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The continuance intention of users toward mobile assisted language learning: The case of DuoLingo

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Abstract: Recently, mobile learning has become a potential approach in education due to its use inside and/or outside the classroom. Considering that the majority of mobile device users are 18-29 years old higher education students and English is the predominant language of the internet, this study aimed to predict the continuance intention of users toward mobile-assisted language learning (MALL) after fourteen weeks experience on a mobile application, namely Duolingo. To do this, we used the Technology Acceptance Model, Theory of Planned Behavior and Expectation Confirmation Model. The participants were 379 students taking the course English I. This cross-sectional survey study revealed that perceived behavioral control, attitude, subjective norms, satisfaction, and perceived usefulness have a significant effect on the university students' continuance intention to use MALL. In turn, it validated our proposed model on the continuance intention to use MALL. Based on the results of this study, some practical and theoretical implications were discussed.

Keywords: mobile learning, language learning, continuance intention, higher education, mobile application.

Highlights

What is already known about this topic:

- One of the main factors for successful integration of mobile-assisted language learning (MALL) is examining users' intentions. Therefore, different adoption and acceptance models can be used.
- The adoption and acceptance studies in MALL focused on participants who had no experience with MALL

What this paper contributes:

- This study investigated factors influencing students' continuance intention to use MALL.
- Our model accounted for 62% of variance in continuance intention to use MALL.
- Perceived behavioral control was the most influential factor in the model.

Implications for theory, practice and/or policy:

- Duolingo and other applications may focus on the proficiency level of newly starting users and tailor their activities upon their levels to increase the self-efficacy of users.
- Higher education institutions should provide organizational support and technical support for mobile applications to increase the use of MALL.
- Especially in Turkish higher education context, teaching large classrooms might become easier with the integration of technology, and low-achieving students in these classrooms might grasp the opportunity to achieve.
- Different learning materials (multimedia, audio record, video, animation, etc.) may be integrated into mobile applications to increase students' level of satisfaction and attitudes.

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Introduction

Mobile technologies have significantly and continuously increased over the past 15 years (Dalvi-Esfahani et al., 2020; Jurkovič, 2019; Loewen et al., 2019; Viberg & Grönlund, 2013; Zhonggen & Xiaozhi, 2019) by exceeding the numbers of desktops and laptops with a dramatic speed (Pegrum, 2014). Not only does this increase find its way for social and entertainment purposes, but it also allows new contexts for informational, academic, and educational purposes (Duman et al., 2015; Godwin-Jones, 2017; Pachler et al., 2010).

Mobile learning, as a developing potential approach of education (Chung et al., 2019), attracts attention at higher education (Botero et al., 2018; Hamidi & Chavoshi, 2018; Tang & Hew, 2017) with the spread of mobile devices and areas of use based on the fact that mobile device users primarily consist of 18-29 years old higher education students (PEW Research Center, 2019). As one of the emerging areas, mobile-assisted language learning (MALL) has received considerable interest of language learners (Al-Otaibi et al., 2016) because it allows them decide where, when, and how to utilize mobile technologies autonomously and study on a second language (Reinders & Benson, 2017).

Mobile learning comes with "a myriad of opportunities to support learning and performance both inside and outside the classroom" (Martin & Ertzberger, 2013, p. 26), and these opportunities have affected the way people learn a second language (Loewen et al., 2019). Therefore, investigating users' acceptance behaviors is essential for the integration of mobile applications in language learning (Botero et al., 2018), and more research is necessary to investigate expectations, intentions, adoption and behaviors to provide language learners with optimal learning opportunities (Plonsky & Ziegler, 2016). However, many previous studies (e.g., Cheon et al., 2012; Raza et al., 2018) criticized the lack of previous mobile learning experience before investigating the intention to use mobile learning. Another limitation was the scarcity of studies scrutinizing the factors that influence use of mobile technologies in higher education, especially in informal online learning of English through smartphones (Lee & Dressman, 2018). This study involved university students in a 14-week experience with a language learning mobile application to overcome these two limitations. Furthermore, this study integrated the Technology Acceptance Model (TAM) (Davis, 1985), the Theory of Planned Behavior (TPB) (Ajzen, 1991) as in the model proposed by Cheon et al. (2012) and the Expectation Confirmation Model (ECM) (Bhattacherjee, 2001b). Thus, it became possible to scrutinize the psychological processes behind continuance intention and reflect on learner perspectives, as suggested by Dai et al. (2020). To the best of our knowledge, this study is one of the first attempts to explore students' continuance intention toward MALL incorporating TAM, TPB and ECM after they were exposed to 14-week mobile language learning application. Additionally, the results of this study have the potential to help decision makers to take actions in terms of MALL in learning and teaching context, instructors to design MALL activities or integrate appropriate mobile technology for language learning courses, and mobile application developers to develop mobile learning experience of learners. Briefly, the aim of this study is to explain the factors influencing students' continuance intention to use mobile-assisted language learning based on the Technology Acceptance Model, Theory of Planned Behavior and Expectation Confirmation Model.

Theoretical Framework

Mobile-Assisted Language Learning (MALL)

Today, mobile learning in higher education typically comes with the idea of language learning. It might be due to two reasons. First, the increase in higher education institutions equipped with wireless networks enables instructors to integrate mobile learning into their classes (Cheon et al., 2012). Available empirical evidence shows that mobile learning effectively supports students in higher education (Crompton & Burke, 2018). Secondly, English is the predominant language of the digital world

(Jarvis, 2014), and users of an online community are necessarily exposed to English through mobile devices (Sockett & Toffoli, 2012). Therefore, integrating mobile technologies into the language of the digital world seems to be an embraced idea.

Compared with the other technological equipment such as computers, mobile technologies have several advantages, and these advantages have been proved by previous studies which confirm the hypothesis that MALL supports and fosters language learning (Jaeseok, 2013; Pérez-Paredes et al., 2019; Sung et al., 2015; Viberg & Grönlund, 2013). The features such as mobility and portability help learners access language learning resources without time and location constraints (Chung et al., 2019; Hamidi & Chavoshi, 2018). This relatively low-cost and ubiquitous learning technology provided psychological comfort and enhanced motivation for learners (Al-Otaibi et al., 2016). Several researchers used mobile devices to improve language learners' vocabulary (e.g., Chen, & Li, 2010; Hao et al., 2019; Okumuş-Dağdeler, 2018), reading (e.g., Hsu et al., 2013; Lin, 2014), writing (e.g., Hwang et al., 2014), listening-speaking (e.g., Hwang & Chen, 2013), and pronunciation (e.g., Saran et al., 2009; Shih et al., 2015). In some further studies (Chen & Li, 2010; Sandberg et al., 2011), the contextualization of digital content and real-world learning environments through mobile devices has been underlined for supporting learners in four main skills.

Despite its strengths, mobile learning imposes technical, psychological, and pedagogical challenges. In addition to the technical limitations such as small screens, low-resolution display, inadequate memory, and limited processing power (Wang et al., 2009), previous studies (e.g., Sarrab et al., 2016) underlined usability, functionality, connectivity, and user interface as the most abstract and generic technical aspects of mobile learning service. Pedagogical limitations have been voiced as lack of concentration, interruption of course flow (Cheon et al., 2012), and the balance between the integration of mobile and face-to-face learning. Considering the increasing significance of psychological limitations for the future of MALL, many studies have recently touched upon the adoption and acceptance (e.g., Al-Emran et al., 2020; Hamidi & Chavoshi, 2018; Qashou, 2021; Panigrahi et al., 2018) in mobile learning. However, there are limited studies on the adoption and acceptance of users toward MALL (e.g., Botero et al., 2018; Kim & Lee, 2016). Moreover, these studies have not employed any mobile device or application for language learning to determine factors that influence users' continuance intention according to their beliefs. Considering the probability that the experience of use for a while might change their adoption and acceptance behavior (Davis et al., 1989), it is well-worth to research continuance intention of users toward MALL after using the application for a while. Therefore, this study gave an opportunity to the participants to experience the application for 14 weeks.

Continuance Intention of MALL

In the Technology Acceptance Model (TAM) proposed by Davis (1985), three constructs influencing the intention to use are perceived usefulness, perceived ease of use and attitude. Davis (1989, p. 320) defined perceived usefulness (PU) as "the degree to which a person believes that using a particular system would enhance his or her job performance" and perceived ease of use (PEU) as "the degree that using a specific technology will be free from effort". Attitude (ATT) refers to one's positive or negative feelings toward particular behavior (Fishbein & Ajzen, 1975). Perceived ease of use predicts perceived usefulness and attitude in TAM. In addition to this relationship, perceived usefulness influences attitude while intention is predicted by attitude and perceived usefulness. There are many studies investigating users' intention through TAM. For example, Kim and Lee (2016) extended TAM with the variables as self-efficacy, content reliability, interactivity, perceived enjoyment to examine students' acceptance of MALL and found that core relationships in TAM were validated and external variables made a significant contribution to the model. Also, Qashou (2021) investigated university students' intentions to adopt m-learning based on extended TAM. The results showed that PU and ATT predicted students' intention to use m-learning. Furthermore, PU and PEU had an effect on ATT, and PU was influenced by PEU. Other constructs such as perceived self-efficacy, perceived enjoyment and perceived mobility were found to be related to some constructs in the model.

Cheon et al. (2012) summarized the external beliefs in mobile learning as attitudinal, normative, and control beliefs. The two determinants of attitudinal beliefs, PU and PEU, are known to influence users' attitudes (Ajzen, 1991) and, in turn, behavioral intention (Davis, 1985). TAM claims causal relationships among PU, PEU, ATT, and intention (Davis, 1989), and these relationships have been confirmed by a recent comprehensive systematic review study by Granić and Marangunić (2019). Hence, the following hypotheses were proposed in this study:

- H1: PU has a positive effect on continuance intention to use MALL.
- H2: PU has a positive effect on attitude towards MALL
- H3: PEU has a positive effect on attitude towards MALL.
- H4: PEU has a positive effect on PU.
- H5: ATT toward MALL has a positive effect on continuance intention to use MALL.

TPB is the extension of the theory of reasoned action (Ajzen, 1991) which explains behavioral intention by two constructs, attitude and social norm (Ajzen, 1985). Attitude is defined as "the individual's positive or negative evaluation of performing the behavior" (Ajzen, 1985, p. 12), and social norms (SN) are described as "an individual's perception that most people who are important to her think she should (or should not) perform a particular behavior" (Fishbein & Ajzen, 2010, p. 131). Attitude as a personal factor and social norm as a social pressure can affect how individuals perform their behavior. However, Ajzen (1985) developed TPB with expanding theory of reasoned action by adding perceived behavioral control (PBC) that "refers to people's perception of the ease or difficulty of performing the behavior of interest" (Ajzen, 1991, p.183). Perceived behavioral control is related to the resources and opportunities an individual pose (Ajzen, 1991). Employing TPB as a theoretical base, some studies attempted to predict the m-learning intentions of students. For example, Cheon et al. (2012) used TPB to explain university students' intention to adopt m-learning and found that attitude, subjective norm and perceived behavioral control were significant factors influencing students' intention to use m-learning with a higher R^2 value. Gómez-Ramirez et al. (2019) explored university students' m-learning adoptions with TPB and TAM, and all constructs were associated with m-learning adoption. Dalvi-Esfahani et al. (2020) used the technology-to-performance chain model, the uses and gratifications theory, the technology acceptance model, and the theory of planned behavior to explain continuance intention of mobile web 2.0 learning. They collected the data from the university students that had experience about mobile web 2.0 learning. The results showed that technological convenience, information exchange, social interaction, perceived usefulness, perceived ease of use, attitude, perceived behavioral control, social norms, task-technology fit influenced the continuance intention to use mobile web 2.0 learning.

Normative beliefs refer to "the likelihood that important referent individuals or groups approve or disapprove of performing a given behavior" (Ajzen, 1991, p. 195). Thus, normative beliefs "constitute the underlying determinants of subjective norms" (Ajzen, 1991, p. 189). SN is one of the direct determinants of behavioral intentions (Fishbein & Ajzen, 2010, p. 131). As the previous studies (e.g., Yeap et al., 2016) suggested peer students (SR) and instructors (IR) as the referent groups at higher education, this study included these two referents and developed the following three hypotheses.

- H6: SN has a positive effect on continuance intention to use MALL.
- H7: Perceived IR has a positive effect on SN for MALL.
- H8: Perceived peer SR has a positive effect on SN for MALL.

The third of the external beliefs, control beliefs, "provide basis for perceptions of behavioral control" (Ajzen, 1991, p. 189) and consist of perceived self-efficacy and learning autonomy constructs in this context. Although Fishbein and Ajzen (2010) touch upon the moderating role of PBC on the behavior and intention relationship, this is rarely scrutinized in an educational context (Cheng, 2019). While self-efficacy (SE) refers to the beliefs of individuals to perform a task (Bandura, 1986), learner autonomy (LA) is defined as the "ability to take charge of one's own learning" (Holec, 1981, p. 3). The higher the self-efficacy levels learners have related to the computers, the higher levels of behavioral intention and the usage of information technologies they develop (Compeau & Higgins, 1995). Autonomy also plays a significant role in behavior control (Raza et al., 2018) and system acceptance-adoption (Liaw et al., 2007). Through the aforementioned studies, it can be hypothesized that:

- H9: PBC has a positive effect on continuance intention to use MALL.
- H10: Perceived SE toward MALL has a positive effect on PBC with MALL.
- H11: Perceived LA toward MALL has a positive effect on PBC with MALL.

Bhattacherjee (2001b) adapted expectation and confirmation theory for information systems. ECM is used to examine individuals' intention to continue using an information system with the constructs of satisfaction, perceived usefulness and confirmation. Bhattacherjee (2001b) emphasized the continued use of information system rather than acceptance of it. The initial acceptance of information system is the first step of its success but its success is related to the continued use of it (Bhattacherjee, 2001b). Confirmation (CON) refers to "the extent to which users' expectation of information system use is realized during actual use" (Bhattacherjee, 2001b, p. 366). Users have expectations about the use of an information system at the beginning, and this expectation can either be confirmed or denied. Moreover, perceived usefulness which is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (1989, p. 320) is about users' belief towards benefits of the information system. When using an information system, the overall evaluation about satisfaction or dissatisfaction influences continuance intention. Also, satisfaction (SAT) is predicted by confirmation and perceived usefulness. Perceived usefulness influences continuance intention and is determined by confirmation (Bhattacherjee, 2001b). Many studies also employed the ECM. For example, Joo et al. (2016) used TAM and ECM as an integrated model to predict continuance intention to use the mobile learning management system of university students who participated in online courses during a semester. The analysis result showed that the relationships between CON and PU, PEU and continuance intention were not statistically significant. However, PU and CON predicted SAT, PU and SAT determined the continuance intention. Alshurideh et al. (2020) investigated the factors related to the continuance intention to use m-learning system through TAM and ECM. In their study, university students used m-learning system for their courses, and the data were analyzed through Partial Least Square Structural Equation Modeling and machine learning technique. The results indicated that all constructs made a significant contribution to the model. Through the aforementioned studies, the following hypotheses were formulated:

- H12: SAT has a positive effect on continuance intention to use MALL.
- H13: PU has a positive effect on SAT with using MALL.
- H14: CON has a positive effect on SAT with MALL.
- H15: CON has a positive effect on PU.

Based on the hypothesis above, this study aims to explain and predict the determinants of continuance intention of users toward MALL by proposing an integrated model including TAM, TPB and ECM.

Methodology

This is a cross-sectional survey study as one type of survey research. In cross-sectional surveys, data are collected from a predetermined population at one point in time (Creswell, 2012; Fraenkel et al., 2012). This study investigated the factors influencing the intentions of participants to continue for using MALL just at the end of 14-week exposure by using a cross-sectional survey design. To do so, this study employed three of the models: TAM, TPB, and ECM. TAM is widely adopted and validated in educational context (Granić & Marangunić, 2019). TPB were validated in the context of mobile learning as a framework in the study of Cheon et al. (2012). Additionally, this study integrated ECM into this model in order to get a new framework for mobile learning in language learning because ECM is good at explaining continuance intention towards mobile assisted language learning of students after initial use (Bhattacherjee, 2001b; Joo et al., 2017). Hence, it was possible to get a holistic view of the factors influencing students' continuance intention to use mobile-assisted language learning. Figure 1 summarizes the research model used in the current study.

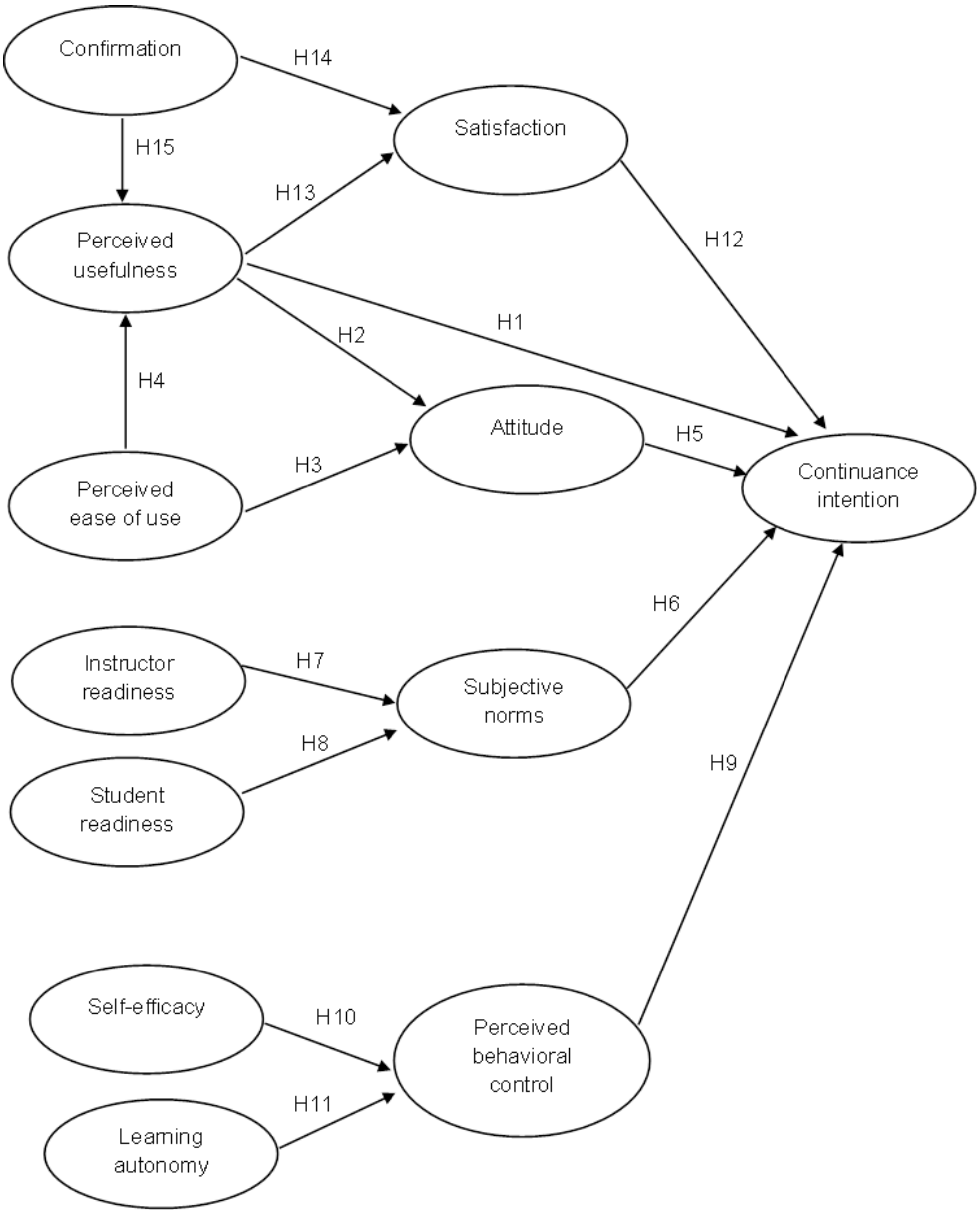


Figure 1. Research model of the study

Participants

This study took place at a state university in Turkey, and the convenience sampling method was employed. 642 students were taking the course English I at the Faculty of Education and Vocational School. Of these, 379 students voluntarily participated in the study. The demographic information about participants was presented in Table 1.

Table 1: Demographic information about participants

Demographic Variable	*Items*	*N*	*%*
Gender	Female	192	50.7
	Male	187	49.3
Academic level	Faculty of education	52	13.7
	Community college	327	86.3
Grade	1	375	98.9
	Other (2-4)	4	1.1
Age	18-22	366	96.6
	23 and above	13	3.4

Table 1 shows that 50.7% (*f*=192) of the participants were female, and 49.3% (*f*=187) were male. This shows the balanced distribution of the participants in terms of their gender. The participants were studying at the Faculty of Education (13.7%, *f*=52) and Vocational School (86.3%, *f*=327) as stated before. The course English I is a compulsory first-year course in all cycles of higher education in Turkey. Therefore, almost all (98.9%) of the students were freshman students, and their ages were between 18 and 22. However, there were also some sophomore and senior students from different age groups.

The Duolingo Case

This study investigated the continuance intention of users toward MALL through a specific application, namely Duolingo. There are many reasons to choose Duolingo in the current study. First, Duolingo is a free popular language learning application with its over 300 million users (Smith, 2019). Due to its investment in worldwide mobile access and its usability in iOS, Android, and Windows operating systems (Loewen et al., 2019), Duolingo offers 95 languages to learners (Shortt et al., 2021). Another reason to choose Duolingo as the case of this study is the opportunity that users can take a placement test and follow their own path in line with their background knowledge because the freshman students at Turkish universities study a basic compulsory A1 (beginner) English course (see the common courses offered by the Council of Higher Education in Turkey at https://yokdersleri.yok.gov.tr/) whatever their proficiencies are. Lastly, Duolingo was found to be one of the most gamified applications out of the 20 MALL applications with 22 gamification elements in the study of Govender and Arnedo-Moreno (2020). However, there is limited research on Duolingo as a language learning tool (García Botero et al., 2019), and none of them, to our knowledge, has focused on the intention of users toward it yet.

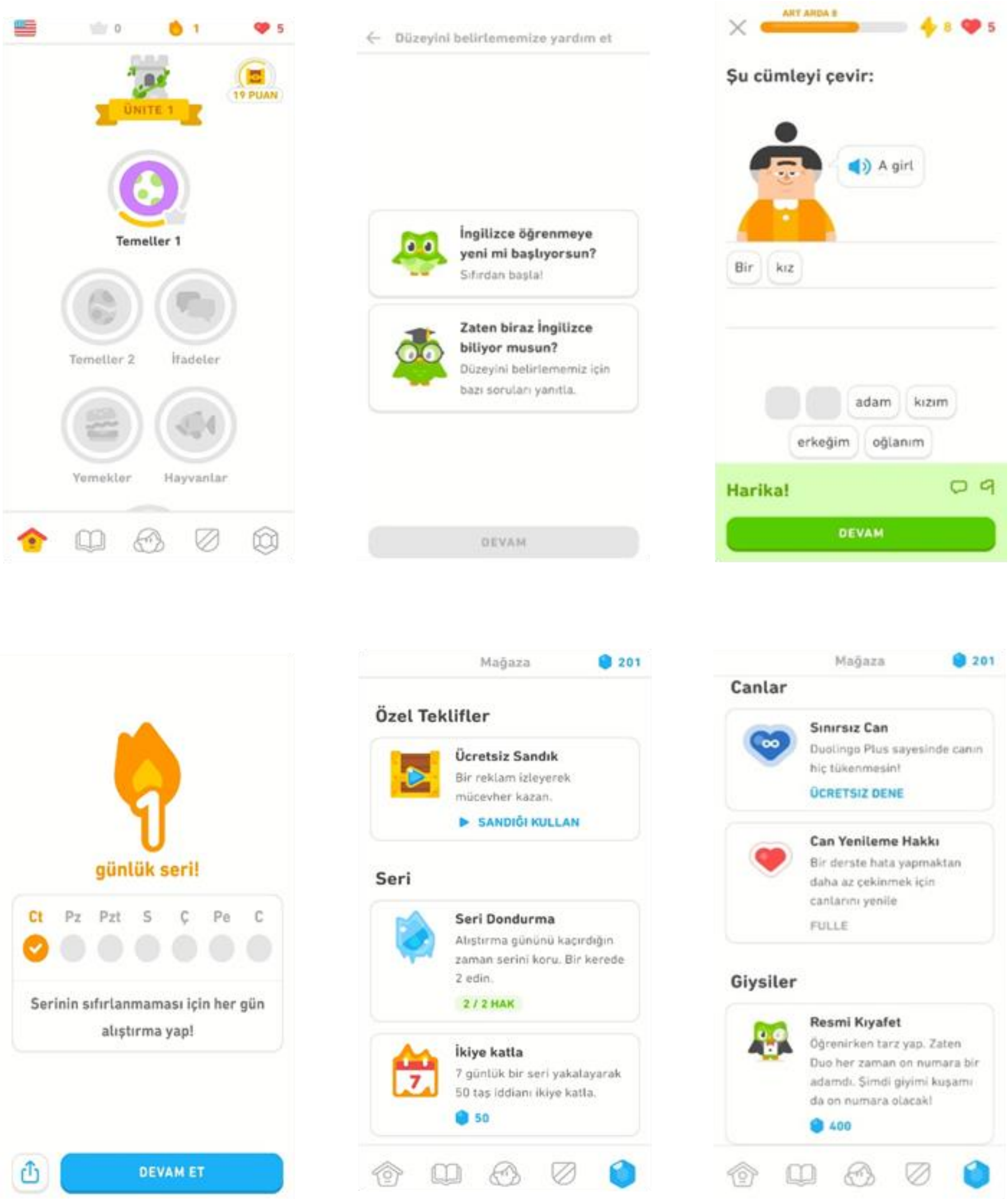


Figure 2. User interface of Duolingo

Following the selection of the application, students were encouraged to learn vocabulary, make sentences, translate sentences, and complete dialogues in Duolingo (see the student interface in Figure 2). Users could also set a certain time period such as 10, 15 and 25 minutes as a daily goal, and were rewarded with bonuses for realizing it. In addition to the use outside the classroom, the participants were allocated twenty minutes to experience mobile applications inside the classroom each week. To reinforce the use on a daily basis, we used the Streak feature that means the completion of one lesson per day with achievement (see Figure 2). Thus, we assured that we created an environment for the students to experience MALL for fourteen weeks throughout the course as other studies emphasized that it is a prerequisite for students to experience mobile learning before investigating the intention to use mobile learning (Cheon et al., 2012; Raza et al., 2018). Certainly, premium users have some advantages such as freezing the Streak and limitless hearts. Ordinary users have five hearts, and it means that they cannot go on playing after doing five mistakes. However, the application offers some features for free to the frequent users or to the ones watching ads (see Figure 2). Furthermore, high achievers earn some diamonds and use these diamonds to buy premium features such as limitless hears and different DuoLingo styles. A 14-week exposure enabled the participants of this study was considered enough to explore these features of the app. At the end of fourteen-week exposure, we collected the data through a cross-sectional survey.

Instruments

The instrument of this study was based on the previously validated studies The items in the study of Cheon et al. (2012) were adopted to measure perceived usefulness, perceived ease of use, attitude, subjective norms, student readiness, instructor readiness, perceived behavioral control, self-efficacy, and learning autonomy. Regarding satisfaction and confirmation, the items were adopted from the studies of Bhattacherjee (2001a, 2001b) and Dağhan and Akkoyunlu (2016). Lastly, the items of continuance intention were adopted from Bhattacherjee (2001a, 2001b), Cheon et al. (2012) and Dağhan and Akkoyunlu (2016). All items were adapted into the MALL context as items were used in different contexts. The items were translated into Turkish language by two researchers independently. The translated forms were compared, and the differences between two forms were discussed in order to get their proper translation. After the control of items, the final scale form was created. The instrument was a 7-item Likert type scale (1 = strongly disagree to 7 = strongly agree), including the demographic questions such as gender, grade, and age. To collect the data, the participants were asked to fill in the form through Google Forms. The participants also used their mobile devices (mobile phones, tablets, etc.) to fill this form.

Data Analysis

Partial Least Square Structural Equation Modeling (PLS-SEM) was used to test the developed comprehensive model in this study. PLS-SEM is an alternative method to Covariance Based Structural Equation Modeling. It aims to predict and explain the target constructs and their relationships instead of testing theories or confirming and rejecting the relationships between multiple variables (Hair et al., 2016). Moreover, PLS-SEM is a causal modeling approach aimed at maximizing the explained variance of the dependent latent constructs (Hair et al., 2011).

There are some reasons to use PLS-SEM in this study. First, this study aims to investigate the factors associated with the continuance intention of users toward MALL. In our model, the continuance intention is the primary dependent variable, and the predictors of this variable can be explored through PLS-SEM, as suggested by Hair et al. (2017). Secondly, Hair et al. (2011) suggest analyzing the data with PLS-SEM in the event of a model consisting of more than one construct as in this study because PLS-SEM allows combining explanation and prediction perspectives to model estimation (Hair et al., 2017).

Due to its strengths mentioned above, this study utilized SmartPLS 3.2.7, which takes its basis from the PLS-SEM approach. As suggested by Hair et al. (2011), the data were analyzed with a two-step process. First, the measurement model was assessed with the reliability and validity of the construct measures. Once the construct measures' reliability and validity were confirmed, the second step was to assess the structural model to determine the relationships among variables.

Results

Measurement Model Analysis

Measurement model was evaluated in terms of internal consistency reliability, indicator reliability, convergent validity, and discriminant validity (Hair et al., 2011). The internal consistency reliability was determined with the composite reliability (CR) and Cronbach Alpha value, while indicator reliability was assessed with the factor loadings of the items. To estimate the convergent validity, average variance extracted (AVE) was taken into consideration. Fornell–Larcker criterion (Fornell & Larcker, 1981) was used to determine the discriminant validity. Table 2 shows the analysis results of the measurement model.

Table 2. Results of measurement model

Construct	*Item*	*Loading*	*AVE*	*CR*	*Alpha*
Attitude			.74	.89	.82
	ATT1	.84			
	ATT2	.87			
	ATT3	.87			
Confirmation			.76	.90	.84
	CON1	.82			
	CON2	.89			
	CON3	.90			
Instructor readiness			.66	.85	.74
	IR1	.82			
	IR2	.86			
	IR3	.77			
Student readiness			.71	.88	.80
	SR1	.86			
	SR2	.89			
	SR3	.79			
Learning Autonomy			.75	.90	.84
	LA1	.87			
	LA2	.87			
	LA3	.87			
Perceived ease of use			.75	.90	.83
	PEU1	.87			
	PEU2	.87			
	PEU3	.85			
Continuance intention to use MALL			.81	.93	.88
	CINT1	.88			
	CINT2	.92			
	CINT3	.90			
Perceived Behavioral Control			.81	.93	.89
	PBC1	.90			
	PBC2	.92			
	PBC3	.89			
Satisfaction			.81	.93	.88
	SAT1	.92			
	SAT2	.90			
	SAT3	.88			
Subjective Norm			.67	.86	.75
	SN1	.86			
	SN2	.70			
	SN3	.88			
Self-Efficacy			.77	.91	.85
	SE1	.85			
	SE2	.88			
	SE3	.91			
Perceived Usefulness			.71	.88	.80

PU1	.86
PU2	.82
PU3	.85

Note: AVE=Average Variance Extracted, CR=Composite Reliability, Alpha=Cronbach's Alpha

In Table 2, the indicators' factor loadings ranged from .70 to .92, and this fulfilled the criteria that indicator loadings should be greater than .70 (Hair et al., 2011). For each construct, CR and Cronbach Alpha values were calculated. CR values ranged from .85 to .93, and Cronbach Alpha values ranged from .74 to .89. These reliability values exceeded the suggested acceptable threshold of 0.7 for CR (Hair et al., 2011) and for Cronbach Alpha (Nunnally, 1978). AVE values, which were used for convergent validity, fluctuated between .66 to .81. These values are above .50 and can be interpreted as "the latent variable explains more than half of its indicators' variance" (Hair et al., 2011; p. 146). For the assessment of discriminant validity, the Fornell-Larcker criterion was used. The square roots AVE of each construct are compared with the correlations between the construct and other constructs (Fornell & Larcker, 1981). Table 3 shows the Fornell-Larcker criterion evaluation.

Table 3. Fornell-Larcker criterion analysis

	ATT	CINT	CON	IR	LA	PBC	PEU	PU	SAT	SE	SR	SN
ATT	**.86**											
CINT	.66	**.90**										
CON	.62	.70	**.87**									
IR	.64	.57	.56	**.81**								
LA	.68	.73	.71	.63	**.87**							
PBC	.57	.70	.67	.55	.71	**.90**						
PEU	.64	.54	.54	.59	.55	.56	**.86**					
PU	.75	.61	.58	.61	.60	.54	.74	**.84**				
SAT	.66	.65	.84	.56	.67	.63	.56	.62	**.90**			
SE	.54	.66	.61	.54	.75	.78	.50	.48	.59	**.88**		
SR	.65	.57	.58	.66	.65	.57	.56	.59	.61	.57	**.85**	
SN	.55	.56	.53	.54	.60	.46	.42	.45	.53	.48	.62	**.82**

Notes. Bold diagonal: square root of AVE, ATT=Attitude, CINT=Continuance Intention, CON=Confirmation, IR= Instructor Readiness, LA= Learning Autonomy, PBC=Perceived Behavioral Control, PEU=Perceived Ease of Use, PU=Perceived Usefulness, SAT=Satisfaction, SE= Self-efficacy, SR= Student Readiness, SN=Subjective Norm.

We presented the square roots of AVE (bold diagonal values) in Table 3. The other values were correlation coefficients between constructs. According to Fornell and Larcker (1981), the square roots of AVE for each construct should be greater than its correlation with other constructs for a given construct, and Table 4 shows that this study fulfilled the Fornell and Larcker criterion. Moreover, we checked the correlations among constructs, and the correlation results met the requirements that correlations among constructs should be lower than .85 (Kline, 2015). Considering that high correlations may cause multi-collinearity problems, we also examined the Variance Inflation Factor (VIF) values. All VIF values were lower than five, and this proved that there were no multicollinearity problems in the model (Hair et al., 2011). The Fornell and Larcker criterion results, the correlations among constructs, and the VIF values revealed that the measurement model had satisfactory discriminant validity. In sum, the results of measurement model analysis did not show any violence for model's validity and reliability. As a second step, we tested the structural model.

Structural Model Analysis

Structural model analysis aimed to reveal relationships between exogenous variables and latent variable. Through this analysis, students' continuance intention to use MALL was examined. The structural model analysis provided path coefficients (β), significance of the path (p), t values, coefficient of determination (R^2), cross-validated redundancy (Q^2) and effect size (f^2) (Hair, Sarstedt, et al., 2014).

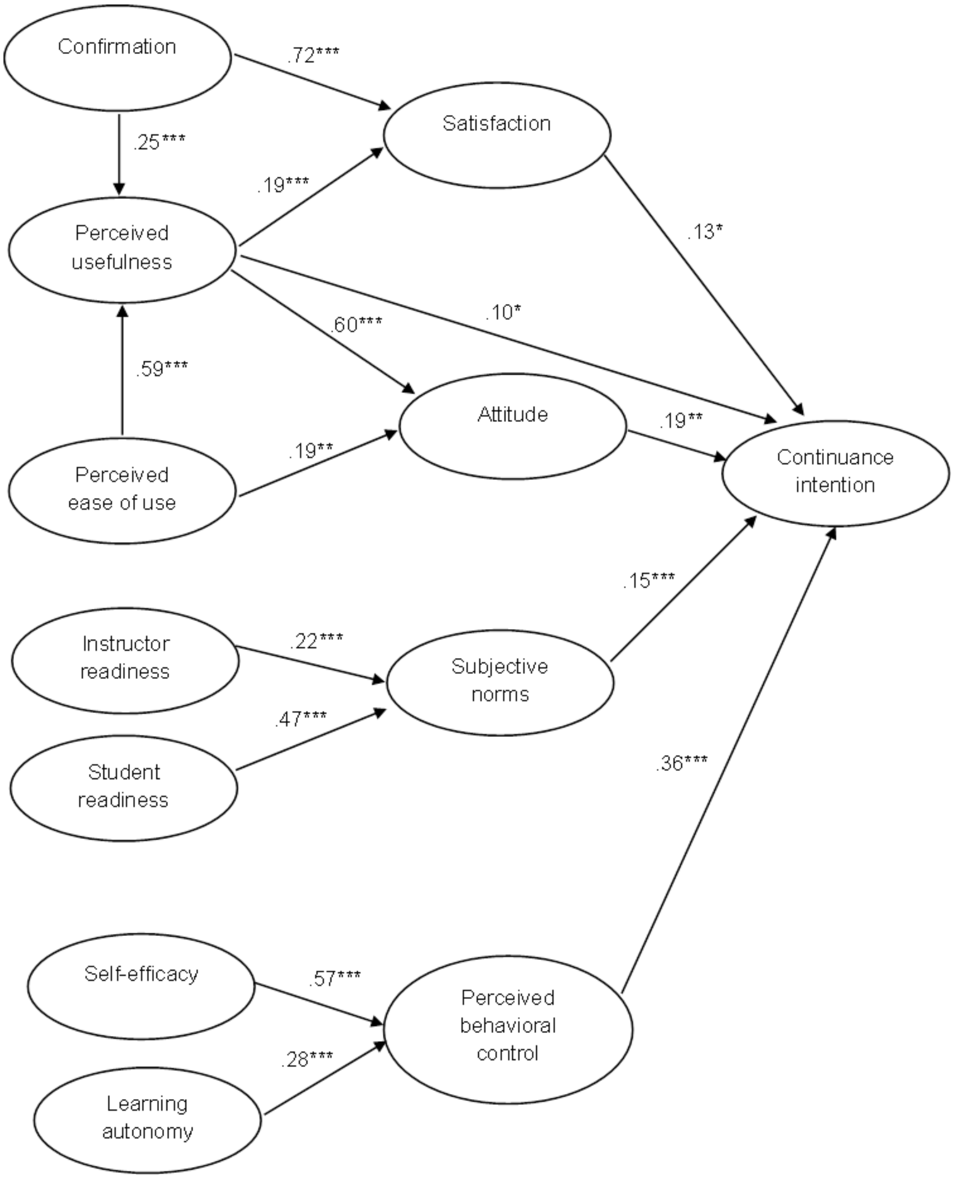
First, we ran a bootstrapping with 5000 resamples on SmartPLS to determine the path coefficients, *t* values, and significance of the paths. Table 4 and Figure 3, indicate the results of the structural model analysis.

Table 4. Results of hypothesis testing

Hypothesis	Relationship	*B*	*t*	*p*	Supported
H1	PU ➔ CINT	0.106	2.007	.045	Yes
H2	PU ➔ATT	0.606	10.132	.000	Yes
H3	PEU ➔ ATT	0.195	3.125	.002	Yes
H4	PEU ➔ PU	0.596	12.622	.000	Yes
H5	ATT ➔ CINT	0.194	3.119	.002	Yes
H6	SN➔ CINT	0.158	3.681	.000	Yes
H7	IR ➔ SN	0.223	4.246	.000	Yes
H8	SR ➔ SN	0.475	9.156	.000	Yes
H9	PBC ➔ CINT	0.369	5.878	.000	Yes
H10	SE ➔ PBC	0.570	6.961	.000	Yes
H11	LA ➔ PBC	0.287	3.654	.000	Yes
H12	SAT ➔ CINT	0.138	1.972	.049	Yes
H13	PU ➔SAT	0.196	4.506	.000	Yes
H14	CON ➔ SAT	0.723	20.053	.000	Yes
H15	CON ➔ PU	0.259	6.018	.000	Yes

Note. ATT=Attitude, CINT=Continuance Intention, CON=Confirmation, IR= Instructor Readiness, LA= Learning Autonomy, PBC=Perceived Behavioral Control, PEU=Perceived Ease of Use, PU=Perceived Usefulness, SAT=Satisfaction, SE= Self-efficacy, SR= Student Readiness, SN=Subjective Norm.

The results confirmed the entire hypothesis. PBC ($\beta=0.369$, $p<.001$), ATT ($\beta=0.194$, $p<.01$), SN ($\beta=0.158$, $p<.001$), SAT ($\beta=0.138$, $p<.05$), PU ($\beta= 0.106$, $p<.05$) had significant effects on the continuance intentions of students toward MALL. In other words, H1, H5, H6, H9, and H12 hypotheses were confirmed. Among these factors, PBC seems to be the most effective factor in users' continuance intentions toward MALL. Furthermore, SE ($\beta=0.570$, $p<.001$) and LA ($\beta=0.287$, $p<.001$) had a significant effect on PBC, and this refers to the confirmation of H10 and H11 hypotheses. PU ($\beta=0.606$, $p<.001$) and PEU ($\beta=0.195$ $p<.01$) predicted the ATT and this result confirms the H2 and H3 hypotheses. Similarly, SR ($\beta=0.475$, $p<.001$) and IR ($\beta=0.223$, $p<.001$) predicted the SN, which confirms H7 and H8 hypotheses. CON ($\beta=0.723$, $p<.001$) and PU ($\beta=0.196$, $p<.001$) predicted the SAT, and this confirmed H13 and H14 hypotheses. Lastly, PEU ($\beta=0.596$, $p<.001$) and CON ($\beta=0.259$, $p<.001$) had effects on PU, which means that H4 and H15 hypotheses were also confirmed.



Note. *$p < .05$; **$p < .01$; ***$p < .001$

Figure 3. *Results of structural model analysis*

Secondly, the predictive ability of the theoretical structural model was determined with the coefficient of determination (R^2), cross-validated redundancy (Q^2), and effect size (f^2). The R^2 value is used to measure the model's predictive accuracy and the amount of variance explained by the independent variables (Hair et al., 2014). The values were presented in Table 5.

Table 5. Results of predictive relevance and effect sizes

Endogenous Variables	R^2	Q^2	*Path*	f^2
CINT	0.627	0.473	ATT➔CINT	0.035
			PU➔ CINT	0.012
			SAT➔ CINT	0.022
			PBC➔ CINT	0.200
			SN➔ CINT	0.042
ATT	0.579	0.403	PU➔ATT	0.399
			PEU➔ATT	0.041
PU	0.590	0.391	CON➔PU	0.116

			PEU→PU	0.610
SAT	0.726	0.554	CON→SAT	1.258
			PU→SAT	0.092
PBC	0.650	0.496	LA→PBC	0.105
			SE→PBC	0.413
SN	0.416	0.257	IR→SN	0.048
			SR→SN	0.218

Note. ATT=Attitude, CINT=Continuance Intention, CON=Confirmation, IR= Instructor Readiness, LA= Learning Autonomy, PBC=Perceived Behavioral Control, PEU=Perceived Ease of Use, PU=Perceived Usefulness, SAT=Satisfaction, SE= Self-efficacy, SR= Student Readiness, SN=Subjective Norm.

In this study, the model explained a significant amount of variance in the dependent variable, continuance intention to use MALL (R^2 = .627). In other words, ATT, PU, SAT, PBC, and SN accounted for a total of 62.7 % of the variance in continuance intention to use MALL. According to Chin (1998), R^2 values of 0.67, 0.33, or 0.19 for structural model can be described as substantial, moderate, or weak, respectively. Thus, the predictive accuracy of this model was moderate. Besides, other constructs were explained by other independent variables. ATT was predicted with its predictors, which were PU and PEU, with an R^2 of 0.579. PU was determined by the PEU and CON, resulting in an R^2 of 0.590. SAT was predicted by its antecedents, PU and CON with an R^2 of 0.726. LA and SE caused changes in PBC with an R^2 of 0.650. SN was determined by the IR and SR resulting in an R^2 of 0.416.

The predictive relevance of the model was assessed with cross-validated redundancy (Q^2) using the Blindfolding procedure in the analysis. "Q^2 is a measure of how well the observed values are reproduced by the model and its parameter estimates" (Eom et al., 2006, p. 226). Q^2 value were calculated as .473 for continuance intention to use MALL, .403 for ATT, .391 for PU, .554 for SAT, .496 for PBC and .257 for SN. The model's predictive relevance for an endogenous construct can be envisaged through a Q^2 value greater than zero for this particular construct (Hair et al., 2011). According to the Q^2 values, the model had a good predictive relevance.

Effect size (f^2) was calculated to determine the relative effect of each independent variable on the dependent variable. According to Cohen (1988), f^2 values of .35, .15, or .02 can be described as small, medium, or large, respectively. f^2 values of constructs on continuance intention to use MALL were .035 for ATT, .012 for PU, .022 for SAT, .200 for PBC and .042 for SN . According to these values, PBC had a medium effect on continuance intention to use MALL. Other constructs had a small effect while PU did not affect continuance intention to use MALL. The effect size of PU on ATT was 0.399, and it could be interpreted as a large effect, while PEU had a small effect on ATT (f^2= 0.041). PEU had a large effect on PU (f^2= 0.610), while the effect of CON was small (f^2= 0.116). CON (f^2= 1.258) and PU (f^2= 0.092) had a large and small effect on SAT, respectively. SE had a large effect on PBC (f^2= 0.413), while LA had a small effect on PBC (f^2= 0.105). Considering the impact of SR on SN was moderate (f^2= 0.218), while the impact of IR was small (f^2= 0.048).

Discussion

The purpose of this study was to explain and predict the determinants of continuance intention of users toward MALL by proposing an integrated model including TAM, TPB and ECM. The fifteen hypotheses were accepted based on the results. Furthermore, the proposed model accounted for %62 of the variance in users' continuance intention toward MALL.

First, perceived behavioral control was the most significant factor in students' continuance intention toward MALL. This result was in line with the findings of previous mobile learning research (e.g., Azizi & Khatony, 2019; Yeap et al., 2016) Furthermore, self-efficacy had a more substantial effect on perceived behavioral control than learning autonomy. Previous mobile learning research (Azizi &

Khatony, 2019; Cheon et al., 2012; Raza et al., 2018; Yeap et al., 2016) revealed similar results that self-efficacy and learning autonomy influenced the perceived behavioral control. This study showed that students believed in their ability of language learning with the mobile application, and students had control over to perform language learning tasks on the mobile application, as stated in the self-efficacy and autonomy definitions of Bandura (1986) and Holec (1981). In other words, students' continuance intention to use MALL was closely related to their confidence. On the condition that students are provided with appropriate resources and develop a control mechanism, they may want to use mobile learning in language learning in future.

Secondly, attitude, on the one hand, significantly influenced the continuance intention of students toward MALL. On the other hand, the attitude was influenced mainly by perceived usefulness when compared to perceived ease of use. These findings were verified by the previous studies (e.g., Chang et al., 2012; Gómez-Ramirez et al., 2019). Attitude refers to one's positive or negative feelings toward certain behavior (Fishbein & Ajzen, 1975). The students in this study had positive feelings toward MALL. They completed the learning activities through their mobile devices during the period of implementation. Hence, they had positive feelings and intended to continue their mobile language learning in the future. This result reminds the argument of Davis (1985) on the existence of a link between attitude and continuance intention. The significant impact of perceived usefulness and perceived ease of use on attitude can be interpreted that students, who believe that using mobile applications for language learning is beneficial for them and think that using mobile application is easy to use, had a positive feeling toward MALL. Furthermore, perceived usefulness had a direct effect on the continuance intention of students toward MALL which is consistent with the previous studies (e.g., Alshurideh et al., 2020; Chen et al., 2013). After some experience or familiarity with MALL, students can think that using a mobile application for language learning is helpful for them, and this belief may affect their continuance intention toward MALL. As another finding, perceived usefulness was predicted by the perceived ease of use. Some previous studies (e.g., Chang et al., 2012; Iqbal & Bhatti, 2015; Qashou, 2021) also confirmed that perceived usefulness is predicted by perceived ease of use. In other words, the longer students use the mobile application, the more positive perception they will have on the ease of use on a mobile application, which might affect the students' perception of perceived usefulness.

Third, the results of this study revealed a significant relationship between subjective norms and continuance intention of users toward MALL. Based on the factors predicting the subjective norms, student readiness was more influential than the construct of instructor readiness. These results were consistent with the previous studies (e.g., Raza et al., 2018; Yeap et al., 2016). Students' opinions about the readiness levels of other students and instructors affected the subjective norms of students. In other words, the views of people around students may positively affect the beliefs of students about using mobile learning for language learning purposes, and students tend to use MALL in the future provided that their social environment encourage them to use it (Botero et al., 2018; Hoi, 2020).

Finally, another significant and influential factor was satisfaction for the continuance intention of students toward MALL. Satisfaction was also predicted by confirmation with a higher coefficient than perceived usefulness similar to the previous studies (e.g., Al-Emran et al., 2020; Chen et al., 2013). The higher satisfaction levels students have for a language learning mobile application, the higher intention to use MALL students will have. Furthermore, the satisfaction levels of students will increase when their expectations are met through MALL. In other words, when students engage with language learning activities through a mobile application, their expectations toward MALL would be confirmed. Then, this confirmation significantly affects their satisfaction level. At the same time, the confirmation of students' expectations would increase their perceptions about the usefulness of the system (Ifinedo, 2018; Limayem & Cheung, 2008). Also, the previous ECM studies (Al-Emran et al., 2020; Bhattacherjee, 2001b; Joo et al., 2016) proved a relationship between perceived usefulness and satisfaction. The participants considered mobile applications useful for language learning in this context, and they were more likely to be satisfied with MALL.

Conclusions and Future Research Directions

This empirical study validated our proposed model on the continuance intention to use MALL by accepting all our hypotheses. In other words, this comprehensive model, including TAM, TPB and ECM theories, can be used as an appropriate framework for examining the continuance intention to use mobile learning in language education. The model results revealed that perceived behavioral control, attitude, subjective norms, satisfaction, and perceived usefulness have a significant effect on the students' continuance intention to use MALL. Furthermore, these constructs were significantly predicted by their antecedents. Theoretically, the study, exploring the factors of what drives students to continue to use MALL with integrating models, revealed reliable and valid results such as determining the significant and essential factors of MALL and predictive power of the model. In this way, the results are expected to contribute to the literature by filling the gap.

Self-efficacy and learning autonomy are the two constructs affecting the perceived behavioral control directly and the continuous intention indirectly. As gamification support mastery experiences, vicarious experiences, social persuasion, and emotional states (Rachels, & Rockinson-Szapkiw, 2018), Duolingo and other applications may focus on the proficiency level of newly starting users and tailor their activities upon their levels to increase the self-efficacy of users. As a drawback of the free version, users cannot continue using the application after five mistakes until the next day, and this becomes a threat to diminish their self-efficacy (Rachels, & Rockinson-Szapkiw, 2018). Also, users should be encouraged to use mobile applications outside the classroom in addition to the classroom activity because mobile devices enhance learner autonomy in informal settings (Chen & Kessler, 2013). Furthermore, Ajzen (1991) stated that perceived behavioral control is related to the beliefs of individuals they have about the resources and opportunities. Therefore, higher education institutions are suggested to provide organizational support (e.g., wireless networks) and technical support (e.g., instruction for the use of mobile devices) for mobile applications to increase the use of MALL. Due to the effectiveness of MALL in higher education, principal administrators are expected to provide fast internet connection and wireless opportunities on campuses (Hoi, 2020). Thus, university students can easily use mobile applications on campuses for following their learning paths. In other words, they will have greater perceived control over their behavior with the belief that they possess necessary resources and opportunities (Ajzen, 1991).

As the ease of use is a significant component for the usefulness of MALL, selecting or developing user-friendly applications is of importance for students to use them with anytime and anywhere principle. In other words, students should access the selected or developed mobile applications without any effort, and, thus, they will be able to spend their time just for learning. Students might develop positive attitudes toward mobile learning through interesting and novel mobile applications that integrate different learning materials (multimedia, audio record, video, animation, etc.) and enable cooperation and collaboration (Hao et al., 2019). Especially in Turkish higher education context, teaching large classrooms might become easier with the integration of technology, and low-achieving students in these classrooms might grasp the opportunity to achieve. Also, positive attitudes might be maximized through collaborative activities, which allows students to communicate and interact with each other (Phielix et al., 2010), and, in turn, collaborative learning might facilitate the acquisition of complex skills in language learning and minimize the levels of cognitive load in learning (Jiang, & Zhang, 2020). Accordingly, their satisfaction levels and intentions to learn might have a change in a positive direction. As a final point, essential individuals such as lecturers and peers play an encouraging role to support students for using MALL (Botero et al., 2018; Hoi, 2020). Therefore, lecturers are expected to introduce adequate mobile applications and mobile learning content.

Our study also has some shortcomings that can be considered for further studies. First, this study was carried out with a specific mobile application, and this study can be repeated with different mobile applications in other contexts. Thus, the results of this study can be generalized without a constraint on application and context. Secondly, the data were collected at the end of the 14-week application experience in the English I course and informal learning outside classrooms. It might be a good idea to analyze acceptance and adoption behaviors with a longitudinal study. Lastly, this study was limited to higher education students, but it might be worth researching the continuance intentions of faculty members and comparing results with the results of students.

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