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The Investigation on First-Year Students' Use Behavior of Online Learning System or "Rain Classroom" in Chengdu, China

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Abstract

Purpose: "Rain classroom" is a smart teaching tool jointly developed by Xuetang and Tsinghua University Online Education Office. This study aims to investigate first-year students' behavior intention and use behavior using the online learning system of Rain Classroom in Chengdu, China. The conceptual framework contains perceived usefulness, self-efficacy, attitude, subjective norms, effort expectancy, behavioral intention, and use behavior. **Research design, data, and methodology:** The study was conducted quantitatively by distributing questionnaires to 500 participants. 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. The sampling procedure involves judgmental, stratified random, and convenience sampling. The data was analyzed through Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). **Results:** The results show that perceived usefulness and subjective norms significantly influence attitude. Furthermore, self-efficacy, attitude, subjective norms, and effort expectancy significantly influence behavioral intention. Behavioral intention and use behavior are also significantly related. Nevertheless, non-support relationships exist between self-efficacy and attitude, and effort expectancy and use behavior. **Conclusions:** The application of rain classrooms can be enhanced by promoting its benefits and how such a system can optimize students' learning efficiency.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The 2020-2021 academic year will be challenging for educational institutions, teachers, and students due to the COVID-19 pandemic (Chadda & Kaur, 2021). Under the global anti-epidemic model, "teaching" and "learning" have undergone major changes. It is urgent to update the education concept, optimize the teaching strategy, improve the teaching methods, realize the seamless connection between online and offline Teaching during and after the epidemic, and improve the classroom teaching effect. Online courses can be designed to stimulate the visual learner with animation, hypertext, and video clicks (Ross et al., 1999). In recent years, the method of implementing online courses is becoming more and more popular. Some universities in India offer students many online or distance learning courses (Beatty & Ulasewicz, 2006). E-learning is not a new environment, and the introduction of online Teaching in Indian educational

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institutions is an important contribution (Kiran et al., 2008).

Many mobile classrooms enable online education, such as Kahoot, Socrative, Verso, Rain Classroom, and ZUVIO (Wu et al., 2019). "Rain classroom" is a smart teaching tool jointly developed by Xuetang online and Tsinghua University Online Education Office. 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, establishes a communication bridge between extracurricular preview and classroom teaching, and makes classroom interaction never offline. It is a perfect hybrid teaching tool integrating online and offline learning.

The research aimed to fulfill the gap in empirical research. After introducing the rain classroom tools into the moral education curriculum of Marx Institute of Chengdu Industrial University, classroom teaching has been transformed into "Internet plus blackboard + mobile terminals," A teaching scene with synchronous Teaching and learning has been established. This study investigated the impact of rain classroom application on the behavior intention of moral education curriculum learning of higher vocational students in Chengdu. Therefore, this study aims to investigate first-year students' 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 refers to the degree to which consumers believe products can improve transaction performance (Chiu et al., 2009). Perceived usefulness refers to "believing in what a person can use" (Davis, 1989). The usefulness perceived by the user and the expected validation after the adoption is two determining factors of user satisfaction (Bhattacherjee, 2001). It also positively and significantly impacts the behavioral intentions of using Google classroom (Al-Maroof & Al-Emran, 2018). This study explores the usefulness of online examinations in assessing students' intention to adapt to the online education system. The utility is measured by understanding the speed at which tasks are completed and the time and social value saved. Therefore, technology awareness and social value lead to the usefulness of technology-oriented online education. Perceived usefulness has a significant positive impact on attitude (Chiu et al., 2009). Hence, the first hypothesis is indicated:

H1: Perceived usefulness has a significant influence on attitude.

2.2 Self-Efficacy

Self-efficacy reflects how Chinese students believe they can successfully implement the use behavior related to mobile library applications. Compared with students with low self-efficacy, students with high self-efficacy are more likely to achieve better academic performance, have a positive attitude toward m-library applications, and are more willing to continue to use them (Tang et al., 2004). Furthermore, almost all studies have shown that self-efficacy strongly influences an individual's attitude (Anderson & Agarwal, 2010; Woon et al., 2005). As knowledge self-efficacy increases, people feel confident about what they can do (Constant et al., 1994). Students with high self-efficacy score higher in the moral education curriculum than those with low self-efficacy, which positively impacts behavior intention and is more active in learning the moral education curriculum (Tang et al., 2004). Therefore, the following hypotheses are set:

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 are defined as a social pressure that enables individuals to engage in behaviors with group behaviors, such as family or friends. Subjective norms are normative beliefs of groups or references (Ajzen, 1991; Tarkiainen & Sundqvist, 2005). Fishbein and Ajzen (1975) believe that faith can be divided into internal and external faith; the subjective norm is part of external faith, which helps promote public behavior (Groening et al., 2017). Subjective standards are individual reference standards based on normative conviction or perceptual preference and individual motivational enormities based on individual preference (Troudi & Bouyoucef, 2020). Ajzen (1991) believes that the subjective norm as external cognition relates to Chinese students' attitude toward social pressure and the influence of teachers, classmates, or important friends on user behavior. Some people also believe that subjective norms are related to students' normative beliefs about the expectations of others (Lee & Jin, 2012). This study shows that the use of subjective norms in the rain classroom of college students in Chengdu higher vocational colleges directly impacts the learning behavior intention of the moral education curriculum. 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 represents "the overall evaluation of a person's behavior" (Ajzen, 1991). Attitude is a belief or object that can be converted into action; it is also a positive or negative evaluation of green products (Troudi & Bouyoucef, 2020). Attitude is an intention that consists of convictions that make up the overall behavior of a person's influence Attitude affects purchase intention and, thus, purchase behavior (Vazifehdoust et al., 2013). In a specific context, such as interchange behavior, a person's attitude indicates the degree and attitude of customer approval or opposition to interchange behavior (Nimako et al., 2013). 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 (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

The expectation of effort refers to the system's ease of use. Venkatesh et al. (2003) pointed out that effort expectancy refers to the degree of ease of use related to the use of the system. The present study found that three constructs of the existing model define effort expectancy, including perceived ease of use (technology acceptance models or TAM), complexity (personal computer utilization model), and ease of use (innovation diffusion theory). The initial experience of being easy to use a specific technology may lead individuals to reuse it frequently and stop using it if it is not easy (Venkatesh et al., 2003). Therefore, effort expectancy can predict behavioral intention. The relationship between effort expectation and use behavior to test the relationship between rain classroom and moral education course learning behavior of Chengdu college students. Effort expectancy is applied in voluntary and mandatory digital technology use. When users do not make enough effort when using a particular technology, they may become more engaged (Venkatesh et al., 2012). 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

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). Based on the empirical evidence that search intention is a powerful predictor of purchase intention (Shim et al., 2001), this study reevaluates a similar reasoning route from a social perspective. Dowling (2007) found that intention is behavior, especially in the theory of planned behavior model (TPB); the behavioral intention is interpreted as a motivational factor determining whether a person's behavioral performance depends on his or her behavioral intention (Ajzen, 1991). The actual use behavior is affected by "behavior intention." 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 determined by the combination of performance assessment and migration credentials; their actions now have their consequences (Troudi & Bouyoucef, 2020). TPB is considered that behavior and behavior intensity, subjective norms, and perceived behavior will control and affect human behavior (Venkatesh et al., 2003). Behavior intention determines behavior (Fishbein & Ajzen, 1975). Generally speaking, the greater the will to participate in an action, the higher the possibility of final implementation (Ajzen, 1991). Cao and Jittawiriyanukoon (2022) posted that the actual system use is the choice to use the online learning system and can also be the frequency or degree of the use of the system.

3. Research Methods and Materials

3.1 Research Framework

As previous research frameworks helped the researchers develop their conceptual framework. Therefore, the conceptual framework of this study (Figure 1) 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).

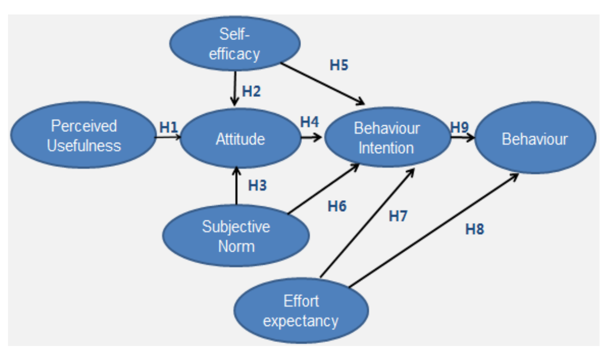

Figure 1: Conceptual Framework

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

Quantitative research tools analyzed the data collected from the questionnaire. 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. The Item-Objective Congruence (IOC) and pilot test of Cronbach's Alpha were used to verify the validity and reliability of all scale items of variables. 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).

For content validity, the item-objective congruence (IOC) index was applied. 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 determines first-year students who use the Rain Classroom online learning system in Chengdu, China. The students come from three higher vocational colleges with over 6,000 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 that can recommend minimum sample sizes for studies using structural equation models (SEM) based on several input parameter values with 425 samples (Soper, 2022). However, the researcher aims to collect 500 participants for efficient data analysis.

3.4 Sampling Technique

The sampling procedure involves judgmental, stratified random, and convenience sampling. The judgmental sampling was to select first-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	Freshman (Total=6203)	Proportional Sample Size (Total=500)
Chengdu Vocational& Technical College of Industry	2341	189
Chengdu Polytechnic	2018	163
Chengdu industry and Trade Vocational and Technical College	1844	148

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. 46.2 percent are male, whereas 53.8 percent are female. Respondents use rain classrooms 1-3 days per week at 37 percent, 4-6 days at 52.4 percent, and 7 days per week at 10.6 percent. Most respondents know about rain classrooms from classmates at 34.8 percent, followed by teachers at 33.4 percent, and family members at 13.2 percent respectively.

Table 2: Demographic Profile

Demographic Characteristics (N=500)		Frequency	Percentage
Gender	Male	231	46.2%
	Female	269	53.8%
Frequent use of Rain Classroom	1-3 days/week	185	37.0%
	4-6 days/week	262	52.4%
	7 days/week	53	10.6%
How do you know rain classroom from?	Teachers	167	33.4%
	Classmates	174	34.8%
	Family Members	66	13.2%
	Advertising and Media	42	8.4%

Demographic Characteristics (N=500)		Frequency	Percentage
	Online Search	33	6.6%
	Others	18	3.6%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is a statistical tool that has been used more and more widely in various studies due to its flexibility and power (Teo, 2011). A value above 0.7 Cronbach α can be considered acceptable for construct reliability (Gable & Wolf, 1993). The acceptable threshold of factor loading is 0.5 or higher (Hair et al., 2006). Composite or construct reliability (CR) and Average variance extracted (AVE) are other measurements of scale items' reliability and consistency (Peterson & Kim, 2013). The value of CR and AVE is acceptable at 0.7, and 0.5 or higher, 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	0.871	0.717-0.921	0.875	0.639
Attitude (ATT)	Hu and Zhang (2016)	5	0.906	0.710-0.900	0.908	0.667
Subjective Norms (SN)	Maity et al. (2018)	4	0.894	0.683-0.942	0.896	0.686
Self-Efficacy (SE)	Maity et al. (2018)	5	0.877	0.683-0.864	0.872	0.579
Effort Expectancy (EE)	Yu and Huang (2019)	6	0.882	0.638-0.792	0.882	0.557
Behavioral Intention (BI)	Yu and Huang (2019)	4	0.898	0.770-0.873	0.899	0.691
Use Behavior (BE)	Yu and Huang (2019)	4	0.890	0.798-0.834	0.890	0.670

Stangor (2014) defined goodness of fit statistics as the range of collected data consistent with the assumed relationship between each variable. The model can be measured by goodness of fit, as in Table 4. 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=2.843, GFI=0.867, AGFI=0.841, NFI=0.884, CFI=0.921, TLI=0.912, and RMSEA=0.061.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1259.604/443 or 2.843
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.867
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.841
NFI	≥ 0.80 (Wu & Wang, 2006)	0.884
CFI	≥ 0.80 (Bentler, 1990)	0.921
TLI	≥ 0.80 (Sharma et al., 2005)	0.912
RMSEA	< 0.08 (Pedroso et al., 2016)	0.061
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 established when the AVE of each proposed construct is greater than its shared variance with another construct (Fornell & Larcker, 1981). In Table 5, these data approved the discriminant validity of the study.

Table 5: Discriminant Validity

	PU	ATT	SE	SN	EE	BI	BE
PU	**0.799**						
ATT	0.429	**0.817**					
SE	0.421	0.340	**0.761**				
SN	0.327	0.330	0.376	**0.828**			
EE	0.419	0.407	0.258	0.261	**0.746**		
BI	0.368	0.529	0.369	0.404	0.409	**0.831**	
BE	0.229	0.282	0.280	0.255	0.145	0.378	**0.819**

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 (SEM) is a comprehensive statistical method used to verify researchers' assumptions about the relationships between the observed and potential variables (Hoyle, 1995). The fitness of the structural model was explicated in the statistical value after adjustment in Table 6. The values were acceptable at CMIN/df=3.191, GFI=0.850, AGFI=0.821, NFI=0.874, CFI=0.910, TLI=0.898, and RMSEA=0.066.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values before adjustment	Statistical Values after adjustment
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1549.617 /425or3.646	1321.145/414 or 3.191
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.829	0.850
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.800	0.821
NFI	≥ 0.80 (Wu & Wang, 2006)	0.852	0.874
CFI	≥ 0.80 (Bentler, 1990)	0.888	0.910

Fit Index	Acceptable Criteria	Statistical Values before adjustment	Statistical Values after adjustment
TLI	≥ 0.80 (Sharma et al., 2005)	0.877	0.898
RMSEA	< 0.08 (Pedroso et al., 2016)	0.073	0.066
Model Summary		**Unacceptable Model Fit**	**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	0.510	6.849*	Supported
H2: SE → ATT	0.120	2.734*	Not Supported
H3: SN → ATT	0.316	4.683*	Supported
H4: ATT → BI	0.369	8.290*	Supported
H5: SN→ BI	0.329	5.101*	Supported
H6: SE → BI	0.164	3.968*	Supported
H7: EE → BI	0.227	4.781*	Supported
H8: EE → BA	-0.006	-0.114	Not Supported
H9: BI → BA	0.406	7.954*	Supported

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

The strongest impact on attitude is perceived usefulness. The path relationship of perceived usefulness and attitude has a standardized path coefficient of 0.510 and a t-value of 6.849 in H1. This supports by previous studies (Al-Maroof & Al-Emran, 2018; Bhattacherjee, 2001; Chiu et al., 2009; Davis, 1989). The interactive and powerful recording function is another important attribute of the usefulness of rain class.

When the standardized path coefficient is 0.120, and the t value is 2.734, the influence of self-efficacy on attitude is not found, so H2 is not supported. Students' self-efficacy will be affected by teachers and their experience with positive guidance, and motivation which is inconsistent with this study (Anderson & Agarwal, 2010; Woon et al., 2005).

Another significant factor impacting attitude is the subjective norm, with a standardized path coefficient of 0.316 and a t-value of 4.683 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 0.369 and t-value at 8.290 in H4 is consistent with previous scholars who believed that the more positive the students' attitude towards the use of rain classroom, the more obvious the behavioral intention of using rain classroom (Troudi & Bouyoucef, 2020; Vazifehdoust et al., 2013).

H5 is supported, reflected the standardized path coefficient of 0.329 and t-value at 5.101. Chinese students' attitude toward social pressure and the influence of teachers, classmates, or important friends on behavioral intention and use behavior (Lee & Jin, 2012).

In H6, self-efficacy has a significant influence on behavior intention with the standardized path coefficient is 0.164, and the t-value is 3.968. Students with high self-efficacy score higher in the moral education curriculum than those with low self-efficacy, which positively impacts behavior intention and is more active in learning the moral education curriculum (Tang et al., 2004).

The result of standardized path coefficient is 0.164, and the t-value is 3.968 confirm that effort expectancy has a significant influence on behaviors intention. Effort expectancy is applied in voluntary and mandatory digital technology use. When users do not make enough effort when using a particular technology, they may become more engaged (Venkatesh et al., 2012).

When the standardized path coefficient is -0.006, and the t-value is -0.114, the influence of effort expectation on behavior is not found, so H8 is not supported. This finding contradicts the previous research of Lee and Jin (2012) and Tarhini et al. (2017), who supported that when students are expected to use the rain class, they will use the rain class.

Behavior intention significantly influences behavior, with a standardized path coefficient of 0.406 and a t-value of 7.954 in H9. When students' behavioral intention to use the rain classroom is obvious, they will directly impact the user behavior (Maity et al., 2018; Yu & Huang, 2019). The use of behavioral intention in the rain classroom has a significant direct impact on the behavior.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study aims to study the influencing factors of the students in Chengdu to use the rain class to learn moral education courses. The subjects of this empirical case study are first-year students from three different vocational colleges in Chengdu, Sichuan, China. In order to form the conceptual framework of the study, the previous literature was studied, and relevant theories and research results were collected. The results show that perceived usefulness and subjective norms significantly influence attitude. Furthermore, self-efficacy, attitude, subjective norms, and effort expectancy significantly influence behavioral intention. Behavioral intention and use behavior are also significantly related. Nevertheless, non-support relationships exist between self-efficacy and attitude, and effort expectancy and use behavior.

The previous research framework, the first one, is proposed by (Hu & Zhang, 2016). They study perceived usefulness from system quality, information quality, and service quality and the relationship between behavioral intention and perceived usefulness and behavioral intention from subjective norms, attitude, and self-efficacy. Maity et al. (2018) developed the second research framework model. They uncovered a gap between the moral compass and users' ultimate actions. This study constructs a new model to explain the normative behavior used by UTAUT and TAM. The researchers proposed and tested a model that identifies cognitive and psychosocial motivations to explain normative behavior in its use. They investigated the relationship between subjective norms, effort expectancy, and behavioral intention. Yu and Huang (2019) developed the third research framework model. Huang Gang focused on the study of perceived ease of use versus perceived usefulness, perceived ease of use versus attitude, perceived usefulness versus attitude, perceived usefulness versus behavioral intention, and subjective norm versus behavior. Positive and direct effects of intention perceived behavioral control on behavioral intention and behavior.

5.2 Recommendation

This study's results show that some factors can significantly or not significantly affect the behavioral intention of using rain classrooms in the moral education curriculum. Behavior intention and use attitude are the strongest predictors of Chengdu college students' use of rain classrooms. Other equally important but indirect predictors are perceived usefulness, subjective norms, expected workload, and self-efficacy. This case study does not prove that self-efficacy has a direct impact on attitude, but self-efficacy can have a direct impact on the behavioral intention of using rain classroom; It is not proved that the expected workload has a direct impact on the behavior, but the expected workload can have a direct impact on the behavior intention of using the rain classroom. These factors can become important considerations for the personnel who develop the rain classroom, the teachers who use the rain classroom, or the teaching managers, emphasizing the purpose of strengthening students' behavior by using the rain classroom in the moral education curriculum.

The developers, teachers or teaching managers, and marketing practitioners of the rain classroom should focus on improving students' awareness of the usefulness and positive impression of the rain classroom and improving the quality and performance of the rain classroom. Encouraging rain classes or other online learning tools in moral education courses is important. Students can continuously build their independent learning ability using rain classrooms and implement new teacher requirements. At the same time, it also provides referential experience and replicable models for moral education curriculum learning of vocational college students in China. When offline learning is interrupted in emergencies such as COVID-19, Rain Classroom can provide online learning to achieve a seamless connection between online and offline learning.

5.3 Limitation and Further Study

This study has certain limitations due to the influence of time and other factors. Firstly, the research object selected in this study is higher vocational college students, and data are collected from three higher vocational colleges selected in Chengdu, Sichuan Province. The scope of selection and the sample size is limited. 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. Finally, the subjects of the survey are only limited to first- and second-year students. The next research will investigate teachers and teaching managers of moral education courses and third-grade graduates to understand their behavior using rain classes.

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