Article

Telepresence and Interactivity in Mobile Learning System: Its Relation with Open Innovation

Na Wei and Zhongwu Li *

National Institute of Development Administration, International College, Bangkok 10240, Thailand;
vina@hotmail.sg
* Correspondence: zhongwu.li@nida.ac.th

Abstract: Mobile learning applications enable people to spend fragmented time to improve their knowledge and competitiveness. Enterprises aim to design innovative applications and create a new learning mode for the public, and the open innovation strategies may help companies achieve their goals. In the current study, the English learning application "LAIX" was investigated, and an online survey was used to obtain data from 289 university students in Guangzhou. This study combines the technology acceptance model (TAM) with flow theory (FT), investigating the psychological experience factors and the system characteristics that influence users' behavior intentions. The exploration of perceptual variables will promote the establishment of an open innovation model of mobile learning applications. The aim of the study was to establish a theoretical framework to more deeply explore users' intentions in mobile learning applications. Structural equation modeling (SEM) was used to help measure the relationship between variables and determine the model fit. This research reveals that telepresence is the most important variable that impacts user intentions to use mobile learning applications. In addition, the mediating effect of the flow experience was tested. Telepresence and interactivity indirectly influence behavioral intention through the variable "flow". Users appear to be more concerned with the flow experience, which shows the highest correlation with intention to use the application. This study may assist companies to innovate system characteristics and improve customers' user experience, for instance, by integrating virtual reality (VR) technology into the mobile learning system to improve their open innovation level and market popularity.

Keywords: flow theory (FT); mobile learning application; open innovation; structural equation modeling (SEM); technology acceptance model (TAM); users' intention

1. Introduction

Due to the development of mobile broadband technology, and the increase in the number of users, the mobile Internet market is continually developing. Mobile phones are becoming more intelligent and more open. Furthermore, the mobile phone is no longer a simple communication tool, and now provides people with a mobile platform for entertainment and learning [1]. People have started to use mobile applications to access highly specified network resources, and more efficiently employ time management to improve their capabilities via use of their fragmented time. Among various applications on mobile phones, mobile learning applications have become a vital tool employed by people on a daily basis. To acquire knowledge and increase skill, application platforms have become a major trend in the market. The knowledge may cover various fields, such as language, expertise, and manipulative skill.

According to iiMedia Research [2], the number of internet education users continues to grow in China. The market demand is also expanding. In addition, the outbreak of COVID-19 has changed the traditional education model to an online education model [3], which could result in a shift in educational learning patterns. Due to the significant

progress of internet technology, users have high expectations of mobile education software characteristics [4]. Technological innovation needs to be accomplished through open innovation strategies, such as technology purchase, research, and development (R&D) investment, mergers, and cooperation with external enterprises [5]. In the development process of the iPhone, Steve Jobs referred to the characteristics of computers, and made the mobile phone have some functions of computers; thus, creating a new era of smart phones. Open innovation in enterprises includes R&D [6], attention to users' needs, establishment of communication channels between enterprises and customers, and integration of user feedback [7]. User experience may serve as a reference point in software development.

The quality of online education can be effectively improved by a constructive theoretical research framework [8]. Since the 1980s, many academics have studied the acceptance of information systems in terms of both theoretical and empirical aspects [9]. Studies of willingness to use information technology have predominantly used the technology acceptance model (TAM) [10], and research on the influence of users' internal motivations on their behaviors is based on the theory of planned behavior (TPB) [11]. Venkatesh and Bala [12] incorporated system characteristics into the traditional model and developed TAM3. Within the high education field, Bahtiasevi [13] discussed the effect of system functionality on students' behavior intentions in an e-learning system. Additionally, Almaiah et al. [1] confirmed that interactivity has a positive influence on users' beliefs.

E-learning requires that users focus on using a computer, whereas mobile learning is more convenient for users [14]. Mobile learning is defined as learning activities, which are based on mobile data and wireless transmission [15]. Masika [16] used descriptive statistical methods to study the acceptance of mobile learning applications. However, more studies have been conducted using empirical analysis to explore adoption behavior. Wang et al. [17] studied the behavioral intention of mobile learning based on the unified theory of acceptance and use of technology model (UTAUT) and the structural equation model (SEM). In addition, the empirical method was used to investigate the acceptance degree of mobile learning among college students by Fagan [18]. Cheon et al. [19] used the TBP model to conduct a comparative study on the influencing factors of mobile learning usage among users in different regions. These studies provided effective suggestions for enterprises to apply and develop new information technology products. By comparison, people appear to be more concerned about the user experience when using e-learning applications [6].

The current market is driven by consumer demand, and no product can survive without consumer demand. Nokia adopted an open innovation strategy to stay ahead of the curve in a changing technological environment [20]. System characteristics should serve the user experience, enabling open innovation by integrating technology and requirements. Based on the original TAM, although users consider applications to be easy to use, the psychological experience, as an intrinsic motivation [21], may affect users' willingness to use the system. For instance, when people learn to play the piano on an application, wrong fingering can be corrected simply by language and demonstration. In accordance with the different learning content in applications, users may generate varying degrees of psychology experience [22] that affect their behavior intention. The core of open innovation is the sharing of information and intelligence [5]. Hence, a theoretical model was developed in the current study. This model can more effectively measure central factors that affect behavior intention in the usage of mobile learning applications. Furthermore, the study aimed to explain the user experience of mobile learning applications, and offer useful recommendations for enterprises regarding the design and development of software, while promoting users' willingness to use mobile learning applications. This research evaluates the importance of system characteristics and validates the status of user experience. It provides theoretical basis for enterprises to establish communication channels with customers on using experience, and gives guidance for enterprises to establish open innovation strategies of technology sharing.

2. Literature Review

Many theories have been documented to account for people's attitudes and behaviors. The most well-known theoretical framework is the theory of reasoned action (TRA), which was proposed by Fishbein and Ajzen in 1975 [23]. This model has been used widely, for example, in social, technological, and health fields. The TRA focuses on changes in users' behavior, which is affected by their attitudes and subjective norms [11]. To remove the research model premise, Ajzen [24] proposed the TRA and added the perceived control factor into the model, and indicated the perceived control may impact people's behavior. Studies of e-commerce and information technology have been conducted to better understand users' acceptance [25]. Many theoretical models have been employed to analyze individuals' adoption behavior. However, the TAM has become an important underpinning model that has been applied in various fields [26]. Two main variables, namely, perceived usefulness and perceived ease of use, were added to the TAM model, and the two constructs are impacted by external variables [27]. The external variables affect users' behavioral intentions through perceived ease of use and perceived usefulness, which in turn influence users' behavior. The technology acceptance model was shown in Figure 1.
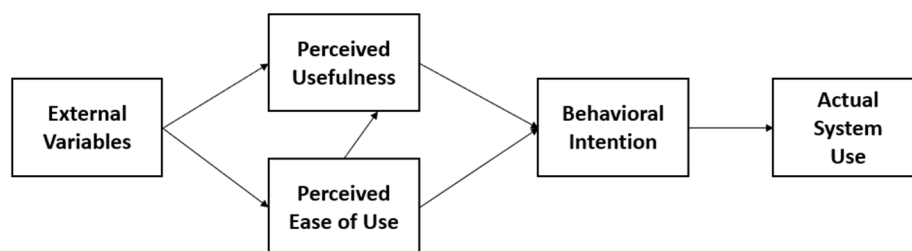

Figure 1. Technology acceptance model [28].

Pai and Huang [29] applied the TAM model to measure information system applications and service quality, and found that perceived ease of use and perceived usefulness acted as mediating factors that positively influence on usage intentions. A few studies have extended the TAM model, and integrated it with other theories, exploring the effect of external variables on perceived ease of use and perceived usefulness. Song et al. [30] introduced users' intentions to use to an electronic file bag application, which confirmed that cognitive constructs in TAM play a mediating role and predict usage intention. The modified TAM has been used for investigating e-learning applications [31]. Moreover, some academics claim that the intrinsic factors impact users' behavior, and have demonstrated the important effects on usage acceptance [1,25,32].

Many studies have focused on the external factors that influence users' behavior in the field of information and communication technology. In the early stage of IT, research was mainly involved with the effect of perceived usefulness and perceived ease of use on behavioral intention [33–35]. The e-learning system possesses two channels, which consist of offering a platform for students to obtain knowledge and for furnishing teaching courses, and system interactivity, which is the most important factor to predict learners' perceived ease of use [36]. People use social media frequently in daily communication, and Chuang et al. [37] demonstrate that telepresence is a key factor that influences people's adoption behavior in information and communication technologies.

Within the iteration of Internet technology, people's behavior and demands are constantly changing. Iksan and Saufian [38] pointed out that teachers use Telegram, a mobile learning software, for teaching innovation. Compared to traditional classrooms, Telegram provides a flexible, more contextual platform that allows students to forget the passage of time and ultimately achieve their learning goals [38]. Previous studies have integrated different theories on consumer behavior to explore the factors that impact users' adoption decisions at different levels [19,39–41]. Chang [42] paid attention to the important role of the user experience in behavioral intention research. Flow theory (FT) refers to the change in an individual's psychology, and was proposed by Csikszentmihalyi [43]. FT has been

broadly applied in many studies. The FT is significant in the psychology study of human behavior. Flow theory has been widely applied in education, vocational training, games, sports, and other fields [34]. As a key psychological parameter, FT is often combined with theoretical models that use behaviors to explore the influence of the user psychological experience on behavioral motivation [44].

When people are in a flow state, they experience little concern about what that may gain, and even ignore challenge and difficulty [45]. The construction of the flow experience was measured to analyze individual's information technology acceptance in online gaming, and the study found that the flow experience was a significant factor, which impacts people's decision making [42]. In addition, the flow experience was considered a mediating effect in the research of smartphone usage [44]. The study of FT has been widely applied in the educational area [46]. Because of different learning abilities and difficulty matching, people may have different psychological experiences when using mobile learning applications, which may impact their willingness to use the software [47]. The study consolidated the TAM and flow theory (FL) to investigate users' acceptance of applications. The aim of the research was to help mobile learning application enterprises design better products and employ good strategies in marketing.

3. Research Hypothesis

3.1. Interaction with Perceived Usefulness, Perceived Ease of Use, and Flow

Although the intrinsic motivation plays an important role in information technology usage, the extrinsic motivation of interactivity has been underlined, and could help users obtain an effective connection [48]. Interactivity has been defined as the degree of interaction with others in software applications [39]. Interactivity is one of the system qualities in information technology applications, and has a positive correlation with perceived usefulness and perceived ease of use in e-learning systems [49]. Interaction among students can promote learning progress and effectivity. Almaiah et al. [1] suggested that the greater interactivity of the system, the greater the usefulness and ease perceived during the use of mobile learning applications. Few studies had verified the relationship between interactivity and users' flow experiences until Novak et al. [50] investigated the behavior of online customers. The research results of Novak et al. [50] suggest that, the faster the interaction with other users or the computer, the stronger the flow experience of users achieved from the system. Furthermore, interactivity and value of usage have a positive relationship with flow experience in playing social online games [42]. Hence, this study illustrated the follow hypotheses:

Hypothesis 1 (H1). *Interactivity has a positive effect on perceived usefulness in mobile learning applications.*

Hypothesis 2 (H2). *Interactivity has a positive effect on perceived ease of use in mobile learning applications.*

Hypothesis 3 (H3). *Interactivity has a positive effect on the flow experience in mobile learning applications.*

3.2. Telepresence with Perceived Usefulness, Perceived Ease of Use, and Flow

Impressive progress has been made in information and communication technology. Applications in visual communication have displayed innovation, which may be considered in mobile learning software development. Telepresence describes the user's experience of the virtual reality environment [51,52]. Steuer [53] explained that telepresence is relevant to people's feelings about the system environment. Park et al. [54] suggested that there is a high positive correlation between telepresence and perceived usefulness in users' adoption of e-tail websites. In addition, Chuang et al. [37] investigated two groups of samples from Taiwan and Thailand, and results from both samples showed that the perceived useful-

ness and perceived ease of use have a positive relationship in social networking services. Hoffman and Novak [55] developed a fundamental model to measure the constructs of telepresence and flow experience, and the results showed that telepresence strongly predicts the flow in the use of the commercial web. Therefore, based on the literature review, this study proposed the following hypotheses:

Hypothesis 4 (H4). *Telepresence has a positive effect on perceived usefulness in mobile learning applications.*

Hypothesis 5 (H5). *Telepresence has a positive effect on perceived ease of use in mobile learning applications.*

Hypothesis 6 (H6). *Telepresence has a positive effect on the flow experience in mobile learning applications.*

3.3. Perceived Usefulness and Perceived Ease of Use

David [11] identified the two new variables of perceived usefulness and perceived ease of use, which were confirmed to be associated with users' behavior intentions. When an individual uses a product, perceived usefulness relates to the degree of usefulness perceived by the user in their work performance, whereas the perceived ease of use means the degree of ease felt by people when using the system [33]. In the traditional TAM model, perceived ease has been demonstrated to be an important positive influence on perceived usefulness, and perceived ease has a greater influence on perceived usefulness than the attitude [28]. Many researchers have tested the relationship between perceived ease of use and perceived usefulness [33]. Liu et al. [40] found that users' perceived ease of use strongly affects perceived usefulness in students' usage of a blackboard system. Said and Al-Gahtani [56] used SEM to measure users' acceptance in an online learning system, and verified that perceived ease of use was positively correlated with perceived usefulness. In addition, Hsu and Lu [34] considered that users' perceived ease of use had a positive effect on flow in online gaming software. The perceived ease of use shows an indirect influence on people's immersion, where immersion means that people engage with what they are doing [57]. Notably, the concept of immersion is closely related to the flow. Thus, based on the above review, this study investigated the following hypotheses:

Hypothesis 7 (H7). *Perceived ease of use has a positive effect on perceived usefulness in mobile learning applications.*

Hypothesis 8 (H8). *Perceived ease of use has a positive effect on the flow experience in mobile learning applications.*

3.4. Perceived Usefulness, Perceived Ease of Use, and Flow Experience with Intention to Use

Perceived usefulness and perceived ease of use indirectly impact behavior intention and attitude, as confirmed in the study of David [11]. Other researchers explored the influence of perceived usefulness and perceived ease of use on the intention to use information technology systems. Szajna [58] tested the effect of perceived usefulness on behavior intention to use, and the result showed that perceived usefulness has a leading effect on intention to use. In addition, Bazelais et al. [59] concentrated on the study of the impact of perceived usefulness and perceived ease of use on behavior intention, implying the two variables have a positive association with behavior intention in online learning systems. Among student users of mobile learning applications, perceived ease of use strongly predicts behavior intention, and the attitude factor is a mediator in the research model [60]. Many studies have referred to the flow experience in individual's usage behavior, and the range declined most significantly in game entertainment. Chang [42] claimed that the

flow experience influences continued usage intention in social online gaming. In addition, the flow experience plays a mediating effect in virtual tours [61]. Based on the previous studies, the following hypotheses were investigated in this study:

Hypothesis 9 (H9). *Perceived usefulness has a positive effect on continued intention to use mobile learning applications.*

Hypothesis 10 (H10). *Perceived ease of use has a positive effect on continued intention to use mobile learning applications.*

Hypothesis 11 (H11). *Flow experience has a positive effect on intention to use mobile learning applications.*

3.5. Research Model

According to the above literature reviews and hypotheses, the following theoretical model was constructed in the current study. As shown in Figure 2, interactivity and telepresence are considered the independent variables. The model was used to test the mediating effects of perceived usefulness, perceived ease of use, and flow experience. In addition, interactivity and telepresence were considered external factors that indirectly affect the continued use intention in mobile learning adoption. Furthermore, the relationship among perceived ease of use, perceived usefulness, and flow experience was determined using the model.
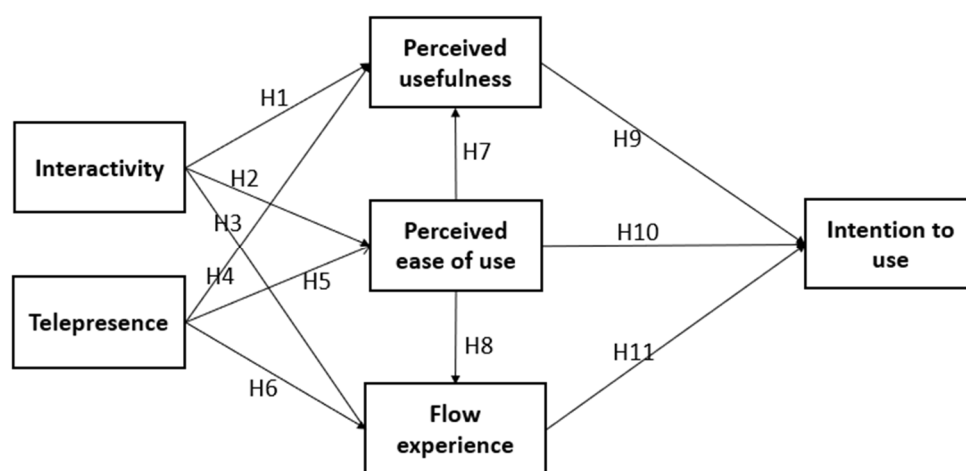

Figure 2. Research model proposed by the authors.

4. Research Methodology

4.1. Measurement

In this study, previous research was reviewed, and a questionnaire scale for the current situation in mobile learning applications was developed. Liu et al. [40] focused on the study of users' behavior intentions in the online learning community, in which the measurement of the interactivity variable was valid, and the research field is closely related to the current study. Four items for telepresence were taken from Novak et al. [50], which represents the main system features in an information technology system. The items of perceived usefulness and perceived ease of use were adapted from the original TAM [62]. Furthermore, in the study of Kim and Hall [58], the flow experience was measured to identify users' psychological experiences. Mohammadi [39] examined the variable of intention to use in online education. Therefore, the present study used the mature items from prior research. Likert 5-point scales were used for the questionnaire measurement.

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Each variable includes 3 to 5 items that were employed from the previous researches. The construct measurement items for this study were showed in Table 1.

Table 1. Construct measurement for mobile learning application adaption.

Variables	Item Description	Source
Interactivity (INT)	INT1: I could have a discussion with others on the application platform. INT2: I could communicate with others on the application platform. INT3: I could send instant messages on the application platform. INT4: In general, I think the learning environment of the application provides a good chance to interact with other users.	Liu et al. [40]
Telepresence (T)	T1: When using the application, I forget about myself. T2: After using the application, I feel I just had a journey. T3: When using the application, it seems that I was put in the world the application created. T4: When I stopped using the application, the application environment suddenly disappears. T5: When using the application, my body is in the room, but my mind is in the virtual world.	Novak et al. [50]
Perceived usefulness (PU)	PU1: Using the application has improved my learning performance. PU2: Using the application has increased my learning productivity. PU3: Using the application helps me to achieve the knowledge. PU4: In general, I found the application was useful in my learning.	Venkatesh and Davis [62]
Perceived ease of use (PEOU)	PEOU1: The interface and information delivery of the application are clear and understandable. PEOU2: The application is easy to handle when I meet a problem. PEOU3: I found the application is easy to learn. PEOU4: In general, I feel the application is easy to use.	Venkatesh and Davis [62]
Flow experience (FE)	FE1: When using the application, I feel trapped. FE2: When using the application, time passed so fast. FE2: When using the application, nothing can interrupt me.	Kim and Hall [61]
Intention to use (IU)	IU1: I intend to use the learning application. IU2: I predict I will use the learning application. IU3: I will use the application continually.	Mohammadi [39]

Developed by authors.

4.2. Data Collection and Analysis

A convenient sampling method was used to collect data for this study. The most common reasons for using non-probabilistic sampling are the low cost and ease of operation of the approach [63]. There are a number of questionnaire design systems available for computer-based surveys that are relatively inexpensive and can reduce the interference of respondents while filling out the questionnaire [64]. Questionnaire Star is a questionnaire data collection system exploited by the Tencent Group in China [65]. The company has a strict performance attitude and technology support to ensure the quality of the data. Therefore, this study designed a questionnaire using Questionnaire Star, and the social media platforms WeChat and Tencent QQ were used to distribute the digital questionnaire.

Among the numerous mobile learning applications, English learning applications, as a form of major learning software, are very popular and commonly used. The market

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competition for this application is fierce. English learning software occupies an important position in the market, so it was selected as the research object in this study. Several English learning applications have a high market share in China. LAIX is an application that helps improve a person's oral English. The application combines spoken English teaching concepts and pronunciation evaluation technology to create a diversified spoken English learning environment for users [66]. A pilot test was processed to improve the survey quality. Guangzhou university students who used the mobile English learning application were chosen as the respondents. The formal investigation period was about two months. After the data collection, a total of 319 respondents completed and submitted the questionnaire, and 289 questionnaires were valid.

To effectively measure the model and identify the relationships among variables, Amos 21.0 software was used to analyze the data and help draw study conclusions. Structural equation modeling (SEM) is a technique that can be used to study and analyze multiple variables, including factor analysis and path analysis [67]. Steenkamp et al. [68] revealed that SEM is a powerful and important research method that may guarantee the quality of the research output. Hence, SEM was conducted to analyze the data information and determine the research results.

5. Research Result

5.1. Reliability and Validity

The reliability was illustrated using the value of Cronbach's alpha, which indicates the consistency and stability of the research result. The specific data can be observed in Table 2. The Cronbach's alpha values of all variables are higher than 0.7, and most of the values are greater than 0.8, which indicates that the reliability of the questionnaire data is acceptable and suitable for further study.

Table 2. Reliability analysis: Cronbach's alpha.

Variable	Corrected Item Total Correlation (CITC)	Cronbach's Alpha if Item Deleted	Cronbach's Alpha
T1	0.679	0.843	
T2	0.682	0.843	
T3	0.642	0.852	0.868
T4	0.688	0.841	
T5	0.767	0.821	
INT1	0.781	0.812	
INT2	0.705	0.843	0.871
INT3	0.644	0.866	
INT4	0.775	0.814	
PU1	0.792	0.851	
PU2	0.761	0.863	0.893
PU3	0.731	0.873	
PU4	0.77	0.860	
PEOU1	0.736	0.766	
PEOU2	0.642	0.808	0.839
PEOU3	0.614	0.821	
PEOU4	0.695	0.785	
FE1	0.763	0.765	
FE2	0.713	0.813	0.856
FE3	0.712	0.813	
IU1	0.734	0.815	
IU2	0.751	0.800	0.864
IU3	0.739	0.811	

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The construct validity was measured by exploratory factor analysis. The results are shown in Table 3. The Kaiser-Meyer-Olkin (KMO) is 0.916; a number higher than 0.7 would be acceptable [69]. Meanwhile, the Bartlett *p*-value is significant, which indicates the correlation among observable variables is strong, and the exploratory factor analysis can be used for the data analysis. Principal component analysis was used, and the factor loading of each item in six types is higher than 0.5, which indicates that the questionnaire scale has good construction validity.

Table 3. Validity analysis results of variables.

	Component					
	1	**2**	**3**	**4**	**5**	**6**
T1	0.712					
T2	0.706					
T3	0.713					
T4	0.733					
T5	0.767					
INT1		0.850				
INT2		0.798				
INT3		0.748				
INT4		0.859				
PU1			0.810			
PU2			0.809			
PU3			0.730			
PU4			0.770			
PEOU1				0.759		
PEOU2				0.767		
PEOU3				0.607		
PEOU4				0.710		
FE1						0.763
FE2						0.850
FE3						0.738
IU1					0.784	
IU2					0.794	
IU3					0.831	
Total	9.309	2.272	1.47	1.43	1.168	1.097
Cumulative %	14.483	27.66	40.782	52.348	62.899	72.814
KMO			0.916			
Bartlett's Test			3171.64 (*p* = 0.000)			

Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalization. a rotation converged in six iterations.

The present study used confirmatory factory analysis (CFA) to test the measurement model. The constructs were tested to measure the relationship and the results of confirmatory analysis are represented in Table 4. The factor loadings under standard estimates are higher than 0.5, which indicates that each item can well explain its dimension [70]. Then, the composite reliability (CR) value is greater than 0.8, and the convergent validity exhibits an acceptable threshold over 0.7 [71]. The collected data show that the absolute value of the kurtosis coefficient and skewness coefficient are less than 1.96, which meets the requirements of a normal distribution. All of the evidence indicates that the questionnaire items were well designed, and would be available for the research investigation. Table 5 shows the discriminant validity among variables, in which each value on the diagonal is greater than the other value of its column, revealing that the measurement has good discriminant validity.

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Table 4. Confirmatory factory analysis of the study.

	The Path		Estimate (std.)	S.E.	t-Value	p	CR	AVE	Skew	Kurtosis
T5	<—	T	0.835						−0.421	−0.979
T4	<—	T	0.744	0.072	12.521	***			−0.361	−0.828
T3	<—	T	0.705	0.072	11.677	***	0.869	0.572	−0.336	−0.660
T2	<—	T	0.748	0.07	12.617	***			−0.497	−0.779
T1	<—	T	0.742	0.068	12.486	***			−0.653	−0.050
INT4	<—	INT	0.855						−0.629	0.080
INT3	<—	INT	0.691	0.062	11.607	***	0.873	0.634	−0.547	−0.294
INT2	<—	INT	0.759	0.063	13.192	***			−0.754	0.135
INT1	<—	INT	0.867	0.066	15.611	***			−0.809	0.386
PU4	<—	PU	0.831						−0.473	−0.828
PU3	<—	PU	0.792	0.069	13.83	***	0.893	0.677	−0.477	−0.932
PU2	<—	PU	0.813	0.072	14.355	***			−0.436	−0.766
PU1	<—	PU	0.854	0.071	15.337	***			−0.427	−0.735
PEOU4	<—	PEOU	0.795						−0.792	−0.269
PEOU3	<—	PEOU	0.697	0.081	10.839	***	0.841	0.571	−0.669	−0.312
PEOU2	<—	PEOU	0.700	0.075	10.899	***			−0.507	−0.648
PEOU1	<—	PEOU	0.822	0.082	13.049	***			−0.644	−0.580
FE3	<—	FE	0.801						−0.327	−0.517
FE2	<—	FE	0.764	0.074	12.26	***	0.856	0.666	−0.045	−0.679
FE1	<—	FE	0.878	0.082	13.951	***			−0.244	−0.491
IU3	<—	IU	0.809						−0.318	−0.244
IU2	<—	IU	0.845	0.079	13.72	***	0.864	0.679	−0.407	−0.122
IU1	<—	IU	0.818	0.078	13.31	***			−0.283	−0.009

*** $p < 0.001$, standard error (S.E.), composite reliability (CR), average variance extraction (AVE).

Table 5. Discriminant validity analysis.

	T	INT	PU	PEOU	FE	IU
T	0.756					
INT	0.365	0.796				
PU	0.544	0.421 **	0.822			
PEOU	0.600	0.394 **	0.549 **	0.755		
FE	0.518 **	0.307 **	0.456 **	0.544 **	0.816	
IU	0.498 **	0.237 **	0.483 **	0.501 **	0.531 **	0.824

** Correlation is significant at the 0.01 level (2-tailed).

When evaluating the model quality, many indexes can be used. However, any single index may not assess model quality [72]. The ratio of the chi-square to the degree of freedom is between 1 and 3. The increment fit indexes include Normed fit index (NFI), Incremental fit index (IFI), Tucker-Lewis index (TLI), and Comparative fit index (CFI), which can be used to estimate the fitness of the research model [73]. All indexes, with the exception of Adjusted Goodness of Fit Index (AGFI), are bigger than 0.9. The value of AGFI is 0.888, which is close to 0.9 and can be accepted [74]. The model fit index is shown in Table 6. The modify space for this model ranges from 0.05 to 0.08, which indicates it is unhelpful for improving the model fit. In addition, the Root Mean Square Error of Approximation (RMSEA) is less than 0.08. According to the fitting index, the model quality is good, and the model can be used in the study to obtain satisfactory analysis results.

Table 6. Model fit index.

	X^2/df	GFI	AGFI	NFI	IFI	TLI	CFI	RMSEA
Index	1.254	0.911	0.888	0.917	0.982	0.979	0.982	0.033

5.2. Path Analysis

The result of the hypotheses test is shown in Table 7. It can be seen that most of the causal relationships of variables are significant because the *p*-value is less than 0.05. In

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contrast, the relationship between interactivity and flow experience shows the *p*-value was higher than 0.05. This indicates that the positive significant relationship between interactivity and flow experience should be rejected. All of the remaining hypothesis tests exhibited significant values, which indicates that the stated positive relationship was demonstrated.

Table 7. Path coefficient analysis of the structural equation.

	The Path		Estimate std.	S.E.	t-Value	*p*
PEOU	<—	T	0.651	0.093	8.164	***
PEOU	<—	INT	0.227	0.050	3.632	***
PU	<—	T	0.329	0.121	3.546	***
FE	<—	T	0.295	0.106	3.111	0.002
FE	<—	INT	0.061	0.050	0.928	0.353
PU	<—	INT	0.220	0.057	3.407	***
PU	<—	PEOU	0.329	0.108	3.400	***
FE	<—	PEOU	0.417	0.098	4.109	***
IU	<—	PU	0.217	0.063	2.677	0.007
IU	<—	PEOU	0.212	0.088	2.095	0.036
IU	<—	FE	0.371	0.080	4.182	***

*** $p < 0.001$.

The path analysis model explains the external factors that affect users' intentions to use mobile learning applications. The two variables of telepresence and interactivity show positive significant effects on both perceived usefulness and perceived ease of use. The result is consistent with previous studies discussed in Section 2. Specifically, the relationship between telepresence and perceived usefulness displays a high degree at 0.65, which illustrates that the two variables have a strong correlation. Nevertheless, the interaction shows no significant correlation with flow experience, which means H3 was rejected. Moreover, the perceived ease of use impact on flow experience and the association coefficient was found to be 0.42, which is higher than the correlation value for perceived usefulness. The flow experience had the strongest effect on intention to use in the research model.

The mediating effect is shown in Table 8. The current study used the bootstrapping method to test the effect, in which the sample was repeated 5000 times and a 95% confidence interval was calculated. With the exception of INT–FE–IU, the mediating path correlations are all significant. In addition, flow experience has a mediating effect between telepresence and intention to use. However, the chain mediation from telepresence, perceived ease of use, and flow experience to intention to use was found to be significant, which implies that telepresence and interactivity will indirectly impact the intention to use the application.

Table 8. Mediating effect analysis.

Parameter std.	Estimate	Lower	Upper	*p*
INT–PU–IU	0.048	0.010	0.118	0.011
T–PU–IU	0.071	0.008	0.172	0.017
INT–PEOU–IU	0.048	0.008	0.113	0.022
T–PEOU–IU	0.138	0.007	0.288	0.038
INT–FE–IU	0.022	−0.026	0.077	0.311
T–FE–IU	0.110	0.031	0.218	0.002
T–PEOU–FE–IU	0.101	0.052	0.182	***
INT–PEOU–FE–IU	0.035	0.012	0.084	***

*** $p < 0.001$.

The structural equation model is shown in Figure 3. Structural equation modeling (SEM) is a statistical method used to analyze the relationship among factors based on the covariance matrix of variables, and the approach may increase the measurement precision

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of the study [62]. The model includes six latent variables, and the squared multiple correlation of PU, PEOU, FE, and IU are illustrated in Figure 3. In brief, the external variables show a positive indirect impact on perceived usefulness and perceived ease of use. Telepresence shows a strong impact on perceived ease of use. Then, perceived usefulness and perceived ease of use play a mediating role in the prediction of the behavior intention to use. Finally, the flow experience has the most powerful effect on intention to use.
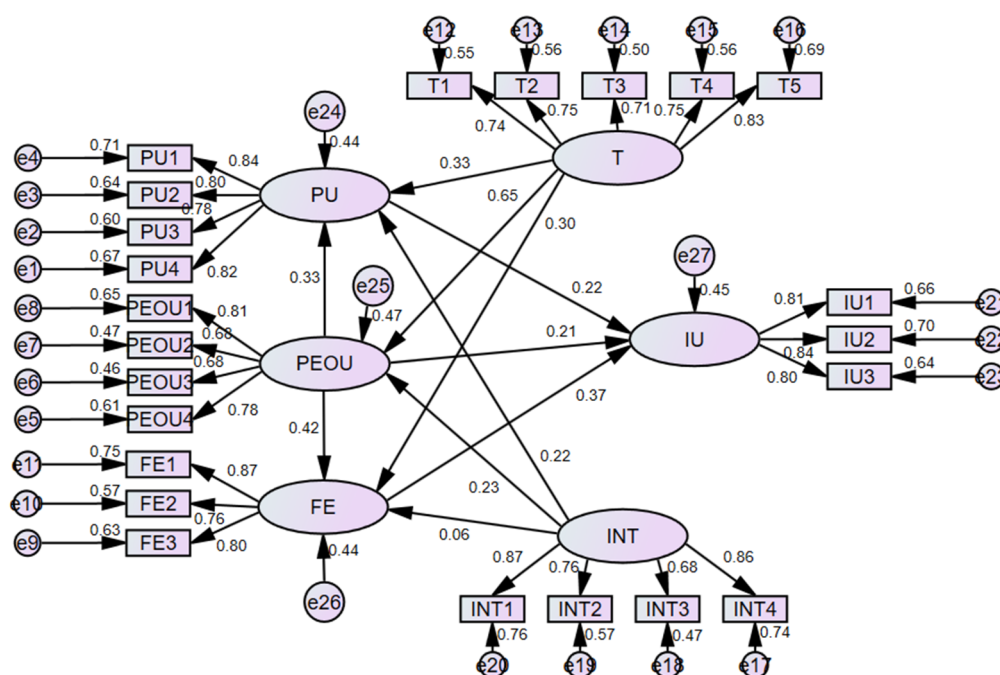
Figure 3. The standardized path estimation for structural equation models.

6. Discussion

6.1. Telepresence, Interactivity, and Mobile Learning System

The results of this study verified the effect of telepresence and interactivity, expanding the influence of system characteristic factors on behavioral intention, as shown in previous studies. Almaiah et al. [1] asserted that interactivity has an impact on behavior intention via perceived usefulness and perceived ease of use in mobile learning acceptance. However, interactivity did not affect flow experience directly in this research, and exhibited a chain effect on behavior intention through perceived ease of use. This suggests that people are concerned about mobile learning applications that can provide interaction with others on software platforms. When people make self-improvement, they tend to consider interaction and communication, which can increase the learning effectivity and ease manipulation of the learning system. This study shows that telepresence is strongly associated with the intention to use in mobile learning applications. When an individual uses the mobile learning application to improve their capability, they feel that the sense of reality is very important and meets their requirements.

The present study explains the importance of intrinsic motivation in individual's behavior intention. The mediating effect of the perceived ease of use, perceived usefulness, and flow experience was proved. Cheon et al. [19] selected the perceptual behavior control from TPB as the variable in the research model, and confirmed the positive influence of perceptual behavior control on behavior intention in terms of mobile learning applications. However, this study explored the role of users' psychological experiences in mobile learning applications, and proved that the flow experience represents the leading influence on behavior intention. The results reveal that, even if the application is easy to manipulate, users' psychological experiences has a mediating effect that may impact the behavior deci-

sion. Users attach importance to the psychological experience of using the mobile learning system, which should be paid attention to when developing applications and software.

Drawing from these results, interactivity as a system characteristic plays a more important role than in the traditional TAM, and telepresence is the significant factor, which impacts people's usage intention. In addition, interactivity indirectly affects the intention to use, and the flow experience plays the main moderating role for usage decision making.

Interactivity and telepresence show their importance in mobile learning system. Through the collection of user information, evaluation of customer experience, and development of comprehensive service system according to the needs, enterprises can continuously obtain positive feedback in the open innovation. The results indicate the main external factors that influence mobile learning applications' adoption, and emphasize the importance of the flow experience in mobile learning. The research results suggest software developers should make their systems more interactive and allow users to experience more realistic scenarios. Specific suggestions are the creation of learning-based interactive games, message boards, and display platforms, and the involvement of virtual reality devices and social media interaction to enhance the flow experience of users. Enterprises can obtain innovation opportunities from multiple channels and resources by combining their own capabilities [75].

6.2. Open Innovation in Mobile Learning System

Open innovation is spreading across industries around the world [5]. Collective intelligence stimulates the open innovation of enterprises, and enterprises improve their innovation ability by integrating internal and external resources [76]. Collective intelligence is regarded as the collective ability to recognize, understand, and learn things [77]. In software design phase, the collective intelligence can enhance the enterprises' product focus, internal communication, improve the introduction of external enterprise software developers, and promote enterprise in the field of patent open innovation [77]. From James Watt in the First Industrial Revolution to Steve Jobs in the Fourth Industrial Revolution, both entrepreneurs advocated the adoption of open innovation in enterprises [78].

Many researchers show the driving force of innovation in the field of mobile learning. The operation interface and interactive design of mobile learning software meet the needs of users [79]. The combination of user information, experience, system function design, and technology are the foundation of open innovation. Nokia built an open information sharing network on mobile software development, engaging in joint research and development with rivals [80]. The sharing of technology and the exploration of user experience support open innovation. It is important to establish an open innovative driving culture in the organization and promote the cooperation between enterprises and external organizations, which is significant for the sharing of intelligence and the development of society [20]. Mobile learning software enterprises integrate customer experience, customer information, and software development to realize open innovation.

The development of mobile learning system relies on open innovation. The progress of mobile teaching tools has brought innovation in teaching methods [38]. Innovative network environment may help enterprises quickly adapt to the changes of market environment. In this study, the interactivity and telepresence of mobile learning system are closely related to open innovation. Companies need to focus on the user experience and create dynamic and innovative corporate culture. To pursue product innovation, enterprises should strengthen external intelligence exchange [81], and explore the open innovation mode in mobile learning system.

7. Conclusions

The empirical study aimed to explore the external factors and mediator variables in mobile learning application adoption. This research proved the importance of system characteristics, and the user experience reflects the user's needs. Therefore, it is of vital importance to understand the information and needs of users, and it is also a significant

path for enterprises to integrate internal and external technologies, design software based on demand, and realize open innovation. Lu and Viehland [14] measured the influence of cognitive variables on behavioral intention of mobile learning technology, whereas the present study focused on the two system characteristics of interactivity and telepresence, and extended the external factors that influence the adoption of mobile learning. The results showed that telepresence and interactivity have varying degrees of positive influence on perceived usefulness, perceived ease of use, and flow experience. The strongest correlation exists between perceived ease of use and flow experience. The research findings are in line with those in previous research [37,50,54]. Additionally, interactivity of the application displays medium effects on perceived usefulness and perceived ease of use. It is noteworthy that there is no direct relationship between interactivity and flow experience. However, interactivity indirectly impacts intention to use via perceived ease of use and flow experience. Regarding the intrinsic motivation, Cheon et al. [19] integrated TAM and TPB, exploring the differences of cognitive variables in different regions from a cross-cultural perspective, such as subjective norm and perceived behavior control. Flow experience was captured to extend the theoretical framework of the TAM and has a stronger effect on the users' intentions compared to the other mediators. Enterprises combine information, demand, intelligence, and technology to make technology serve the user experience, providing a broader boundary for the implement of open innovation.

Theoretically, the study integrated the external factors into the TAM model. The main external factors were identified. The research captured the flow experience as an intrinsic motivation mediator and extended the TAM. In addition, the mediating effects of perceived usefulness, perceived ease of use, and flow experience were verified. Nevertheless, the optimized TAM has a better fit to reality. In addition, in terms of research methods, the studies of Masika et al., and Lu and Viehland [14,16] used qualitative research. However, this paper used SEM to test the fitness degree of the model and the relationship between variables, which enriches the research methods used for mobile learning applications.

Regarding the practical implications, the study results provide valuable suggestions to mobile learning application enterprises. By considering the flow experience, these companies can identify better means to improve their software designs and marketing promotions. Furthermore, companies should pay more attention to system design and promote telepresence. More importantly, users' learning efficiency should be considered. To create better customer relationships, a customer community should be developed to spread positive speech. Build a mutual understanding and sharing environment with customers, and open innovation takes place in a shared value network [82,83]. In brief, this research promotes the TAM, and helps mobile learning application companies to strengthen their product and employ open innovation strategies in the market.

This research is also subject to some limitations. First, many external influence factors of the TAM have been explored by many academics in information technology. However, the current study only examined two external variables. Because the usage intention of people might be affected by many factors, the other determinants should be tested in future research. In addition, the sample of participants who were involved in the survey was simple, and this study was limited to the selection of an English learning application. The respondent sample can be expanded to fulfill the prospective theoretical research on information technology adoption. Furthermore, other intrinsic motivations may be identified to complete the underlying theoretical frameworks in users' behavior intentions of mobile applications. Finally, factors in FT can be included in the empirical test, and more variables can be identified that affect the intention to use mobile learning applications, and promoting the open innovation of the enterprises.

References

1.   Almaiah, M.A.; Jalil, M.A.; Man, M. Extending the TAM to examine the effects of quality features on mobile learning acceptance. *J. Comput. Educ.* **2016**, *3*, 453–485. [CrossRef]
2.   Analysis of Typical Knowledge Payment Platforms in 2020. Available online: https://www.iimedia.cn/c1020/69147.html (accessed on 19 February 2020).
3.   Joshi, A.; Vinay, M.; Bhaskar, P. Impact of coronavirus pandemic on the Indian education sector: Perspectives of teachers on online teaching and assessments. *Interact. Technol. Smart Educ.* **2020**, *17*, 41–59. [CrossRef]
4.   Deng, X.; Yuan, L. Integrating technology acceptance model with social capital theory to promote passive users' continuance intention toward virtual brand communities. *IEEE Access.* **2020**, *8*, 73061–73070. [CrossRef]
5.   Yun, J.J.; Won, D.; Park, K. Dynamics from open innovation to evolutionary change. *J. Open Innov. Technol. Market Complex.* **2016**, *2*, 1–22.
6.   Jiafu, S.; Yu, Y.; Tao, Y. Measuring knowledge diffusion efficiency in R&D networks. *Knowl. Manag. Res. Pract.* **2018**, *16*, 208–219.
7.   Su, J.F.; Yang, Y.; Zhang, X.F. Knowledge transfer efficiency measurement with applications for open innovation networks. *Int. J. Technol. Manag.* **2019**, *81*, 118–142.
8.   Means, B.; Toyama, Y.; Murphy, R.F.; Baki, M. The effectiveness of online and blended learning: A meta-analysis of the empirical literature. *Teach. Coll. Rec.* **2013**, *115*, 1–47.
9.   Kucuk, S.; Richardson, J.C. A structural equation model of predictors of online learners' engagement and satisfaction. *Online Learn.* **2019**, *23*, 196–216. [CrossRef]
10. Ahmed, A.A.; Patrick, P.; Karsten, L. The effect of universal design for learning (UDL) application on e-learning acceptance: A structural equation model. *Int. Rev. Res. Open Distance Learn.* **2017**, *18*, 54–87.
11. Davis, F.D. Perceived usefulness perceived ease of use, and acceptance of information technology. *Mis. Quart* **1989**, *13*, 340–391. [CrossRef]
12. Venkatesh, V.; Bala, H. Technology Acceptance Model 3 and a research agenda on interventions. *Decis. Sci.* **2008**, *39*, 273–315. [CrossRef]
13. Bhatiasevi, V. Acceptance of e-learning for users in higher education: An extension of the technology acceptance model. *Soc. Sci.* **2011**, *6*, 513–520.
14. Lu, X.; Viehland, D. Factors Influencing the Adoption of Mobile Learning. In Proceedings of the 19th Australasian Conference on Information Systems, Christchurch, Australia, 2–3 December 2008.
15. Attwell, J. Mobile Learning: Reaching Hard-to-Reach Learners and Bridging the Digital Device. In *Methods and Technologies for Leaning*; Chiazzese, G., Allegra, M., Chifari, A., Ottaviano, S., Eds.; WIT Press: Southampton, UK, 2005; pp. 361–365.
16. Masika, M.M.; Omondi, G.B.; Natembeya, D.S.; Mugane, E.M.; Bosire, K.O.; Kibwage, I.O. Use of mobile learning technology among final year medical students in Kenya. *Pan Afr. Med. J.* **2015**, *21*, 127–139. [CrossRef] [PubMed]
17. Wang, R.M.; Xiang, D.L.; Wang, Z.Y.; Tang, H.Y. An empirical study on the influencing factors of college students' adoption of mobile learning. *J. ZhenJiang Coll.* **2016**, *29*, 26–30.
18. Fagan, M.H. Factors influencing student acceptance of mobile learning in higher education. *Comput. Sch.* **2019**, *36*, 105–121. [CrossRef]
19. Cheon, J.; Lee, S.; Crooks, S.M.; Song, J. An investigation of mobile learning readiness in higher education based on the theory of planned behavior. *Comput. Educ.* **2012**, *59*, 1054–1064. [CrossRef]
20. Yun, J.H.J.; Zhao, X.F.; Jung, K.H.; Yigitcanlar, T. The culture for open innovation dynamics. *Sustainability* **2020**, *12*, 5076. [CrossRef]
21. Wang, Z. Understanding the intrinsic motivations of user acceptance of hedonic information systems: Towards a unified research model. *Commun. Assoc. Inf. Syst.* **2012**, *30*, 255–274. [CrossRef]
22. Csikszentmihalyi, M. *Finding Flow: The Psychology of Engagement with Everyday Life*; Basic Books: New York, NY, USA, 1996.
23. Ajzen, I. From Intentions to Actions: A Theory of Planned Behavior. In *Action—Control: From Cognition to Behavior*; Springer: Berlin/Heidelberg, Germany, 1985; pp. 11–39.
24. Ajzen, I. *Attitudes, Personality, and Behavior*; Dorsey Press: Chicago, IL, USA, 1988.
25. Chandio, F.H.; Lrani, Z.; Zeki, A.M.; Shah, A.; Shah, S.C. Online banking information applications acceptance: An empirical examination of applications characteristics and web security. *Inform. Appl. Manag.* **2017**, *34*, 50–64.
26. Taylor, S.; Todd, P.A. Understanding information technology usage: A test of competing models. *Inf. Appl. Res.* **1995**, *5*, 91–108. [CrossRef]

27. Chang, C.T.; Hajiyev, J.; Su, C.R. Examining the students' behavioral intention to use e-learning in Azerbaijan? The general extended technology acceptance model for e-learning approach. *Comput. Educ.* **2017**, *111*, 128–143. [CrossRef]

28. Davis, F.D. User acceptance of information technology: System characteristics, user perceptions and behavioral impacts. *Int. J. Man Mach. Stud.* **1993**, *38*, 475–487. [CrossRef]

29. Pai, F.Y.; Huang, K.I. Applying the technology acceptance model to the introduction of healthcare information systems. *Technol. Forecast Soc. Chang.* **2010**, *78*, 650–660. [CrossRef]

30. Song, Z.X.; Cheung, M.F.; Homme, S.P. Theoretical frameworks and research methods in the study of MOOC/e-learning behaviors: A theoretical and empirical review. *New Ecol. Educ. Commun.* **2017**, *8*, 47–65.

31. Sholikah, M.; Sutirman, S. How Technology Acceptance Model (TAM) factors of electronic learning influence education service quality through students' satisfaction. *TEM J.* **2020**, *9*, 1221–1226. [CrossRef]

32. Tan, P.J.B.; Hsu, M.H. Designing an application for English evaluation and teaching devices: A PZB and TAM model analysis. *Eurasia J. Math. Sci. Technol. Educ.* **2018**, *14*, 2107–2119. [CrossRef]

33. Venkatesh, V.; Morris, M.G.; Davis, D.F.D. User acceptance of information technology: Toward a unified view 1. *Mis. Quart.* **2003**, *27*, 425–478. [CrossRef]

34. Hsu, C.L.; Lu, H.P. Why do people play on-line games? An extended TAM with social influences and flow experience. *Inform. Manag. Amster.* **2004**, *41*, 853–868. [CrossRef]

35. Alenezi, A.R.; Abdul Karim, A.M.; Veloo, A. Institutional support and e-learning acceptance: An extension of the technology acceptance model. *Int. J. Instr. Technol. Dist. Learn.* **2011**, *8*, 3–16.

36. Kaya, T.; Erkut, B. Tacit knowledge capacity: A comparison of university lecturers in Germany and North Cyprus. *Electron. J. Knowl. Manag.* **2018**, *16*, 131–142.

37. Chuang, S.H.; Lin, S.; Chang, T.C.; Kaewmeesri, R. Behavioral intention of using social networking site: A comparative study of Taiwanese and Thai Facebook users. *Int. J. Hum Comput. Int.* **2017**, *13*, 61–81. [CrossRef]

38. Iksan, Z.H.; Saufian, S.M. Mobile learning: Innovation in teaching and learning using telegram. *Int. J. Pedagog. Teacher Educ.* **2017**, *1*, 19–26. [CrossRef]

39. Mohammadi, H. Investigating users' perspectives on e-learning: An integration of TAM and is success model. *Comput. Hum. Behav.* **2014**, *45*, 359–374. [CrossRef]

40. Liu, I.; Chen, M.C.; Sun, Y.S.; Wible, D.; Kuo, C. Extending the TAM model to explore the factors that affect intention to use an online learning community. *Comput. Educ.* **2010**, *54*, 600–610. [CrossRef]

41. Tarmuji, N.H.; Ahmad, S.; Abdullah, N.H.M.; Nassir, A.A.; Idris, A.S. Perceived resources and technology acceptance model (PRATAM): Students' acceptance of e-learning in mathematics. *Soc. Sci.* **2019**, *1*, 135–144.

42. Chang, C.C. Examining users' intention to continue using social network games: A flow experience perspective. *Telemat. Inform.* **2013**, *30*, 311–321. [CrossRef]

43. Csikszentmihalyi, M. *Beyond Boredom and Anxiety*; Jossey-Bass: San Francisco, CA, USA, 1975.

44. Chen, C.; Zhang, K.Z.K.; Gong, X.; Zhao, S.J.; Lee, M.K.O.; Liang, L. Understanding compulsive smartphone use: An empirical test of a flow-based model. *Int. J. Inform. Manag.* **2017**, *37*, 438–454. [CrossRef]

45. Csikszentmihalyi, M. *Flow: The Psychology of Optimal Experience*; Harper and Row: New York, NY, USA, 1990.

46. Foutsitzi, S.; Asteriadis, S.; Caridakis, G. An overview of Affective Models and ICT in Education. In Proceedings of the 2019 10th International Conference on Information, Intelligence, Systems and Applications (IISA), Patras, Greece, 15–17 July 2019.

47. Hassanzadeh, A.; Kanaani, F.; Elahi, S. A model for measuring e-learning systems success in universities. *Expert Syst. Appl.* **2012**, *39*, 10959–10966. [CrossRef]

48. Senaratne, S.I.; Samarasinghe, S.M. Factors affecting the intention to adopt M-learning. *Int. Bus. Res.* **2019**, *12*, 150–164. [CrossRef]

49. Cheng, Y.M. Effects of quality antecedents on e-learning acceptance. *Internet Res.* **2012**, *22*, 361–390. [CrossRef]

50. Novak, T.P.; Hoffman, D.L.; Yung, Y.F. Measuring the customer experience in online environments: A structural modeling approach. *Market Sci.* **2000**, *19*, 22–42. [CrossRef]

51. Kim, T.; Biocca, F. Telepresence via television: Two dimensions of telepresence may have different connections to memory and persuasion. *J. Comput. Mediat. Commun.* **2004**, *3*, 45–62. [CrossRef]

52. Held, R.M.; Durlach, N.I. Telepresence. *Presence* **1992**, *1*, 109–112. [CrossRef]

53. Steuer, J. Defining Virtual Reality: Dimensions Determining Telepresence. *J. Commun.* **1992**, *42*, 73–93. [CrossRef]

54. Park, J.S.; Hyun, J.; Fairhurst, A.; Lee, K.H. Perceptions of presence as antecedents to e-tail shopping- An extended technology acceptance model. *Res. J. Costu. Cult.* **2012**, *20*, 451–462. [CrossRef]

55. Hoffman, D.L.; Novak, T.P. Marketing in hypermedia computer-mediated environments: Conceptual foundations. *J. Market.* **1996**, *60*, 50–68. [CrossRef]

56. Al-Gahtani, S.S. Empirical investigation of e-learning acceptance and assimilation: A structural equation model. *Appl. Comput. Inform.* **2016**, *12*, 27–50.

57. Lowry, P.B.; Gaskin, J.E.; Twyman, N.W.; Hammer, B.; Roberts, T.L. Taking "fun and games" seriously: Proposing the hedonic-motivation system adoption model (HMSAM). *J. Assoc. Inf. Syst.* **2013**, *14*, 617–671. [CrossRef]

58. Szajna, B. Empirical evaluation of the revised technology acceptance model. *Manag. Sci.* **1996**, *42*, 85–92. [CrossRef]

59. Bazelais, P.; Doleck, T.; Lemay, D.J. Investigating the predictive power of TAM: A case study of CEGEP students' intentions to use online learning technologies. *Educ. Inf. Tech.* **2007**, *23*, 1–19. [CrossRef]

J. Open Innov. Technol. Mark. Complex. **2021**, *7*, 78

17 of 17

60. Salloum, S.A.; Emran, M.A. Factors affecting the adoption of e-payment systems by university students: Extending the tam with trust. *Int. J. Elect. Bus.* **2018**, *14*, 371–390. [CrossRef]
61. Kim, M.J.; Hall, C.M. A hedonic motivation model in virtual reality tourism: Comparing visitors and non-visitors. *Int. J. Inform. Manag.* **2019**, *46*, 236–249. [CrossRef]
62. Venkatesh, V.; Davis, F.D. A model of the antecedents of perceived ease of use: Development and test. *Decis. Sci.* **1996**, *27*, 451–481. [CrossRef]
63. Battaglia, M.P. *Non-Probability Sampling. Encyclopedia of Survey Research Methods*; SAGE Publications: Thousand Oaks, CA, USA, 2008; pp. 1–4.
64. Burns, A.C.; Bush, R.F. *Marketing Research*, 7th ed.; Pearson Education: London, UK, 2014; p. 151.
65. Ying-Yan, X.; Hai-Bo, Y.U.; Xiao-Fang, L.; Wei, L.I.; Guang, C. Investigation and analysis on the present situation and demand of the cultural market of Chinese medicine in Foshan. *Guid. J. Tradit. Chin. Med. Pharm.* **2016**, *6*, 47–58.
66. Yan, J.; Gao, S.; Luo, M. Application and development of English learning Apps. *Knowl. Econ.* **2020**, *2*, 108–109.
67. Ho, R. *Handbook of Univariate and Multivariate Data Analysis and Interpretation with SPSS*; Chapman & Hall: London, UK, 2000; pp. 281–355.
68. Steenkamp, J.B.E.M.; Hans, B. On the Use of Structural Equation Models for Marketing Modeling. *Int. J. Res. Mark.* **2000**, *17*, 195–202. [CrossRef]
69. Morgan, G.A. *IBM SPSS for Introductory Statistics: Use and Interpretation*; Lawrence Erlbaum: Mahwah, NJ, USA, 2007.
70. Kline, R.B. *Principles and Practice of Structural Equation Modeling*, 4th ed.; Guilford Press: New York, NY, USA, 2015.
71. Bagozzi, R.P. Evaluating structural equation models with unobservable variables and measurement error: A comment. *J. Market Res.* **1981**, *18*, 375–381. [CrossRef]
72. Schumacker, R.E.; Lomax, R.G. *A Beginner's Guide to Structural Equation Modeling*; Lawrence Erlbaum Associates: Mahwah, NJ, USA, 1996.
73. Barrett, P. Structural equation modelling: Adjudging model fit. *Personal. Individ. Differ.* **2007**, *42*, 815–824. [CrossRef]
74. Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E. *Multivariate Data Analysis*, 7th ed.; Prentice Hall: Upper Saddle River, NJ, USA, 2010.
75. Su, J.; Yang, Y.; Duan, R. A CA-based heterogeneous model for knowledge dissemination inside knowledge-based organizations. *J. Intell. Fuzzy Syst.* **2018**, *34*, 2087–2097. [CrossRef]
76. Zhang, X.; Su, J. An integrated QFD and 2-tuple linguistic method for solution selection in crowdsourcing contests for innovative tasks. *J. Intell. Fuzzy Syst.* **2018**, *35*, 6329–6342. [CrossRef]
77. Leimeister, J.M. Collective intelligence. *Bus. Inf. Syst. Eng.* **2010**, *2*, 245–248. [CrossRef]
78. Yun, J.J.; Jung, K.H.; Yigitcanlar, T. Open innovation of James Watt and Steve Jobs: Insights for sustainability of economic growth. *Sustainability* **2018**, *10*, 1553–1569. [CrossRef]
79. Kukulska, H.A.; Sharples, M.; Milrad, M.; Arnedillo, S.I.; Vavoula, G. Innovation in mobile learning: A European perspective. *Int. J. Mobile Blended Learn.* **2009**, *1*, 13–35. [CrossRef]
80. Soontornthum, T.; Cui, L.; Lu, V.N.; Su, J. Enabling SMEs' learning from global value chains: Linking the logic of power and the logic of embeddedness of interfirm relations. *Manag. Int. Rev.* **2020**, *60*, 543–571. [CrossRef]
81. Zhang, X.F.; Su, J.F. A combined fuzzy DEMATEL and TOPSIS approach for estimating participants in knowledge-intensive crowdsourcing. *Comput. Ind. Eng.* **2019**, *137*, 106085. [CrossRef]
82. Bogers, M.; West, J. Managing Distributed Innovation: Strategic utilization of open and user innovation. *Creat. Innov. Manag.* **2012**, *21*, 61–75. [CrossRef]
83. Yang, J.; Su, J.; Song, L. Selection of manufacturing enterprise innovation design project based on consumer's green preferences. *Sustainability* **2019**, *11*, 1375. [CrossRef]