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Can COVID-19 pandemic influence experience response in mobile learning?

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ABSTRACT

The mass spreading of COVID-19 has changed the paradigm of the education industry. In China and many other nations, universities have introduced compulsory remote education programs such as mobile learning (m-learning) to prevent public health hazards caused by the pandemic. However, so far, there is still a lack of understanding of student's learning experience responses in compulsory m-learning programs. As such, there is a necessity to explore the factors and mechanisms which drives students' experience. This paper evaluates the influence of both pedagogy and technology on learner's compulsory m-learning experience response (ER) by extending the mobile technology acceptance model (MTAM) during the COVID-19 pandemic. An online self-administered questionnaire was used to collect the data, which was then analysed through SmartPLS 3.2.9. Importance-performance matrix analysis was applied as a post-hoc procedure to gauge the importance and performance of the exogenous constructs. The results revealed that perceptions of m-learning's learning content quality, user interface, and system's connectivity affect the perceived mobile usefulness and easiness which in turn affects ER. This paper validates MTAM in the field of education by integrating MTAM with pedagogy and technology attributes under a social emergency setting such as the COVID-19 pandemic. In addition, the current research explains users' ER rather than behaviour intention which is commonly adopted in past studies.

1. Introduction

Information Communication Technology (ICT) is currently one of the most influential modern technologies in the world. The number of global internet users in 2019 has reached approximately 4.1 billion, which accounts for 53.6 percent of the current total population (ITU, 2020). The rise of mobile technology has also contributed to the further increased in internet usage over the past two decades. ICT has been widely applied to facilitate the development of a new mobile business model and to deliver better consumer services such as in mobile taxi service (Ooi et al., 2018a), mobile payment (Loh et al., 2019), mobile learning (Ooi et al., 2018b), etc. In 2020, the spread of Coronavirus Disease (COVID-19) has altered the way the user behaves. Mandatory rules such as social distancing

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and quarantine were introduced to prevent the spread of disease. Mobile-based ICT thus has become important for bridging and binding society together and allows people to complete their daily tasks remotely.

The COVID-19 pandemic has also impacted the education industry in which the feasibility of performing physical teaching activities have been limited. To cope with the pandemic situation, universities in China have introduced compulsory mobile learning (m-learning) courses which enable students to learn without attending face to face classes. M−learning is a notion originated from the concepts of distance learning and electronic learning and has been described as the learning process performed via using mobile devices (m-devices). This learning process provides students with a new learning affordance that involve seamless interactions across learning content and learning community (Bernacki et al., 2020; Kearney et al., 2020).

M−learning fulfils students' needs of learning without the restrictions which can be seen in brick-and-mortar classrooms. The platform allows learners to participate in formal learning activities outside the physical classroom and access learning materials without the restriction on schedule (Bernacki et al., 2020). In addition, the functions of m-learning support the process of collaborative learning through facilitating interactions in the learning community such as holding remote group discussions, share materials, and ask questions (Diacopoulos and Crompton, 2020). Many empirical studies have confirmed the benefits of m-learning such as increasing learners' creativity (Jahnke and Liebscher, 2020), enhancing self-regulation (Zheng et al., 2016), building collaborative capacities as well as improving student's academic results (Chang et al., 2017).

China is one of the leading m-learning markets in the world (Hao et al., 2017). The vast market potentials are driven by the high diffusion rate of m-devices. A survey between 2017 and 2018 indicated that the young Chinese generation accounts for 92 percent of the country's internet users with 90 percent of them owning an m-device (CSIS, 2018). Besides, the majority of Chinese universities are equipped with wireless internet services to facilitate and support teaching needs (Hao et al, 2017). Researchers so far have been to investigate the interactions between different factors of student's m-learning acceptance (Hamidi and Chavoshi, 2018).

However, the current m-learning applications during the pandemic period are also with some issues. From a practical view, although remote checking-in and online questions and answers mechanism ensure students attend and participate in the daily classes, there is still a lack of ways to measure their experiences gained from the instructor's teaching and mobile system. Besides, since the mobile-based courses are compulsory rather than voluntary, there are no guarantees in learners' positive feedback of learning experience. In terms of theoretical development, many studies were primarily based on generic adoption models, for example, the Technology Acceptance Model (TAM) developed by Davis (1989), and the Unified Technology Acceptance and Use Theory (UTAUT) proposed by Venkatesh et al. (2003). Both models, however, were not explicitly designed to meet the mobile adoption context as Davis (1989) and Venkatesh et al., (2012) developed TAM and UTAUT respectively to study factors affecting technology acceptance in the working environment (Ooi and Tan, 2016). As both studies focused on employees and are mandatory, the findings do not draw a meaningful comparison when adopted in mobile contexts. To the best of our knowledge, previous studies on m-learning were majorly focused on either the integration of technology and pedagogy (Kukulska-Hulme, 2012; Cook and Santos, 2016) or technology acceptance (e.g., Al-Azawei and Alowayr, 2020; Nie et al., 2020). There is still insufficient research that focused on non-voluntary m-learning acceptance under the context of a social emergency such as the outbreak of COVID-19 disease. Hence this study aims to understand how pedagogy and technical features influence the experience response of learners in the sense of mandatory m-learning under this pandemic background. The results from this investigation will enhance student's willingness to learn through m-device and help course and apps designers to further improve on their teaching and learning materials.

This study applies the Mobile Technology Acceptance Model (MTAM) proposed by Ooi and Tan (2016) which focused explicitly on mobile adopters and therefore fits the context of m-learning. Moreover, during the COVID-19 pandemic period, online-based education is obligatory in China, so students must attend their online classes regardless of whether they are willing to do so. Heller (1991) argued that the evaluation of instructional software should be discussed from a comprehensive view in which it should cover the different systemic parameters as well as content and instructional characteristics. Therefore, MTAM was extended with system quality factors namely User Interface (UI), Connectivity (CO) and pedagogical attributes factors namely Learning Content Quality (LCQ) and Interactivity (INT) to reflect on the learner's perceived perceptions. This study adopted an online self-administered questionnaire and was analysed using Partial Least Squares-Structural Equation Modelling (PLS-SEM) through SmartPLS 3.2.9. According to Hair et al. (2016), the PLS-SEM approach is effective in theory development and prediction to maximize the explained variance. Additionally, PLS-SEM is also considered a suitable method for complicated models with multifaceted constructs (Tan and Ooi, 2018; Ooi et al., 2020). In addition, a post-hoc procedure to assess the importance and performance of the exogenous variables was performed via Importance-performance matrix analysis to gauge the importance and performance of the exogenous constructs.

This paper is structured as follows. Firstly, the theories related to the theoretical background and an overview of m-learning studies are presented in Section 2. Subsequently, the study discusses the hypotheses development in Section 3. This is followed by the methodology of this study, data analysis and discussion in Sections 4–6. Section 7 includes the research implications, while the final section presents the limitation of the study and conclusion.

2. Literature review

2.1. Theories in technology acceptance

There are many theories expended in past literature to examine the causes of an individual to adopt new IS/IT. TAM conceptualized by Davis (1989) is one of the most widely studied adoption models. TAM works with two variables, namely perceived usefulness (PU) and perceived ease of use (PEOU), to justify how technological features influence the intention to accept the use of technology. PU reflects how the user believes that IS adoption will increase the performance of their task, while PEOU reflects the perceived degree of effort by the user to handle IS (Davis, 1989). The model suggests that users may have more intention to adopt new IS if the system is useful in terms of assisting users to complete their tasks and easy to handle without investing too much learning efforts. In the field of education, based on a hybrid structural equation modelling-artificial neural networks (SEM-ANN) approach, Tan et al. (2014), for example confirmed that university students' PU and PEOU have significant impacts on their intention to adopt m-learning system. However, since TAM was initially conceptualised to examine the acceptance of technology among employees in the workplace (Ooi and Tan, 2016), it may therefore provide less explanatory power to explain the adoption of IS/IT for non-working purposes. Additionally, TAM has been criticized as an one-dimensional mobile that oversimplifying the meaning of technology acceptance (Bagozzi, 2007). Lee and Larsen (2003) also argued that the model has insufficient exogenous variables to explain how certain attributes are transformed into intention and decision. As such, researchers usually extend TAM with new constructs to improve the model's explanatory and predictive powers.

Another widely explored model offered by Venkatesh and Davis (2000) is UTAUT. Four primary constructs comprise the UTAUT framework, namely performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating condition (FC). The model also includes moderators such as hedonic motivation, age and genders. It should be noted that PE in UTAUT has the same meaning as PU in TAM in which reflect the user's perception of usefulness on using new IS/IT. Similar to PEOU, EE in UTAUT reflect the user's perceived easiness in operating new IS/IT. Unlike TAM, UTAUT explains user's BI not only based on technological features but also from social and resource perspectives. SI refers to a user's perception of how other people in his or her social network thinks about the acceptance of new IS/IT. FC reflects the perceived support of a user when using IS/IT. Like all models, UTAUT is also restricted in terms of limitations. Again, this model was originally intended to investigate the intention of users to adopt new IS/IT within the context of commercial organizations (Venkatesh et al., 2012). Moghavvemi et al. (2016) argued BI in UTAUT cannot fully reflect the exogenous variables that lead to actual behavior, because UTAUT has an overemphasis on the perceptions that derived from an individual's external circumstances, while other potential attributes of people's BI was ignored.

MTAM was therefore used with that intention to fill the above gaps (Ooi and Tan, 2016). In the setting of mobile technology acceptance research, MTAM is designed specifically to confirm whether users have the intention to adopt mobile innovations. MTAM revised the original TAM with two core constructs namely Mobile Usefulness (MU) and Mobile Ease of USE (MEOU), and has been validated under different mobile adoption settings, for instance, retailing (Yan et al., 2021) and hospitality (Lew et al., 2020). MU has the same meaning as PU, which reflects the increase in user's work performance by adopting the mobile IS/IT. MEU, meanwhile, is similar to PEOU, which describes the user's perception of the efforts of using certain IS/IT from the viewpoint of mobile context. However, in this study, the two core MTAM constructs are not convincible enough to explain the experience response of university students, because student's usage of technology is neither voluntary nor consumption-oriented. MTAM lacks exogenous variables that explain how multiple attributes are transformed into BI. As such, the current study introduces additional exogenous constructs including, Learning Quality Content (LCQ), Interactivity (INT), User Interface (UI) and Connectivity (CO). To the best of the authors' knowledge, this model has not been adopted in any subjects related to the m-learning context. Therefore, this study provides an opportunity to validate MTAM's feasibility and credibility further.

2.2. Mobile learning

The beginning of m-learning research may be traced back to the 1970s when a notebook-sized device with a calculator, calendar and memos was conceptualized and used as a tool for learning (Bernacki et al., 2020). Then, along with the development of m-devices, the paradigm of m-learning has gradually evolved from learning anytime and anywhere into a seamless and customized learning paradigm. The changing learning paradigm has offered educators an opportunity to develop new pedagogies by integrating these new learning approaches with technologies (Bernacki et al., 2020). Hao et al. (2017) argued that m-learning is a complex process that involves theoretical-based pedagogical designs to address learning needs. As such, the technological side of m-learning should appropriately fit with aspects such as learning process, objectives, needs, experiences, material contents and learning outcomes. Apart from pedagogy concerns, m-learning involves m-devices such as smartphones and tablets as learning media. Therefore, any of the technological factors that relate to IT infrastructure support, mobile hardware and mobile application could determine m-learning's quality (Chavoshi and Hamidi, 2019). And user's perceptions of the system's quality are usually reflected in the device accessibility, user-interface friendliness, customization, speed, security, reliability and so on. M−devices are naturally carried with communication attributes. As a result of this, m-learning is embedded with social factors, as its users can perform activities such as knowledge sharing and group discussion during the learning process. Finally, past studies have disclosed that an individual's physical and psychological characteristics, such as demographic profile and cognitive status, could also affect users to adopt m-learning (Lin et al., 2020). Thus, demographic profile and/or personality variables may be useful in explaining m-learning acceptance.

Some researchers investigate this direction based on a techno-pedagogy perspective. Almaiah et al. (2016) examined how IS's quality features affect student's BI towards m-learning acceptance. By extending TAM with the IS success model, the result indicated that both system features (e.g. functionality and user-interface) and pedagogy attributes (e.g. learning content quality) are positively associated with university students' perceptions on m-learning usefulness. Furthermore, the perception of individuals in technology is another type of variables that influence the intention of users. Ferreira et al. (2013) argued that several characteristics such as utility, easiness, innovativeness, mobility, enjoyment, self-efficacy, subjective norms and compatibility decide user expectations of m-learning. However, since m-learning is a new approach applied in education, its diffusion is with some resistance. From the teaching side, researchers explained the reasons why instructors in universities do not adopt m-learning in their teaching is associated with the lack of techno-pedagogical training (Aznar-Díaz et al., 2020). Despite pedagogical reasons, there are also challenges derived from learner's experiences. For example, the small screen size of devices, poor internet connections, duration of battery life, as well as hazards in information security limits its use (Chavoshi and Hamidi, 2019). Additionally, there are also contextual factors that undermine the usage of m-devices for educational purposes. For instance, cultures and values such as teacher-centred educational philosophy and the habit of seeing m-devices as an entertainment tool also inhibit the growth of m-devices used for education (Hoi, 2020). Given the fact that the existing m-learning practices are obligatory under the COVID-19 pandemic, it is more difficult to explain the m-learning acceptance of students from the viewpoints of individual diversity and social attributes. Specifically, under this circumstance, variables such as social influence, innovativeness and intention may not be suitable to explain students' perceptions on m-learning, because they have to attend online classes as it compulsory.

3. Hypotheses development

3.1. Mobile usefulness (MU)

MU shares a similar meaning with PU in TAM and PE in UTAUT which refers to the student's increased performance from adopting the m-learning system (Ooi and Tan, 2016). Compared to face to face, the m-learning system not only overcomes the physical and time restrictions between instructors and learners but also brings a new perspective by offering new digitalized content. Previous studies have shown that learner's perception of the improvement in learning efficiency is positively correlated with their intention to adopt m-learning (Hao et al., 2017). Since the primary purpose of learning activities is to acquire knowledge, users' positive perceptions of the learning outcomes are believed to be beneficial to their attitudes towards the system. Following this logic, if a student has an affirmative attitude to the benefits of m-learning during the COVID-19 pandemic, such as learning anywhere and at any time he or she may also respond to the experience of using m-learning positively. The hypothesis, therefore, is proposed as below:

H1: MU has a positive impact on user's experience responses (ER) on m-learning usage.

3.2. Mobile ease of use (MEU)

MEU, in this study, refers to the level of perceived ease of learning through a m-device (Ooi and Tan, 2016). Hamid et al. (2016) argued that if a new system requires fewer efforts from its users, they would be more willing to take a step forward and to adopt to this new learning system. Previous research has revealed that users' perception of the ease of the m-learning system is positively related to their attitudes towards adoption (Althunibat, 2015). If the learners have less perceived difficulties during the use of the system, it is unlikely for him or her to feel frustrated towards the system and vice versa. It is therefore confident to argue that the easier the operation of the m-learning system during the COVID-19 pandemic, the user will also respond to the experience favourably. As such, the following hypothesis is hypothesized:

H2: MEU has a positive impact on the user's experience responses (ER) on m-learning usage.

3.3. Learning content quality (LCQ)

Learning Content (LCQ) represents both digital and non-digital forms of material sources that have been used for education and training. In this research, LCQ reflects learner's perceptions of the reliability, correctness and currentness of online learning materials (Almaiah et al., 2016). In reality, learner's expectations on suitable digital learning sources in learning platforms would reflect whether the learning system would meet their effort and performance expectancies (Hoi, 2020). Moreover, from the instructor's perspectives, Aznar-Díaz et al. (2020) found that the demographic attributes and contextual factors could affect the adoption and teaching outcome of the m-learning system. This implies that the pedagogical design of learning material needs to be adjusted specifically to meet the needs of context and audiences. It is therefore, reasonable to argue that learners would feel much simpler to learn if the style of learning material suits the adopted learning system during the COVID-19 pandemic. Consequently, the third and fourth hypotheses are hypothesized as:

H3: LCQ has a positive impact on the user's MU.

H4: LCQ has a positive impact on the user's MEU.

3.4. Interactivity (INT)

In this study, the interactions between students and their instructors are reflected by interactivity (INT) (Almaiah et al., 2016). Participating in a learning community helps the learner to effectively internalise the knowledge learned through collective learning (Shah 2014). As such, the interaction with others can help to address an atmosphere for knowledge sharing that enhances an individual's learning process. In the case of digital learning, if students feel that the interactions between teachers and learners are effective through the learning system, they may consider the system as useful (Chavoshi and Hamidi, 2019). Since m-devices such as smartphones are naturally communicative, m-learning should be able to assist INT, which in turn benefits learner's PU during the COVID-19 pandemic (Almaiah et al., 2016). Also, when a student assumed that m-learning will provide more efficient interactions within their learning group, it is more likely that learners would consider m-learning easy to use. Therefore, a learner's perceived easiness of using m-learning will be enhanced (Almaiah et al., 2016). The above results postulate the following hypotheses:

H5: INT has a positive impact on the user's MU.

H6: INT has a positive impact on the user's MEU.

3.5. User interface (UI)

In practice, the design of user interface (UI) is considered as one of the key elements in application development, because UI assists a user's control and interaction capacities and is an essential determinant of in the conversion of technology into a functional product (Chavoshi and Hamidi, 2019). The UI construct is measured by three dimensions in the present research, namely visual design (Nikou and Economides, 2017), layout and navigation (Lee et al., 2015) which have been assessed in many previous relevant studies (Joo et al., 2014). With an accessible UI design, a user can operate a IS/IT without difficulties and unlock its benefits. On the contrary, a UI design with complexity and barriers could lead to user's confusion and discarding of technology (Rezae et al., 2020). Previous remote learning studies have found that UI is a key factor that affects the usefulness and ease of use of a user (Joo et al., 2014). A user-friendly UI will also result in less effort for the learner to operate the learning tool, thus enhancing the perception of the system's ease of use (Almaiah et al., 2016). When the UI architecture meets the navigation and visual expectations of the user during the COVID-19 pandemic, the user would feel that the m-learning system is both useful and straightforward to handle. As such, we hypothesize:

H7: INT has a positive impact on the user's MU.

H8: INT has a positive impact on the user's MEU.

3.6. Connectivity (CO)

So far, several terms have been used to explain how IS/IT adoption is supported by infrastructures. For instance, availability describes the degree to which data and system resources are available to all users without the restriction of time and place (Almaiah et al., 2016), and responsiveness (e.g. downloading speed), according to the DeLone and McLane's IS success model, is one of the key metrics in assessing the quality of the system (Delone and McLean, 2014). Connection quality is the shared aspect between the above terms. Connectivity (CO) is used in this research to describe the quality aspects of an internet connection. The connection is one of the main determinations of user's usefulness and ease of use, as a fast, secure and stable internet connection increases learning process efficiency (Sarrab et al., 2016). In the adoption of m-learning, the fast connection speed between an m-device and learning platform helps to facilitate the learning process. As such, the user's perception of usefulness and ease of use is guaranteed by good connectivity. Therefore, hypothesises the following:

H9: CO has a positive impact on the user's MU.

*H*10: CO has a positive impact on the user's MEU.

Given the above hypotheses, the present study proposes the following research model (see Fig. 1) to evaluate the influences of pedagogy and technology on the experience response of the user to adopt m-learning during the current COVID-19 pandemic.

4. Research methodology

4.1. Research instrument

The current study used a self-administered questionnaire survey that is commonly adopted in mobile studies (Ooi and Tan, 2016;

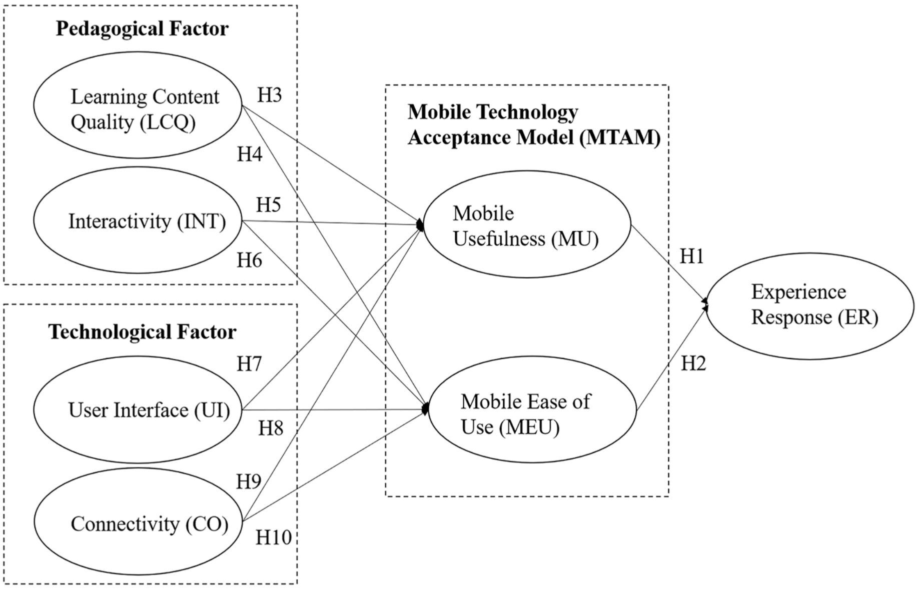

Fig. 1. Proposed Conceptual Framework.

Sim et al., 2014). The questionnaire was developed based on validated measurements that have been adopted in previous studies. Of which, measurements for ER were adapted from Hao et al. (2017) and Almaiah et al. (2016); MU and MEU were adopted from Ooi and Tan (2016); LCQ and INT were adapted from Almaiah et al. (2016) and Cheng (2012); Cho et al. (2009) and Lee et al. (2009) were adapted for UI; and the items for CO were adapted from Sabah (2016). For measuring respondent responses, the questionnaire items in this study use the 7-point Likert scale from 1 “Strongly Disagree” to 7 “Strongly Agree”. Furthermore, questions explaining the demographic profile of the respondent were added to the questionnaire. Based on previous research on relevant topics (Chavoshi and Hamidi, 2019; Tan et al., 2014), the questionnaire items in Table I were selected and further revised to fit the culture and general context of the population studied.

4.2. Data collection and respondent profile

The questionnaire was prepared in electronic form and delivered via the leading internet survey platform in China known as “SoJump” to achieve an effective sample size. The content validity of the survey was checked by three independent researchers specialised in pedagogy research, and then minor changes were made to the questionnaire structure, layout and question phrasing. This is followed by a pilot test to verify the reliability and validity of the scale. There was a total of 627 effective responses collected from individuals who are university students from universities in China. Before filling out the questionnaire, the participants were required to read through the instruction section to notify the confidential use of their information and declaring the purpose of the survey. The online questionnaire was divided into two sections. In section one, participants’ profiles include gender, age, m-device usage frequency, education background and number of device owned, were recorded anonymously. And in section two, participants’ opinions of mobile learning were asked through measurement items based on 7-point Likert scale. The demographic profile of respondents is shown in Table 1. In general, females (61.7 percent) received more responses than males (38.3 percent). However, the result from the male sample may also produce statistical significance, considering the large sample size collected. Most of the students are between the ages of 17–23 (94 percent of the total respondents), which covers the main age group of those attending university in China. 532 respondents were pursuing their undergraduate degree (84.8 percent), 64 are taking diplomas (10.2 percent), and 31 respondents (5 percent) were obtaining postgraduate degrees. Most respondents use mobile devices between 1 and 8 h (82.1 percent) per day in terms of mobile use frequency. Additionally, for study and other purposes, most of the respondents have 2 to 3 mobile devices (73.5 percent).

5. Analysis of data

5.1. Statistical analysis

With Partial Least Squares-Structural Equation Modelling (PLS-SEM) through SmartPLS (Version 3.2.9) software, the research model of this study is examined. A variance-based approach is considered an effective method since this study focuses primarily on theory building (Yadegaridehkordi et al., 2019; Loh et al., 2020). Specifically, the paper combines the MTAM with pedagogical and technological influences. In addition, without the presumption of data normality, PLS-SEM is still sufficient for handling different sample volumes (Ramayah et al., 2020). Mardia’s multivariate skewness and kurtosis ($\beta = 28.24174$, $p < 0.001$; $\beta = 171.13077$, $p < 0.001$, respectively) imply that multivariate assumption has been violated. According to G* Power (version 3.1.9.2), the analysis using 627 samples also surpassed the minimum sample size of 98 by using 0.80 power level, 0.05 alpha value, 0.15 impact size, and 6 predictors.

Table 1
Respondent Profile.

Characteristics		Number	Percentage (%)
Gender	Male	240	38.3
	Female	387	61.7
Age	Below 17	4	0.6
	17–19	146	23.3
	20–23	443	70.7
	Above 23	34	5.40
Frequency of using m devices in a day	<1 h	22	3.50
	1–4 h	246	39.2
	5–8 h	269	42.9
	Above 8 h	90	14.4
Education level	Diploma	64	10.2
	Undergraduate Degree	532	84.8
	Postgraduate Degree	31	5.00
Number of mobile devices	One	141	22.5
	Two	389	62.0
	Three	72	11.5
	Four	14	2.20
	Five and above	11	1.80

5.2. Common method variance

We follow the approach by Liang et al. (2007) to confirm that common method variance (CMV) does not affect the analysis. In the common method factor, 28 indicators from the research model were included. Square factor loading was then estimated for substantive factor loading (Ra^2) and method factor loading (Rb^2). At the $P < 0.001$ level, all items in Ra^2 are empirically significant and the average is 0.924 higher than the average of 0.015 for Rb^2. It is, therefore, in this analysis, CMV shown in Table 2 is not an issue.

5.3. Assessing the outer measurement model

Table 3 showed that all values in the measurement model ranged from 0.945 to 0.975 for both composite reliability (CR) and Dijkstra-Henseler's rho (rhoA) above the minimum threshold of 0.70 (Lee et al., 2020; Hew et al., 2019; Wong et al., 2015a). The internal reliability of consistency has therefore been verified. Table 3 also indicates that all factor loadings surpass the recommended value of 0.70, in calculating convergent validity (Al-Saedi et al., 2020; Loh et al., 2019). In addition, all values of the average variance extracted (AVE) were above 0.5 (see Table 3), which is the suggested threshold (Ooi et al., 2011; Hair et al., 2016; Wong et al., 2015b). Convergent validity therefore has been confirmed based on both results. Using Hetero-Trait-Mono-Trait (HTMT) inference through 5000 bootstrapping samples, Discriminant Validity (DV) in Table 4 was performed. Since the required indicator of 1 is not achieved by either of the lower and upper bounds using a 95% confidence interval, it indicates that every construct in the sample are statistically distinct and that discriminant validity has been identified (Hew et al., 2020).

5.4. Inspecting the inner Structural model

The saturated and estimated Standardized Root Mean Square Residual (SRMR) models show that indicators of 0.029 and 0.038 are below 0.08, indicating a good fit of the model (Hu and Bentler, 1999). The NFI values also indicate a strong march, as the two saturated and estimated models were 0.92 and 0.91, which are above the 0.90 limits (Hu and Bentler, 1999). The root means square residual covariance (RMStheta) is also below 0.12, indicating that the model has a good fit for the sample data (Hair et al., 2016). In this research, the problem of multicollinearity does not exist as all values were below the 5.0 threshold (Tan and Ooi, 2018; Ooi and Tan, 2016). A bias-corrected and accelerated (BCa) bootstrap method with 5000 subsamples at a two-tailed 0.05 significance level was used to test the hypothesized relationships to generate the p-value for each path coefficient. Table 5 and Fig. 2 reveals that all hypotheses suggested are positive and significant at the level of $p < 0.001$, with the exception of the relation connecting UI ->MEU, which is only positive at $p < 0.01$. The result indicates that the both INT -> MEU ($\beta = 0.111$, $P > 0.05$) and INT -> MU ($\beta = 0.018$, $P > 0.05$) could not establish association connecting.

Table 2
Common Method Factor Analysis.

Latent construct	Indicators	Substantive factor loading (Ra)	Ra^2	Method factor loading (Rb)	Rb^2
CO	CO -> CO1	1.234	1.522756***	−0.336	0.112896***
	CO -> CO2	1.092	1.192464***	−0.185	0.034225*
	CO -> CO3	0.967	0.935089***	−0.037	0.001369 NS
ER	ER -> ER1	1.056	1.115136***	−0.11*	0.0121*
	ER -> ER2	0.94	0.8836***	0.027	0.000729 NS
	ER -> ER3	0.879	0.772641***	0.082	0.006724 NS
INT	INT -> INT1	1.022	1.044484***	−0.089	0.007921*
	INT -> INT2	0.997	0.994009***	−0.033	0.001089 NS
	INT -> INT3	0.828	0.685584***	0.122	0.014884*
LCQ	LCQ -> LCQ1	1	1***	−0.136	0.018496*
	LCQ -> LCQ2	0.996	0.992016***	−0.096	0.009216 NS
	LCQ -> LCQ3	0.918	0.842724***	0.029	0.000841 NS
	LCQ -> LCQ4	0.8	0.64***	0.139	0.019321*
	LCQ -> LCQ5	0.849	0.720801***	0.056	0.003136
MEU	MEU -> MEU1	0.738	0.544644***	0.202	0.040804**
	MEU -> MEU2	1.024	1.048576***	−0.091	0.008281NS
	MEU -> MEU3	1.031	1.062961***	−0.083	0.006889NS
	MEU -> MEU4	0.992	0.984064***	−0.046	0.002116NS
	MEU -> MEU5	0.87	0.7569***	0.021	0.000441NS
MU	MU -> MU1	0.852	0.725904***	0.088	0.007744NS
	MU -> MU2	0.993	0.986049***	−0.061	0.003721NS
	MU -> MU3	1.142	1.304164***	−0.197	0.038809***
	MU -> MU4	0.687	0.471969***	0.255	0.065025**
	MU -> MU5	1.012	1.024144***	−0.083	0.006889NS
UI	UI -> UI1	0.859	0.737881***	0.083	0.006889NS
	UI -> UI2	1.01	1.0201***	−0.055	0.003025NS
	UI -> UI3	1.035	1.071225***	−0.085	0.007225NS
	UI -> UI4	0.895	0.801025***	0.059	0.003481NS
	Average	***0.954214286***	***0.92431821***	***−0.02***	***0.015867***

Notes: a. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$, NS insignificant.

Table 3
Loadings, Composite Reliability, Dijkstra Henseler and Average Variance Extracted.

Constructs	Items	Loadings	rho_A (ρA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
CO	CO1	0.962	0.962	0.975	0.928
	CO2	0.965			
	CO3	0.963			
ER	ER1	0.953	0.955	0.971	0.918
	ER2	0.965			
	ER3	0.955			
INT	INT1	0.941	0.945	0.964	0.9
	INT2	0.967			
	INT3	0.939			
LCQ	LCQ1	0.877	0.95	0.961	0.83
	LCQ2	0.909			
	LCQ3	0.944			
	LCQ4	0.925			
	LCQ5	0.899			
MEU	MEU1	0.925	0.963	0.971	0.869
	MEU2	0.939			
	MEU3	0.954			
	MEU4	0.95			
	MEU5	0.89			
MU	MU1	0.936	0.966	0.973	0.879
	MU2	0.935			
	MU3	0.954			
	MU4	0.932			
	MU5	0.932			
UI	UI1	0.937	0.964	0.974	0.903
	UI2	0.958			
	UI3	0.955			
	UI4	0.951			

Table 4
Hetero-Trait-Mono-Trait (HTMT inference).

Latent construct	Original sample (O)	Sample mean (M)	Bias	2.50%	97.50%
ER -> CO	0.819	0.82	0.000	0.763	0.865
INT -> CO	0.826	0.826	0.000	0.771	0.87
INT -> ER	0.83	0.83	0.000	0.765	0.875
LCQ -> CO	0.758	0.758	0.000	0.695	0.812
LCQ -> ER	0.823	0.823	0	0.766	0.869
LCQ -> INT	0.868	0.869	0	0.812	0.909
MEU -> CO	0.823	0.823	0	0.768	0.865
MEU -> ER	0.914	0.914	0	0.879	0.942
MEU -> INT	0.813	0.813	0.001	0.749	0.859
MEU -> LCQ	0.81	0.81	0	0.758	0.853
MU -> CO	0.909	0.909	0	0.875	0.937
MU -> ER	0.928	0.928	0	0.901	0.951
MU -> INT	0.844	0.844	0	0.777	0.89
MU -> LCQ	0.828	0.828	0	0.78	0.867
MU -> MEU	0.907	0.907	0	0.871	0.934
UI -> CO	0.881	0.881	0	0.834	0.918
UI -> ER	0.882	0.882	0	0.845	0.911
UI -> INT	0.89	0.89	0	0.841	0.927
UI -> LCQ	0.853	0.853	0	0.808	0.888
UI -> MEU	0.841	0.842	0.001	0.792	0.88
UI -> MU	0.916	0.916	0	0.887	0.94

5.5. The predictive relevance and effect size

The effect sizes of the outcome variables are tested using the f^2 effect size (Table 6). Thresholds of 0.35, 0.15 and 0.02 are recognized as high, medium and small effects (Teo et al., 2018). It was further revealed by Tan and Ooi (2018) that values below 0.02 have no effect. According to these parameters, the effect size of paths varying from no effect to a significant effect is shown in Table 6. Table 7 also indicates that all Q^2 values are greater than zero, suggesting that predictive relevance is provided to ER, MU and MEU (Bae and Lee, 2020; Wong et al., 2020). Finally, using the criteria suggested by Hair et al. (2016) and Ooi et al. (2018c), R^2 indicators of all predictor variables can be calculated, with 0.75 for substantial, 0.50 for moderate and 0.25 for weak. The Analysis shows that ER and MU indicators are substantial while MEU is moderate. While Q^2 helps to predict the omitted data points, Shmueli et al., (2019) pointed

Table 5
Outcome of the Structural Model Examination.

PLS Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	2.50%	97.50%	Remarks
CO -> MEU***	0.316	0.315	0.062	5.113	0	0.194	0.433	Supported
CO -> MU***	0.428	0.429	0.052	8.164	0	0.32	0.525	Supported
INT -> MEU^{NS}	**0.111**	**0.112**	**0.076**	**1.468**	**0.142**	**−0.028**	**0.268**	**Not supported**
INT -> MU^{NS}	**0.018**	**0.02**	**0.053**	**0.33**	**0.742**	**−0.084**	**0.126**	**Not supported**
LCQ -> MEU***	0.264	0.264	0.058	4.576	0	0.154	0.381	Supported
LCQ -> MU***	0.166	0.166	0.046	3.636	0	0.081	0.259	Supported
MEU -> ER***	0.411	0.414	0.06	6.822	0	0.296	0.531	Supported
MU -> ER***	0.532	0.53	0.06	8.894	0	0.414	0.647	Supported
UI -> MEU**	0.232	0.233	0.083	2.811	0.005	0.069	0.393	Supported
UI -> MU***	0.37	0.367	0.076	4.889	0	0.222	0.522	Supported

Notes:
a.* Significant at 5% level, $p < 0.05$.
b.** Significant at 1% level, $p < 0.01$.
c.*** Significant at 0.1% level, $p < 0.001$.

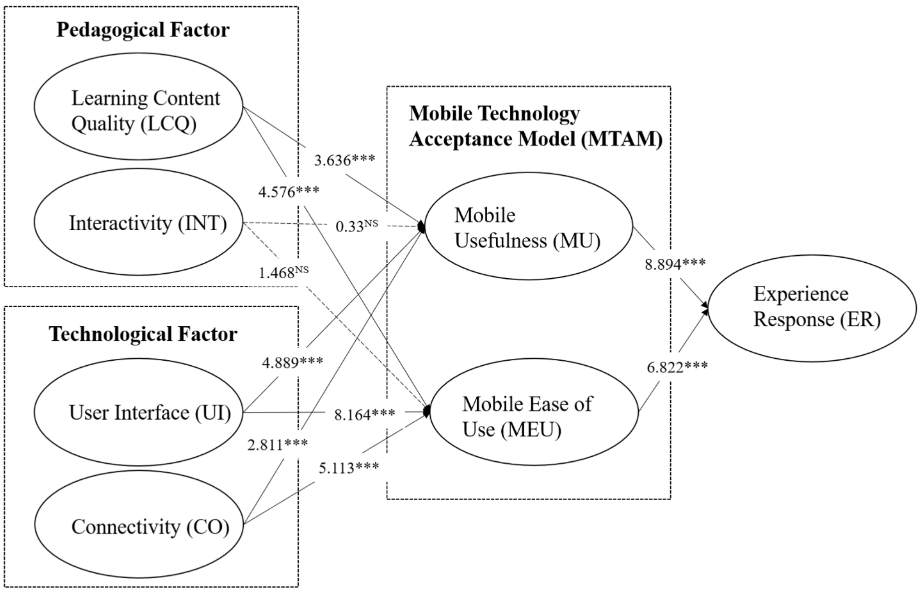

Fig. 2. Structural Model Testing.

Table 6
Effect Size (f^2).

Predictor Constructs/dependent Constructs	CO	ER	INT	LCQ	MEU	MU	UI
CO					0.097	0.319	
ER							
INT					0.01	0	
LCQ					0.07	0.05	
MEU		0.241					
MU		0.403					
UI					0.034	0.156	

out that the value does not indicate whether a model exhibits predictive power or good explanatory fit. In view of the limitation, the study adopts the PLSpredict developed by Shmueli et al., (2019) to address the predictive model assessment in PLS-SEM. All Q^2 in Table 8 shows that the value is >0 indicating sufficient predictive relevance (Ahmad et al., 2019). As none of the indicators in PLS have higher root mean squared errors (RMSE) values corresponding to the linear regression model (LM), which is suggested to has high predictive performance (Shmueli et al., 2019).

6. Ex-Post analysis

6.1. Importance performance map analysis (IMPA)

The Importance-performance matrix analysis (IPMA) was applied as a post-hoc PLS procedure to gauge the importance and performance of CO, INT, LCQ, MEU, MU and UI. IMPA's goal is to identify predecessors that have high importance for the target construct but also low performance so that effective managerial focus can be given to the particular construct. Results from Table 9 and Fig. 3 show that the highest importance is MU (0.53), MEU (0.44), CO (0.34), UI (0.29), LCQ (0.22) and INT (0.06). On performance, LCQ (79.68) tops the list, followed by INT (77.54), MEU (77.52), UI (76.58), MU (75.06), and CO (74.58).

7. Discussion

Both MU and MEU have a major impact on the respondent's experience of using m-learning. Tan et al. (2014)'s study reaffirms the findings of prior work on learner's intention to adopt m-learning. Based on questionnaires collected from 216 Malaysian students, Tan et al. (2014) found that both usefulness and ease of use affect BI significantly. Yan et al. (2021) argued that if users obtain more benefits from the system, adoption would be more preferable. In this study, m-learning's benefits can be, for example, better learning outcomes or convenience. The learners would also have a more positive user experience, as the m-learning system helps them to achieve better learning performance. As such, H1 is supported. Moreover, H2 which indicates the significant relationship between MEU and ER is also confirmed. When adopting technology innovations, time and effort are usually required from users to learn and adapt to this new system. The difficulty of learning and using might offset or even outweigh the users' positive feelings towards the system's benefits (Loh et al., 2019). Therefore, the user's perceived easiness in m-learning will reflect on ER.

LCQ, on the other hand, has significant positive interactions, with both MU and MEU as theorized. The finding of this study implies that good learning content can enhance the utility and easiness of m-learning which further results in learner's higher ER. As such, H3 and H4 are supported. These findings are backed by past research conducted by Almaiah et al. (2016) in which LCQ was found to have a significant positive effect on both usefulness and ease of user respectively. According to the constructive learning theory, the knowledge transfer between the instructor and a learner cannot rely purely on the instructor, because an experience gap exists between instructor and learner. Therefore the educators believe that an effective and satisfactory learning process should combine the instructor's experience with good learning content that is interesting, easily understood and remembered (Reychav and Wu, 2015).

H7 and H8 are also supported which implies that UI has a significant positive relationship with both MU and MEU. The finding is consistent with previous works (e.g., Chavoshi and Hamidi, 2019) which found that UI design of the m-learning platform has a significant impact on learner's perceived ease of use. Joo et al. (2014) also revealed that higher ratings on UI would lead to higher ratings on PU. And this positive relationship is also confirmed by Cheng (2012) who investigated student's m-learning acceptance from system quality perspectives. As such a good UI design not only reflect on the easiness to use but also fulfil learner's needs on enhancing learning performance.

CO has been seen as one of the key factors affecting ICT diffusion (Li et al., 2017). Accordingly, many previous research studies have revealed that the internet connection is crucial in determining user's perceptions of system benefits and easiness (Hew et al., 2018). In m-learning, a good internet connection not only guarantees success in delivering quality learning content but also facilitate knowledge sharing and group discussion. Results from this study are in line with an early study on m-learning in Pakistan universities (Iqbal and Bhatti, 2016). Therefore, H9 and *H*10 are supported.

Surprisingly, H5 and H6 regard the relationships between INT and MTAM's two core constructs that are not supported. The results are partly supported by a recent study in which knowledge interaction with members in the learning community was positively and significantly related to MU, but no significant association with MEU (Al-Emran et al., 2020). It seems that students' perceptions of MU and MEU are not influenced by the interactions in their learning group. A potential explanation is that Chinese educational philosophy is traditionally based on teacher-directed and instructive pedagogical paradigm, as such experiences such as a group discussion do not typically occur (Li et al., 2012).

8. Implication

8.1. Theoretical implications

The study validates MTAM in the education field. MTAM is a suitable model in explaining the adoption of m-learning as compared to traditional electronic commerce models as it focuses on users' actual responses under the mobile and non-organization settings. In addition, MTAM's core framework is flexible and therefore render rooms for researchers to incorporate other constructs within the model to achieve a better understanding of mobile technologies acceptance from the perspectives of learners. Also, as most of the previous works in the adoption of m-learning were developed based on a controlled setting, the constructs developed in past studies

Table 7
Predictive Relevance (Q^2) and R^2.

Endogenous construct	SSO	SSE	Q^2 (=1−SSE/SSO)	Predictive Relevance	R^2
CO	1881.00	1881			
ER	1881.00	448.31	0.762	$Q^2 > 0$	0.835
INT	1881.00	1881.00			
LCQ	3135.00	3135.00			
MEU	3135.00	1166.245	0.628	$Q^2 > 0$	0.729
MU	3135.00	815.62	0.74	$Q^2 > 0$	0.848
UI	2508.00	2508.00			

Table 8
PLSpredict Results.

ER	PLS-SEM			Linear model benchmark	
	Q^2_predict	RMSE	MAE	RMSE	MAE
ER1	0.636	0.737	0.479	**0.751**	0.48
ER2	0.698	0.681	0.444	**0.685**	0.431
ER3	0.712	0.682	0.452	**0.691**	0.446

Table 9
Importance Performance Map Results.

Latent variables	Importance (Total Effect)	Performance (Index Value)
CO	0.34	74.18
INT	0.06	77.54
LCQ	0.22	79.68
MEU	0.44	77.52
MU	0.53	75.06
UI	0.29	76.58
Mean Value	**0.31**	**76.76**

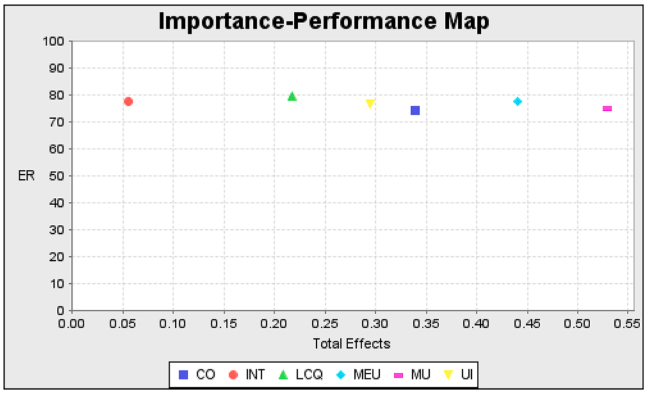

Fig. 3. IPMA for ER.

may not reflect well on the user's actual responses in a real-life setting such as compulsory attendance during the COVID-19 pandemic. The current study also introduces four new constructs, namely LCQ, INT, UI, and CO in supporting the theoretical development in m-learning. The four new constructs may offer a more accurate and practical explanation of m-learning adoption from a developing country viewpoint.

8.2. Managerial implications

Developing a new m-learning system requires considerable resources in terms of money and time, therefore it is important to plan carefully before launching the system. Compare with traditional learning methods, m-learning breaks the restrictions of time and location which brings time-saving and convenience to both learners and instructors. In this study, the student's MU is significant with ER. To deliver a better ER to the learners, m-learning suppliers should enhance the utility of their learning platform, because the improvements in the learning environment allow students to achieve higher learning productivity and more effective cooperation with instructors which in turn speed up the progress of accomplishing leaning tasks and obtain a better learning experience (Sabah, 2016).

Since MEU is also significant with ER, m-learning service suppliers should improve the learning tool by reducing the difficulties of usage. An easy-to-use system will not only maximize the performance of the m-learning system but also implies that the system will meet student's value and learning needs, therefore contributing to wider adoption in the future (Chavoshi and Hamidi, 2019). According to the results, the enhancements in m-learning systems' MU and MEU can be achieved through improving pedagogical and technological factors including LCQ, UI and CO. In the m-learning context, the quality of learning content can be seen from the richness of teaching content and updates frequency. Hence to deliver better quality learning content, course developers should concentrate on producing learning materials that fit the requirements in the m-learning setting. Similar improvements should also be focused on technological perspectives. From the system developers' perspective, better UI design is a key enhancement on user experience, because of UI design facilities the human-device interaction.

In m-learning, a well-structured and clear interface allows students to search, find and digest the knowledge much easier. This will result in a higher level of perceptions of the system's benefits and easiness. A further improvement in the m-learning system can be achieved by delivering CO. A stable and fast-speed connection to the internet is vital for the proceeding of m-learning. Without adequate infrastructure supports, the operation of any forms of mobile application may not be possible. As such, telecommunication suppliers must provide high-quality internet services.

9. Conclusion and limitation

The current study shows that during the COVID-19 pandemic, pedagogical and technological factors may influence the experience of students in adopting m-learning. Factors include CO, UI and LCQ have significant impacts on students' perceptions of the m-learning system, which eventually reflects their ER. Also, substantial effects were found between MU and MEU and ER from student's experience, thus demonstrating the applicability of MTAM in m-learning. While MU shows high importance and has the strongest relationship in this study, the performance is lower than MEU and should be given priority for performance. The result of this study also revealed that m-learning could be considered as an effective alternative to physical teaching during this COVID-19 pandemic. However, IN seems to be a major challenge experienced by students, and therefore considerations should be given on how to improve the interaction between teachers and learners. Some drawbacks are found in this current research. Firstly, this research is carried out within a university setting, so the results cannot be generalized to other m-learning users in a different industry such as in the organizational environment. In addition, this research was carried out in the context of China. As such, the finding might not accurately reflect m-learning acceptance in other countries, because the differences between countries are plentiful. For instance, in terms of cultural differences, technology readiness as well as other possible attributes that could affect technology acceptance. Finally, the current study solely focuses on the extension of MTAM to explore the student's ER on m-learning. Future studies should concentrate on other attributes, for example, personal attributes and cross-culture effects to expand this framework.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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