit and hedonic motivation are the strongest influences in mobile learning behaviors among higher education students	PE, EE, SI, FC, HM, PV, HT, BI	-	Malaysia	Moorthy et al., (2019)

Note(s): AT = Attitude, BI = Behaviour intention, EE = Effort expectancy, FC = Facilitating condition, HM = Hedonic motivation, HT = Habit, LA = Learning autonomy, PU = Perceived usefulness, PEU = Perceived ease of use, PE = Performance expectancy, PBC = Perceived behavioral control, ENJ = Perceived enjoyment, PM = Perceived mobility, PV = Price Value, SN = Subjective norm, SE = Self efficacy, SI = Social influence

2.2 PPM theory

The PPM theory initially aims to describe human migration from the original place to a new destination (Lu & Wung, 2021; Fan et al., 2021). Three effects mainly influence the decision to migrate: push, pull, and mooring effects (Yoon, 2021). The push effect refers to the negative factors from the current location that force people to move to a better destination, while the pull effect relates to the positive factors from a new destination that attracts people to come (Kim et al., 2020; Chen & Keng, 2018). Mooring effect, however, correlates with personal and social factors that affect people to decide whether to migrate or not (Liu & Lee, 2020; Xu et al., 2021; Fan et al., 2021).

Due to the similarity between migration and an individual's switching behavior, many researchers adopted PPM as an underlying theory to examine individual behavioral transformation. Table 2 presents the recent studies of switching behavior based on the PPM framework in several contexts, including the various factors adopted in each effect. However, no scholars focused on student intention to switch toward the ML platform, specifically in HEIs. Furthermore, most of the studies were conducted in developed countries such as China, Korea, and Taiwan, but very limited in developing countries.

3 Theoretical model and hypotheses development

Push Effect

This study refers to the push effect as the factor that pushes students away from the existing traditional learning methods (Kim et al., 2020). Meanwhile, Chen et al. (2020) argued that the push effect relates to negative factors that generate bad student learning experiences and influence student switching intentions. Previous studies agreed that learning convenience is one of the important push factors that affect the decision of university students to leave attending physical classes and change to use online learning platforms (Jin et al., 2021; Lin et al., 2021a; Chen & Keng, 2018). Learning convenience is defined as the ability of the students to perform learning activities in unlimited time and space (Lin et al., 2021a). Meanwhile, according to Pramana (2018), the feeling of the inconvenience of being present in physical class-

Table 2 Prior studies based on PPM theory

Authors	Context	Country	Factors			DV	MF
			Push	**Pull**	**Mooring**		
Yoon and Lim (2021)	Internet-only banking services	Korea	DS, Operation policy	PU, Low cost, Peer influence	SC, Low IT innovativeness	SWI	-
Fan et al. (2021)	Mobile payment	China	DS on system quality, DS on service quality	Relative advantage of substitute IT, Critical Mass	SC, PI	SWI	SC, PI
Xu et al. (2021)	Online learning platforms	China	DS, Information overload	Functional value, Network externalities	SC, Affective commitment	Switching behavior	-
Lu and Wung (2021)	Mobile payment	Taiwan	Perceived trouble, Perceived no record for transaction, Difficult to pay large amount in cash	LC, Perceived benefit, Saving time	HT	SWI	Age, Gender
Lin et al. (2021a)	Online learning platforms	China	LC, PR, Service quality	TF, PEU, PU, Teacher's teaching attitude	HT, SC	SWI	HT, SC
Sun et al. (2017)	Mobile instant messaging (MIM) apps	China	DS with incumbent MIM, Fatigue with incumbent MIM	AA, Subjective norm	IN	SWI	-
Kim et al. (2020)	AR/VR	Korea	Low usefulness, Functional simplicity, Perceived inefficiency	Interactivity, Experienceability, Amplified enjoyment	PI	SWI	PI
Zhou (2016)	Mobile stores	China	DS with system quality, DS with information quality, DS with service quality	AA	SC, SI	SWI	-

Table 2 (continued)

Authors	Context	Country	Factors			DV	MF
			Push	**Pull**	**Mooring**		
Hsieh (2021)	Medical mobile payment	Taiwan	PR, Low satisfaction	PEU, The relative advantages, Compatibility, Trialability, Image	SI, IN, SC, Sunk costs, Regret avoidance, Perceived net benefits, Uncertainty costs	SWI	-
Mu and Lee (2021)	Proximity mobile payment	Korea	DS	PEU, PU, Perceived substitutability	PR, Perceived technical compatibility	SWI	-
Jin et al. (2021)	Online learning teaching	China	LC, Security, Service quality	PU, PEU, TF, Instructor attitude	HT	SWI	HT
Liu and Lee (2020)	Mobile game	China	DS	Relative challenge	HT, Bridging social capital	SWI	HT, Bridging social capital
Chen et al. (2020)	VR-based online education platforms	Korea	Afunction, Loyalty index	Interactivity, Personalization	PR, System quality, Relationship quality	learners' willingness	-
Chen and Keng (2018)	Online real-person English learning platforms	Taiwan	LC, Service quality, Perceived price	PU, E-learning motivation	SC, Learning engagement, Social presence	SWI	-
Li (2018)	Mobile apps	Taiwan	Poor aesthetic design	Locatability, Transaction convenience, Economic benefit, Gamification	IN, Perceived substitutability	SWI	IN, Perceived substitutability

Note(s): AA=Alternative attractiveness, DS=Dissatisfaction, HT=Habit, IN=Inertia, LC=Learning Convenience, PU=Perceived usefulness, PEU=Perceived ease of use, PI=Personal innovativeness, PR=Perceived risk, SC=Switching costs, SWI=Switching Intention, SI=Social influence, TF=Task-technology fit

rooms is the main driver influencing the behavior intention of university students to adopt the ML platform. Further, some authors also confirmed the importance of convenience in students' willingness to use ML in HEIs (Qashou, 2021; Saroia and Gao, 2019). Thus, this hypothesis is proposed:

> H1: Learning convenience positively influences students switching intention to adopt ML

Pull Effect

The pull effect is associated with the positive factors offered by the ML platform that enchant students to use it. According to Lin et al., (2021a), if students feel that the new alternative learning platform provides better services, they will replace the existing one. This study proposes two pull factors: learning autonomy and perceived enjoyment, which may attract students to use ML.

Learning autonomy, also known as self-management of learning, refers to the ability of students to control their learning process (Pramana, 2018). It enables students to gain their knowledge personally based on their own style and cognitive skill (Chen et al., 2020). Qunfei et al.'s (2020) study revealed that learning autonomy was the most motivational factor for college students to accept online learning. In the context of ML, some studies confirmed the significance of learning autonomy on students' behavior intention in HEIs (Yeap et al., 2016; Raza et al., 2018; Masrek & Samadi, 2017). However, from the PPM perspective, the effect of learning autonomy on switching behavior intention was still underexplored. Hence, this study develops this hypothesis:

> H2: Learning autonomy positively influences students switching intention to adopt ML

The second pull effect factor employed in this study is perceived enjoyment. This study defines perceived enjoyment as the extent to which students believe that using ML to gain their knowledge is perceived to be enjoyable in its own right, regardless of any performance consequences that may be anticipated (Kim et al., 2020). One of the important factors in the educational environment is how to make the learning process unstressful and enjoyable (Rehman et al., 2016). Additionally, if ML as new innovative technology gives the students greater enjoyment in performing their learning activities, they intend to switch to using it. Several authors reported that perceived enjoyment strongly affects students' intention to adopt ML systems (Pramana, 2018; Lisana & Suciadi, 2021). Conversely, a study by Rehman et al., (2016) found that the influence of perceived enjoyment on student behavioral intention was insignificant. Therefore, the following hypothesis is proposed:

> H3: Perceived enjoyment positively influences students switching intention to adopt ML

Mooring Effect

The mooring effect relates to intervention variables that facilitate or hinder movement determination (Yoon & Lim, 2021). According to Kim et al., (2020), the intervening variables that complement the push-pull paradigm in the PPM framework are related to the environment and personal factors. As a result, this study proposes two mooring factors: student innovativeness as a personal factor and network externalities as an environmental factor.

This study defines student innovativeness as the students' willingness to switch and actively use ML in gaining new knowledge (Pramana, 2018). More innovative individuals expressed a greater willingness to accept new technologies. Prior studies confirmed that the personal trait factor strongly affects innovation technology

adoption behavior in various contexts, such as mobile payment (Fan et al., 2021), internet-only banks (Yoon & Lim, 2021), and both augmented and virtual reality (Kim et al., 2020). In the context of ML, highly innovative students are expected to have a more positive intention to incorporate ML as an innovative method into their learning process. However, the innovativeness factor is rarely considered in research on the switching behavior toward ML. Thus, the following hypothesis is developed:

> H4: Student innovativeness positively influences students switching intention to adopt ML

In this study, the network externalities factor is defined as the extent to which the perceived value of ML increases as the number of users grows (Lisana, 2021). It implies that the network's behavior toward the ML platform positively correlates with students' acceptance of the platform. The network refers to the friends, teachers, or family members who use ML. Meanwhile, some scholars argued that the network externalities factor is a critical driver in developing an individual's switching behavior to use new services in various contexts (Xu et al., 2021; Lisana, 2021; Fan et al., 2021). However, the role of this factor in investigating the switching behavior, especially in ML platforms, is still under investigation. Thus, this study proposes the following hypothesis:

> H5: Network externalities positively influence students switching intention to adopt ML

The theoretical model is developed based on recent literature on the acceptance of ML that has been described comprehensively in the hypotheses development. The model comprises five constructs that drive the students' intention to switch using the ML platform. All constructs are categorized into push, pull, and mooring effects, as depicted in Fig. 1. There are five direct effects, each of which is related to the aforementioned hypotheses (H1-H5). Meanwhile, in order to enrich the findings, this study employs two moderating factors: gender and experience in the relationship between constructs and intention to adopt ML.

4 Research methodology

This study uses a quantitative cross-sectional approach, following the guidelines from Neuman (2014). An online self-administered questionnaire was used to collect data about a student's experience when using the ML platform. The questionnaire is divided into two parts. The first part relates to the personal characteristics of the participants. The second part concerns the questions corresponding to the constructs of the theoretical model. The construct measurement items were developed based on prior research and adjusted to enhance the reliability and validity of the measures, as presented in Table 3. A five-point Likert scale was used to capture the respondent's agreement level with each measuring instrument. A nominal variable determined the
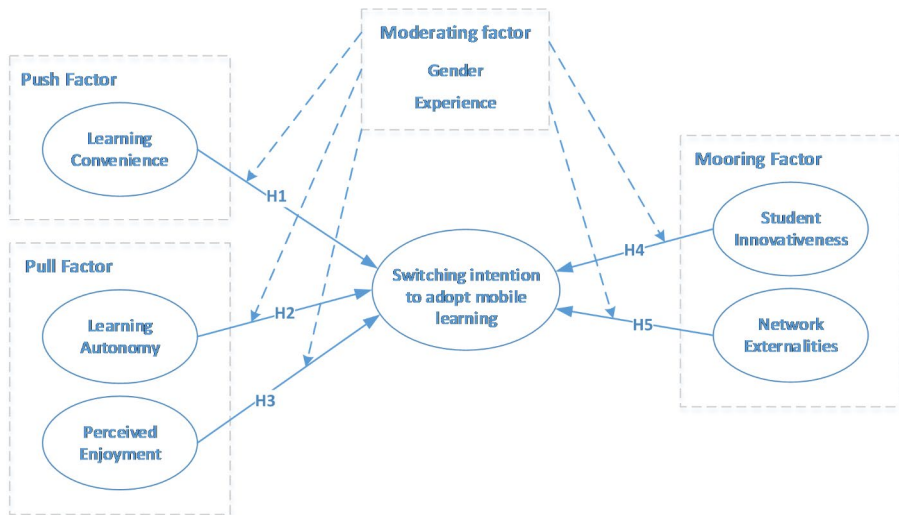
Fig. 1 The theoretical model

moderating factor of gender using the value of male or female. Meanwhile, the moderating factor experience used an interval scale variable.

To assure the survey's validity, the questionnaire was assessed by five experts in ML platforms, who provided insightful comments and recommendations. Ten respondents were then invited to do a pilot study to obtain feedback to finalize the questionnaire. The targeted respondents are Indonesian students currently studying in HEIs who have used ML. In order to achieve a 95% confidence level and 5% precision, a minimum sample size of 400 respondents is required, as suggested by Israel (2003). Further, this study used a purposive sampling method to disseminate surveys to the target respondents using Google Forms.

This study applied the components factor analysis (CFA) to assess the validity of the indicators of the constructs, following the guidelines from Straub et al., (2004). Additionally, the measurement's internal consistency was examined using cronbach's α coefficients, and the interpretation of the values was determined based on George & Mallery (2003) criteria. The descriptive statistics were then conducted to ascertain the data collected were ready to be analyzed using structural equation modeling (SEM).

5 Preliminary analysis

The data was collected during the covid 19 pandemic period, where the teaching and learning activities were conducted online. Consequently, most students have used ML more frequently for their learning activities. The targeted respondents were university students who have used ML in their learning activities. The questionnaires were distributed to 720 students from several universities in various Indonesian cities through an online survey. Initially, a total of 674 completed responses were obtained.

Table 3 Construct measurement items

Latent Variable (Symbol)	Indicator	Measuring instrument	Reference
Learning Convenience (LC)	LC1	With mobile learning, I can perform learning activities anytime.	Lu and Wung (2021)
	LC2	With mobile learning, I can perform learning activities anywhere.	
	LC3	I only need a mobile phone to perform learning activities.	
	LC4	I believe mobile learning is a very convenient learning tool.	
Learning Autonomy (LA)	LA1	Mobile learning enables me to be a self-directed learner.	Pramana (2018)
	LA2	I can be a self-disciplined learner when using mobile learning in my study.	
	LA3	Mobile learning enables me to manage my study time effectively.	
	LA4	I believe I can perform learning activities at my own pace by using mobile learning.	
Perceived Enjoyment (PE)	PE1	I believe mobile learning is more entertaining.	Lisana & Suciadi (2021)
	PE2	I am very excited about using mobile learning in my learning activities.	
	PE3	Using mobile learning is fun.	
	PE4	Using mobile learning in my study is more enjoyable.	
Student Innovativeness (SI)	SI1	I like to experiment with mobile learning as new information technology.	Yoon and Lim (2021)
	SI2	I am always the first to use new innovative technologies among my peers.	
	SI3	Overall, I am interested in mobile learning as a new way of acquiring new skills.	
Network Externalities (NE)	NE1	Many friends of mine use mobile learning.	Xu et al., (2021)
	NE2	My respected people, such as superiors and lecturers, recommend me to use mobile learning.	
	NE3	I believe more people will use mobile learning.	
Switching Intention (SW)	SW1	I would like to use mobile learning in the near future	Li (2018)
	SW2	Given the opportunity, I prefer to use mobile learning.	
	SW3	if possible, then I intend to switch to using mobile learning.	

Then, data cleaning was conducted using the SPSS worksheet, and found that 58 responses were excluded. Finally, the study used 616 questionnaires to be analyzed, and their detailed profile can be seen in Table 4.

Then, the convergence and discriminant validity of all constructs were assessed using principal factor analysis. As presented in Table 5, all variables were found to have satisfactory construct validity, with indicators loading significantly onto only their associated latent variable with loadings of magnitude exceeding the minimum level of 0.4 (Straub et al., 2004). Meanwhile, Cronbach's alpha coefficients were used to test the internal consistency of the existing sets of indicators. According to the interpretation provided by George & Mallery (2003), all constructs surpassed the threshold limit of 0.7, as shown in Table 6.

Furthermore, the descriptive statistics of all latent variables are presented in Table 7. The computation of the skewness and kurtosis values was carried out in order to guarantee that the data was suitable for use with the SEM (Structural Equation Modeling) approach to data analysis. Table 7 shows the results and indicates that

Table 4 Characteristics of respondents

	Frequency	Percent (%)		Frequency	Percent (%)
Gender			*Experience (month)*		
Male	330	53.6	1 to 38	311	50.5
Female	286	46.4	>38	305	49.5
Total	616	100	Total	616	100
Age (year)			*Field of Study*		
18	129	20.9	SE	294	47.7
19	178	28.9	Non-SE	322	52.3
20	163	26.5	Total	616	100
21	93	15.1	**Note**: SE = Science and Engineering		
22	33	5.4			
23	9	1.5			
24	11	1.8			
Total	616	100			

Table 5 Final factor analysis results

Indicator	Component					
	1	2	3	4	5	6
LA2	0.866					
LA3	0.863					
LA4	0.838					
LA1	0.817					
PE3		0.844				
PE4		0.843				
PE2		0.806				
PE1		0.781				
PC1			0.808			
PC2			0.805			
PC3			0.703			
PC4			0.659			
NE1				0.890		
NE2				0.878		
NE3				0.832		
SW1					0.840	
SW3					0.839	
SW2					0.821	
SI1						0.856
SI3						0.835
SI2						0.814

Notes: Extraction method: principal component analysis; Rotation method: equamax with Kaiser normalization; Rotation converged in six iterations.

skewness and kurtosis met the standard threshold (skewness < 3 and kurtosis < 7), as recommended by Kline (2016). The data was then ready to be analyzed using the

Table 6 Cronbach alpha coefficients

Latent Variable	Indicators	Cronbach Alpha	Interpretation	Latent Variable	Indicators	Cronbach Alpha	Interpretation
Perceived Convenience	PC1, PC2, PC3, PC4	0.778	Acceptable	Learning Autonomy	LA1, LA2, LA3, LA4	0.880	Good
Network Externalities	NE1, NE2, NE3	0.858	Good	Perceived Enjoyment	PE1, PE2, PE3, PE4	0.889	Good
Student Innovativeness	SI1, SI2, SI3	0.811	Good	Switching Behaviour	SW1, SW2, SW3	0.842	Good

SEM technique. Lastly, all correlation coefficients of the relationship between factors and switching intention are significant and positive (p<0.05), as seen in Table 8.

6 Result and discussion

6.1 Direct and Moderating Effects

All direct effects in the theoretical model were tested using the SEM technique applied in AMOS software. Figure 2 presents the values of each direct effect using the following format. The unstandardized effect and statistical significance level are written sequentially. There are four levels of statistical significance: 0.05, 0.01, 0.001, and not statistically significant, symbolized by *, **, ***, and NS, respectively. Meanwhile, the value written in the bracket represents the standardized effect with the magnitude using interpretation from Cohen (1988).

The goodness of fit for the causal model was assessed using several fit indices. Table 9 displays the complete results of all criteria and their interpretations based on the recommendation from Kline (2016). All results indicate that the model fit is satisfactory.

The SEM analysis results confirmed that all proposed hypotheses, excluding H5, were supported, as shown in Fig. 2. The one and only push factor, learning convenience (H1), had a positive significant direct effect on students' switching intention from the incumbent platform (classroom teaching) to ML at a level of 0.01. This is consistent with prior studies on switching intentions to online learning platforms (Lin et al., 2021; Jin et al., 2021; Chen & Keng, 2018) and mobile payment (Lu & Wung, 2021). For university students in Indonesia, the inconvenient feeling of attending physical classroom teaching becomes a significant push effect switching to ML. In other words, when ML provides the students with a convenient learning platform without being limited by time and space, a greater possibility of switching behavior occurs.

For two pull factors, the findings claimed that learning autonomy (H2) and perceived enjoyment (H3) positively influenced students' switching intention to ML at a level of 0.05 and 0.001, respectively. More specifically, perceived enjoyment was the major influencing factor leading to ML. The feeling of enjoyment and learning freedom perceived by students in HEIs when using ML are the main attractors for them to switch to using ML. The finding supports a study from Kim et al., (2020) that

Table 7 Descriptive statistics

Variable/Indicator	Mean	SD	Skewness	Kurtosis	Variable/Indicator	Mean	SD	Skewness	Kurtosis
LC	4.332	0.4661	−0.290	−0.697	LA	3,662	0.6363	0.072	−0.399
LC1	4.40	0.587	−0.390	−0.704	LA1	3,77	0.737	−0.008	−0.495
LC2	4.43	0.602	−0.531	−0.622	LA2	3,55	0.763	0.248	−0.436
LC3	4.31	0.594	−0.222	−0.615	LA3	3,63	0.741	−0.061	−0.306
LC4	4.20	0.624	−0.175	−0.572	LA4	3,69	0.727	0.115	−0.491
NE	3.516	0.6444	0.313	,0.065	PE	3,944	0.5807	0.279	−0.620
NE1	3.38	0.706	0.507	,0.081	PE1	3,95	0.671	0.024	−0.685
NE2	3.43	0.725	0.316	−0.162	PE2	4,02	0.628	−0.016	−0.458
NE3	3.73	0.758	0.026	−0.537	PE3	3,88	0.695	0.100	−0.796
SI	3.771	0.6217	0.054	−0.546	PE4	3,92	0.680	0.066	−0.758
SI1	3.82	0.744	−0.024	−0.573	SW	3,954	0.5784	0.258	−0.586
SI2	3.52	0.714	0.344	−0.301	SW1	4,30	0.620	−0.297	−0.647
SI3	3.97	0.731	−0.198	−0.478	SW2	4,08	0.652	−0.080	−0.652
					SW3	4,15	0.622	−0.114	−0.500

claimed the significance of perceived enjoyment on switching intention to AR/VR content services. In addition, the result also strengthened other research that argued the willingness of students to adopt mobile-based learning with 3D simulation only if they think it would be fun for them to use (Lisana & Suciadi, 2021). Meanwhile, most prior studies also affirmed the significant impact of learning autonomy on intention toward ML acceptance (Yeap et al., 2016; Raza et al., 2018; Masrek & Samadi, 2017).

With regard to the mooring factors, the results showed that the first factor, student innovativeness (H4), had a positive impact on switching intention to ML at a level of 0.01. The finding emphasizes the significance of personal innovativeness on individuals' switching intentions in various contexts, as reported by Fan et al., (2021) and Yoon & Lim (2021). Student innovativeness plays an essential role in increasing the switching behavior of university students in Indonesia. More innovative students produce higher positive switching intention to ML. However, this study failed to show the influence of the second mooring factor, network externalities (H5), on students' switching intention to ML. It indicates that students in HEIs did not connect emotionally to their network in developing their switching intention to use ML. This result is consistent with the investigation study of mobile payment adoption from Lisana (2021) but contradicts the findings from several prior studies, which argued that network externalities positively affect switching behavior (Xu et al., 2021; Fan et al., 2021). The possible reason is caused by the data obtained during the coronavirus pandemic, in which the learning process has been conducted online for nearly two years. This condition may create a weak emotional connection between students and their network, including friends and teachers.

Lastly, this study investigated the significance of gender and experience moderating effects on the relationship between each PPM factor and students' intention to switch using ML. The AMOS multi-group analysis was conducted by creating two groups for each moderating factor as follows: gender: male (330) and female (286); experience: between 1 and 38 usage/month (311) and more than 38 usage/month (305). The final analysis confirms that experience is the only moderating factor that moderates the two direct effects of perceived enjoyment (Pull factor) and student innovativeness (Mooring factor) on students' switching intention to accept ML, as presented in Table 10.

6.2 Theoretical implication

This study has two theoretical contributions to ML acceptance research, specifically in HEIs. Firstly, the findings provide a comprehensive understanding of how university students develop their intention to switch using ML platforms using a PPM framework perspective, which has not been explored yet by many authors. The existing studies mainly focused on the factors that directly affect individuals' intention to use ML. Moreover, this research develops a novel theoretical model to describe the factors that affect Indonesian HEIs' students to accept ML based on push, pull, and mooring categories.

Secondly, the results related to the moderating factors were also considered new findings. Many authors often neglected the role of moderating factors on the causal

Table 8 Correlations coefficients

	Gender	Exp	LC	NE	SI	LA	PE	SW
Gender	1	0.055	−0.019	−0.015	−0.198[**]	−0.018	−0.095[*]	−0.111[**]
Exp	0.055	1	0.100[*]	−0.019	−0.075	−0.050	0.048	0.044
LC	−0.019	0.100[*]	1	0.255[**]	0.136[**]	0.105[**]	0.421[**]	0.409[**]
NE	−0.015	−0.019	0.255[**]	1	0.175[**]	0.099[*]	0.258[**]	0.261[**]
SI	−0.198[**]	−0.075	0.136[**]	0.175[**]	1	0.243[**]	0.186[**]	0.195[**]
LA	−0.018	−0.050	0.105[**]	0.099[*]	0.243[**]	1	0.121[**]	0.129[**]
PE	−0.095[*]	0.048	0.421[**]	0.258[**]	0.186[**]	0.121[**]	1	0.983[**]
SW	−0.111[**]	0.044	0.409[**]	0.261[**]	0.195[**]	0.129[**]	0.983[**]	1

Notes: **=Correlation is significant at the 0.01 level (2-tailed), *=Correlation is significant at the 0.05 level (2-tailed).
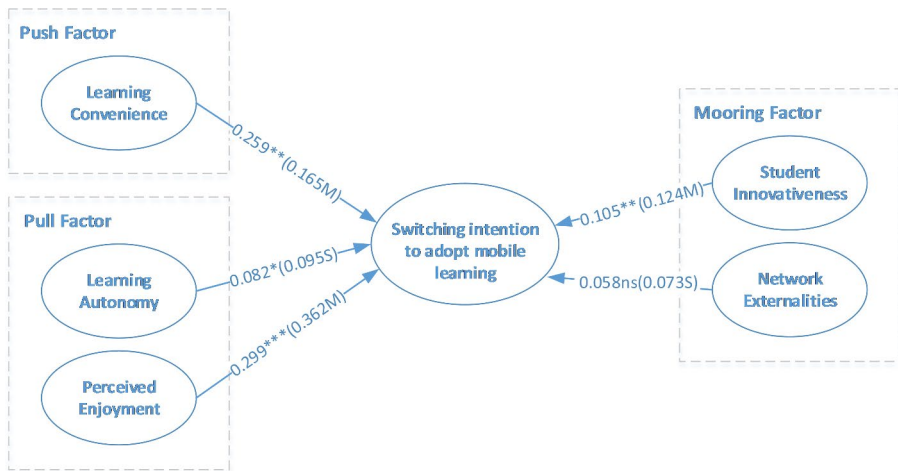
Fig. 2 Result of SEM analysis

effects in their proposed research model, especially for the moderating factor of experience. The assessment of moderating factors may enrich the research findings. Gender, as the most adopted moderating factor in many adoption studies, was not significant to any direct effect in this ML switching study. Therefore, the finding supplies additional insight into ML acceptance studies.

6.3 Practical implication

This study provides some important practical contributions to the decision-makers in HEIs to boost more users to use ML. First, the finding reveals that university students are more likely to switch to ML when physical classroom teaching is inconvenient. Managers of HEIs who want to attract potential students are encouraged to run advertising campaigns that highlight the benefits of ML over traditional classroom teaching. Promotional campaigns can be run in educational institutions, and the emphasis may be placed on how the ML platform makes the learning process more accessible

Table 9 Model fit statistics

Model Fit Statistics	Value	Interpretations
χ^2 / df (Normed Chi-square, NC) where df is the degree of freedom	287.183/174 = 1.650	A reasonable model fit
RMR (Root Mean Square Residual)	0.015	A good model fit
GFI (Goodness of Fit Index)	0.957	A good model fit
AGFI (Adjusted GFI)	0.943	A good model fit
NFI (Normed Fit Index)	0.955	A good model fit
IFI (Incremental Fit Index)	0.982	A good model fit
CFI (Comparative Fit Index)	0.982	A good model fit
RMSEA (Root Mean Square Error of Approximation)	0.033	A close model fit

Table 10 The moderating effect results

Effects	Experience (in months)				Difference = UE Group1 - UE Group2	Magnitude of the Critical Ratio for the Difference
	Group1: 1 to 38 (311)		Group2: > 38 (305)			
	UE	SE&M	UE	SE&M		
PE → SW	0.208***	0.250 M	0.371***	0.452 M	−0.163	1.972*
SI → SW	0.014ns	0.018 S	0.187**	0.205 M	−0.173	2.169*

Notes: UE = Unstandardized Effect, SE&M = Standardized Effect and Magnitude

to students, allowing them to study whenever and wherever is most convenient for them.

Second, the findings show that both pull factors: perceived enjoyment and learning autonomy, are crucial antecedents to determining students' switching intention to use ML systems. The managerial level in the university should advise the faculty members and ML developers to develop entertaining and playful learning materials under ML platforms, especially for experienced students as the targeted users, according to the moderating factor result. Consequently, students can improve their cognitive level in a more fun way using their mobile devices.

Third, related to the mooring factor, student innovativeness plays an important role in increasing the switching behavior of Indonesian university students. The lecturers and ML developers have to periodically create innovative designs and functions, thereby being more attractive to potential students with a high level of personal innovativeness. This strategy can effectively attract more innovative students to use ML systems.

7 Conclusion and Limitations

This study thoroughly analyzes the factors affecting university students' switching intention to use ML systems based on the PPM framework. The results confirm the pull factors: perceived enjoyment and learning autonomy are the most influential determinants that play a role in the students' decision of whether or not to switch behavior in the setting of ML adoption. The push factor, learning convenience, also significantly influences the development of students' intention to switch. With regard to mooring factors, while student innovativeness positively impacts students' intention to switch ML platforms, the network externalities factor is found insignificant. Furthermore, the analysis of two moderating factors: gender and experience, indicates that only experience moderates significantly the direct effect of the perceived enjoyment pull factor and student innovativeness mooring factor on students' intention to adopt ML systems.

This study has some limitations that can be improved for future research. First, this research was carried out exclusively in Indonesia. The culture of learning using mobile devices may vary in other countries. Thus, in order to generalize the findings of the research, further research needs to be conducted in various countries. Second, the factors used to measure the students' switching intention in the theoretical model were categorized based on the PPM perspective. However, to enhance the explanation of this study, future research is encouraged to add other important constructs that may affect the development of students' intention to switch using ML. Third, this study examined the role of moderating factors: gender and experience on the direct effects of determinants on the switching intention. Future research may extend the findings by exploring other moderating factors.

Data Availability Available from the corresponding author on reasonable request.

Declarations

Conflict of interest None.

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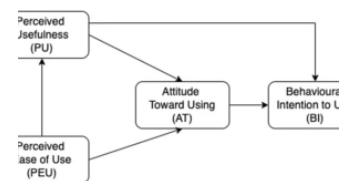
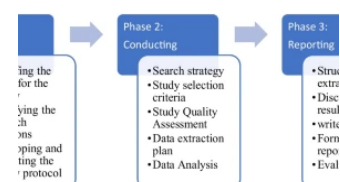### A systematic review of teaching and learning machine learning in K-12 education

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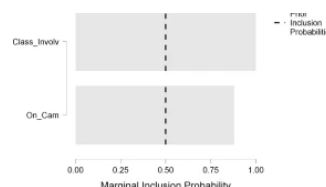
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