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Determining the factors that affect the uses of Mobile Cloud Learning (MCL) platform Blackboard- a modification of the UTAUT model

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Abstract

The aim of this study was to unveil the factors that affect the use of Mobile Cloud Learning (MCL) platform Blackboard. Considering the nature of MCL, the Unified Theory of Acceptance and Use of Technology (UTAUT) model was applied and modified with two additional variables, i.e. mobility and self-management learning to understand the use behaviour of the users. A survey was conducted through a structured questionnaire to collect quantitative data for analysis. Structural equation modelling (SEM) was used to analyse the data and test the hypotheses of this study. In outcome, performance expectancy, effort expectancy and self-management learning are found as significant factors. Blackboard platform provider and users' can be benefited through the outcome of this study by looking at the significant factors and understanding the use behaviour of the users.

Keywords Mobile cloud learning · Mobile learning · Cloud computing · Factors · UTAUT model · Blackboard

1 Introduction

In these days, the uses of technology in the area of education are growing. Different applications, software, and platforms are using to facilitate the learning experience of the learner. Mobile Cloud Learning (MCL) is a blend of mobile learning and cloud computing which ensures convenient and interactive learning experience without limitations regarding location, time and accessibility (Hirsch and Ng 2011; Dinh et al. 2011). The uses of MCL platform is in growing in the educational institutions around the world. In a survey by Walker et al. (2016) showed that educational institutions in the UK at least use one MCL platform to provide interactive learning

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experience to the learners. Commonly used platforms for mobile cloud leaning are- 'Moodle', 'Blackboard', 'Canvas', 'Future learn', 'BrightSpace', 'Coursera', 'Joule' (Capterra 2017). MCL platforms also known in different names, i.e. e.g. Virtual Learning Environment (VLE), Learning Management System (LMS), Course Management System (CMS), Personal Learning Environment (PLE) etc. Educational institutions are using multiple platforms for ensuring interactive learning experience in case of distance learning, online learning, anytime learning. Institutions had to bear a huge cost for using multiple platforms. Confusion and complexity regarding the use of platforms can also get increase among the users by the uses of multiple platforms. In order to deal with the confusion and complexity among the users, it is better to use a single interactive platform to provide a better learning experience. This motivates this study to investigate the factors that work behind the uses of MCL platforms. Therefore, the research question that this study wants to answer is- "What are the determinants behind the uses of MCL platform?"

This study considered the second largest highly used MCL platform Blackboard as a research context (Falvo and Johnson 2007). Blackboard is currently capturing highest market share through merger, accusation, and integration (Bradford et al. 2007; Carrillo 2015). Among all the industry, the uses of Blackboard are 37% high in the educational industry. (idatalabs 2017). Developed countries are ahead in the uses of Blackboard in comparison to developing and underdeveloped countries. Nevertheless, the growth of Blackboard is slow and the switching rate of the blackboard is growing continuously (Kronk 2017). This motivates this study to take blackboard into consideration. Because in order to increase the uses of the blackboard and the providing better user experience it is important to understand the background feeding for the uses of the particular platform.

2 Literature review

In blended technology Mobile Cloud Learning (MCL), Mobile learning focuses on the mobility of the learning at anytime and anywhere using mobile device (Crompton 2013; Sharples et al. 2007). On the other hand, Cloud computing ensure on demand access to remote resources situated on the cloud (Mell and Grance 2009). In Mobile learning, with the help of mobile devices learners can access resources without any concern regarding time and place (Wu and Chang 2016; Goh 2009).learners can also use many mobile devices parallally as mobile devices as lighter and easy to carry (Sharlples 2003; Georgiev et al. 2004). However, because of the low processing power of mobile devices, poor infrastructure, low memory of mobile devices, and inability to access heavy softwares through mobile devices; mobile learning encountered a lot of challenges (Al-Hunaiyyan et al. 2018; Kaliisa and Picard 2017; Cheon et al. 2012). Additionally, compatibility with MCL platform, using multiple resources with mobile devices and difficulty in input are also some challenges with mobile learning. Through the application of cloud computing in educational institutions, resources can be made available on demand in an elastic and cost-effective way (Chandra and Borah 2012; Isaila 2014). The problem of storage, computing, processing and accessing high demand resources of mobile learning can be deal with the application of cloud computing (Li 2010; Chen et al. 2010; Sagenmüller 2016). Nevertheless, confidentiality, network performance, privacy and control of cloud provider are the concerns regarding cloud computing.

Through amalgamating cloud computing and mobile learning together, the advantage of both can be boosted up and the challenges can be handled; so does Mobile Cloud Learning (MCL). MCL make learning interactive, autonomous, and collaborative which ensure ubiquitous access, sharing and storing of resources (Chen et al. 2010; Wang et al. 2014). Educational institutions can provide access to huge resources and interactive learning experience without owning the resources which are more cost effective (Lakshmi and Dhanalakshmi 2016; Verma et al. 2012). Even the students who don't have pc or laptops can also access the resource from anywhere in anytime through mobile devices (Palmer and Dodson 2011).

Previously, researchers are conducted research either on mobile learning or cloud computing. However, the focus on mobile cloud learning is low. An exploratory work was conducted on the uses and benefit of mobile cloud learning platform by Chaubey and Bhattacharya (2015), where cost-effectiveness, elasticity, development of providing education was pointed as the main advantages. Similarly, advancement in performance, cost-effectiveness, access, and management to resources was highlighted as the benefit by Rimale et al. (2016). On another study by Gurung et al. (2016) focused on the effect of MCL on traditional learning where flexibility, self-learning management, access and sharing of resources was also highlighted benefits. On the other hand, network ability, difficulty in finding resources, and distraction with other mobile applications through using MCL platform by mobile devices was pointed as main challenges (Gurung et al. 2016). However, these studies pointed benefits and challenges from a different context, some of these benefits and challenges may be related to the platform only and some of these related to overall MCL environment. These studies did not highlight the reasons behind the challenges.

Some explanatory and empirical work was conducted on mobile learning or cloud computing previously. In a study by Lai et al. (2012), facilitating condition, attitude and compatibility were found as significant while investigating the determinants behind the uses of technology for learning. A particular cohort of a student was taken as a sample on that study. Therefore, a sample of the student from the different group can provide a different outcome. In another study by Lowenthal (2010), behaviour intention was evaluated through focusing three factors, performance-expectancy, effort-expectancy and self-learning management where self-learning management turned insignificant among these three. However, behavioural intention and use behaviour the complex and multidimensional which is less explainable in this simple three factor model. On other focus, Stantchev et al. (2014) investigated the acceptance of LMS through Technology Adoption Model (TAM). Nevertheless, other models were also available with more explanatory power (power of explaining the use behaviour of technology) as the explanatory power of TAM is between 17% - 52% (Dwivedi 2009). While the other models (i.e. UTAUT) has more than 70% explanatory power (Dwivedi 2009). Some studies also used the UTAUT model through modifying or integrating, but either on mobile learning or on cloud computing. Nassuora (2013) applied the UTAUT model by modifying it by adding attitude in order to understand the intention of the students to use mobile learning. A relationship was found between attitude and behavioural intention as an outcome. In another study by Wang et al. (2009), two more variables i.e. perceived playfulness and self-management learning were added and facilitating condition was removed on the UTAUT model for investigating the acceptance of mobile learning. Similarly, Liu (2008) also modified the UTAUT model by adding

five more variables with the core variables of UTAUT to propose an adoption model of mobile learning. The newly added variables were- mobility, self-efficacy, self-management learning, attainment value, and perceived enjoyment. Considering all the previous modification of the UTAUT model for mobile learning this study modified the UTAUT model for MCL.

3 Theoretical framework and hypothesis

In this study Unified Theory of Acceptance and Use of Technology (UTAUT) is used for determining the factors regarding the uses of MCL in higher education. UTAUT model was developed by intensive examination of eight different popular models i.e. "TRA", "TAM", "Motivational Model (MM)", "TPB", "Combined TAM and TPB (C-TAM-TPB)", "Model of PC Utilization (MPCU)", "Innovation Diffusion Theory (IDT)", "Social Cognitive Theory (SCT)" (Venkatesh et al. 2003, p. 428). UTAUT model is considered now a latest and powerful model for investigating different technology uses and adoption. UTAUT model is considered because of its wide applicability, good explanatory power of use behaviour of technology (as more than 70%) and capability (Bradley 2009). There is also a UTAUT 2 model which developed by adding more variables to the original UTAUT model. However, this study will not use UTAUT 2 model because the additional variables, i.e. price, habit are less related to MCL platform blackboard. As this study conducted on the university users of Blackboard platform which is mainly provided by the university, users are not directly responsible for the payment regarding the uses of Blackboard platform. Additionally, users might not have previous experience of using Blackboard platform. Therefore, use of additional variables of UTAUT 2 model can put the respondent in paradox.

The four main factors of the UTAUT model, Performance expectancy (PE), Effort expectancy (EE), Social influence (SI), Facilitating Condition (FC) are taken into consideration in this study. All these four factors are argued to have affected the behavioural intention (BI) and use behaviour (UB) of the technology. Additionally, considering the nature of the MCL, the UTAUT model is modified by adding two variables; i.e. Mobility (Mob) and Self-management learning (SML), shown in Fig. 1. These two factors are found crucial in mobile learning in different previous studies (Prajapati and Patel 2014; Abar and Loken 2010; Smith et al. 2003; Liu 2008). However, as the UTAUT model was developed considering the nature of the organization which means that UTAUT was tested within the organization and in mandatory context. As in mobile cloud learning the uses of MCL platform can be anytime and anywhere, so the nature of MCL is necessary to consider. Therefore, mobility and self-management learning is taken for consideration as factors. Moreover, six factors are considered in this study on which the research model is developed. The description of factors and development of hypotheses are given in the following section-.

3.1 Performance expectancy (PE)

Performance expectancy refers to the expectation regarding the goal attainment through the use of technology or system (Venkatesh et al. 2003; Abu-Al-Aish and Love 2013). In MCL, PE implies the effectiveness and efficiency of learning and retrieving

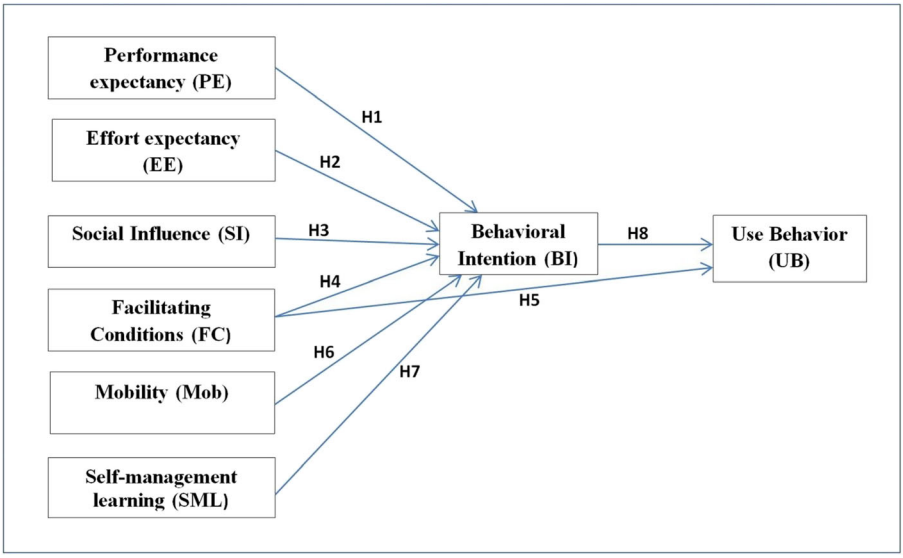

Fig. 1 Research model and hypotheses (extended on Venkatesh et al. (2003))

necessary information through MCL at any time anywhere (Wang et al. 2009). A study by Carlsson (2006) highlighted that PE has direct effect on the BI to use mobile devices. Venkatesh et al. (2003) and other research (Chiu and Wang 2008; Ong et al. 2004; Saade and Bahli 2005) on mobile learning have found a significant relationship between PE and BI. Therefore, the following hypothesis derived-

H1- PE has a positive impact on BI of the learner to use MCL platform Blackboard

3.2 Effort expectancy (EE)

According to Venkatesh et al. (2003, p.450) "Effort Expectancy (EE) refers to the degree of ease associated with the use of the system". In MCL, EE implies that the learners' perceived ease regarding the use of MCL platform. EE found as important factor that can directly influence behavioural intention of using mobile learning by previous studies (Abu-Al-Aish and Love 2013; Venkatesh et al. 2003; Wang et al. 2009). So, considering the above discussion EE need to count in MCL platform use behaviour. Therefore, the following hypothesis has emerged-

H2- EE has a positive impact on BI of the learner to use MCL platform Blackboard

3.3 Social influence (SI)

The views of important persons regarding the use of technology are considered as the social influence (SI). In MCL context, the views of teachers, university and other peer-students can work as important persons who can be the SI. According to Venkatesh

et al. (2003), SI turned significant where the use of new technology or system is mandatory than a voluntary situation. In voluntary context, SI can impact the perception about the technology. In a study by, Lu et al. (2005) have identified that users' behavioural intention to use technology highly affected by the SI. Other previous studies aslo find SI as significant on BI to use MCL platform (Venkatesh and Davis 2000; Harrison et al. 1997). Therefore, the following hypothesis has developed-

H3- SI has a positive impact on BI of the learner to use MCL platform Blackboard

3.4 Facilitating condition (FC)

FC refers to the support provided by the organization to use the technology and the systems (Venkatesh et al. 2003). In case of MCL platform, generally support provided by university or organization i.e. providing access to the resources remotely, training to use the platform, handling challenges regarding the use of the system are the FC. Previous studies (Cheong et al. 2004; Wu et al. 2007) reported FC as significant to BI. Venkatesh et al. (2003) also claim that FC can have a direct effect on UB of the technology. In a study by, Yi et al. (2006) found that FC can have direct impact on BI and UB of technology. Based on this discussion, following hypotheses emerged-

H4- FC has a positive impact on BI of the learner to use MCL platform Blackboard
H5- FC has a positive impact on UB of MCL platform Blackboard

3.5 Mobility (mob)

Mobility (Mob) refers to the flexibility of accessing the MCL platform without any limitation of time and location (Peters 2007). Previous studies on mobile learning found mobility as a significant factor that has an influence on the BI to use technology or system (Kaigin and Basoglu 2006; Mallat et al. 2008). In MCL, mobility also can have direct impact on behavioural intention to use MCL platform. Therefore the following hypothesis has posited-

H6- Mob has a positive impact on BI of the learner to use MCL platform Blackboard

3.6 Self-management learning (SML)

SML refers to the autonomous learning through self-direction (Smith et al. 2003). Previously, studies pointed SML as an important factor in mobile learning (Prajapati and Patel 2014; Al-Adwan et al. 2018; Smith et al. 2003; Abar and Loken 2010). However, Lowenthal (2010) and Al-Adwan et al. (2018) found SML as insignificant to BI. Nevertheless, this study still considers SML for investigation as the focus of previous studies was different and didn't consider MCL. Therefore, the following hypothesis considered-

H7- SML has a positive impact on BI of the learner to use MCL platform Blackboard

The above considered variables might have an impact in BI of the learner to use MCL platform Blackboard. BI refers to the willingness to use a particular technology (Ajzen, 1992). According to Venkatesh et al. (2003), BI affects the use behaviour of the technology. Even previous studies found BI as significant to use behaviour (UB) of technology (Venkatesh et al. 2003; Venkatesh and Davis 2000; Al-Adwan et al. 2018; Abu-Al-Aish and Love 2013). Hence the following hypothesis has emerged-

H8**:** BI has a positive impact on the use behaviour (UB) of MCL platform Blackboard

4 Methodology

4.1 Measurement instrument

All the measurement items for each of the factors in this study are taken from previous study in order to ensure the validity of the measurement instruments. Measurement items of the factors are given with sources in Table 1.

4.2 Questionnaire design and data collection

In this study, a structured questionnaire was developed to conduct the survey for collecting data. Survey was taken as a data collection method because the survey is considered as an appropriate tool for collecting quantitative data (Wright 2017; Saunders et al. 2015). The survey was conducted on the Blackboard users of University of Leeds, UK. The University of Leeds was chosen for study because; firstly the University of Leeds use Blackboard platform. Secondly, University of Leeds is an international university with world ranking within 150 with students from diverse country and background which will help to capture diverse opinion (topuniversities 2018). Thirdly, the author has stayed in Leeds, UK on that time for an academic purpose which facilitates data collection and communication with respondents. The questionnaire was developed in English only as all the blackboard users of the University of Leeds, UK are either native English speaker or process good proficiency in English. There were two parts with an introductory part in the questionnaire, i.e. part A, part B. Notes regarding purpose, respondents rights, followed ethical standard and time requirements were given in the introductory part of the questionnaire. Part A aimed to engage the respondents and understand the background of the respondents, through collecting demographical information. In part B self-exploratory statements on the measurement items (Table 1) of factors were put for collecting the important views on the uses of Blackboard platform using a five-point Likert scale ranging from 1(strongly disagree) to 5 (strongly agree). Five-point Likert scale was chosen because it avoids cognitive biases and respondents' confusion with eleven scales (Revilla et al. 2014; Babakus and Mangold 1992). Furthermore, five-point Likert scale provides quality of data and recommended by researchers (Sachdev and Verma 2004; Bouranta et al. 2009; Revilla et al. 2014).

A pilot study was conducted to test the appropriateness and ability to understand by the respondents. Respondents for the pilot study were chosen based on their expertise,

Table 1 Factors with measurement items

Factors	Measurement items	Adapted Source
Performance Expectancy (PE)	PE1- I found Blackboard is useful for leaning or teaching PE2- I think through Blackboard I can do my work more quickly PE3- I think Blackboard makes learning and getting information more effective	Venkatesh et al. (2003); Zhou et al. (2010);
Effort Expectancy (EE)	EE1- Learning how to use Blackboard is easy EE2- My interaction and navigation with Blackboard is clear and understandable EE 3- Overall I found that Blackboard is easy to use	Venkatesh et al. (2003);
Social Influence (SI)	SI1- I use Blackboard because University of Leeds use it SI2- I use Blackboard because all teachers and students use it.	Venkatesh et al. (2003); Lai et al. (2012);
Facilitating Condition (FC)	FC1-IT dept. provide support for using Blackboard FC2- I have necessary resources and knowledge to use Blackboard FC3- Use of Blackboard is suitable with my work	Zhou et al. (2010); Venkatesh et al. (2003);
Mobility(Mob)	Mob1- I can access Blackboard from anywhere Mob 2- I can access Blackboard with mobile devices	Shorfuzzaman and Alhussein (2016); Liu (2008)
Self-Management Learning (SML)	SML1- Blackboard increases learner autonomy SML2- It is possible to do self-directed learning through Blackboard	Liu (2008); McFarlane et al. (2007)
Behavioural Intention (BI)	BI 1- I try to use the system daily. BI 2- I predict I will use Blackboard frequently BI 3- I intend to use this system (Blackboard) in future.	Venkatesh et al. (2003); Abu-Al-Aish and Love (2013);
Use Behaviour (UB)	UB 1- Blackboard is pleasant experience UB 2- I use Blackboard currently UB 3- I spend a lot of time on Blackboard for learning and working	Venkatesh et al. (2012)

current position, and educational background. Total ten responses were collected from the different group of users; i.e. two academic staff, two admin staff, and six students. The questionnaire was modified based on the feedback of the respondents. There are variations in views regarding the size of the sample among the research studies. Sample size should be calculated based population, confidence level, variance and margin of error (Austin 1983; Martin 2016). According to Roscoe (1975), the sample size should be calculated based on the total number of items. Considering the statistical analysis Wang and Wang (2018) argued that the sample size should not less than 150. However, total 166 responses were collected on which statistical analysis was conducted. Data

were collected for 2 months from July 2018 to August 2018. Considering the time frame and the representation of the study population the sample size of this study can be considered as the good sample size for performing statistical analysis. All the respondents were approached directly at different places of the University of Leeds in a random convenient way. The author asked respondents (especially students) at the different time in different places, whoever available during that time on those place. In case of Academic and admin staff, email was sent with a questionnaire link asking their valuable responses. Before the survey, all the respondents were made aware of the purpose and their rights regarding participation and withdrawal through face to face or written message. This study has taken ethical approval from the University of Leeds. Additionally, throughout the conduct of the study British Psychological Society Ethical Code (2009) and Data Protection Act (1998) were followed.

4.3 Data analysis

Structural Equation Modelling (SEM) was used through AMOS (version 22) to test and validate the hypothesized relationship among the constructs. According to researchers SEM was a good way to test the model and hypothesized relationship (Gefen et al. 2003; Hair et al. 2010; Byrne 2016). At first, data was collected from the questionnaire in an excel format. Data screening was conducted based on standard deviation to remove unengaged responses (who responded with the same value for every question). Total 3 data was removed and rest of the data (163) were imported into Statistical Package for the Social Sciences (SPSS) for analysis. The reliability test (Cronbach's Alpha reliability test) and exploratory factor analysis (EFA) was conducted in SPSS. In order to understand the multidimensional relationship confirmatory factor analysis (CFA) was conducted. Composite reliability and convergent validity were also tested through CFA. Afterward, the fitness of the measurement model and structural model were tested. All the hypotheses of this study were based on the outcome of the structural model.

5 Results

5.1 Demographic characteristics of the respondents

The overview of demographical features of the respondents given in Table 2, shows that the percentage of female is high with 55.8%. Majority of the respondents are within age group of 26–35 and students responded mostly as they are easily accessible. About 63.2% of the respondents were masters' degree holder and there were no respondents below o-level. In case of ethnicity, a good level of diversity is apparent which ensures collection of diverse opinion.

5.2 Measurement model

Each of the constructs reliability was tested using the Cronbach's Alpha reliability test. The reliability value between .50 to .70 implies moderate reliability, on the other hand value above .70 shows high reliability and below .50 presents low reliability (Hinton

Table 2 Demographical characteristics of respondents

Variable		Frequency	Percentage
Gender	Male	70	42.9%
	Female	91	55.8%
	Prefer not to say	2	1.2%
Age	18–25	57	35%
	26–35	84	51.5%
	36–45	12	7.4%
	46–55	4	2.5%
	56+	6	3.7%
Occupation	Student (Undergrad, Post-grad and PhD)	124	76.1%
	Academic Staff (Teaching and research)	21	12.9%
	Other Staff (Support and Admin)	18	11%
Level of education	O- Level	1	0.6%
	A- Level / Higher Secondary School	4	2.5%
	Vocational Qualification	0	0%
	Bachelor	36	22.1%
	Masters	103	63.2%
	PhD	19	11.7%
Ethnicity	UK (Home)	58	35.6%
	EU	21	12.9%
	International (Non-EU)	84	51.5%

et al. 2004). As shown in Table 3, all the constructs' reliability value is above .70 except SI. However, as the reliability value of SI is more than .6, therefore it can be considered reliable (Loewenthal 2004).

After testing the constructs reliability, EFA was conducted. Based on the outcome, item BI3 was removed due to cross loading. In order to test Composite reliability (CR) and Convergent Validity (CV) further, a measurement model was developed. Afterwards, CFA was conducted to retrieve the value of CR and CV (explained in Average Variance Extracted

Table 3 Measurement model

Constructs	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
PE	.842	0.851	0.655
EE	.932	0.933	0.822
SI	.628	0.607	0.440
FC	.770	0.784	0.555
Mob	.701	0.703	0.542
SML	.871	0.874	0.777
BI	.716	0.763	0.629
UB	.733	0.703	0.501

(AVE)) (Byrne 2016). The value of CR should be more than .70 and for CV, the recommended value of AVE is more than .50 (Hair et al. 2010). Therefore, Table 3 shows that all the constructs ensures CR and CV test expect SI. However, CFA is tactful toward the number of items per conducts and also a firm measure of reliability and validity (Malhotra and Dash 2011). Nevertheless, using more items to represent SI might affect the output.

5.3 Hypothesis testing

A structural model was developed based on the relationship of the research model of this study. The causal relationship of the constructs evaluated through structural model (Hair et al. 2010). In this study, the relationship between independent and dependent variable tested by path co-efficient (beta), T-statistics and the p value. Table 4 presents the output of the structural model. According to the results, the relationship between PE to BI ($\beta = .179$, $t = 2.989$, $p < 0.05$), EE to BI ($\beta = .147$, $t = 2.774$, $p < 0.05$), SML to BI ($\beta = .190$, $t = 3.570$, $p < 0.001$), BI to UB ($\beta = 1.482$, $t = 5.342$, $p < 0.001$) were significant. Therefore, hypotheses H1, H2, H7, and H8 are supported by this study. On the other hand, relationship between SI to BI ($\beta = .041$, $t = 1.044$, $p > 0.05$), FC to BI ($\beta = .066$, $t = .671$, $p > 0.05$), FC to UB ($\beta = .017$, $t = .115$, $p > 0.05$), Mob to BI ($\beta = .045$, $t = 1.051$, $p > 0.05$) were turned insignificant. So, hypotheses H3, H4, H5, and H6 are not supported in this study.

6 Discussion

This study applied and modified the UTAUT model to determine the factors that affect the uses of mobile cloud learning. The empirical finding provides insight that PE, EE, SML, and BI affect the use behaviour of the MCL platform users. The outcome of this study supports some previous study and contradicts with some study. This study finds PE as a significant factor, which implies that the performance of the technology is crucial to use behaviour. For PE, this study supports studies by Venkatesh et al. (2003); Abu-Al-Aish and Love (2013); Wang et al. (2009); Chiu and Wang (2008); Ong et al.

Table 4 Hypothesis testing

Hypothesis	Path	Standardized path coefficient (Beta)	T-statistics	Interpretation
H1	PE —> BI	.179	2.989**	Supported
H2	EE —> BI	.147	2.774**	Supported
H3	SI —> BI	.041	1.044	Not Supported
H4	FC —> BI	.066	.671	Not Supported
H5	FC —> UB	.017	.115	Not Supported
H6	Mob —> BI	.045	1.051	Not Supported
H7	SML —> BI	.190	3.570***	Supported
H8	BI —> UB	1.482	5.342***	Supported

***$p < 0.001$, ** $P < 0.05$

(2004) and Saade and Bahli (2005), as they also found PE significant for different technology uses. For EE, this study supports previous studies (Abu-Al-Aish and Love 2013; Wang et al. 2009), as EE also turned significant. Therefore, it can be argued that ease to use is crucial on use behaviour of the technology. Studies by Venkatesh and Davis (2000), Venkatesh et al. (2003) argued that SI is significant to UB. However, this study contradicts with those studies as SI turned insignificant in this study. As SI doesn't process high reliability and validity, therefore further research needs to conduct for strong argument on SI with more measurement items. In case of, FC and mob, both turn insignificant in this study which contradicts with some previous studies (Cheong et al. 2004; Wu et al. 2007; Venkatesh et al. 2003; Kaigin and Basoglu 2006; Mallat et al. 2008). Venkatesh et al. (2003) claimed that FC can turn insignificant if both PE and EE are significant. Therefore, in this study, FC turned insignificant for both BI and UB. For mobility, it is possible that the significance is more related to technology as it turned significant for other technology while insignificant for the blackboard. Another new factor SML turned significant in this study which supports studies by Wang et al. (2009); Prajapati and Patel (2014) and Smith et al. (2003) and contradicts with studies by Lowenthal (2010) and Al-Adwan et al. (2018). However, as SML doesn't show any reliability and validity issue, it can be argued that SML is significant to UB by this study. Furthermore, like previous studies, this study also confirms that BI facilitates the use behaviour of the technology.

7 Implications

The finding of this study has a theoretical, methodological and practical contribution in the MCL area. In case of the theoretical contribution, this study enriches the literature on MCL and related terms. Maximum previous studies used other model or basic UTAUT model for mobile learning or explored MCL only. With the best knowledge of the author, this is the first study which extended and modified UTAUT model focusing on MCL. This study also enriches the theoretical knowledge of extended factors. In case of the methodological contribution, this study shows that the use of two measurement item can also confirm the reliability and validity. As some research argued that to ensure validity and reliability three items is essential (Gaskin 2016; Hair et al. 2010). Instead of two items Mob and SML passed the reliability and validity test which implies items itself is more crucial than numbers. This will contribute methodologically to future research. This study also has some practical contribution. The outcome of this study will help the Blackboard platform provider to improve their user experience and reduce their switching rate. New platform provider can also get insight from this study regarding which factor needs more consideration. Institutions who are using MCL platform especially blackboard can also improve their user experience focusing on significant factors as those factors will lead to impact more of use behaviour.

8 Limitations and future research

This study has some limitations; firstly, the impacts of moderating variables (i.e. age, sex, and experience) were not investigated in this study. In future studies, moderating

variables can be looked. Secondly, construct SI process moderate reliability and validity. So, more or different items can be used for ensuring high reliability and validity in future studies. Lastly, due to a cross-sectional study, long-term causal relationship among factors cannot be confirmed by this study. Therefore, a longitudinal study needs to be conducted to confirm the long-term causal relationship.

9 Conclusion

This study aimed to investigate the factors behind the MCL through extending and modifying the UTAUT model with two additional variables, i.e. Mobility and self-management learning. Empirical findings of this study pointed Performance expectancy, effort expectancy, and self-management learning as a significant factor behind the uses of MCL of Blackboard platform. This study also shows, facilitating condition, social influence and mobility are insignificant in behavioural intention and use behaviour of MCL platform Blackboard. The outcome of this study contributes to future study in MCL arena, to the Blackboard platform provider, to Blackboard platform users and also to the organization who use multiple platforms to provide interactive education without understanding the feeding behind the use behaviour of MCL platform.

Data availability The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Compliance with ethical standards

Competing interests Not Applicable.

Abbreviations *MCL*, Mobile Cloud Learning; *UTAUT*, Unified Theory of Acceptance and Use of Technology; *SEM*, Structural Equation Modelling; *PE*, Performance Expectancy; *EE*, effort expectancy; *SI*, Social Influence; *FC* Facilitating Condition; *SML* Self-Management Learning; *Mob*, Mobility; *BI*, Behavioural Intention; *UB*, Use Behaviour; *EFA*, Exploratory Factor Analysis; *CFA*, Confirmatory Factor Analysis; *CV*, Convergent Validity; *CR*, Composite reliability; *AVE*, Average Variance Extracted; *SPSS*, Statistical Package for the Social Sciences; *VLE*, Virtual Learning Environment; *LMS*, Learning Management System; *CMS*, Course Management System; *PLE*, Personal Learning Environment

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