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Examining Third-Year Students on Their Behavioral Intention and Use Behavior of DingTalk Learning Platform in Chengdu, China

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Abstract

Purpose: This study aims to investigate the factors that influence students' learning behavior in vocational colleges in Chengdu, China, using the DingTalk learning platform for mental health courses. The variables in this conceptual framework are perceived ease of use, perceived usefulness, attitude, self-efficacy, subjective norm, behavioral intention, and use behavior. **Research design, data, and methodology:** The study was conducted quantitative research to employ a questionnaire as the research instrument. The target group consisted of third-year students (n=500) from three collages with prior experience using the DingTalk Learning Platform in Chengdu, China. In this study, sampling procedures are judgmental, stratified random, and convenience sampling. The main statistical tools employed in this study were confirmatory factor analysis and structural equation modeling. These analyses were used to assess the data quality, validate the proposed model, and examine the influence of key variables. **Results:** The results show that all hypotheses are supported. Additionally, perceived ease of use has the strongest influence on attitude. **Conclusions:** Educational institutions and platform developers can enhance third-year students' behavioral intention and use behavior towards the DingTalk Learning Platform in Chengdu, China. This, in turn, can lead to improved learning experiences, increased engagement, and better academic outcomes for these students.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

With the rapid development of the Internet, online learning, with the help of flexible communication and digital learning resources, has brought a new learning experience to learners and profoundly changed the traditional relationship between teachers and students (Hu & Wang, 2014). Online learning gives learners more time to think so that they can comment on discussion topics on a thoughtful basis to promote the development of their critical thinking (Saade et al., 2012). Compared with traditional face-to-face teaching, online collaboration generally does not need to rearrange and plan time, and learners can participate in online learning at their own convenient time and place (Song et al., 2004).

Online learning also allows like-minded learners in different places to form a virtual learning community (Palloff & Pratt, 2007). More importantly, research and practice also confirm that online learning can achieve the same learning effect as traditional face-to-face teaching and replace the function of traditional teaching to a certain extent (Hu & Wang, 2014).

Like other colleges and universities, to meet the challenge of educational informatization and better meet the learning needs of students, Chengdu Polytechnic has begun to use the DingTalk learning platform to provide online learning services for students in recent years. However, in-depends to be more of students' use intention,

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and the learning effect needs to be improved. This study takes the application of the DingTalk learning platform in mental health education courses in Higher Vocational Colleges as an example, constructs a new research model based on perceived ease of use, perceived usefulness, attitude, self-efficacy, subjective norm, behavioral intention, and use behavior. It aims to examine influencing factors of the DingTalk learning platform on the learning behavior intention of mental health courses, and provides relevant theoretical guidance for online teaching practice and management, Better improve the effectiveness of students' online learning.

2. Literature Review

2.1 Perceived Ease of Use

The term "perceived ease of use" implies the degree to which an individual expects the new technology to be effortless and free from complexities (Davis, 1989). perceived ease of use, which refers to the degree that technology frees consumers' efforts, is the primary determinant of consumers' technology adoption behavior (Davis et al., 1989). perceived ease of use is the degree to which a person believes that using a particular system would be free from effort. Perceived ease of use refers to "the degree of ease associated with using the system" (Venkatesh et al., 2003, p. 450).

In addition, perceived ease of use directly determines the usefulness of the factors under the technology acceptance model or TAM. Individuals who think using the technology is effortless will find it useful. Evidence has accumulated much experience over two decades of perceived ease of use to verify the direct and indirect effects on the perception of the usefulness (Davis, 1989)

The attitude towards the use of free voluntary service is affected by user ease of use and usefulness, and the user perceived usefulness will affect the willingness of users to use free volunteer service (Feng et al., 2022). In past TAM studies, the first underlying relationship is that ease of use will positively impact the user's attitude toward usage (Bhattacherjee, 2000).

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

According to Davis (1989), perceived usefulness refers to a person's belief that using a specific system will improve the level of his or her job performance (Davis, 1989). Perceived usefulness is when consumers believe a product will improve its trading performance level (Chiu et al., 2009). Perceived usefulness is "a person believes that using a particular service can improve the level of his or her job performance" (Davis, 1989).

Accordingly, users' perceptions of ease of use and usefulness influence attitudes toward using a free voluntary service. In contrast, users' perceived usefulness affects users' intentions to use a free voluntary service. Davis (1989) uses information technology to interpret and predict the adoption of TAM. The model shows that Pu and PEOU affect the attitude of use, which affects the intent of the action, and also affects actual use. Aboelmaged (2010) stated that the realization of using e-business applications to improve performance or efficiency positively influences users' attitudes to these applications. Prior research also shows that the perceived usefulness of electronic services enhances the attitude toward usage (Bhattacherjee, 2000).

H3: Perceived usefulness has a significant influence on attitude.

2.3 Self-Efficacy

Self-efficacy, on behalf of individual knowledge and effectiveness of implementing target behavior, is a component of perceived behavioral control (Jugert et al., 2016). In health, self-efficacy refers to an individual's perception of his or her ability to undertake healthy behaviors (Hu & Zhang, 2016). Self-efficacy researchers believe that the change in self-efficacy expectations positively correlates with behavior change (Bandura et al., 1980). in addition, almost all safety-related research, including self-efficacy, individual attitude, or security behavior, has a strong influence (Anderson & Agarwal, 2010; Woon et al., 2005).

In addition, almost all security-related research, including self-efficacy, indicates that self-efficacy strongly influences personal attitudes or safe behavior (Anderson & Agarwal, 2010; Woon et al., 2005). when increasing their knowledge of self-efficacy, people can do things confidently (Constant et al., 1994). Some scholars believe that self-efficacy as an internal User cognition plays an important role in influencing personal motivation, Attitudes, and behavioral intentions (Ajjan et al., 2014). The non-supported hypothesis of self-efficacy to behavior intention may indicate that current university students are confident in their technical abilities and qualified to use m-library apps (Goh, 2011).

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 directly or indirectly influence the external stimulus of individual-specific behaviors on knowledge-sharing willingness (Bock et al., 2005; Zhou & Chen, 2009) Intend predictors of subjective norms also involve behavior (Ajzen, 1991). In the TPB model, subjective norm refers to the perceived social pressure to perform or not perform behavior (Ajzen, 1991, p. 188). Fishbein and Ajzen (1975) argue that belief can be divided into external and internal beliefs and faith; the Subjective norm is part of the external belief and helps explain public behavior (Groening et al., 2017).

The relationship between attitude and subjective norm has been discussed (O'Keefe et al., 2015) through the mechanism of the effect of the cross. A relatively high correlation between consumer attitudes and subjective norms has been found, higher than 0.40 (Rivis & Sheeran, 2003). In addition, it was found in the literature that empirical evidence of TPB's significant direct impact on the attitude of subjective norms of mobile commerce (Shimp & Kavas, 1984; Vallerand et al., 1992).

In other words, they will have a stronger will to use. Previous studies have highlighted the perceived usefulness relationship between attitudes and behavioral intentions. Previous studies provide empirical evidence that consumer attitudes will affect their intention to use online banking services (Chang et al., 2005).

H5: Subjective norm has a significant influence on attitude.
H8: Subjective norm has a significant influence on behavioral intention.

2.5 Attitude

This shows that attitude determines an individual's willingness to engage in certain behaviors (Park et al., 2014). Attitude is formed by internal contact and evaluation process (Adams & De Kock, 2015) and directly influence the formation of positive or negative intentions (Kang & Hustvedt, 2013). In the transformation behavior of a specific background, a person's attitude shows that the customer is in favor of or against the degree of transformation behavior and attitude (Nimako et al., 2013). Attitudes are derived from important behavioral beliefs that reflect an individual's perceived and related transformation outcomes' desirability (Ajzen, 1991).

Teo (2012) found that subjective norms have a significant impact on attitudes and the use of BI. The relationship between subjective norms and attitudes and purchase intention results from significant behavioral intention Fishbein model and has an important significant supportive attitude and subjective norms positive impact in many cases of intent (Shim et al., 2001). The researchers also concluded that the relationship between subjective norms and the intention to share knowledge is very strong. The promotion of a positive organizational climate influenced them.

H7: Attitude has a significant influence on behavioral intention.

2.6 Behavioral Intention

Yi et al. (2006) believe behavioral intention is the subjective probability of the behavior leading to the use of intention. Behavioral intention is defined as individuals performing some behavior intention and intends (Keong et al., 2012). Ajzen and Fishbein (1980) interpret behavioral intention as an assessment of people's motivation to act or complete a specific behavior. According to Venkatesh et al. (2003), behavior intention can predict desired behavior or technology use.

Another study conducted by De Haan et al. (2019) found that increasing mobile penetration will lead to positive mobile device use behaviors. The use of mobile devices in stores is also associated with active shopping behaviors (Grewal et al., 2018). Human behavior is the behavior of a situation and others. According to TPB (Ajzen, 1991), attitude toward behavior, subjective norms, behavioral intentions, and perceived behavioral control guide human behavior (Venkatesh et al., 2003).

H9: Behavior intention has a significant influence on use behavior.

2.7 Use Behavior

Using behavior is to form knowledge, skills, behaviors, and habits into certain steps in a certain way and order, then adopt appropriate reinforcement methods and gradually train according to the sequence determined by task decomposition. Finally, they can complete the task independently and apply their learned knowledge and skills on other occasions (Macedo, 2017). 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. For e-government services, convenience significantly impacts usage behavior (Weerakkody et al., 2013).

3. Research Methods and Materials

3.1 Research Framework

As depicted in Figure 1, the conceptual framework underpinning this study encompasses seven variables and

nine assumptions, incorporating elements from perceived ease of use, perceived usefulness, attitude, self-efficacy, behavioral intention, subjective norm, and use behavior. The development of this framework was informed by three primary prior research frameworks, which served as foundational pillars for advancing and refining the present study's conceptual underpinning.

The initial research framework, formulated by Watjatrakul (2013), laid the groundwork for understanding the intricate relationships among pivotal technological factors. This empirical investigation aimed to elucidate the dynamics between these factors, thus contributing to the formation of the broader conceptual framework.

The second research framework, crafted by Hu and Zhang (2016), targeted the exploration of Chinese college students' utilization patterns concerning mobile library applications. This framework provided valuable insights into students' interactions with digital platforms, subsequently enriching and bolstering the construction of the current study's conceptual model.

Lastly, the third research framework, introduced by Samsudeen and Mohamed (2019), probed into the determinants impacting the intention and behavior of students at the National University of Sri Lanka in their adoption of the e-learning system. The insights garnered from this research framework further fortified the foundations of the present study's conceptual framework.

In synthesizing these diverse research frameworks, the current study's conceptual framework was fortified by a fusion of empirical investigations, each contributing a distinct facet to the overarching understanding of factors influencing technology adoption, user behavior, and attitudes. This integration culminated in the robust framework guiding the investigation into freshmen's use behavior of the DingTalk Learning Platform for mental health courses in Chengdu, China.

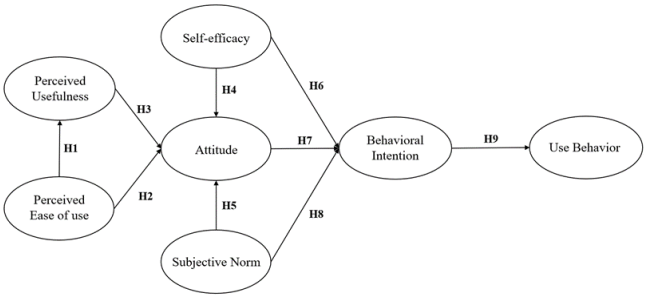

Figure 1: Conceptual Framework

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 primary approach employed in this study is quantitative research. Quantitative research has emerged as the foundational paradigm for basic research in the social sciences and is recognized as one of the most significant scientific research methods (Roni et al., 2020). It systematically investigates various issues within a specific context, with numerical data expressing and analyzing problems and phenomena. This analytical process identifies and explains the relationships and patterns between different factors, thereby providing a structured research method and process (Stangor, 2014). The researchers used a self-administered questionnaire as a research tool to collect data. As Saunders et al. (2007) highlighted, the questionnaire serves as a means for respondents to provide data, and participants must read and respond to the questionnaire themselves. The structure questinnaire comprises screening questions, measuring items with five-point Likert scale, and demographic data.

Before being distributed, the questionnaires were subjected to assessment through the item-objective congruence (IOC) index, which received ratings of above 0.6 from three experts for all scale items. Furthermore, a pilot test was carried out with a sample size of 50, using the Cronbach alpha coefficient to assess reliability. The findings revealed robust internal consistency for all items, exceeding a threshold of 0.6.

3.3 Population and Sample Size

The target population for this study consists of 500 students in their third year who have received art education at three universities in Chengdu, China. These universities include Sichuan University, Southwest Jiaotong University, and Chengdu University. According to the calculator developed by Soper (2023), the computed minimum sample size is 425. However, considering the potential for inefficiency and incomplete responses, the researchers opted for a sample group size of 500 participants in this study

3.4 Sampling Technique

The researchers employed nonprobability sampling methods in this study. One such method was judgmental sampling, which allows researchers to select factors based on their judgment to achieve the study's objectives. It is important to note that judgmental sampling involves researchers deciding which factors to include in the sample.

Additionally, stratified sampling was utilized to divide the entire population into smaller groups based on specific criteria such as gender and age. This approach helps to ensure representation from various subgroups within the population.

Furthermore, convenience sampling was also employed, which involves selecting participants based on availability. This method is convenient for researchers as it allows for selecting participants who are easily accessible or readily available for participation in the study.

Table 1: Sample Units and Sample Size

College	Third Year
Chengdu Polytechnic	165
Chengdu Textile College	155
Chengdu Industry and Trade College	180
Total	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

According to the data presented in Table 2, the study involved a total of 500 participants who were students in their third year of study. The participants' demographic information included their gender and the duration of their usage of the DingTalk learning platform. Of the total sample, 211 participants were females, representing 42.2% of the sample, while 289 participants were males, accounting for 57.8%. Regarding the duration of usage of the DingTalk learning platform, 29.2% of the participants reported using it for below 1 year, 25.6% reported using it for 1-3 years, and 45.2% reported using it for above 3 years.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	289	57.8%
	Female	211	42.2%
DingTalk Experience	Below 1 Year	146	29.2%
	1-3 years	128	25.6%
	Above 3 years	226	45.2%

4.2 Confirmatory Factor Analysis (CFA)

Before analyzing the measurement model with the structural equation model (SEM), a Confirmatory Factor Analysis (CFA) was conducted. The results of the CFA indicated that all items within each variable were found to be significant and had factor loadings that demonstrated discriminant validity. According to Stevens (1992), an item is considered satisfactory in Confirmatory Factor Analysis if its loading is greater than 0.40, with a p-value lower than 0.05. Additionally, in line with the recommendation of Fornell and Larcker (1981), the convergent validity of a construct is considered adequate if the Average Variance Extracted (AVE) is less than 0.5. However, the Composite Reliability (CR) is higher than 0.6.

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	0.899	0.738-0.845	0.900	0.643
Perceived Usefulness (PU)	Watjatrakul (2013)	5	0.866	0.691-0.805	0.867	0.567
Attitude (ATT)	Watjatrakul (2013)	6	0.825	0.570-0.694	0.828	0.446
Self-Efficacy (SE)	Hu and Zhang (2016)	5	0.852	0.666-0.798	0.854	0.539
Subjective Norm (SN)	Hu and Zhang (2016)	4	0.766	0.657-0.712	0.769	0.455
Behavioral Intention (BI)	Samsudeen and Mohamed (2019)	5	0.829	0.690-0.728	0.830	0.494
Use Behavior (UB)	Samsudeen and Mohamed (2019)	5	0.856	0.672-0.793	0.857	0.545

The analysis results are presented in Table 4, which demonstrates the model fit in the confirmatory factor analysis (CFA) testing. The calculated values for these indices are as follows: CMIN/DF = 2.338, GFI = 0.874, AGFI = 0.855, NFI = 0.850, CFI = 0.907, TLI = 0.900, and RMSEA = 0.052. 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)	1288.102/551 = 2.338
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.874
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.855
NFI	≥ 0.80 (Wu & Wang, 2006)	0.850
CFI	≥ 0.80 (Bentler, 1990)	0.907
TLI	≥ 0.80 (Sharma et al., 2005)	0.900
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.052

Fit Index	Acceptable Criteria	Statistical Values
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

By the guidelines proposed by Fornell and Larcker (1981), the assessment of discriminant validity involved calculating the square root of each Average Variance Extracted (AVE). In this study, the obtained discriminant validity values were greater than all inter-construct/factor correlations, indicating strong support for discriminant validity. Moreover, the study successfully established both convergent and discriminant validity. As a result, the evidence obtained is deemed sufficient for establishing construct validity.

Table 5: Discriminant Validity

	ATT	PEOU	PU	BI	UB	SN	SE
ATT	**0.668**						
PEOU	0.654	**0.802**					
PU	0.421	0.345	**0.753**				
BI	0.498	0.544	0.131	**0.703**			
UB	0.238	0.315	0.113	0.239	**0.739**		
SN	0.659	0.659	0.261	0.631	0.260	**0.675**	
SE	0.584	0.465	0.349	0.483	0.182	0.632	**0.734**

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, all of the hypotheses were supported at $p<0.05$.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEOU→PU	0.345	6.837*	Supported
H2: PEOU→ATT	0.410	7.370*	Supported
H3: PU→ATT	0.198	3.904*	Supported
H4: SE →ATT	0.267	5.288*	Supported
H5: SN →ATT	0.349	6.262*	Supported
H6: SE →BI	0.190	3.638*	Supported
H7: ATT→ BI	0.176	3.001*	Supported
H8: SN→ BI	0.431	6.797*	Supported
H9: BI→ UB	0.241	4.453*	Supported

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

The statistical data relevant to **H1** supported the hypothesis that perceived ease of use significantly impacts perceived usefulness, with a standardized coefficient value of 0.345. As a result, H1 was supported. In the structured method, the standardized route coefficient value was found to be 0.410, confirming **H2** that perceived ease of use significantly influence attitude. The analysis findings for **H3** revealed that perceived usefulness is a crucial component of attitude, with a standardized path coefficient value of 0.198. The statistical results for **H4** supported the hypothesis that self-efficacy has a considerable impact on attitude, with a standardized path coefficient of 0.267. In **H5**, it was found that subjective norm significantly influences attitude, with a standardized path coefficient of 0.349. This finding is consistent with previous studies. **H6** demonstrated that self-efficacy influences behavioral intention, with a standard coefficient value of 0.190. **H7** indicated that attitude

motivations positively impact behavioral intention, with a standard coefficient value of 0.176. Additionally, **H8,** which had a standard coefficient value of 0.431, showed that subjective norm influences behavioral intention. Lastly, **H9** demonstrated a significant impact of behavioral intention on use behavior, with a standard coefficient value of 0.241. Overall, the statistical analysis supported each hypothesis, indicating significant relationships between the variables under study.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The following conclusions can be drawn behavioral intention was a significant factor influencing third-year students' use behavior of the DingTalk Learning Platform. Students who strongly intended to engage with the platform were likelier to use it. Perceived ease of use emerged as a crucial determinant of use behavior. When the platform was perceived as user-friendly and convenient, third-year students were more inclined to utilize it for their learning needs. Perceived usefulness was found to influence use behavior significantly. Students who believed that the DingTalk Learning Platform provided valuable benefits for their academic pursuits were likelier to engage with it. Self-efficacy played a significant role in determining use behavior. Higher levels of self-efficacy, reflecting students' confidence in their ability to use the platform effectively, were associated with increased engagement. Subjective norm, or the perceived social pressure to use the platform, notably impacted use behavior. When students perceived that their peers or instructors endorsed and encouraged platform use, it positively influenced their engagement. Attitude towards the platform was a significant determinant of use behavior. Students who were positive toward the DingTalk Learning Platform were likelier to utilize it for their learning activities.

In conclusion, this study revealed important insights into third-year students' behavioral intention and use behavior towards the DingTalk Learning Platform in Chengdu, China. The findings highlight the significance of behavioral intention, perceived ease of use, perceived usefulness, self-efficacy, subjective norm, and attitude in influencing students' engagement with the platform. These findings can inform educational institutions and platform developers in designing and promoting effective online learning platforms to enhance third-year students' learning experiences and outcomes.

5.2 Recommendation

Based on the findings of this study examining third-year students' behavioral intention and use behavior of the DingTalk Learning Platform in Chengdu, China, the following recommendations can be made the educational institutions and platform developers should focus on improving the user-friendliness and convenience of the DingTalk Learning Platform. This can be achieved by providing clear instructions, intuitive navigation, and responsive design, making it easier for third-year students to access and utilize the platform. Efforts should be made to highlight the benefits and value of the DingTalk Learning Platform for third-year students' academic pursuits. This can be done through targeted communication and marketing campaigns emphasizing the platform's features, functionalities, and how it can support their learning needs.

Strategies should be implemented to boost third-year students' confidence in using the DingTalk Learning Platform effectively. This can include providing comprehensive training and support resources, offering opportunities for hands-on practice, and encouraging peer-to-peer knowledge sharing to build students' skills and self-assurance—support, reinforcing the subjective norm of platform use.

Continuously monitor and improve the platform: Regular evaluation and feedback collection from third-year students can help identify areas for improvement in the DingTalk Learning Platform. Educational institutions and platform developers should actively seek student input, listen to their suggestions, and implement necessary updates and enhancements to ensure the platform remains relevant, effective, and engaging.

By implementing these recommendations, educational institutions and platform developers can enhance third-year students' behavioral intention and use behavior towards the DingTalk Learning Platform in Chengdu, China. This, in turn, can lead to improved learning experiences, increased engagement, and better academic outcomes for these students.

5.3 Limitation and Further Study

While studying third-year students' behavioral intention and use behavior towards the DingTalk Learning Platform in Chengdu, China, it is important to acknowledge certain limitations that may have influenced the study's findings. These limitations are that the study focused specifically on third-year students in Chengdu, China. Therefore, the findings may need to be more generalizable to other student populations or educational contexts. The unique characteristics and circumstances of the participants in this particular setting may influence the results.

The study was conducted within the specific context of a mental health course in Chengdu, China. The findings may be influenced by the specific nature of this course and the cultural context in which it was implemented. Therefore, caution should be exercised when applying the results to other academic disciplines or cultural settings and focused on a specific set of determinants, including perceived ease of use, usefulness, self-efficacy, subjective norm, and attitude. This study did not explore other factors that may influence behavioral intention and use behavior, such as individual motivation, technological infrastructure, and institutional support.

Future research should address these limitations by expanding the sample size, considering diverse educational contexts, utilizing multiple data collection methods, incorporating longitudinal designs, and exploring a broader range of determinants. This will help enhance the generalizability and validity of the findings and provide a more comprehensive understanding of students' behavioral intention and use behavior towards the DingTalk Learning Platform.

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