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Exploring the factors influencing student's intention to use mobile learning in Indonesia higher education

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Abstract
This study proposes to explore the key factors influencing the university students' intention to use mobile learning system in Indonesia. For this purpose, four direct factors incorporated into the Unified Theory of Acceptance and Use Technology (UTAUT): performance expectancy, effort expectancy, external influence, quality of services and another additional factor — individual innovativeness were examined. The study is based on an online survey being conducted among 284 respondents. Exploratory factor analysis is performed at the beginning of the analysis to extract six factors (5 independents, one dependent) using IBM SPSS then tested confirmative factor analysis employed structural equation modeling. All five investigated factors (independent) are significantly influencing the intention of the student to use mobile learning (dependent). The result is also indicated that the UTAUT obtained two extra factors that are personal innovativeness and prior mobile social media experiences as a catalyst.

Keywords Technology use · Mobile learning · Higher education

1 Introduction

The trends of the learning method in higher education have more and more pointed towards enhanced student collaboration using mobile devices over the past few years. Horizon Report identified learning primarily based mobile applications as one of the quickest growing mobile technologies in higher education (Johnson et al. 2012). The

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speedy development of mobile technologies has not solely enabled individuals to access the knowledge on the move handily, however conjointly extended online learning approaches from electronic learning (e-learning) to mobile learning (m-learning) (Jeng et al. 2010). M-learning supports, with the assistance of mobile or wireless devices, never-ending access to the learning process anywhere, anytime (Park 2011). Some types of devices used for m-learning include smartphones, palmtops, personal digital assistants (PDAs), hand-held computers, tablet PCs, laptops, and private media players (Kukulska et al. 2005; Mohamed et al. 2012). With recent innovations in handheld devices have facilitated the use of multimedia in mobile applications, which allows mobile learners to have access to a wide variety of richly diversified learning materials (Mohamed et al. 2012).

The popularity of mobile devices on university campuses makes higher education institutions a suitable place to integrate student-centered m-learning (Cheon et al. 2012). M-learning that utilizes ubiquitous devices will be a successful approach currently and in the future as a result of these devices are more attractive among higher education students for several reasons. The big idea is that mobile devices are cheaper compared with traditional PCs; and, they are satisfactory and economical (Mohamed et al. 2012). Additionally, mobile devices became more cost-effective, more affordable, and simple to use (Syafar and Husain 2017; Syafar et al. 2017). These devices extend the benefits of e-learning systems (Motiwalla 2007) by offering university students opportunities to access course materials and ICT, learn in a collaborative environment (Syafar and Gao 2013), and obtain formative evaluation and feedback from instructors (Crawford 2007). Furthermore, mobile technologies can easily be integrated/interoperable and synchronize with other devices and systems (Syafar et al. 2015, 2014a). Therefore, it is expected to become one of the foremost effective ways of delivering teaching materials in higher education (El-Hussein and Cronje 2010). Syafar et al. (2014b), emphasized that mobile technologies support the individual and work capability of the users (students and lecturers).

Several pedagogical issues are facing the adoption of m-learning, and the use of mobile devices in classrooms (Park 2011). For example, will both students and lecturers use this technology? They may not just accept m-learning (Wang et al. 2009). Besides, some university lecturers do not want to apply this technology or would possibly face difficulties in making an attempt to use it effectively as this new technology may require a lot of effort to implement (Abu-Al-Aish et al. 2012).

In the Indonesia context, however, there is still no common ground yet among higher education stakeholders about what factors influence the student to use m-learning. Therefore, it is critical to conduct research, at the initial step of implementing, that identify what factors of university students have to be thought-about necessary to use of the m-learning system. The objective of this study is to investigate whether the following factors: Performance Expectancy, Effort Expectancy, External Influence, Quality of Services, and Individual Innovativeness, are positively influence the intention of the university students of Indonesia to use mobile learning in Indonesia higher education context.

This paper is structured as follows: the second section describes the literature background, including the benefit and potential of mobile learning, changing dynamics of education, and UTAUT model review. The methodology used in this study describes in section 3. Section 4 presents the research result and discusses it in the consecutive part. Chapter 6 concludes the paper.

2 Theoretical foundation

M-learning refers to the exploitation of mobile hand-held devices (Mohamed et al. 2012; Cheon et al. 2012), in teaching materials and learning process. As computer and Internet become essential tools for education, technology becomes more accessible, ubiquity, affordable, practical and straightforward to use (Syafar et al. 2015, 2014a, b). This widens participation and access learning materials from the Internet. Mobile devices such as phones and PDAs are far more reasonable than desktop computers and therefore represent more cost-effective access to the Internet (even if the cost of the internet connection may be higher).

In universities, mobile learning enhances the accessibility, interoperability, and reusability of teaching materials resources and also to improve flexibility and interactivity of learning behaviors at convenient times and places (Bohm and Constantine 2016). Mobile learning focuses on the mobility of the learner as well as the mobility of the learning materials and process (Johnson et al. 2012).

2.1 Benefit and potential of mobile learning

In contrast to a desktop computer that needs a fixed location and continuous supply of power, mobile devices have numerous unique characteristics, including portability, connectivity, convenience, expediency, immediacy, accessibility, individuality, and interactivity (Motiwalla 2007). These characteristics and opportunities provide many advantages, such as the freedom to work with flexibility and timely application (Syafar et al. 2015). Park argued that portability and accessibility are the strongest advantages of learning using mobile technologies (Park 2011).

2.2 Changing the dynamic of learning

Mobile technologies can support social constructivist approaches to learning (Mohamed et al. 2012). With the increased use of social media, students easily to communicate with other people for online chat, text messaging, photo sharing, video streaming, and at the same time, they form a collaborative learning community with those who have the same interests. The social network brings educational advantages through personalization, collaboration, information sharing, cultivating common interests, language development and learning, active participation, and knowledge creation (Cheon et al. 2012). Numerous mobile applications are accessible for free, for example, SkillPill, BoostHQ, Evernote and Udemy. SkillPill can post and edit and comes with push notification that allows the lectures to keep up with their student's social networking in real-time. BoostHQ is a content-sharing app that enables the students to see and collaborate. Evernote which allows the users to take notes, save link and images and sort the work into multiple projects mode. Unfortunately, most of the applications are not interoperability with the university database.

Consequently, the apps mentioned above can not be used to support administrative purposes. Figure 1 illustrates one of the mobile learning applications called Udemy (https://www.udemy.com). This application database provides thousands of courses. For example, we had to try to seek an IT Forensic Course and found there were around 4925 students had been explored this course by January 19, 2018.

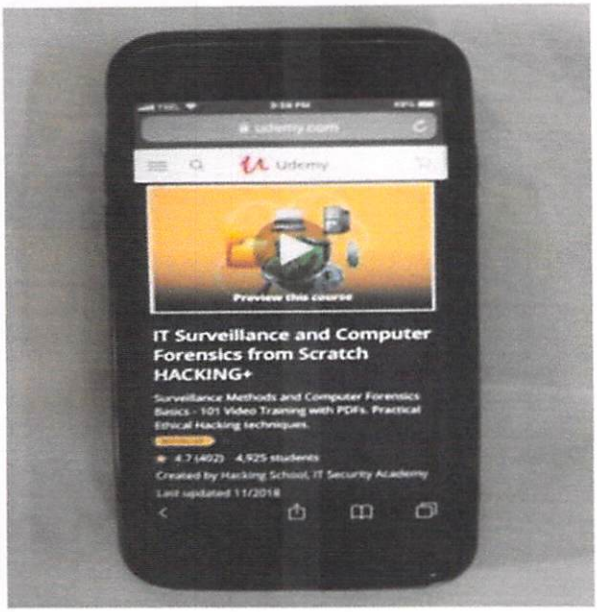

Fig. 1 Mobile learning application

2.3 Review of the UTAUT model

The famous model in information technology acceptance is the unified theory of acceptance and use of technology (UTAUT). The UTAUT theory integrates and empirically compares elements from different technology acceptance models in technology acceptance. UTAUT theorizes that performance expectancy, effort expectancy, social influence, and facilitating conditions are direct determinants of behavior intention or user behavior (Venkatesh et al. 2003).

After considering the factors which may affect users' acceptance of m-learning, we combined two additional constructs into UTAUT in order to investigate the factors that might affect university student intends to use m-learning: quality of service and personal innovativeness. Also, we oriented the social influence construct in UTAUT to the external influence (including family, a close friend (classmate), and lecturers' influence) on the intention to use. As m-learning has not been implementing yet massively throughout at all universities in Indonesia, it is; therefore, this study attempted to investigate the effect of the above constructs on the intention to use m-learning. The student's experience in using mobile social media was also tested to saw it is influenced by the above factors on intention to use, whereas facilitating conditions and user behavior was not tested in this research. The research model tested in this study is shown in Fig. 2.

The five independents factors are outlined as follows:

> **Performance expectancy (PE),** refers to the degree to which an individual believes that using the system can facilitate him or her to realize gains in job performance (Venkatesh et al. 2003). Originally, this construct is also called perceived usefulness in the Technology Acceptance Model (TAM). Adapting

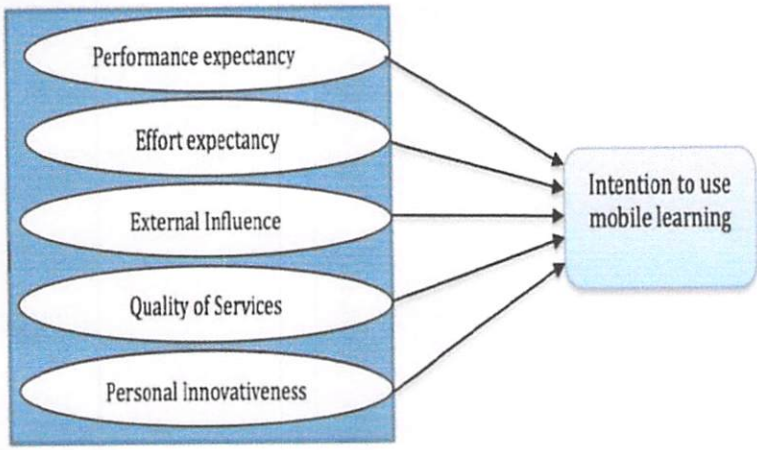

Fig. 2 Research model

performance expectancy to mobile learning suggests that university students will find mobile learning useful because it enables learners to accomplish learning activities more quickly, effectively, and flexibly (Wang et al. 2009). This research attempted to study that PE influences the student intends to use m-learning. This study tested the following hypothesis:

H1: Performance expectancy will have a positive effect on the student's intention to use m-learning.

Effort expectancy (EE), which is the degree of ease associated with the utilization of the system (Venkatesh et al. 2003). This implies that the convenience of the use of a designed information system is one of the key factors of accepting information technology (Wu et al. 2008). The easier the user can access the mobile learning applications, the more is the intention to use it. Based on UTAUT, it had been expected that students' intention to use the m-learning system would rely upon whether or not it is easy for them to use. Therefore, it is hypothesized:

H2: Effort expectancy will have a positive effect on the student's intention to use m- learning.

External influence (EI), which is the degree to which an individual perceives that essential others believe he or she should use the new system (Wu et al. 2008). This study incorporates one essential side of (superior) social influence and examines its effect on students' intention to use of m-learning. In this study, excellent social control, which is adapted as an external influence, in this study, refers to the family, classmate, and lecturers' influence, which expected could directly encourage or motivate students' intention to use m-learning services. Several studies indicate that supervisors and tutors influence a person's behavior to adopt new technology (Karahanna and Straub 1999; Hung and Chang 2005). External influence is, therefore, an important construct to encourage students to adopt new technologies in their learning setting. This study tested the following hypothesis:

H3: External influence has a positive effect on the student's intention to use m-learning.

Quality of services (QoS), which is the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system (Venkatesh et al. 2003). The excellence of services being provided to users can affect the level of acceptance of new technology (Wang et al. 2009). Also, students' perception of online support service quality might be considered as a critical factor affecting their intention towards the acceptance of e-learning (Lee 2010). This study tested the following hypothesis:

H4: Quality of service has a positive effect on the student's intention to use m-learning.

Personal Innovativeness (PI), refers to an individual's willingness to try out any new product or service of information technologies (IT) (Agarwal and Karahanna 2000). Several studies investigated the effect personal innovativeness has on an original IT behavioral intention (Hung and Chang 2005; Lian and Lin 2008). For the adoption of mobile technology in a learning context, most students do not have much experience or knowledge to help them form an apparent perception belief. It was expected that students with high personal innovativeness would be more risk-taking and have a more positive intention to use m-learning in their study. Therefore the following hypothesis was tested:

H5: Personal innovativeness has a positive effect on the student's intention to use m- learning.

3 Methods

This study used an online structured questionnaire as an instrument for data collection. Perceptual measures in the form of statements were used for measuring each variable with a corresponding to five Likert scales anchored as 1 for "Strongly Disagree," 2 for "Disagree," 3 for "Neither Agree Nor Disagree," 4 for "Agree" and 5 for "Strongly Agree." The questionnaire was pre-tested with relevant experts, and prospective respondents, followed by a pilot tested with 20 university students. The results of the pilot test showed that the Cronbach-Alpha value for all items of the questionnaire was higher than 0.7, indicating that the survey was reliable.

The targeted population of the study was Indonesian university students. A total of 373 students with randomly sampled received the online questionnaire link within four public and two private of selected universities across the four biggest islands (Java, Sulawesi, Sumatra, and Kalimantan) of Indonesia. From this 373 of targeted respondents, there was a 298 returned questionnaire received. However, 14 were found incomplete and could not be further analyzed. The remaining 284 were analyzed using IBM SPSS and AMOS version 24. Table 1 presents the profile of the respondents.

As can be seen in Table 1 above, a set of personal characteristics of 284 selected university students: sex, age, e-learning knowledge, mobile social media experience, and mobile learning knowledge/experience have been examined in their frequency and proportion.

Table 1 Profile of respondents

Profile	Frequency	Percent	Percent in total
Gender			
Male	133	46.9	100
Female	151	53.1	
Age			
Less than 20	212	74.8	100
20–22	51	18.1	
More than 20	21	7.1	
E-learning knowledge			
Moderate	35	12.1	100
Good	156	55.3	
Very good	93	32.6	
Experience of mobile (smart) phone			
Less than one years	12	3.9	100
1–3 years	79	27.7	
3–5 years	193	68.4	
Experience of Mobile Social Media			
Three years or less	204	72	100
More than three years	80	28	
Using m-learning			
Yes	103	36.2	100
No	181	63.8	
Frequency using m-services for learning			
Never/Not yet	44	15.5	100
1–5 (times per day)	188	66.7	
5–10 (times per day)	26	8.9	
More than 10	26	8.9	
m-learning knowledge			
Poor	18	6.4	100
Moderate	61	21.3	
Good	104	36.5	
Very good	101	35.8	

3.1 Data analysis

The data analysis technique consisted of three steps. Step one contained the assessment of the measurement model to look at if the model is a good fit with the data collected, based on the satisfactory results, then proceed to step two (structural model) to examine the significant correlation between independent factors and dependent factor with hypothesis testing. The last step was tested the fundamental value of the extra factor (i.e., the mobile social media experience). All data analysis employed package software of IBM SPSS and Amos version 22.

3.2 Measurement model

Firstly, conducted an exploratory factor analysis (EFA) with principal components extraction to explore the six factors. Secondly, conducted confirmatory factor analysis (CFA) to measure factors loading, reliability, convergent, and discriminant validity.

Based on Fornell and Larcker (1981) determination, convergent validity can be determined with three criteria (1) Factor loading higher than 0.50 considered as highly significant; (2) composite reliability should be higher than 0.8; (3) average variance extracted should higher than 0.5.

4 Result

Descriptive statistics (mean and standard deviation (SD) values) for all of the six factors analyzed in this research are listed in Table 2.

Analyzed the measurement model presented in Table 3. The results indicate that all items fit their individual factors quite well. All the factor loadings (ranged from 0.584 to 0.875) exceeded the threshold of 0.50. The Cronbach's alpha coefficient for all factors ranged from 0.720 to 0.846, which are all over the 0.7. In addition, the composite reliability values (CR) were above 0.8 (ranged from 0.84 to 0.918) and the average extracted variances (AVE) were all above the recommended 0.5 level, indicating the correlation between all factors and the intention to use m-learning has been met internal consistency reliability (consistency the factors within the scale) (Fornell and Larcker 1981).

Table 3 also implies that the more factor loading divergent (fluctuated) among items within the same factor, the higher the gap between the value of CR and Cronbach's Alpha.

To examine the discriminant validity, this study compared the square root of the average variance extracted for each construct and the correlation between this construct and any other construct (Fornell and Larcker 1981). Discriminant validity determines whether the constructs in the model are highly correlated among them or not. It compares the square root of AVE of a particular construct with the correlation between that construct with other constructs. (Fornell and Larcker 1981). The value of the square root of AVE should be greater than that the correlation. As presented in Table 4, the square roots of the AVE of all constructs are higher than the correlation estimate with the other constructs.

In summary, the measurement model exhibits adequate reliability, convergent validity, and discriminant validity. The bold numbers on the diagonal represent the square root of AVE; off-diagonal elements are the correlation estimates.

4.1 Hypothesis testing

Data pertaining to hypothesis testing is reported in Table 5. The results of the model testing, including the standardized regression coefficient, the critical ratio (t-value), and the probability (P value). The model tested in this study indicated the significance of all five factors to the intention of the students to use m-learning (Table 5).

As listed in Table 5, overall factors were identified significantly influencing the student's intention to use mobile learning. Determined significant level was 5% ($p < 0.05$).

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Table 2 Descriptive statistics of factor influencing M-learning adoption (Nationwide)

Factors and indicators	Mean	SD
Performance expectancy (PE)		
PE1: I find M-learning help in accomplishing my studies tasks more quickly	4.14	0.731
PE2: M-learning improve the studies performance	3.43	0.623
PE3: Using m-learning will result in increased learning productivity	3.48	0.660
PE4: Using m-learning will increase the effectiveness	3.69	0.737
PE5: Using m-learning improve collaborative learning with classmates and lectures	3.36	0.576
Effort Expectancy (EE)		
EE1: I would find m-learning is flexible and easy to use	3.72	0.733
EE2: I would say that using m-learning does not require many efforts	3.40	0.595
EE3: It is easy to become skillful at using M-learning	3.79	0.825
EE4: Interaction between student and m-learning would be clear and understandable	3.62	0.727
External Influences (EI)		
EI1: People who influence my intention will think that I should use m-learning	3.56	0.730
EI2: My classmates told the benefits of using m-learning	3.69	0.796
EI3: In general, the university supported the use of m-learning	3.64	0.762
EI4: I will use m-learning because of my lecturers advice me	4.07	0.884
Quality of Services (QoS)		
QoS1: M-learning to become accurate, reliable and real-time	3.72	0.807
QoS2: I do hope that m-learning services increase the quality of learning outcome	3.90	0.882
QoS3: It is critical that the services of m-learning be secure and controllable	3.82	0.826
QoS4: It is critical that the services of m-learning be accessible more quickly	3.87	0.824
QoS5: I do hope that collaboration between students and lecturer facilitated by the m-learning system	3.82	0.856
QoS6: It is preferable that navigating, browsing and downloading services of m-learning are satisfied	3.68	0.795
Personal Innovativeness (PI)		
PI1: I, sometimes, like to experience a new IT product/applications	3.92	0.842
PI2: When I have heard something new about IT application, I seek to practice it	3.52	0.665
PI3: As long as I know, I am the first one who did a trial on a new innovation of technology	3.66	0.776
Intention to use M-Learning (ItoU)		
ItoU1: I intend to use mobile devices for educational purposes	3.41	0.626
ItoU2: I have sufficient knowledge and skills to use mobile devices for educational purposes	3.94	0.827
ItoU3: I will prefer m-learning over other media of learning	3.43	0.640
ItoU4: I will recommend other colleagues to use mobile devices for educational purposes	3.55	0.740
ItoU5: I will use m-learning as frequently as I can	3.62	0.770
ItoU6: I will enjoy using m-learning	3.64	0.742

4.2 Influences of prior mobile social media experience

Prior to mobile social media, experience is one of the important factors that affected the student's intention to use m-learning. Hence, the factor 'mobile social media experience' was also investigated. Tables 6 and seven present the estimates (coefficients)

Table 3 Measurement model

Construct	Factor extracted	Cronbach's alpha	Standardized factor loading	Squared multiple correlations	Composite reliability	Average variance extracted
PE1	0.771	0.788	0.721	0.520	0.843	0.503
PE2	0.743		0.584	0.340		
PE3	0.751		0.620	0.380		
PE4	0.798		0.875	0.770		
PE5	0.808		0.710	0.480		
EE1	0.738	0.815	0.627	0.390	0.909	0.538
EE2	0.847		0.795	0.630		
EE3	0.790		0.745	0.560		
EE4	0.810		0.754	0.570		
EI1	0.890	0.823	0.850	0.720	0.898	0.602
EI2	0.880		0.820	0.670		
EI3	0.850		0.640	0.410		
EI4	0.790		0.680	0.460		
QoS1	0.860	0.720	0.790	0.620	0.840	0.502
QoS2	0.870		0.600	0.360		
QoS3	0.880		0.640	0.410		
QoS4	0.778		0.710	0.500		
QoS5	0.810		0.700	0.610		
QoS6	0.780		0.730	0.570		
PI1	0.820	0.846	0.840	0.710	0.918	0.670
PI2	0.840		0.680	0.460		
PI3	0.810		0.780	0.600		
ItoU1	0.840	0.835	0.730	0.530	0.892	0.617
ItoU2	0.850		0.680	0.460		
ItoU3	0.790		0.750	0.560		
ItoU4	0.720		0.700	0.490		
ItoU5	0.740		0.720	0.510		
ItoU6	0.780		0.750	0.560		

output and the critical ratio (*t*-value) of the effect of students' prior experience of mobile social media as moderator or catalyst factor on the intention of students to use m-learning.

Table 6 shows the structural value of 3 years or less of the mobile social media experience of selected respondents.

Table 4 Correlation matrix and discriminant validity

Factors	PE	EE	EI	QoS	PI	ItoU
PE	**.712**					
EE	.450	**.730**				
EI	.305	.487	**.766**			
QoS	.391	.503	.459	**.704**		
PI	.313	.428	.324	.457	**.799**	
ItoU	.549	.674	.492	.495	.567	**.721**

Table 5 The coefficient of relationship and the critical ratio of hypothesis

Relationship	Reg. Coef.	t-Value	P Value	Significance
PE → ItoU **(H1)**	.268	2.19	0.02	Yes
EE → ItoU **(H2)**	.366	2.29	0.01	Yes
EI →ItoU **(H3)**	.228	1.87	0.03	Yes
QoS → ItoU **(H4)**	.256	1.99	0.03	Yes
PI → ItoU **(H5)**	.313	2.16	0.02	Yes

As shown in Table 6 above, the highest P value is the correlation between performance expectancy (PE) and the intention of students to use (ItoU) m-learning.

The structural value of students who have experience of using mobile social media in more than three years presented in Table 7.

Unlike Table 6, the highest P value shown in Table 7 is the correlation between external influence (EI) and the intention of students to use (ItoU) m-learning.

Having established an acceptable model fit for both groups (3 years or less and More than three years), then run the multiple group covariance analyzed. As presented in Tables 6 and 7, the structural value for both two groups was all significant statistically, where P values are less than 0.05.

5 Discussion

Both the proposed research model and hypothesis are satisfactorily clarified and able to illustrate student intends to use m-learning. Tested constructs (factors): performance expectancy, effort expectancy, external influence, quality of service, and personal innovativeness were all significant factors to influence the student's intention to use m-learning. The two modified constructs — quality of service ($\beta = 0.28$, $P < 0.04$) and personal innovativeness ($\beta = 0.33$, $P < 0.04$) were significant for all students' responses.

The results of this study support previous relevant research. Wang et al. (2009); Venkatesh et al. (2003) have found a significant contribution of performance

Table 6 Structural values of prior-mobile social media experience (3 years or less, $N = 204$)

	Estimate	t-Value	P Value
PE → ItoU	.25	2.77	0.03
EE → ItoU	.39	4.70	0.00
EI →ItoU	.29	3.05	0.01
QoS → ItoU	.26	2.38	0.02
PI → ItoU	.27	2.81	0.02

Table 7 Structural values of prior-mobile social media experience (more than three years, $N = 80$)

	Estimate	t-Value	P Value
PE → ItoU	.33	2.84	0.01
EE → ItoU	.34	2.77	0.01
EI →ItoU	.25	2.13	0.04
QoS → ItoU	.30	2.45	0.01
PI → ItoU	.26	2.22	0.03

expectancy (PE) on the acceptance of mobile learning. This study implied that students with high-performance expectancy (who believe that using an m-learning system will support their studies, and will increase their learning productivity and affectivity) tend to use m-learning compared to students with lower performance expectancies.

Effort expectancy (EE) proved to be a significant influence on student intends to use m-learning. This result implies that students suppose that the mobile learning system will be easy to use, and they would not like a lot of instruction on the way to use it. Additionally, m-learning, they believe, will aid them in being skilfully in accessing learning materials. These give some indicators to m-learning service designers to provide higher education with easier to operate and more user-friendly of m-learning applications in future development.

External influence (EI) was found to have a significant contributing factor in students' intention to use m-learning. As the study explored the intended use of m-learning by university students, the researchers explored the influence of the external of the students, including institutions, classmates, and lecturers in effect their intention to use m-learning. External influence is one amongst five independent factors (substituted of social influence — the original factor of UTAUT theory). Generally, student intends to use m-learning affected directly by their classmates, university/institution support, and advice from their lecturers. These indicators encapsulated in EI motivate them to use or not to use m-learning services. This finding is in line with previous research results (Igbaria et al. 1994; Suwantarathip and Orawiwatnakul 2015; Sim et al. 2012). Therefore, lecturers, close friends, and higher education institutions should be placed under consideration as a part of the UTAUT investigation. This particular factor required more in detail research in the future.

Quality of service (QoS) identified to be a significant influence on a student's intention to use m-learning. Students intending to use an m-learning system when the provided quality of service is compatible and beneficial as a high-quality method for their learning resources. This explained that the quality of reliability, real-time, accessibility, portability, and interoperability of the m-learning services are some indicators that students believed will facilitate their learning outcome. It is. Therefore, those some indicators of QoS positively affect the level of the intention of students to use an m-learning system. This supports the finding of previous researches (Park 2011; Agarwal and Karahanna 2000; Syafar et al. 2015).

Personal Innovativeness (PI) shows a significant influence on the intention of students to use m-learning. This suggested that student who equipped with personal knowledge, perception, experience, and innovativeness in a new technology comes,

have a more positive intention to use m-learning. Several of previous studies elucidated that individuals with stronger PI have more courage (Garry et al. 2014), capacity and possess better socio-economic status needed to use any new technology including m-learning, contrarily, individuals with weaker PI, tend to use the status quo technology (Lu et al. 2005).

5.1 Prior experience of mobile social media

Prior use of mobile social media reported, in this study, significantly influencing the intention of university students to use the m-learning system. The results indicated that this 'extra' factor positively supports all of the independent factors — performance expectancy, effort expectancy, external expectancy, quality of services and personal innovativeness on students' intention to use m-learning. The result showed a significant influence for both groups of students who are having experience of using mobile social media within three years or less and those who were using mobile social media in more than three years. This result is supported by previous similar research in a different domain. Syafar et al. (2015) have found that the technicians/engineers who have prior competencies on several mobile applications will be more likely to accomplish given maintenance tasks.

Similarly, for any particular assignment, it will be appropriate to choose a technician with prior mobile technology skills or experience—beginning with what they apprehend. The main reason is that such prior competency facilitates them to use the new system quicker than people who are not. The factor of experience of mobile social media is likely to be a 'catalyst' and therefore becomes an important factor out of the five other main independent factors discussed earlier. Riddell and Song (2017) highlighted that employees with work experience in using computers more easily adopt new computer-related technologies than others.

The result suggests that when higher education institutions design to implementing the M-Learning system, the expectation of the students has to be considered to meet the better performance of the systems, both in learning material contents and mobile technology features as intended in this research. The content of M-Learning should be compatible and interoperable with other mobile devices. The result is also indicated that the students require a simple service and not too complicated and difficult to understand. Therefore, M-Learning providers have to consider to develop user-friendly and easy to use of the system. The features include easy navigating, browsing and downloading services as well as secure and controllable input and output devices.

5.2 Limitation and future research

This study limited to: First, the respondents are Indonesian (developing country) university students. Thus the result could benefit from comparison with other developing and developed countries. Second, this study was conducted in a short period, while the student perception regarding PE, EE, EI, QoS and PI toward the student's intention to use M-Learning may change within a particular time as the accumulation of new students perspectives, knowledge and prior experience of mobile social media.

Therefore, we do hope that future studies could employ other main factors and moderator variable(s).

6 Conclusion

Essentially, this study provides both theoretical and practical contributions to understanding the predictors of intention to use mobile learning and should be of interest to both researchers and higher education practitioners. As for the researcher, the model utilized in the study can be tested with an alternative setting involving different kinds of a population, inside or outside of Indonesia. As for the higher education practitioners, this study, we believe, will be sent a robust message on the importance of technological features such as performance expectancy, quality of services and effort expectancy that need to be addressed when developing mobile learning applications.

Mostly, technologies are adopted and used without critical examination of how they help students learn, and this becomes a particularly important challenge for the modern higher education sectors. The results indicated that higher education sectors have to develop strategic plans and provide guidelines considering students' intention in order to include all critical success factors for the sustainable deployment of the m-learning system. The results of this study expected to provide insight into what factors need to be considered for designing a mobile learning system in Indonesia's higher education.

This study does not provide particular mobile technologies, for m-learning systems that best fit in supporting a particular learning process in Indonesia higher education context, but the finding set of factors of students' intention to use it, could be a basis for future research in order to investigate: (1) advantages and disadvantages of every type of mobile computing device to support the application functionality of m-learning context, (2) which variants of a software application need to be developed in order to cover the specific m-learning systems, and (3) what the functionality could be included in each variant.

The number of the benefits offered positively by m-learning are favorable for productive learning, therefore implementing the m-learning system is not just the option but a necessity in the modern way of learning toward Indonesia Higher Education Industry 4.0 readiness.

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