pISSN: 1906 - 3296 © 2020 AU-GSB e-Journal.
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http://www.assumptionjournal.au.edu/index.php/AU-GSB/index

Determinants of Freshmen' Use Behavior of DingTalk Learning Platform to Study Mental Health Course in Chengdu, China

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Received: August 19, 2023. Revised: October 9, 2023. Accepted: October 12, 2023.

Abstract

Purpose: The purpose of this study is to explore the influencing factors of DingTalk learning platform on the learning behavior of mental health course of students in Vocational Colleges in Chengdu, China. There are seven variables and nine hypotheses in the conceptual framework of this study, including perceived ease of use, perceived usefulness, attitude, self-efficacy, subjective norm, behavioral intention, and use behavior. **Research design, data, and methodology:** The researcher conducted this study based on quantitative research methods. The researchers used a self-administered questionnaire as a research tool. The target group is 500 first-year students who have experienced using DingTalk Learning Platform in Chengdu, China. This study uses the sampling procedure, including judgmental, stratified random, and convenience sampling. This study focuses on confirmatory factor analysis and structural equation modeling as a statistical tool to check the data, the accuracy of the model, and the impact of key variables. **Results:** Most hypotheses are supported except the significant influence of subjective norm on attitude. Furthermore, behavioral intention has the strongest influence on use behavior. **Conclusions:** This study contributes to the ongoing improvement and development of online learning platforms, ensuring their effectiveness and relevance in enhancing students' learning experiences and outcomes in mental health courses.

Keywords : Perceived Ease of Use, Perceived Usefulness, Self-Efficacy, Subjective Norm, Behavioral Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

College Students' mental health education course is a public basic course to promote college students' mental health under the rapid development of society in the new era (Hua & Chen, 2015). In most cases, this course will be offered to first-year students in higher vocational colleges (Tang et al., 2017). With the increasing attention of education departments and society to college student's mental state, this course has gradually changed from an elective to a compulsory course, an important part of cultivating College Students' comprehensive quality (Wang & Liu, 2016). However, many colleges and universities have set up compulsory courses due to the limitation of class hours, teaching staff, and other practical factors. However, they often adopt the form of large class teaching or specialized lectures (Zhang & Lu, 2014).

DingTalk is an intelligent working platform created by Alibaba Group to support tens of millions of enterprises to achieve higher working efficiency with the new digitalized working, a professional mobile learning platform for smartphones, tablet computers, and other mobile terminals. It provides PC, Web, Mac, and mobile versions and supports file transfer between mobile phones and computers. DingTalk was born out of Chinese companies and helps Chinese companies improve their communication and collaboration efficiency in an all-around way through systematic solutions (micro-applications). Users can self-

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help complete the library collection borrowing query, electronic resources search and download, library information browsing, learn school courses, group discussion, and view the school address book. At the same time, e-books, newspaper articles, and Chinese and foreign literature metadata provide users with convenient and fast mobile learning services (Xu & Zhang, 2016). DingTalk learning platform is a classroom interactive learning tool developed by DingTalk, including a teacher management platform and a mobile terminal; it has the functions of sign-in, test, voting, questionnaire, theme discussion, notice release, and live broadcast for teaching and training, It can realize the interaction and feedback between teachers and students in and out of class, and record students' learning process and learning situation in real-time, to provide important evidence for effective and real teaching evaluation In addition, learners can browse e-books, documents, and other extracurricular materials through the learning platform (Zhang, 2016).

2. Literature Review

2.1 Perceived Ease of Use

Perceived ease of use is defined as “the degree to which a perceived ease of use is "the degree to which a person believes that using a particular system would be free from effort." In contrast, perceived usefulness is "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p.320). Numerous research studies have found that perceived ease of use is also a key factor in behavioral intentions to use information technology (Davis et al., 1989, 1992)

Think easy-to-use user systems are likelier to think they are pleasant Systems (Teo et al., 2008). According to the theory of self-efficacy, Igbaria et al. (1995) assume that ease of use should be treated as a self-efficacy perception to enjoy a significant impact. By increasing the convenience of using the system, users can greatly appreciate and enjoy online system services (Liao & Lu, 2008). In addition, previous studies have proposed and demonstrated the impact of perceived ease of perception of enjoyment (Davis et al., 1992; Der Heijden, 2004; Igbaria et al., 1995).

According to the theory acceptance model, perceived ease of use and perceived usefulness of the impact on the user's intent to use technology attitudes and techniques used in empirical research has been conducted in several IT / IS literature (Davis, 1989). Previous studies of applying these two variables to measure the use of various techniques found them consistent with TAM (Ma & Liu, 2004).

H1: Perceived ease of use has a significant influence on perceived usefulness.

H2: Perceived ease of use has a significant influence on attitude.

2.2 Perceived Usefulness

Perceived usefulness is "a person believes that using a particular system would enhance the level of his or her job performance" (Davis, 1989, p. 320). Perceived usefulness (PU) refers to the people who believe that using a particular technology will improve the performance of their degree (Davis, 1989). Perceived usefulness affects individuals' willingness to adopt and use new technologies. Previous studies (Gefen et al., 2003; Igbaria et al., 1995; Venkatesh & Davis, 2000) found a strong link between perceived usefulness and the adaptability of new technologies in different contexts, including e-banking technologies. Economy-shopping-oriented consumers usually try to save money to achieve their goals (Tai, 2008).

The effects of perceived ease of use and perceived usefulness on users' attitudes toward technology adoption and intentions to use technology have been empirically investigated in many IT/IS literatures (Davis, 1989). Previous studies applied the two variables to measure the adoption of various technologies and found them consistent with the TAM (Chan & Lu, 2004; Lee, 2009; Ma & Liu, 2004).

H3: Perceived usefulness has a significant influence on attitude.

2.3 Self-Efficacy

Bandura (1997) defines self-efficacy for users of its organization and implementation to specify the action needed for the performance ability of judgment. Self-efficacy is for a person to perform the recommended expectations of adaptive behavior ability (Bandura et al., 1980). Self-efficacy is a perception of one's ability rather than a unique attribute of self-concept (Bong & Skaalvik, 2003; Zimmerman & Cleary, 2006).

Self-efficacy reflects that Chinese students can conduct successful execution of the extent of the use of mobile library applications. Compared with low self-efficacy of students, higher self-efficacy is more likely to achieve better academic achievement and have a positive attitude and a more intense continued use willingness (Tang et al., 2014). Some scholars believe self-efficacy plays an important role as an intrinsic cognitive user impact on individual motivation, attitude, and behavioral intention (Ajjan et al., 2014; Hsiao & Tang, 2015).

Self-efficacy reflects the degree to which a Chinese student thinks he or she can successfully execute the usage behavior of m-library applications. Those Students with higher self-efficacy are more likely to achieve better academic performance. For m-library applications,

compared with patients with low self-efficacy, they are more willing to continue to use it (Tang et al., 2014).
H4: Self-efficacy has a significant influence on attitude.
H6: Self-efficacy has a significant influence on behavioral intention.

2.4 Subjective Norm

Subjective norms are extracted from the social domain; It is the influence of an individual's social environment, such as friends, family, colleagues, and neighbors, on the purchase intention (Wu, 2023). Yang et al. (2014) found that *subjective norm* is defined as a kind of social pressure to make individual and group behavior (e.g., family or friends) related behavior. Subjective norms are normative beliefs or reference communities (Ajzen, 1991; Tarkiainen & Sundqvist, 2005). Hsu et al. (2014) also found that subjective norms directly or indirectly affect users' attitudes and behavioral intentions in using information systems. Subjective norm refers to family members, friends, colleagues, and other important social pressure (Farah et al., 2016).

The user intends to use the system at TAM to use the system's overall attitude premise (Davis, 1989). Researchers have been discussing the theoretical construction of attitudes to identify the causes of intent for decades. Many studies have shown that the attitude of using the system has a positive effect on the willingness to use the system (Davis, 1989; Lee, 2009). When Chinese students think it is useful, they will use the mobile library to form a positive attitude, affecting their behavior intention.
H5: Subjective norm has a significant influence on attitude.
H8: Subjective norm has a significant influence on behavioral intention.

2.5 Attitude

According to Ajzen (1991), attitudes are composed of beliefs that affect a person's overall behavioral intentions. Attitude is the psychological tendency of individuals to evaluate certain behavioral advantages (Ha & Janda, 2012). Attitude is a belief in an object or an action that can be translated into an action. This is also a positive or negative evaluation of green products (Troudi & Bouyoucef, 2020).

Parker et al. (2006) determined that the students' subjective norms influence the relationship between attitudes and behavior intentions. Xu et al. (2014) also found that subjective norms directly or indirectly impact attitudes and behavior intention to use user information systems. A positive attitude to certain consumer behavior is more likely to act this way. Based on previous assumptions of the hypothesis, consumers' buying sustainable clothing intentions can be predicted by their clothing environmental attitudes. In addition, consumer behavior is influenced by subjective norms and the intention of perceived behavioral control (Park & Ha, 2012).
H7: Attitude has a significant influence on behavioral intention.

2.6 Behavioral Intention

Behavioral intention refers to an individual's willingness to change from the existing learning method to the future use of the e-learning system (Samsudeen & Mohamed, 2019). As mentioned earlier, behavioral intent refers to the extent to which a person plans to perform or not perform a function in the future (Venkatesh et al., 2003). *behavioral intention* is defined as a person's planned possibilities for using technology (Ukut & Krairit, 2019). It is the precursor of using behavior. It indicates that the user is prepared to perform a particular behavior (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003).

The behavior of using smartphones for mobile shopping is affected by the intention of use (Hubert et al., 2017). For research studies related to business executives, lecture acquisition system uses, acceptance, and usage behavior are strongly influenced by UTAUT and UTAUT2 factors. For higher education, self-reported habits significantly positively impact the e-learning system's self-reported frequency of use (Agudo-Peregrina et al., 2014). According to Šumak and Sorgo (2016), teachers in interactive whiteboard adopters have a positive attitude and behavioral intentions supported by adequate facilities, resulting in positive behaviors in using whiteboards.
H9: Behavior intention has a significant influence on use behavior.

2.7 Use Behavior

Use behavior can be defined as a user using a technical strength (Venkatesh et al., 2003). Usage behavior is usually measured in terms of the actual frequency of technology use. Venkatesh et al. (2012) have conducted several studies on technology use using the concept of 'usage behavior.' convenient conditions, and behavior intention of question-and-answer service based on the network have a significant positive influence on the use of behavior (Deng et al., 2011). Usage behavior dynamically responds to user actions or performs specific tasks (Venkatesh et al., 2003). Mobile shopping via smartphones has been confidently promoted by the intention of use (Hubert et al., 2017). The research of Celik (2016) found that convenience positively influences the behavioral intention and use behavior of online shopping.

3. Research Methods and Materials

3.1 Research Framework

According to Figure 1, the conceptual framework of this study includes seven variables and nine assumptions, including factors from the perceived ease of use, perceived usefulness, attitude, self-efficacy, behavior intention, subjective norm, and use behavior. There are three main prior research frameworks to support and develop the conceptual framework of this research. The model of the first research framework was researched and developed by Watjatrakul (2013). This empirical study aims to understand the relationship between the key technology of factors. The second research framework was researched and developed by Hu and Zhang (2016), aiming to investigate Chinese college students' use of mobile library applications. Third, Samsudeen and Mohamed (2019) studied the factors that influence the intention and behavior of the students of the National University of Sri Lanka to use the e-learning system.

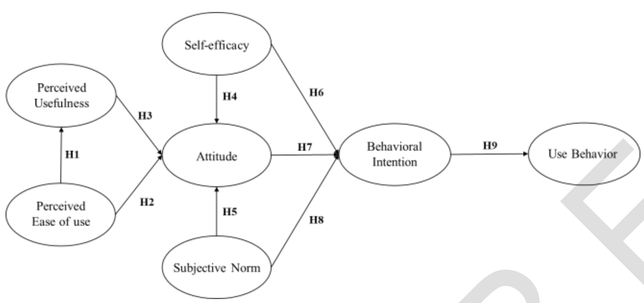

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant influence on perceived usefulness.
H2: Perceived ease of use has a significant influence on attitude.
H3: Perceived usefulness has a significant influence on attitude.
H4: Self-efficacy has a significant influence on attitude.
H5: Subjective norm has a significant influence on attitude.
H6: Self-efficacy has a significant influence on behavioral intention.
H7: Attitude has a significant influence on behavioral intention.
H8: Subjective norm has a significant influence on behavioral intention.
H9: Behavioral intention has a significant influence on use behavior.

3.2 Research Methodology

The core of this study is the quantitative method. The quantitative research method has become the paradigm of basic research in social science and one of the most important scientific research methods (Roni et al., 2020). Quantitative research is a form of scientific research aimed at identifying several issues in a particular context. Problems and phenomena are expressed in numbers and then analyzed, examined, and explained to obtain a research method and a process to change the law between some factors (Stangor, 2014). The researchers used a self-administered questionnaire as a research tool, consisting of three parts; screening questions, measuring items with five-point Likert scale, and demographic data.

3.3 Population and Sample Size

The population are first year of undergraduate students who have experienced arts education at three universities in Chengdu, China, including Sichuan University, Southwest Jiaotong University, and Chengdu University. Soper (2023)'s calculator calculates a minimum sample size of 425. In view of the inefficient and incomplete response, the investigators determined the size of the 500 participants for sample group in this study.

3.4 Sampling Technique

This study uses the sampling procedure, including judgmental, stratified random, and convenience sampling to achieve the study objective. Per judgmental sampling, the researcher selects undergraduate students who have experienced arts education at three universities in Chengdu, China, including Sichuan University, Southwest Jiaotong University, and Chengdu University. Stratified random sampling is a method that divides the whole group according to certain standards into several smaller groups, as shown in Table 1. Moreover, the researcher used convenience sampling, defined as sampling procedures to select researchers according to availability for online survey's responses.

Table 1: Sample Units and Sample Size

College	First Year
Chengdu Polytechnic	177
Chengdu Textile College	148
Chengdu Industry and Trade College	175
Total	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Based on the data presented in Table 2, the study involved a total of 500 participants. The participants' demographic information included their gender and the duration of their usage of the DingTalk learning platform. The questionnaire was distributed among 500 students in their third year of study. Of these respondents, 266 were females, accounting for 53.2% of the total sample, while 234 were males, making up 46.8%. Regarding the duration of usage of the DingTalk learning platform, 33% of the participants reported using it for below one year, 36.8% reported using it for 1-3 years, and 30.2% reported using it for more than 3 years.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	234	46.8%
	Female	266	53.2%
DingTalk Experience	Below 1 Year	165	33%
	1-3 years	184	36.8%
	Above 3 years	151	30.2%

4.2 Confirmatory Factor Analysis (CFA)

Prior to analyzing the measurement model within the structural equation model (SEM), Confirmatory Factor Analysis (CFA) was conducted. The outcomes of the CFA underscored the significance of all items within each variable, as evidenced by their substantial factor loadings, substantiating the concept of discriminant validity. Following the guidelines of Stevens (1992), an item was deemed satisfactory when its loading surpassed 0.40, coupled with a p-value below 0.05 for Confirmatory Factor Analysis. Additionally, adhering to the recommendations of Fornell and Larcker (1981), it was considered that while an Average Variance Extracted (AVE) value lower than 0.5 might be acceptable, a Composite Reliability (CR) exceeding 0.6 ensures the construct's convergent validity remains intact.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Ease of Use (PEOU)	Watjatrakul (2013)	5	0.870	0.615-0.842	0.872	0.579
Perceived Usefulness (PU)	Watjatrakul (2013)	5	0.878	0.676-0.881	0.881	0.598
Attitude (ATT)	Watjatrakul (2013)	6	0.823	0.489-0.719	0.829	0.450
Self-Efficacy (SE)	Hu and Zhang (2016)	5	0.809	0.636-0.734	0.809	0.459
Subjective Norm (SN)	Hu and Zhang (2016)	4	0.816	0.691-0.760	0.817	0.528
Behavioral Intention (BI)	Samsudeen and Mohamed (2019)	5	0.810	0.651-0.717	0.812	0.463
Use Behavior (UB)	Samsudeen and Mohamed (2019)	5	0.906	0.751-0.887	0.908	0.663

Table 4 presents several indices that were used to assess the model fit in the confirmatory factor analysis (CFA) testing. The calculated values for these indices were as follows: CMIN/DF = 1.796, GFI = 0.902, AGFI = 0.885, NFI = 0.892, CFI = 0.948, TLI = 0.943, and RMSEA = 0.040. These values indicate how well the model fits the observed data.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	967.832/539 = 1.796
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.902
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.885
NFI	≥ 0.80 (Wu & Wang, 2006)	0.892
CFI	≥ 0.80 (Bentler, 1990)	0.948
TLI	≥ 0.80 (Sharma et al., 2005)	0.943
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.040
Model Summary		**In harmony with empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker–Lewis index and RMSEA = Root mean square error of approximation

Following the framework proposed by Fornell and Larcker (1981), an assessment of discriminant validity involved calculating the square root of each Average Variance Extracted (AVE). In line with the findings of this investigation, the computed value of discriminant validity exceeded all inter-construct or inter-factor correlations. This observation reinforces the validity of discriminant relationships. With both convergent and discriminant validity established, the accumulated evidence is deemed substantial for the establishment of construct validity.

Table 5: Discriminant Validity

	ATT	PEOU	PU	BI	UB	SN	SE
ATT	**0.671**						
PEOU	0.211	**0.761**					
PU	0.558	0.213	**0.773**				
BI	0.544	0.246	0.484	**0.680**			
UB	0.585	0.291	0.460	0.675	**0.815**		
SN	0.220	0.179	0.337	0.517	0.363	**0.727**	
SE	0.574	0.181	0.594	0.605	0.600	0.352	**0.678**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

A structural equation model (SEM) is a statistical tool used to analyze data by incorporating path analysis, confirmatory factor analysis, and multiple regression analysis. It is employed to explain the relationships between independent variables and dependent variables. The goodness of fit indices for the SEM are presented in Table 6. To calculate the fit indices and adjust the model, SPSS AMOS was utilized. The results indicate a good fit, as demonstrated by the following fit indices: CMIN/DF = 2.256, GFI = 0.875, AGFI = 0.857, NFI = 0.861, CFI = 0.917, TLI = 0.910, and RMSEA = 0.050. These values were compared to the acceptable values mentioned in Table 6 to assess the model fit.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	1242.983/551 = 2.256
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.875
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.857
NFI	≥ 0.80 (Wu & Wang, 2006)	0.861
CFI	≥ 0.80 (Bentler, 1990)	0.917
TLI	≥ 0.80 (Sharma et al., 2005)	0.910
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.050
Model Summary		**In harmony with empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker–Lewis index and RMSEA = Root mean square error of approximation

4.4 Research Hypothesis Testing Result

The analysis of standardized coefficient values and t-values, as shown in Table 7, yielded the results. Based on these results, eight out of nine hypotheses were supported at $p<0.05$.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEOU→PU	0.214	4.258*	Supported
H2: PEOU→ATT	0.093	1.964*	Supported
H3: PU→ATT	0.396	7.515*	Supported
H4: SE →ATT	0.388	7.072*	Supported
H5: SN →ATT	-0.015	-0.320	Not Supported
H6: SE →BI	0.374	6.565*	Supported
H7: ATT→ BI	0.376	6.612*	Supported
H8: SN→ BI	0.372	7.221*	Supported
H9: BI→ UB	0.698	10.649*	Supported

Note: * $p<0.05$
Source: Created by the author

The relevant statistical data for **H1** supported the hypothesis of a significant impact of perceived ease of use on perceived usefulness with a standardized coefficient value of 0.214. In the structured method, the standardized route coefficient value is 0.093, and **H2** has been validated a significant impact of perceived ease of use on attitude. According to **H3** analysis findings, perceived usefulness is one of the crucial components of attitude, with a standardized path coefficient value is 0.396. The statistical results of **H4** support the hypothesis that self-efficacy considerably impacts attitude. In **H5**, the subjective norm does not significantly influence the attitude with a standardized path coefficient -0.015. **H6** shows that self-efficacy influences behavioral intention with the standard coefficient value of 0.374. **H7** demonstrated that attitude motivations positively impact behavior intention with a result of 0.376 for the standard coefficient value. Additionally, **H8**, which indicates this standard coefficient value at 0.372, shows that subjective norm influences behavior intention. At last, in **H9,** the demonstration of the value is 0.698 on the standard coefficient, which verifies that behavior intention supports use behavior significantly.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study aimed to investigate the factors influencing the use behavior of freshmen in utilizing the DingTalk Learning Platform for studying mental health courses in Chengdu, China. The findings provide valuable insights into the intricate relationships between various determinants and their impact on technology adoption and use behavior in the context of mental health education.

Consistent with established research, the results affirmed H1, indicating that freshmen's perceptions of the ease of using the DingTalk Learning Platform significantly influenced their perceived usefulness of the platform. This suggests that when the platform is perceived as user-friendly, students are more likely to recognize its value in supporting their mental health education.

The findings corroborated H2, highlighting that students' perceptions of the platform's ease of use played a pivotal role in shaping their attitudes towards the technology. This supports the idea that a positive perception of ease of use contributes to favorable attitudes, fostering a conducive learning environment.

H3 received robust support, indicating that students' perceptions of the usefulness of the DingTalk Learning Platform influenced their attitudes. This finding emphasizes the importance of students recognizing the platform's benefits in shaping their overall attitudes toward its usage.

The study's outcomes supported H4, affirming that students' self-efficacy beliefs significantly influenced their attitudes towards the platform. This suggests that students' confidence in their ability to effectively use the technology positively impacts their overall attitudes.

Contrary to expectations, H5 did not find significant support, indicating that subjective norms might not be a prominent factor influencing attitudes in this context. This result suggests that external opinions or peer influences might have limited impact on shaping attitudes towards the DingTalk Learning Platform for mental health courses.

The findings substantiated H6, indicating that students' self-efficacy beliefs significantly influenced their behavioral intention to use the DingTalk Learning Platform for mental health studies. This underscores the pivotal role of self-efficacy in boosting students' confidence and intention to engage with the platform.

H7 received strong empirical support, highlighting the crucial link between students' attitudes and their behavioral intentions towards using the DingTalk Learning Platform. This finding underscores that a positive attitude can strongly predict students' intention to continue engaging with the platform.

The results affirmed H8, indicating that subjective norms significantly influenced students' behavioral intentions. The impact of perceived expectations from peers or instructors is a noteworthy driver in shaping students' intention to utilize the platform for mental health education.

The study's findings supported H9, reinforcing the notion that students' behavioral intentions towards using the DingTalk Learning Platform substantially influenced their actual use behavior. This underscores the predictive power of intentions in determining whether students will ultimately adopt and use the platform for mental health studies.

In summary, this study contributes to our understanding of the determinants influencing freshmen's use behavior of the DingTalk Learning Platform for studying mental health courses in Chengdu, China. By uncovering the relationships between various factors, the findings offer valuable insights for educators, administrators, and policymakers aiming to enhance technology adoption and educational outcomes in the field of mental health education.

5.2 Recommendation

Based on the findings of the study of perceived ease of use will promote platform use, it is crucial to ensure that the DingTalk Learning Platform is designed to be user-friendly and intuitive. Improving the interface, providing clear instructions, and offering technical support can enhance first-year students' perceived ease of use. Emphasize the benefits and advantages of using the platform for studying a mental health course. Highlight features such as interactive learning materials, real-time feedback, and access to additional resources that can enhance the learning experience and outcomes.

Implement interventions to boost first-year students' self-efficacy in using the platform. This can include providing training sessions, tutorials, and resources that help build their confidence in utilizing the platform effectively. Encouraging peer support and creating a supportive learning environment can also increase self-efficacy. Foster a culture of platform use by actively involving instructors and peers in promoting and endorsing the DingTalk Learning Platform. Encourage instructors to integrate the platform into their teaching methods and provide positive feedback on its benefits. Facilitate peer discussions and collaboration on the platform to create a sense of social pressure and acceptance.

Continuously monitor and improve the platform's features, content, and overall user experience to maintain a positive attitude toward the DingTalk Learning Platform. Incorporate student feedback and suggestions to address any concerns or issues and ensure that the platform meets first-year students' evolving needs and expectations. Develop strategies to strengthen first-year students' behavior and intention to use the platform. This can include providing incentives or rewards for consistent platform engagement, showcasing success stories of previous users, and highlighting the long-term benefits of using the platform for their academic and personal development.

Regularly assess and monitor first-year students' use behavior on the DingTalk Learning Platform. Collect feedback, analyze usage patterns, and identify areas for improvement. Continuously update and enhance the platform to align with first-year students' evolving needs and preferences. By implementing these recommendations, educational institutions in Chengdu, China, can effectively promote and facilitate first-year students' use of the DingTalk Learning Platform for studying mental health courses. This can enhance student's learning experience, engagement, and overall outcomes.

5.3 Limitation and Further Study

Investigate the specific aspects of the user experience on the DingTalk Learning Platform that contribute to or hinder platform usage. This can involve assessing platform responsiveness, ease of navigation, content relevance, and overall satisfaction with the platform.

Explore the relationship between platform use behavior and academic performance or learning outcomes. Investigate whether higher engagement and use behavior on the platform are associated with improved knowledge acquisition, skill development, and overall academic success in mental health courses.

Examine how user demographics, such as gender, age, and prior technological experience, may influence platform use behavior. Investigate whether certain groups of freshmen are more likely to engage with the platform and identify any specific factors that may impact their use behavior.

Investigate the role of instructors in promoting and facilitating platform-use behavior among first-year students. Assess the impact of instructor support, guidance, and encouragement on first-year students' engagement with the platform and their perceived benefits. Examine the sustainability of platform use behavior over an extended period. Investigate whether first-year students continue using the DingTalk Learning Platform beyond their initial engagement and explore the factors contributing to long-term use behavior.

By conducting further studies in these areas, researchers can gain deeper insights into the determinants of first-year students' use behavior of the DingTalk Learning Platform in Chengdu, China. This will contribute to the ongoing improvement and development of online learning platforms, ensuring their effectiveness and relevance in enhancing students' learning experiences and outcomes in mental health courses.

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