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The Adoption of the "Rain Classroom" Online Learning System among Sophomores in Chengdu, China

De-Rong Zhang*

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Abstract

Purpose: This study aims to examine the second-year students' behavior intention and use behavior towards Rain Classroom online learning system in Chengdu, China. The major variables are used to develop a conceptual framework which are contains perceived usefulness, self-efficacy, attitude, subjective norms, effort expectancy, behavioral intention, and use behavior. **Research design, data, and methodology:** The quantitative study applied the questionnaire as a tool to collect the data from 500 students in selected three collages in Chengdu. The data were prior approved for content validity and constructs' reliability in The Item-Objective Congruence (IOC) and pilot test (n=50) of Cronbach's Alpha. The sampling techniques used are judgmental, stratified random, and convenience sampling. The data was analyzed through Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). **Results:** The results show most of hypotheses were supported, excepted the relationship between effort expectancy and use behavior. The support relationships are that perceived usefulness, self-efficacy and subjective norms significantly influence attitude. Additionally, self-efficacy, attitude, subjective norms, and effort expectancy significantly influence behavioral intention. Behavioral intention and use behavior are also significantly related. **Conclusions:** Rain Classroom can provide online learning to achieve a seamless connection between online and offline learning, which can be endorsed by the successful adoption of students in China.

Keywords : Online Learning, Attitude, Effort Expectancy, Behavioral Intention, Use Behavior

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Affected by the COVID-19 outbreak in 2020, the Ministry of education called for the extension of the school in spring and issued guiding opinions. It pointed out that the teaching goal of "ceasing teaching, ceasing teaching and learning without stopping" has brought serious challenges to the educational front of our country. China's novel coronavirus pneumonia outbreak was the most serious public health emergency in China since the founding of new China, which has the fastest speed of spread, the most extensive infection area, and the most difficult control and prevention. For us, this is a crisis and a big test. In response to the call of the Ministry of education, our teachers have broken through the classroom teaching mode and carried out online Teaching to meet the requirement of "substantial equivalence" of online learning and offline classroom teaching quality proposed by the Ministry of education. This widespread situation has led to the adoption of e-learning methods worldwide. Most educational institutions are exploring this web-based, resource-based approach to learning to achieve academic excellence (Chadda & Kaur, 2021).

After the epidemic, students still like to have classes in the classroom face to face (Fatoni et al., 2020). More than 265 million students are taking online courses, unleashing student demand. It also stressed that students could still use the Internet during the pandemic to complete their studies while in lockdown and isolation (Ray & Srivastava, 2020). In the face of the huge demand for online learning, online education enterprises actively respond by releasing free

1*De-Rong Zhang, School of Marxism, Chengdu Vocational & Technical College of Industry, China. Email: 80778711@qq.com

courses and online and offline linkage. The industry presents an explosive growth trend. After the popularity of online learning, the demand for online learning increased sharply. In response to the demand, online learning education enterprises launched many free online courses to achieve online and offline linkage, and the online learning industry showed an explosive growth trend (Calamlam, 2021).

"Rain classroom" is an online teaching tool jointly developed by Xuetang online and Tsinghua University online education Office; it has a high degree of intelligence and complete functions (Wang, 2020). It is a plug-in of PowerPoint through WeChat and PPT plug-in. Rain classroom realizes the intelligent terminal interconnection between teachers and students comprehensively improves the classroom teaching experience in many aspects of Teaching; it sets up a bridge of communication between pre-class preview, after-class review, and classroom teaching, forming an organic unity of pre-class, in-class, and after-class, never offline. It is a perfect hybrid teaching tool integrating online and offline learning (Han & Lu, 2020). Therefore, this study aims to investigate sophomores' behavioral intention and use behavior using the online learning system of Rain Classroom in Chengdu, China. The key factors derived from previous studies are perceived usefulness, self-efficacy, attitude, subjective norms, effort expectancy, behavioral intention, and use behavior.

2. Literature Review

2.1 Perceived Usefulness

Perceived usefulness is defined as "the degree to which users think that using a specific system will increase performance and is not difficult for a person to use a specific system" (Davis, 1989). Perceived usefulness affects users' intentions. Experience and available data show that perceived risk reduces perceived utility and attitude toward using online auction markets (Verhagen et al., 2006). Bhattacherjee (2001) intends to study how cognitive beliefs and influences affect the will of individuals to continue using the online Bank and proposes that the usefulness perceived by users is one of the key factors affecting attitude. Perceived usefulness also positively and significantly impacts the attitude of using Google classroom (Al-Maroof & Al-Emran, 2018). Hence, the first hypothesis is indicated:

H1: Perceived usefulness has a significant influence on attitude.

2.2 Self-Efficacy

Self-efficacy represents an individual's perceptual knowledge and effectiveness of target behavior and is a component of perceptual behavior control. (Jugert et al., 2016). Bandura (1997) defined independence as an assessment of the ability of users to organize and implement necessary actions to achieve specific performance. Students with high self-efficiency are more likely than those with low self-efficiency to achieve better academic performance, have a positive attitude to M-Library application and are ready to continue using it (Tang et al., 2004). If someone believes that his knowledge can improve his work efficiency and affect the improvement of productivity, he/she will develop attitude and in imparting knowledge. (Bock et al., 2005). It was also concluded that self-efficacy, as the internal cognition of users, plays an important role in personal motivation, attitude, and behavior intention (Ajjan et al., 2014). Therefore, self-efficacy has an important impact on behavioral intention, as demonstrated in hypotheses:

H2: Self-efficacy has a significant influence on attitude.

H6: Self-efficacy has a significant influence on behavioral intention.

2.3 Subjective Norm

Subjective norms relate to the social pressure exerted by important others, such as family members, friends, and colleagues (Farah, 2017). Subjective norms are also predictors of participation intention (Ajzen, 1991). It will be established that subjective norms directly or indirectly affect the external stimulus of a person's specific behavior for the willingness to share knowledge (Zhou et al., 2007). Social norms often influence a person's decision to participate in activities (Ruefenacht et al., 2002). Therefore, the authors predict a causal relationship between subjective norms and attitudes concerning previous studies. Students in vocational colleges are often influenced by classmates, teachers, and other social factors. Venkatesh et al. (2012) also concluded through research that subjective norms directly or indirectly impact users' attitudes and behavioral intentions in using information systems. Therefore, subjective norms will directly affect the behavior intention of learning moral education courses. Accordingly, two hypotheses are suggested:

H3: Subjective norm has a significant influence on attitude.

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

2.4 Attitude

Attitude is an intention that consists of convictions that make up the overall behavior of a person's influence. Attitude is the psychological tendency of an individual to evaluate a certain behavioral advantage (Ha & Janda, 2012; Lim & Ting, 2014). The attitude can test a particular behavior's positive or negative assessment and predict the expected results according to the formed opinions (Lee et al., 2009). Attitudes are formed through internal contact and evaluation processes and directly affect the formation of positive or negative intentions (Kang & Hustvedt, 2013). If students feel useful, they will have a positive attitude to apply for rain classes, which will affect their behavioral intention to learn moral education courses and ultimately positively impact moral behavior. In addition, student's willingness to use rain classes became more active. Many researchers have also emphasized the relationship between attitude and behavioral intention in various studies (Kang & Hustvedt, 2013; Park, 2013). Accordingly, a relationship between attitude and behavioral intention is developed:

H4: Attitude has a significant influence on behavioral intention.

2.5 Effort Expectancy

Effort expectancy is related to users' expectations of ease of use (Venkatesh & Morris, 2000). Zhou et al. (2007) illustrated "when the user feels that internet banking is easy to use and does not require much effort, they would have a high chance to adopt internet banking." Assuming users think online banking is easy to use, more and more people will use it. When using a new information system, users pay more attention to its ease of use and consider the ease of use of information systems more important (Venkatesh & Morris, 2000). Users of different age groups have different retrieval abilities for information systems. Older users have weaker information retrieval abilities, and older end users are more adaptable to new environments than younger users (Burton-Jones & Hubona, 2005). The use of effort expectancy in the classroom may positively impact users' intended learning behavior. Therefore, as long as students in higher vocational colleges find it effortless to use rain classrooms to learn moral education courses, effort expectancy will positively impact their behavioral intention and use behavior. Based on the above assumptions, this study develops the following hypotheses:

H7: Effort expectancy has a significant influence on behavioral intention.

H8: Effort expectancy has a significant influence on behavior.

2.6 Behavior Intention

Ajzen (1991) argued that what is the intent of a person to perform a particular act core to explain why he does so. Then, intention is a direct precondition for actual behavior, and if measured properly, intention can provide an accurate prediction of behavior. Behavioral intention refers to the extent to which a person plans to perform or not perform a particular function in the future (Venkatesh et al., 2003). Behavioral intention is defined as the degree to which a person consciously plans to perform or not to perform certain future behaviors (Westerbeek & Shilbury, 2003). Indeed, behavioral intention is usually measured as a form of customer loyalty, measured by repurchase intention and word-of-mouth, which affect use behavior (Eastin, 2002; Hong & Yang, 2009). The user's intention will affect the actual behavior. The actual use behavior is affected by "behavior intention." That is, the higher the intention to use technical products, the stronger the actual use behavior of technical products (Venkatesh et al., 2003). Subsequently, a developed hypothesis is projected:

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

2.7 Use Behavior

Use behavior is implicated as behavior intensity, subjective norms, and perceived behavior control that affects human behavior (Venkatesh et al., 2003). Research shows that behavior is an important indicator for explaining future customer behavior (Sutton, 1994). If the user's effort to use a specific technology is reduced after the first experience, she will do this behavior more often (Venkatesh et al., 2012). Social influence or subjective norms shape people's attitudes and use behaviors (Venkatesh et al., 2003). Ajzen (1991) aims to explain the driving force of individual action in a specific way. The formation of each individual's intention includes goal-centered and goal-centered processes and finally forms intentional or planned behavior (Davis et al., 1989).

3. Research Methods and Materials

3.1 Research Framework

According to Figure 1, the conceptual framework of this study has been developed based on three previous research models. Hu and Zhang (2016) put forward a theory, including this study, which also integrates perceived usefulness, subjective norms, attitudes and self-efficacy to descrobe the use of m-library. Maity et al. (2018) proposed and tested a model that identifies cognitive and psychosocial motivations to explain normative behavior in its use. Finally, Yu and Huang (2019) assumed that the "actual use" of information technology is determined by "behavioral intention."

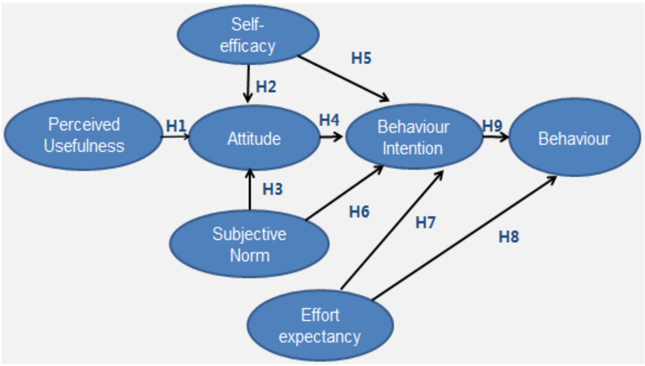

Figure 1: Conceptual Framework

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

3.2 Research Methodology

This quantitative research used questionnaire as a tool to collect the data. The survey has three parts: screening questions, measuring items with a 5-point Likert scale, and demographic inflammation. The data was analyzed through Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). Before collecting the data, the data were primarily tested for content validity and constructs' reliability in The Item-Objective Congruence (IOC) and pilot test (n=50) of Cronbach's Alpha. Three experts are invited to rate each item. Two of all 33 scale items did not meet the minimum requirements of IOC 0.6 and were revised. The two revision items are "EE6: I never understand the learning characteristics of rain class" and "BE3: I am not good at using rain class to study moral education courses." Cronbach's alpha coefficient reliability test was used to examine a pilot test (n=30). A value above 0.7 Cronbach α can be considered acceptable for construct reliability (Gable & Wolf, 1993). The results showed that perceived usefulness (0.903), attitude (0.815), subjective norm (0.865), self-efficacy (0.738), effort expectancy (0.867), behavioral intention (0.902), and use behavior (0.806).

3.3 Population and Sample Size

The target population of this study is second-year students who use the Rain Classroom online learning system from three higher vocational colleges with over 4,000 students in Chengdu, including Chengdu Industrial Vocational and technical college, Chengdu Vocational and technical college, and Chengdu industry and Trade Vocational and Technical College. A prior sample size calculator by Soper (2022) suggested minimum sample sizes for with 425 samples. To maximize the accuracy, the researcher aims to collect 500 participants for the further analysis.

3.4 Sampling Technique

The sampling techniques in this research are judgmental, stratified random, and convenience sampling. The judgmental sampling was to select second-year students who use the online learning system of Rain Classroom from three colleges in Chengdu, China. In Table 1, the stratified random sampling was calculated to a proportionate sample size of 500 respondents. Convenience sampling was to distribute an online questionnaire to the target participants.

Table 1: Sample Units and Sample Size

Higher vocational colleges in Chengdu	Sophomore (Total=4056)	Proportional sample size (Total=500)
Chengdu Vocational& Technical College of Industry	1526	188
Chengdu Polytechnic	1556	192
Chengdu industry and Trade Vocational and Technical College	974	120

Source: Constructed by author.

4. Results and Discussion

4.1 Demographic Information

The demographical data is obtained from 500 participants, as shown in Table 2. 50.2 percent are male, whereas 49.8 percent are female. Respondents use rain classrooms 1-3 days per week at 35 percent, 4-6 days at 56.8 percent, and 7 days per week at 8.2 percent. Most respondents know about rain classrooms from teachers at 34.4 percent, followed by classmates at 30.6 percent, and advertising and media at 17 percent respectively.

Table 2: Demographic Profile

Demographic Characteristics (N=500)		Frequency	Percentage
Gender	Male	251	50.2%
	Female	249	49.8%
Frequent use of Rain Classroom	1-3 days/week	175	35.0%
	4-6 days/week	284	56.8%
	7 days/week	41	8.2%
How do you know rain classroom from?	Teachers	172	34.4%
	Classmates	153	30.6%
	Family Members	32	6.4%
	Advertising and Media	85	17.0%
	Online Search	46	9.2%
	Others	12	2.4%

4.2 Confirmatory Factor Analysis (CFA)

Stangor (2014) interpreted that CFA as a case of structural equation model (SEM), which checks whether a set of data collected by researchers conforms to the assumed factor load. CFA reveals the relationship between measurement items, potential variables, and evaluation assumptions. According to Table 3, CFA's value should be above 0.7 of Cronbach alpha's α (Gable & Wolf, 1993). The acceptable threshold of factor loading is 0.5 or higher (Hair et al., 2006). The acceptable values of Composite or construct reliability (CR = ≥0.7) and Average variance extracted (AVE ≥ 0.5), respectively (Fornell & Larcker, 1981).

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 Usefulness (PU)	Hu and Zhang (2016)	4	0.879	0.743-0.912	0.883	0.655
Attitude (ATT)	Hu and Zhang (2016)	5	0.911	0.713-0.899	0.913	0.679
Subjective Norms (SN)	Maity et al. (2018)	4	0.888	0.701-0.880	0.888	0.667
Self-Efficacy (SE)	Maity et al. (2018)	5	0.877	0.690-0.870	0.880	0.596
Effort Expectancy (EE)	Yu and Huang (2019)	6	0.895	0.652-0.833	0.896	0.591
Behavioral Intention (BI)	Yu and Huang (2019)	4	0.899	0.790-0.874	0.900	0.693
Use Behavior (BE)	Yu and Huang (2019)	4	0.902	0.689-0.853	0.903	0.653

CFA allows researchers to test the effectiveness of their measurement model by goodness of fit, as in Table 4 (Hoekstra et al., 2008). The results demonstrated that the fitting degree of the measurement model had the goodness of fit, and all index values met the requirements. The data results were CMIN/df=1.671, GFI=0.913, AGFI=0.897, NFI=0.929, CFI=0.970, TLI=0.966, and RMSEA=0.037.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	792.264/474 or 1.671
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.913
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.897
NFI	≥ 0.80 (Wu & Wang, 2006)	0.929
CFI	≥ 0.80 (Bentler, 1990)	0.970
TLI	≥ 0.80 (Sharma et al., 2005)	0.966
RMSEA	< 0.08 (Pedroso et al., 2016)	0.037
Model summary		**Acceptable Model Fit**

Remark: 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.

Discriminant validity is confirmed when the AVE's square root is larger than any intercorrelated construct's coefficient (Fornell & Larcker, 1981). The square root of AVE for all constructs at the diagonal line was greater than the inter-scale correlations. Hence, the discriminant validity was guaranteed, as shown in Table 5.

Table 5: Discriminant Validity

	PU	ATT	SE	SN	EE	BI	BE
PU	**0.809**						
ATT	0.460	**0.824**					
SE	0.399	0.419	**0.772**				
SN	0.352	0.356	0.387	**0.817**			
EE	0.410	0.369	0.249	0.296	**0.769**		
BI	0.365	0.526	0.393	0.400	0.373	**0.832**	
BE	0.270	0.324	0.346	0.286	0.230	0.436	**0.808**

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

4.3 Structural Equation Model (SEM)

The structural equation model is used to evaluate the structural model to confirm the suitability of the model, the causal relationship between variables, and the factors that affect the behavioral intention of using rain class in the moral education curriculum. Table 6 shows the fitness of the structural model was explicated in the statistical value without an adjustment. Therefore, the acceptable values are concluded, including CMIN/df=2.351, GFI=0.870, AGFI=0.850, NFI=0.897, CFI=0.938 TLI=0.933, and RMSEA=0.052.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1142.740 /486 or 2.351
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.870
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.850
NFI	≥ 0.80 (Wu & Wang, 2006)	0.897
CFI	≥ 0.80 (Bentler, 1990)	0.938
TLI	≥ 0.80 (Sharma et al., 2005)	0.933
RMSEA	< 0.08 (Pedroso et al., 2016)	0.052
Model Summary		**Acceptable Model Fit**

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

Based on Table 7, the correlation magnitude among the independent and dependent variables proposed in the hypothesis is measured by standardized path coefficients and t-value. The significant degree is also verified by $p<0.001$.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PU → ATT	0.490	7.475*	Supported
H2: SE → ATT	0.243	5.579*	Supported
H3: SN → ATT	0.292	4.583*	Supported
H4: ATT → BI	0.363	7.734*	Supported
H5: SN→ BI	0.305	4.808*	Supported
H6: SE → BI	0.181	4.167*	Supported
H7: EE → BI	0.212	4.053*	Supported
H8: EE → BA	0.056	1.341	Not Supported
H9: BI → BA	0.322	8.116*	Supported

Note: *=p-value<0.05
Source: Created by the author

The strongest impact on attitude is perceived usefulness. In H1, the normalized path coefficient of the path relationship between perceived usefulness and attitude is 0.490, and the t-value is 7.475. This supports previous studies that interactive and powerful recording function is another important attribute of the usefulness of rain class. Bhattacherjee, 2001; Verhagen et al., 2006).

Self-efficacy has a significant influence on attitude, with standardized path coefficient of 0.243 and t-value at 5.579 in H2. Students' self-efficacy will be affected by experience accumulation, positive guidance and motivation of teachers Ajjan et al., 2014; Bock et al., 2005).

Another significant factor impacting attitude is subjective norm with standardized path coefficient of 0.292 and t-value at 4.583 H3. Therefore, the powerful recording function of Rain Classroom is used to record students' attendance, answer questions and other classroom interactions, so that each student can better understand their daily performance and timely adjust their learning norms (Hu & Zhang, 2016).

The influence on the behavior intention of using the rain classroom mainly comes from the attitude, followed by the direct influence on the ease of use of subjective norms, self-efficacy and effort expectation. In standardization, the direct impact of attitude on behavioral intention is the most significant. path coefficient of 0.363 and t-value at 7.374 in H4. Kang and Hustvedt (2013) believed that the more positive the students' attitude towards the use of rain classroom, the more obvious the behavioral intention of using rain classroom.

In H5, subjective norm has a significant influence on behavioral intention with the standardized path coefficient is 0.305 and the t value is 4.808. Venkatesh et al. (2012) also confirmed that subjective norms directly or indirectly impact users' attitudes and behavioral intentions in using information systems.

The results oh H6 show the support relationship between self-efficiency and behavioral intention, reflecting the standardized path coefficient is 0.181 and the t value is 4.167. Self-efficacy is the internal cognition of users that plays an important role in personal motivation, attitude, and behavior intention (Ajjan et al., 2014).

Effort expectancy significantly influences behavioral intention. The statistical results reveal the standardized path coefficient is 0.212 and the t value is 4.053. Thus, H7 is supported as aligned with previous claims that as long as students in higher vocational colleges find it effortless to use rain classrooms to learn moral education courses, effort expectancy will positively impact their behavioral intention and use behavior (Burton-Jones & Hubona, 2005).

When the standardized path coefficient is 0.056 and the t value is 1.341, the influence of effort expectation on behavior is not found, so H8 is not supported. This finding contradicts the previous research of Tarhini et al. (2017) posited that when students are expected to use the rain class, they will use the rain class.

Behavior intention has a significant influence on behavior. with standardized path coefficient of 0.322 and t-value at 8.116 in H9. Behavioral intention has a significant impact on behavior. The standardized path coefficient of H9 is 0.322, and the t value is 8.116. When students' behavioral intention to use the rain classroom is obvious, they will have a direct impact on the use behavior (Maity et al., 2018; Yu & Huang, 2019). The use behavior intention of the rain classroom has a significant direct impact on the behavior.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

Rain Classroom can provide online learning to achieve a seamless connection between online and offline learning, which can be endorsed by the successful adoption of students in China. This study aims to examine the second-year students' behavior intention and use behavior towards Rain Classroom online learning system in Chengdu, China. The conceptual framework of this study has been developed based on existing theories and previous empirical research of Hu and Zhang (2016), Maity et al. (2018), and Yu and Huang (2019). The data was analyzed through Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). The results show most of hypotheses were supported, excepted the relationship between effort expectancy and use behavior. The support relationships are that perceived usefulness, self-efficacy and subjective norms significantly influence attitude. Additionally, self-efficacy, attitude, subjective norms, and effort expectancy significantly influence behavioral intention. Behavioral intention and use behavior are also significantly related.

Researchers modified the conceptual framework in this study based on four core theories and three previous major studies. Gray (2017) defined theory as the concept, definition, and proposition of explaining the systematic view of phenomena. To describe the vocational students' behavioral intention of rain classroom application, attitude towards the use as defined as the use of special information systems for the evaluation of individual wish can predict that use intention. The findings of this study are consistent with the theories and studies of Jaiyeoba and Iloanya (2019) and Lau and Woods (2008). That is, the use of attitude directly impacts the use of behavioral intention. Students' positive impression of rain class will affect their intention to use rain class. The technology acceptance and use unified theoretical model (UTAUT) developed by Maity et al. (2018) believes that managers need to let users understand the rain classroom used and help users participate in normative behavior.

The behavioral intention is that the behavior of using a rain classroom has the most direct impact, which is consistent with the research (Schwartz, 1977), but the expected workload has no direct impact. Attitude, self-efficacy, subjective norms, and effort expectancy all have a direct impact on students' behavioral intention to use the rain classroom, especially students' attitude has the greatest impact on the behavioral intention to use the rain classroom, which is consistent with the research of (Davis et al., 1989). Among subjective norms, self-efficacy, and perceived usefulness, perceived usefulness is the biggest influencing factor of students' attitude towards using rain classrooms to learn moral education courses.

5.2 Recommendation

The researchers identified the key factors that affect the use behavior of second-year students in three vocational colleges in Chengdu, Sichuan Province using rain classes to learn moral education courses, such as perceived usefulness, attitude, self-efficacy, subjective norms, effort expectancy, and behavioral intention. The above key factors should be developed and promoted to gain intention among academic practitioner and online learning system developers.

In order to obtain the influencing factors of the behavior of using rain classrooms among vocational students, in this study, behavioral intention is a strong measure of the behavior of using rain classrooms. Therefore, developers, teachers, and teaching managers of rain classrooms must improve students' behavioral intention of using rain classrooms. Through the strong interaction, recording, and other functions of the rain class, the synchronization of teaching and learning is realized, and the students' behavioral intention of using the rain class is improved. At the same time, attitudes, self-efficacy, subjective norms, and expected efforts directly impact students' behavior and intention to use the rain class, especially students' attitudes. Teachers should fully mobilize students' enthusiasm before, during, and after class through the rain class and give full play to teachers' leading and students' main roles.

The study also found that perceived usefulness is the strongest measure of students' attitude towards using rain classes to learn moral education courses in subjective norms, self-efficacy, and perceived usefulness. Therefore, the developers of Rain Classroom must improve its usefulness. This also tells us that if higher vocational students think that the rain class is useful for studying moral education courses, they will tend to use the rain class to improve their performance in studying moral education courses. The developers, teachers, and teaching managers of the rain classroom should ensure that the functions of the rain classroom meet the needs of moral education curriculum learning when using the rain classroom. These can stimulate or increase positive attitudes, as well as the use of rain classes in learning moral education courses.

In conclusion, this study explains in detail the various factors that affect the use of rain classes by vocational college students. It provides important reference for developers, teachers, and teaching managers of the rain classroom to determine the variables that affect the use of rain classroom behavior of vocational students, continuously improve the function of rain classroom, and make the use of rain classroom more common. Only the first letter of the first word should be capitalized.

5.3 Limitation and Further Study

Certain limitations are addressed to guide the future scholars for the better development of research. Firstly, this study scopes to higher vocational college students in Chengdu, Sichuan Province. The extension should be in a wider groups or other regions in China. Secondly, the online teaching tool of this study is only based on a rain class. Other types of online learning systems or systems for other purposes can be further studied, such as Superstar, Tencent conference, QQ, nail, and other online learning tools can also be compared. Lastly, the qualitative study should be considered to provide more effective data analysis and results for future studies.

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