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Extended Unified Theory of Acceptance and Use of Technology in Mobile Learning: A Systematic Review

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Abstract
Technology acceptance, as a prerequisite for the successful implementation of mobile learning, has received much academic effort based on different theories. As a comprehensive theory in exploring individual technology acceptance, the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) has gained increasing attention in information systems and beyond. Nevertheless, there is a gap in existing knowledge regarding literature that systematically synthesizes research on UTAUT2 in an educational context. Given this, the present study was conducted to comprehensively review existing studies on the acceptance of mobile learning (m-learning) so as to get a clear and in-depth understanding of learners' needs and preferences. We searched studies that empirically examined m-learning acceptance based on UTAUT2 from four databases in October 2020. Following the guidelines in the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) statement, 20 studies were identified and included. The results highlighted the current research trend of previous studies in terms of year of publication, distribution of country and journal, type of technology, and research method. Besides, the determinants of the acceptance of m-learning were identified. The main findings include that hedonic motivation was the most validated predictor of users' behavioural intention, followed by performance

expectancy, habit and social influence, while effort expectancy, facilitating conditions and price value were reported to be nonsignificant in more than half of the studies reviewed. Most studies applied a part of UTAUT2 in a particular research context, but a few studies extended the model with external variables such as trust, technological innovativeness, and personal innovativeness. The findings also reveal that the investigation of moderating effects was lacking in the existing literature. Most studies were undertaken in developing countries in Asia in the context of higher education and self-reported questionnaire surveys were the single method of data collection used in all studies with the partial least squares structural equation modeling (PLS-SEM) being the most frequently adopted data analysis method. Further efforts can be dedicated to extending UTAUT2 with external variables to tailor to the m-learning context and to further examine the effect of moderating variables. A great diversity of respondents is also encouraged in future studies so that deeper insights can be gained from students and teachers at different educational stages. Furthermore, longitudinal studies are needed to explore technology acceptance at various phases such as adoption, initial use, or post-adoptive use.

Keywords: Mobile Learning, Technology Acceptance, UTAUT2, Systematic Review

Introduction

With the advancement of wireless and mobile technologies, mobile learning (m-learning) is becoming increasingly important (Chu et al., 2010). Scholars have not yet reached a consensus on the definition of m-learning since it is novel and still evolving (Peng et al., 2009). Moreover, it is challenging to conceptualize m-learning due to its 'noisy' characteristics—personal, contextual, and situated (Traxler, 2007, p.1). A commonly used definition is 'using mobile technologies to facilitate learning' (Hwang & Tsai, 2011, p. 65). However, the availability and accessibility of mobile devices neither mean users are mobile learners (Hao et al., 2017), nor guarantee their achievement in an educational context (Godwin-Jones, 2017; Liu, Li & Carlsson, 2010). Any learning technology system can work effectively only when learners start to make full use of its wide range of features (Saade & Bahli, 2005), and when they experience that it facilitates their learning process and satisfies their learning needs (Sharma et al., 2016). Moreover, as argued by Bennett et al (2008), young people, though immersed in technology, have much more complex relationships with technology than the digital native characterization assumes, and their technology use and skills vary.

In consideration of the financial investment, as well as time and effort to implement any kind of information system (IS), experts have always taken users' acceptance as a prerequisite to ensure its success (Davis, 1989; Al-Emran et al., 2018). Thus, an understanding of influential factors for users to accept and use technology has become a key branch in IS research over the past few decades (Teo et al., 2019; Sabah, 2016; Marangunic & Granic, 2015), aiming at providing feedback to relevant stakeholders for their decision or policy making (Teo et al., 2019).

To this end, a growing panoply of theoretical models has been developed. Venkatesh et al (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating eight dominant IT acceptance models. UTAUT comprises four core constructs that affect users' acceptance and use: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). Of these constructs, PE, EE, and SI are theorized as direct determinants of an individual's behavioral intention (BI), while FC is a direct determinant of actual use behaviour (UB). Furthermore, four moderators, gender, age, experience, and voluntariness of use, are included to explain users' differences in their technology acceptance. With the prevalence of individual usage of technology, Venkatesh, Thong and Xu (2012) proposed extended Unified Theory of Acceptance and Use of Technology (UTAUT2) by adding additional constructs, namely, hedonic motivation (HM), price value (PV), and habit (HT), focusing on the consumers' perspective. Age, gender, and experience are also included as moderators (Venkatesh et al., 2012) (Fig. 1).

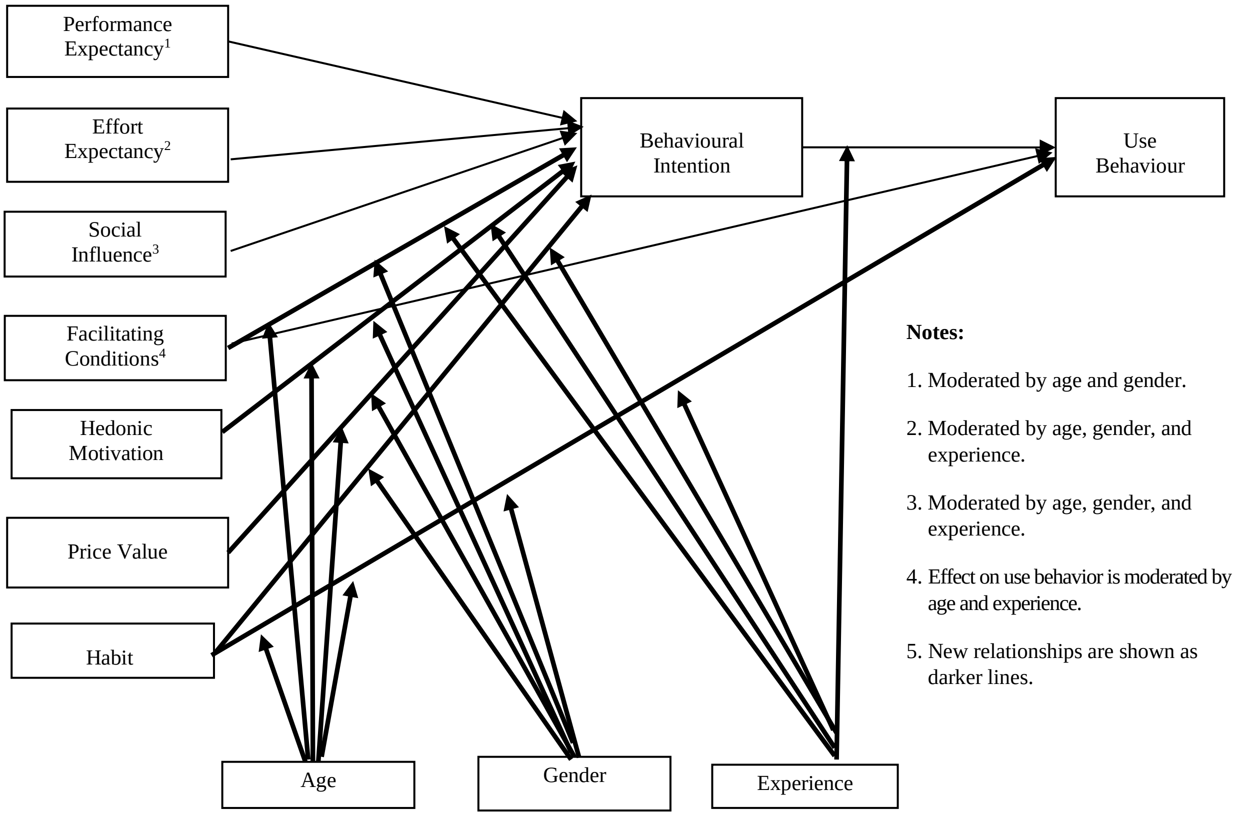

Fig. 1 UTAUT2 Model (Venkatesh et al., 2012, p. 160).

In comparison with UTAUT which has explained 56% and 40% of the variance in behavioural intention and use behaviour, UTAUT2 has improved considerably, explaining 74% and 52% of the variance in behavioural intention and use behaviour respectively (Venkatesh et al., 2012). As the most comprehensive theoretical frame in exploring individual technology acceptance and use (Tamilmani et al., 2020), UTAUT2 has gained high popularity from strong empirical validation for its powerful predicting ability (Tamilmani et al., 2018; Morosan & Defranco, 2016), which has been regarded as superior to other frameworks (Moorthy, Yee, T'ing & Kumaran, 2019; Rodriguez & Trujillo, 2014).

Despite the prevailing nature of mobile learning and the great potential it promises, acceptance of mobile learning is fraught with challenges from both practice and research since it is still in its infancy and embryonic phase (Motiwalla, 2007). In practice, learners' acceptance of m-learning is still very low (Almaiah et al., 2019; Almaiah et al., 2016). In research, there are few empirical studies pertaining to the technology acceptance and use of m-learning (Almaiah & Mulhem, 2019; Al-Emran et al., 2018), particularly in developing countries (Teo et al., 2019). In addition, the determinants of m-learning remain at an ongoing exploration phase, where all stakeholders in education, including researchers, educators, m-learning service providers, still have not gained a clear and in-depth understanding about learners' needs and preferences (Almaiah et al., 2019; Kumar & Chand, 2019; Almaiah et al., 2016; Al-Emran et al., 2018; Mohammadi, 2015).

Recently, increasing attention has been given to the development of UTAUT2 from various perspectives. However, only a few review studies were carried out to provide a comprehensive understanding of UTAUT2. For instance, Tamilmani et al (2018) synthesized consumer adoption of mobile applications by weight analysis. Later, they conducted a meta-analysis to analyse the path relationships in UTAUT2 model (Tamilmani et al., 2020). We believe each study provided valuable insight into UTAUT2, but there is still a gap in the existing knowledge regarding the literature that systematically synthesizes research on UTAUT2 in an educational context. Therefore, this study aims to synthesize the research trend of UTAUT2 studies regarding m-learning and identify the determinants of m-learning acceptance. By doing so, we expect to obtain specific and deeper insight into the applicability of UTAUT2 in the m-learning context, revealing the limitation of the extant literature from which future research implications and promising directions can be charted. Specifically, this study is guided by two overarching questions:

RQ1. What is the current research trend of UTAUT2 based studies regarding m-learning in terms of year of publication, distribution of country and journal, type of technology, and research method?

RQ2. Based on the review of the related studies published between 2012 and 2020, what are the determinants of the acceptance of m-learning?

Methodology

Guided by the principles of analysis proposed in Moher et al (2009) in the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA), this review was undertaken in these distinct stages: data sources and search strategies, inclusion and exclusion criteria, quality assessment, and data extraction and synthesis. The procedures are elaborated in the following sub-sections.

Data Sources and Search Strategies

We conducted an extensive search of literature in the following databases: Web of Science, Scopus, ERIC, and ProQuest. The search terms include (“Extended Unified Theory of Technology Acceptance and Use of Technology” OR UTAUT2) AND (“Mobile learning” OR m-learning). The search for these articles was undertaken in October 2020. The search was limited to an 8-year period from 2012 (the year of introduction of UTAUT2) to 2020. The detailed search strings are elaborated in Table 1. Initially, we retrieved 45 studies in total, 18 of which were removed as they were duplicated, leaving 27 articles for screening. By screening from title and abstract, 5 articles were filtered out based on the inclusion and exclusion criteria. At the quality assessment stage, 2 articles were removed since the results were not reported clearly. Thus, the total number of articles included in our final analysis was reduced to 20. The search process of this systematic review and the retrieval of articles from every stage is elaborated in Fig. 2.

Table 1
Search Strings

Database	Results	Keyword searching and other applied filters
Web of Science	14	#1 TS= "Extended Unified Theory of Technology Acceptance and Use of Technology" OR TS=UTAUT2 (437) #2 TS= "Mobile learning" OR TS= m-learning (7475) #1 AND #2 (14) Time span:2012-2020
Scopus	12	TITLE-ABS-KEY (("Extended Unified Theory of Technology Acceptance and Use of Technology" OR UTAUT2) AND ("Mobile learning" OR m-learning))
ERIC (via EBSCOhost)	12	("Extended Unified Theory of Technology Acceptance and Use of Technology" OR (UTAUT2) AND "Mobile learning" OR m-learning) Search mode: Boolean/phrase. Expanders: apply related words, apply equivalent subjects. Date published: from January 01 2012 to December 31 2020.
ProQuest	7	ab("Extended Unified Theory of Technology Acceptance and Use of Technology" OR UTAUT2) AND ab("Mobile learning" OR m-learning) limit by: Publication Date: From 2012 to 2020

Inclusion/Exclusion Criteria

To be considered appropriate for this review, the research articles must fulfill the inclusion and exclusion criteria in Table 2.

Table 2
Inclusion and Exclusion Criteria

Inclusion criteria	Exclusion criteria
1. Should be empirical studies.	1. Review papers other than empirical studies.
2. Should utilise UTAUT2.	2. Studies using other models than UTAUT2.
3. Should involve m-learning.	3. Studies using UTAUT2 in contexts other than m-learning.
4. Should be written in English.	4. Articles written in languages other than English.

Quality Assessment

Another factor that should be considered is the quality assessment of the selected studies. In this review study, a quality assessment checklist with five criteria was formulated to measure the credibility and validity of the studies that were retained for further analysis (N = 22). The checklist is elaborated in Table 3. Of these articles, 2 articles were removed since the reports of the results were not clear. Therefore, 20 studies are qualified to be used for further analysis.

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Table 3
Quality Assessment Checklist

#	Question
1	Is the research model specified?
2	Is the research methodology adequately detailed?
3	Does this study explain the reliability and validity of the measures?
4	Are the statistical techniques used for data analysis adequately described?
5	Are the results clearly and completely reported?

Data Extraction and Synthesis

To ensure that all the studies were analysed consistently, a coding scheme about study characteristics and the results was created. For each study, the following information was extracted: (a) the authors and the year of study, (b) the source of publication, (c) the country where the study was conducted, (d) m-learning technology types, (e) methodology (including the type of study, data collection method, sample size, user type, and data analysis method), (f) the variables involved in each study and the variables that were identified to be significant predictors.

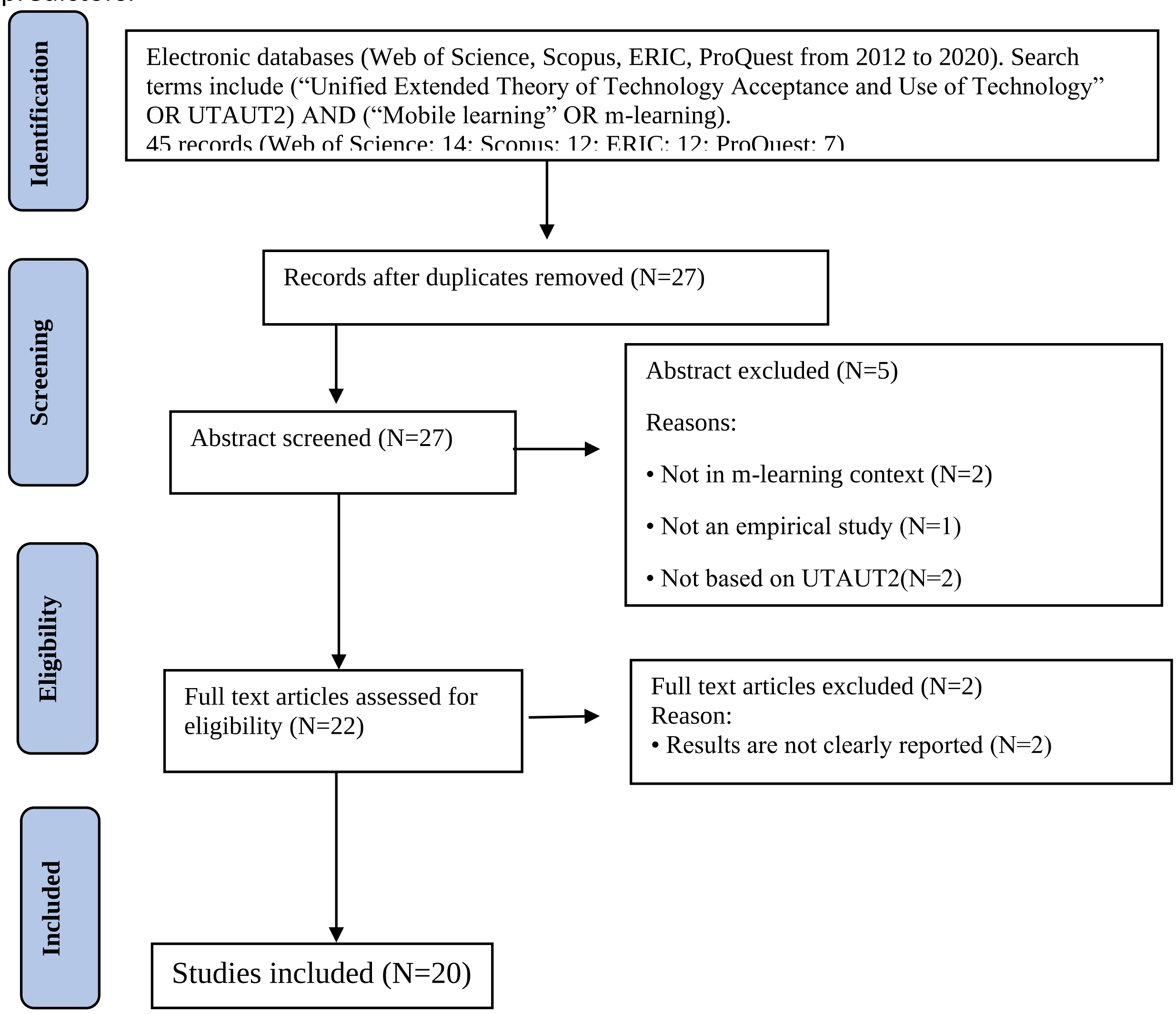


Fig. 2. Systematic review flow diagram.

Results and Discussion

Among the 20 selected studies, 3 studies investigated two different groups of users, such as faculty members and students, or respondents from two countries. To synthesize the findings accurately, for studies that test models with separate samples, we considered each sample as a separate trial (Higgins & Green, 2011). Therefore, this review study covered 23 records in total when reporting the effects of variables in section 3.6.

Distribution of studies by year of publication

Since its recent introduction in 2012, UTAUT2 has been a research interest in different fields. In our findings, UTAUT2 based empirical studies in m-learning emerged in 2013. The year 2018 was the top on the list with five studies, followed by the years 2019 and 2020 with four studies for both years. It is notable that more articles may still be in the process of publication in 2020 since we searched for the articles in October 2020. Though the total number of UTAUT2 based studies in m-learning is relatively small, the overall increasing trend indicates that more scholars may start to explore UTAUT2 in m-learning acceptance and more papers may emerge in the near feature. Fig. 3 shows the results of publications records for the study.

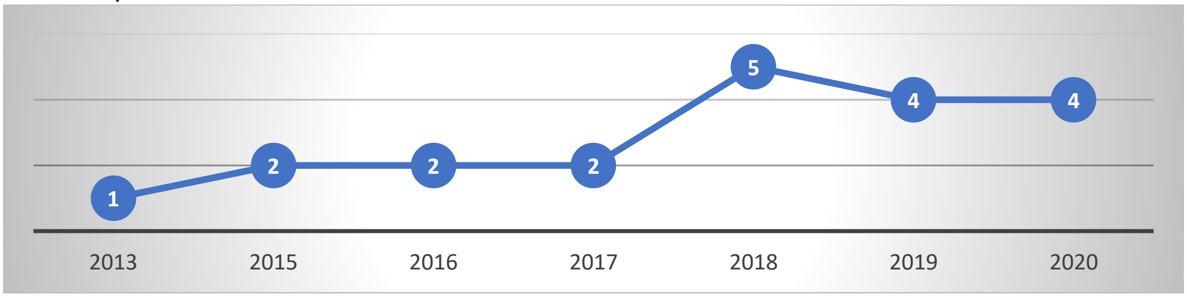


Fig. 3. Distribution of studies by year.

Distribution of Countries

The studies were widely distributed across various regions, such as Asia, North America, Europe, and Africa. As depicted in Fig 4, a great majority of research regarding UTAUT2 in the m-learning context was from Asia (75%). China and Malaysia were on top of the list with 3 studies respectively, followed by USA and Iraq with 2 studies each. The rest of the studies were distributed among nine countries including Thailand, Tanzania, Pakistan, South Korea, Iran, India, Greece, Siri Lanka, and Saudi Arabia, with one study each. There was one study which did not specify the country from which the data was elicited.

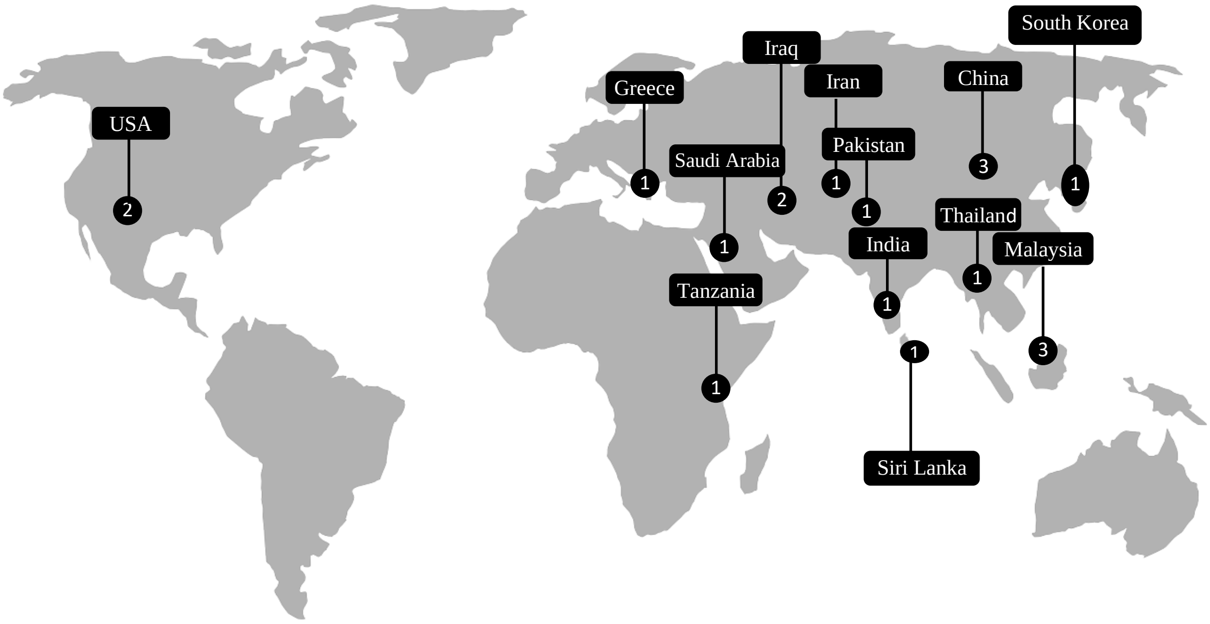


Fig. 4. Distribution of studies in terms of country.

Distribution of Journals

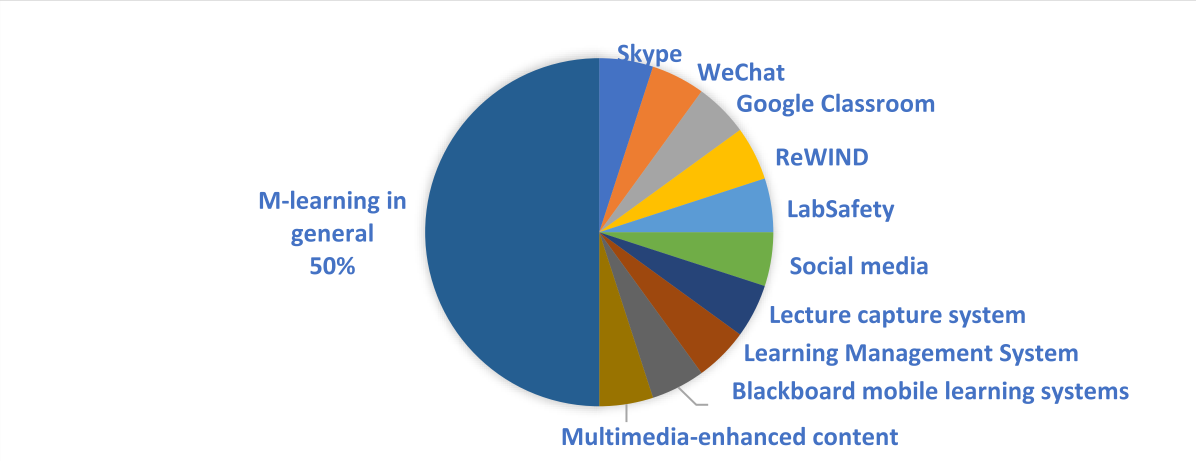
Table 4 presents the distribution of studies in terms of published journals excluding 2 conference papers and 4 PhD dissertations. The publication source was varied; there were 14 papers in 10 different journals. *Education and Information Technologies,* as well as *Interactive Technology and Smart Education* emerged as the topmost with 3 papers each. The rest of the studies were distributed among the other journals such as *Australian Journal of Education Technology*, *Technology in Society*, and *Universal Access in the Information Society* and so forth.

Table 4
Journal base Publications

Publication source	Count of papers (total=20)
1. Education and Information Technologies	3
2. Interactive Technology and Smart Education	3
3. Australasian Journal of Educational Technology	1
4. Technology in Society	1
5. Universal Access in the Information Society	1
6. Journal of Critical Reviews	1
7. International Review of Research in Open and Distributed Learning	1
8. Journal of Convergence Information Technology	1
9. International Journal of Interactive Mobile Technologies	1
10. International Journal of Learning and Change	1
11. Conference paper	2
12. Dissertation & Thesis	4

Type of Technologies

Regarding the technology type involving in the extracted studies, 10 studies investigated m-learning system in general, and another 10 studies focused on a particular technology or system. The variety of m-learning technologies or systems is elaborated in Fig. 5. Some systems are designed to support learning, such as Google Classroom, while some are social media applications that have been adopted for teaching and learning purposes such as Skype



and WeChat. There are also systems that have been developed specifically for users in a particular field, such as the learning system for pharmacy students, LabSafety.

Fig. 5. M-learning technology type.

Research Methods of Extracted Studies

Table 5 reveals that UTAUT2 in m-learning studies were dominated by quantitative studies (20 studies). For data collection, all the studies adopted self-reported questionnaire surveys. This could be attributed to the advantages of questionnaires, which can be used to effectively evaluate respondents' perceptions (Al-Emran et al., 2018), and to identify the relationship among the constructs in a model (Malhotra & Grover, 1998). Moreover, questionnaires enable scholars to gather information from a comparatively large number of respondents despite geographical constrains (Rowley, 2014). For data analysis, scholars primarily adopted PLS-SEM, followed by regression with 7 studies and SEM with 2 studies. Compared to SEM, PLS can effectively estimate complex model that includes many constructs, indicators, and structural paths, with relatively smaller sample sizes and non-normal data (Hair et al., 2019). Due to these distinctive features, the application of PLS has increased exponentially in the past few years (Hair et al., 2017).

In terms of the distribution of studies by education levels, our findings revealed that all the studies were conducted in the higher education settings with only one exception that is in secondary school. Most respondents were university students (N=16), with only 3 groups of university faculty members and 1 group of secondary school teachers. This indicates that m-learning is more mature and active at higher education levels (Al-Emran et al., 2018), but future research may also focus on the m-learning acceptance from different educational stages. Moreover, teachers should also be taken into consideration in the acceptance of m-learning since they play a significant role in the teaching and learning process (Baharin et al., 2015). More importantly, teachers play a central role both in integrating technology in the classroom (Chen et al., 2009) and in forming students' attitudes toward technology (Hu et al., 2003). Hence, it is critical to understand teachers' technology acceptance and use (Pynoo et al., 2011).

As for sample size, the majority of the study samples were between 300 and 500 (7 studies), followed by 100 to 300 (6 studies), more than 500 (5 studies), and less than 100 (2 studies). The minimum sample size was 44, and the maximum was 1137, revealing that the sample size varied greatly even in a similar research setting. To draw a valid conclusion, an appropriate and informed sample size is vital. To address this problem, researchers are encouraged to read and understand, but not blindly follow, the widely adopted rules of thumbs, and to apply any of them with reference to their specific study contexts such as nature of research problem, research design, analytical method, number of variable or model complexity, data analysis program, and population characteristics (Memon et al., 2020).

Table 5
Research methods of extracted studies

	Type	Count of numbers
Type of study	Quantitative	20
Data collection	Cross-sectional questionnaire	20
	University students	16
Type of users	University faculty members and students	3
	Secondary school teachers	1
	Less than 100	2
Sample size	100 to 300	6
	300 to 500	7
	More than 500	5
Data analysis	PLS-SEM	10
	SEM	2
	Regression	7
	ANOVA	1

Effects of Variables

Table 6 in Appendix lists all the extracted studies in terms of the authors, constructs, and moderators that studies utilised. We synthesized the constructs that influenced BI and UB, as well as the moderators. The effects of these variables are presented in the following sections.

As shown in Fig. 6, PE, EE, and SI were the most frequently utilised constructs among all the seven predictors of BI in UTAUT2, spanning across all 23 studies. HM ranked as the second commonly used construct in m-learning (22 studies), followed by FC (20 studies), HT (19 studies), and PV (13 studies). PV was found to be the least used construct in UTAUT2 based studies in the educational setting. Researchers opted to exclude PV because in most cases m-learning technologies do not include any extra cost for learners especially in a formal learning context (Zwain, 2019).

With regards to the determinants of behavioural intention that have been validated in the selected studies, HM ranked on the top, having been proved to be significant in 91% of the cases (20 out of 22 studies), followed by PE (18 studies), HT (17 studies), SI (15 studies), EE (10 studies), FC (9 studies) and PV (6 studies). Reviewing the existing literature, PE has consistently been shown to be the strongest predictor of BI (Venkatesh et al., 2003). However, this review identified HM as the most validated predictor in behavioural intention to use m-learning. This is an interesting finding, highlighting the difference between the organizational and individual consumer contexts. In an organizational context, utilitarian motivation is the main factor that determines employees' behavioural intention while hedonic motivation becomes more important than performance expectancy in the consumer setting (Venkatesh et al., 2012). However, HM mostly influences users during early adoption, but when they become experienced, HM may diminish and the efficiency of the technology may be the priority of users (Venkatesh et al., 2012). Therefore, m-learning service providers can attract users by novel features at the early adoption stage, but to obtain continuous usage of learners, they should guarantee the compelling product function that can efficiently facilitate users' learning process and outcome. Hence, we can conclude that both utilitarian benefits and hedonic benefits are equally crucial determinants in technology acceptance and use. Another important predictor of BI is HT. Specifically, 89% of cases, i.e., 17 out of 19 studies reported its significant effect on BI. Similarly, 18 out of 23 studies supported the effect of SI on BI.

Compared to PE, HM, and HT which were identified as strong predictors in most studies, EE, PV, and FC, however, were only reported to be significant in a minority of studies. EE, as one of the most employed UTAUT2 construct, turned out to be the factor that generated the most inconsistent findings. This result is in line with a meta-analytic evaluation of UTAUT2 (Tamilmani et al., 2020). In our result, only 43% of cases (10 out of 23) reported its significant effect on BI. Another inconsistent finding is the effect of FC on BI, with significant effect validation in 45% of studies. Additionally, only 6 out of 13 studies reported its positive effect of PV, as the least used construct in m-learning, on BI.

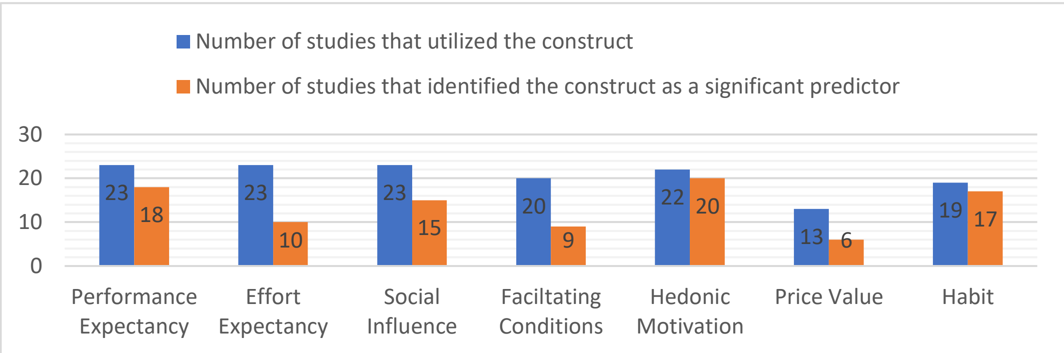


Fig. 6. UTAUT2 constructs that influence behavioural intention.

In the original UTAUT2 model, two endogenous variables, BI and UB are used. However, of the 23 analysed records, only 9 studies included UB in their models, while 14 studies utilised BI as proxies for actual use. This phenomenon is caused by the long-held notion of IS researchers that behavioural intention is a good indicator of usage for evolving technology (Tamilmani et al., 2020). Moreover, there is a lack of consensus on how use behaviour should be measured (Agudo-Peregrina et al., 2014; Botero et al., 2019), and it is very challenging to gauge actual use of such an evolving technology (Schuitema et al., 2013), especially in informal m-learning context (Karimi, 2016). Yet, more attention should be given to the congruency between the user acceptance and actual use (Pynoo et al., 2011).

As seen from Fig. 7, FC, HT, and BI were hypothesized to have effects on UB. Consequently, 7 out of 9 studies supported the effect of FC on UB, and all the 9 studies identified the effect of HT on UB. Moreover, it is worth noting that the study of Kumar and Bernell (2018) reported that there was an insignificantly negative effect of BI on UB. They reported HT as the main predictor of use behaviour, rather than BI. The reason for the spurious effect between BI and UB could be when students' usage of a particular system becomes a habit for them, their intention formation is eliminated (Kumar & Bernell, 2018). In this case, habit could limit or weaken the effect of BI on UB (Venkatesh et al., 2012).

Overall, inconsistent findings emerged from the existing studies with regard to the effect of variables. A plausible explanation for this is that the success of technology adoption varies across cultures, societies, user types, and technology types (Venkatesh et al., 2012; Venkatesh & Zhang, 2010; Park et al., 2012; Chung et al., 2015). For instance, as one of the best predictors of BI, PE could be insignificant in certain contexts. Besides, EE, which generated the most inconsistent findings, is continuously used to investigate m-learning adoption. This reminds researchers to be more cautious while applying the theory. In addition, to tailor to the specific research context, some adaptations are necessary rather than replicating all the constructs in a single underpinning theory (Tamilmani et al., 2020).

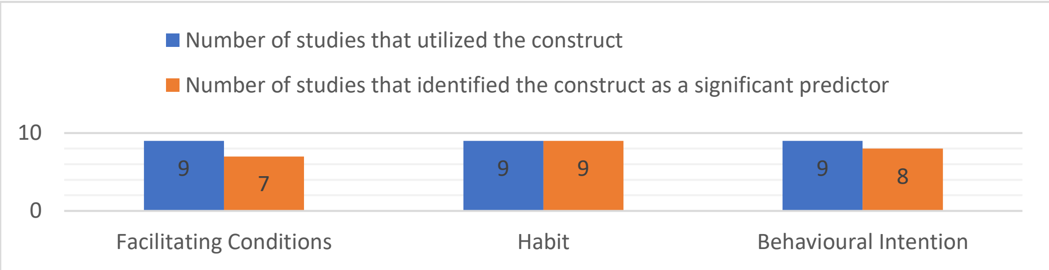
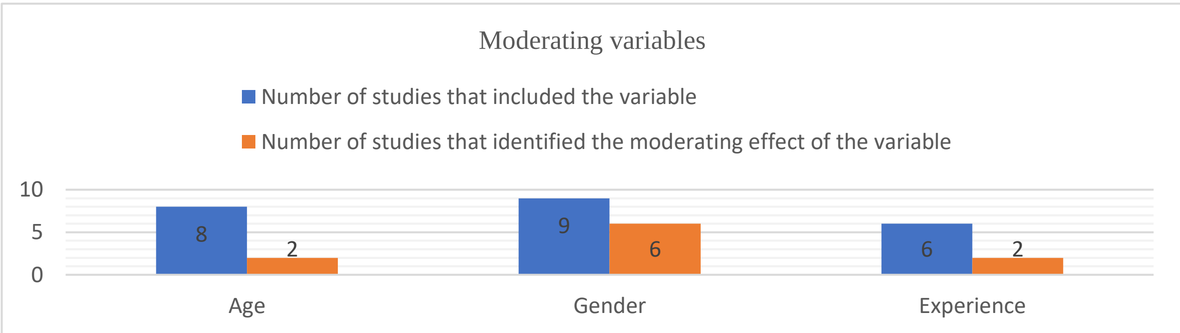


Fig.7. UTAUT2 constructs that influence use behaviour.

Another noticeable trend is the lack of investigation on moderating effects. As seen from Fig. 8, only around 1/3 of the studies reviewed examined moderating variables. The finding is consistent with the review article of Venkatesh et al. (2016). They pointed out that this was "surprising and disappointing" since researchers should not reach a conclusion in



terms of the generalizability of UTAUT or other possible boundary conditions merely based on the empirical evidence (Venkatesh et al., 2016, p.332).

Fig. 8. Moderating variables.

Ventekash et al (2016) classified empirical UTAUT-based studies into three categories: UTAUT application, UTAUT integration, and UTAUT extensions. Following this classification, we found that of 20 articles, 12 articles are merely UTAUT2 applications, applying either part of or the complete UTAUT2 in a specific setting. Only 8 studies were UTAUT2 integration or extensions, which either integrated UTAUT2 with other theoretical models or extended it with new mechanisms. Among these new constructs which have been identified as predictors of behavioural intention, trust, persona innovativeness, and technological innovativeness were identified by 2 studies. Besides, other factors such as learning value, work life quality, information quality, system quality, quality of service, ubiquity, satisfaction, and interactive visual information are found to be significant with 1 study each.

Conclusion

This systematic review sheds light on the current research trend of UTAUT2-based empirical studies of m-learning acceptance in terms of year-wise publication, distribution of countries and journals, type of technology, and research methods. Moreover, by synthesizing the existing empirical studies, we identified the strong predictors and the contradictory factors in m-learning adoption. Specifically, this study presents eight findings. First, the total number of UTAUT2-based studies in m-learning is still small, indicating this field is relatively underexplored. However, the overall increasing numbers of studies published reveal that the significance of the research direction, and more studies may emerge in the near future. Second, most UTAUT2-based studies in m-learning contexts were conducted in Asia. Third, *Education and Information Technologies*, as well as *Interactive Technology and Smart Education*, emerged as the top journals which published the most UTAUT2 based studies involving m-learning. Fourth, half of the studies investigated the m-learning system in general while another half focused on a particular technology or system. Fifth, in terms of research methods, all the studies were quantitative studies with the questionnaire survey as the only instrument used. Samples were dominated by university students and the sample size mainly fell into the category of 300 to 500. As for data analysis, PLS-SEM was the most used technique followed by SEM and regression. Sixth, HM was the most validated significant predictor of BI, followed by PE, HT, and SI, while EE, FC, and PV produced inconsistent findings in most studies. Seventh, there was a lack of investigation of moderating variables in the selected studies. Eighth, most of the studies merely applied UTAUT2 to a new context, while only a few studies extended it with new constructs.

The studies in this systematic review were limited to four databases, Web of Science, Scopus, ERIC, and ProQuest. Therefore, we may have missed some studies published in other databases or other sources. Future research could expand their studies to a wider range of databases. Finally, this study only included articles written in English; thus, the reviewed studies in this paper may not represent all UTAUT2-based studies involving m-learning.

Future Research Recommendations

The findings in this review could provide worthwhile references for researchers, educators, and educational service suppliers. Overall, we believe that more studies are still needed to verify the effectiveness of variables of UTAUT2, especially the moderating effects. Moreover, to further investigate the acceptance of m-learning, scholars should extend UTAUT2 with additional factors from related theories or models so that it can tailor to m-learning setting. This accords with the future research direction highlighted by Venkatesh et al (2016) in their review study, one of which is to integrate task attributes as contextual factors to engender different UTAUT extensions to make significant theoretical contributions to the technology acceptance and use domain (Venkatesh et al., 2016). This article also reveals the limitation of the user type in existing studies. Given this, future studies could encompass a broader sample of participants going beyond the focus of university students and faculty. In addition, it is highly recommended to conduct longitudinal research that can capture the technology acceptance at different phases such as adoption, initial use, or post-adoptive use. Last but not least, another concern lies in the fact that only a few studies measured the actual usage of m-learning technology, while most studies utilised behavioural intention as proxies for actual use. To conclude, this systematic review provides a deep insight into the current research trend and findings of UTAUT2 based empirical studies, forming an essential reference for future studies in acceptance of m-learning from the perspective of UTAUT2.

Appendix Table 6 Constructs utilised in extracted studies.

Study	UTAUT2 constructs that influence BI							UTAUT2 constructs that influence UB			UTAUT2 moderators			New constructs
	PE	EE	SI	FC	HM	PV	HT	FC	HT	BI	Age	Gender	Experience	
Farooq et al (2017)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓				Personal innovativeness
Nair (2015)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓				
Zwain (2019)	✓	✓	✓	✓	✓		✓	✓	✓	✓				technological innovativeness, information quality; learning value
Kumar & Brevell (2019)	✓	✓	✓	✓	✓		✓	✓	✓	✓				
Ameri et al (2020)	✓	✓	✓	✓			✓	✓	✓	✓	✓	✓	✓	
Arain et al (2019)	✓	✓	✓	✓	✓		✓					✓		Ubiquity; satisfaction; information quality, system quality; appearance quality
Moorthy et al (2019)	✓	✓	✓	✓	✓	✓	✓					✓		
Al-Azawei et al (2020)	✓	✓	✓		✓	✓		✓						Trust
Nawaz & Mohamed (2020)	✓	✓	✓	✓	✓		✓				✓	✓	✓	
Nikolopoulou Gialamas & Lavidas (2020)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Bharati & Srikanth (2018)	✓	✓	✓	✓	✓	✓								Interactive visual information; quality of service
Issaramanoros et al (2018)	✓	✓	✓	✓	✓									Personal innovativeness
Edwards (2017)	✓	✓	✓	✓	✓		✓				✓	✓	✓	
Kang et al (2015)	✓	✓	✓	✓	✓	✓	✓							
Forehand (2018)	✓	✓	✓	✓	✓	✓	✓	✓			✓			New moderator (level of education; type of program)

AlMarwani (2016)	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓		✓	
Yang et al (2018)	✓	✓	✓	✓	✓	✓	✓					✓			
Huang (2018)	✓	✓	✓	✓	✓		✓				✓	✓		✓	
Yang et al (2013)	✓	✓	✓		✓	✓	✓								Self-management of learning
Mtebe et al (2016)	✓	✓	✓	✓	✓		✓								

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