



## Factors Affecting Students' Intentions to Use the LMS Platform During the Paradigm Shift of the Epidemic Situation in the Rain Classroom

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### Abstract

**Background and Aims:** To understand how to make students adapt to online teaching under a clear paradigm shift. This article therefore uses the domestic LMS platform - Rain Classroom as a case study to study what factors affect students' willingness to use the platform. Therefore, this article aims to understand undergraduate students' willingness to use the platform. Beijing to use domestic LMS software platform - Rain Classroom.

**Materials and Methods:** This study used a quantitative method to assess the intention of undergraduates in Beijing to use the domestic LMS platform, namely Rain Classroom. Data were collected using a five-level Likert scale questionnaire. The reliability and effectiveness of the instrument have been fully verified by expert evaluation and Cronbach's Alpha value. Data were collected through statistical analysis, including regression. Students' intention to use is influenced by subjective norms and attitudes, and the influence of subjective norms on intention to use is more intuitive.

**Results:** The paper studies the influencing factors of undergraduates' intention to use rain classes in three colleges and universities in Beijing, provides a reference for colleges and universities to carry out online education better, and puts forward suggestions for schools to pay attention to and for the improvement of LMS platform.

**Conclusion:** In the end This study contributes to our understanding of the dynamics behind students' choices regarding LMS adoption, highlighting the importance of social influences and individual attitudes in shaping their intentions.

**Keywords:** Rain Classroom; Epidemic; Undergraduate Students; Behavior Intention to Use

### Introduction

At the time, online education was called distance learning. It originated in the United States in the 19th century, when faculty and students from different locations at the University of Chicago attempted to establish contact through correspondence courses (McIsaac & Gunawardena, 1996). Since then, Western online learning research has developed rapidly and achieved many achievements and iterations. Online education in China will not be widespread until 2020. However, due to the COVID-19 epidemic, schools across the country have responded to the state's call to "not suspend classes." They started using classroom-based software for online teaching activities. This sudden change does not give teachers and students much time to adapt, which is a challenge for both students and teachers. Kirmizi (2015) believes that online learning requires students to have strong self-regulation and organizational abilities, but different students have different abilities in this respect, which may affect their learning effect. Changes in the learning environment during the pandemic may affect students' motivation and make it difficult for them to focus on their studies. At the same time, the lack of face-to-face interaction may reduce students' learning engagement and satisfaction (Martin & Bolliger,



2018).

To understand how to make students adapt to online teaching under the obvious paradigm shift, this paper takes the domestic LMS platform - Rain Classroom as a case study to research what factors will affect students' intention to use the platform. Rain Classroom is a new intelligent teaching tool launched by Tsinghua University on WeChat in 2016 (Shu et al., 2019). The Beijing area soon took the lead in using it, and the three target schools have long experience in using Rain Classrooms. The three target universities have supporting teaching tools and hardware facilities, and there are numerous campuses in various areas of Beijing. In this way, we can first understand what factors affect students' usage intention, and adjust the online learning mode from the perspective of students in terms of the software itself, the surrounding environment, and other aspects, so that students can adjust themselves as soon as possible and get rid of the impact of a sudden paradigm shift on online learning. In this way, students' intention to use online learning can be strengthened, and their participation and satisfaction can be enhanced.

### Objective of Research

This article aims to understand the willingness of undergraduate students in Beijing to use the domestic LMS platform software - Rain Classroom. Quantitative analysis is needed to study students' intentions to use online learning. Project research can guide related technical research and allow students to better participate in online learning.

### Literature Review

#### Technology Acceptance Model (TAM)

This model was developed by the Theory of Reasoned Action (TRA). TAM proposes two primary constructs for understanding individuals' acceptance of technology: perceived usefulness and ease of use. These two beliefs influence an individual's attitude towards using a system, which affects the intention to use and, finally, the actual usage of the system (Davis, 1989). TAM proposes two primary constructs for understanding individuals' acceptance of technology: perceived usefulness and ease of use. These two beliefs influence an individual's attitude towards using a system, which affects the intention to use and, finally, the actual usage of the system (Davis, 1989). Perceived usefulness, perceived ease of use, attitude, and behavioral intention were selected as potential variables of the conceptual framework to understand the technology-level influencing factors on Rain Classroom usage intention.

#### Decomposed Theory of Planned Model (DTPB)

Taylor and Todd (1995) systematically proposed the Decomposition theory of planned Behavior (DTPB). The model decomposes behavioral attitudes into perceived usefulness, ease of use, and compatibility, subjective norms into peer influence and superior influence, and perceived behavioral control self-efficacy, resource facilitation conditions, and technological facilitation conditions, which can more completely explain the determinants of behavioral intention and usage behavior in the original TPB model.

In the model, subjective norms can also affect behavioral intentions, and subjective norms can be decomposed into peer influence and superior influence. Therefore, the DTPB model provides a more comprehensive understanding of the determinants of individual intentions and behaviors (Wu & Chen, 2017).

The conceptual framework of this study selected peer influence, superior influence, and

subjective norms as potential variables to understand the impact of the surrounding environment on students' behavioral intentions.

### **Task Technology Fit**

Task technology fit is the foundational support for individuals using technology to carry out specific tasks. It establishes a basis for the value created by matching task demand with technology (Goodhue et al., 2000). Li et al. (2022) believe that it indirectly influences the inclination of college students toward utilizing online learning, primarily via the intermediation of perceived usefulness, perceived ease of use, and attitude. College students believe that the more an LMS platform can cater to their requirements, the more beneficial and convenient they perceive it to be. Zhi (2018) emphasizes how adapting to task technology fit positively influences online learning behavior. This suggests that the operational functionality of an online learning platform plays a crucial role in determining whether a learner will utilize the platform to fulfill their educational requirements. The more users use mobile learning software to learn and the software's technical features they understand, the higher the user's perception of the ease of use and usefulness of mobile learning application software (Jing, 2015).

This article selects task technology fit as a latent variable in this article's conceptual model to measure the impact of technology matching on students' perceived usefulness and perceived ease of use.

### **Subjective Norm**

Subjective norms refer to the person's perception that most people who are important to him think he should or should not perform the behavior in question (Fishbein & Ajzen, 1975). Liaw et al. (2007) study found that subjective norms affect student satisfaction and perceived learning outcomes in an online learning environment. Yan and Horwitz's (2008) research consider subjective norms influencing students' intention to participate in online learning projects. Kumar et al. (2020) emphasized that subjective norms positively shape learners' attitudes toward e-learning. Al-Emran et al. (2016) found that subjective norms primarily affect students' behavioral intentions to adopt mobile learning. Park (2009) argued that subjective norms positively affect students' behavioral intentions to use e-learning systems. Subjective norms greatly influence students' adoption and effective use of online learning technologies (Chang et al., 2013).

### **Attitude**

Attitude is the personal perception of feelings or emotions associated with using target technology (Davis, 1989). Chen and Jang (2010) found that students with a positive attitude toward online learning are more likely to be actively engaged in online classes and perform better. Previous research has also found that online learning can help develop self-directed learning skills. However, success depends mainly on learners' attitudes toward learning and their ability to adapt to the online environment (McLoughlin & Lee, 2007). Artino (2008) When examining students' attitudes and satisfaction with online courses and their impact on academic performance, it was found that their attitudes positively correlated with their satisfaction with online learning and their perceived learning outcomes.

### **Behavior Intention to Use**

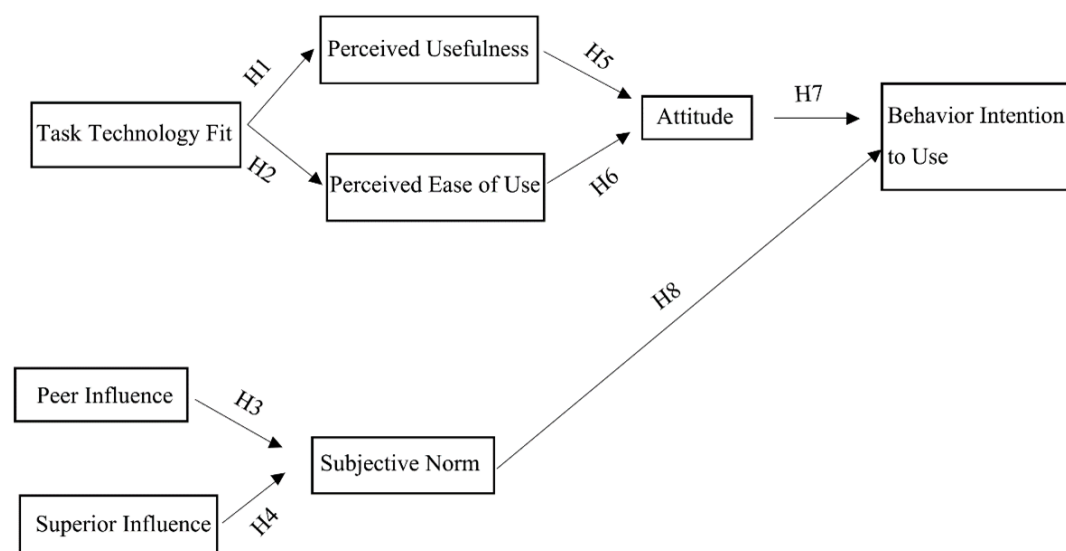
behavioral intention to use refers to a user's predicted or planned future behavior, and it is theorized to be an immediate antecedent of actual system use (Davis et al., 1989). Venkatesh and Bala (2008) found behavioral intention to use technology in the context of online learning, stating that student acceptance and use of technology are crucial for the success of online learning environments.

Tarhini et al. (2013) examined the factors influencing users' behavioral willingness to use e-learning in higher education in the UK and Lebanon. It concludes that subjective norms, performance expectations, and facilitating conditions significantly predict behavioral intent using e-learning. Bag et al. (2022) found that perceived usefulness, perceived ease of use, attitude, and subjective norm significantly affect the use of students' online learning. Budu et al. (2018) also found that perceived usefulness, ease of use, and attitudes toward e-learning significantly impact the behavioral intention to use e-learning. Furthermore, based on the theory of planned behavior, Huang et al. (2020) showed that attitude, subjective norm, and perceived behavioral control significantly influence the behavioral intention to adopt virtual reality in online learning.

### Conceptual Framework

To establish the framework of this study, the researcher drew on the TAM model and two other model frameworks to conduct research. Zhi (2018) integrated the DTPB and TAM models to study the influencing factors of college students' online learning behavior. Peer influence and superior influence were found to have a significant impact on subjective norms. Wu and Chen (2017) integrated the TAM model and task Technology Fit model, studied students continued use intention of online MOOC teaching, and found that task technology fit has a positive impact on perceived usefulness and perceived ease of use.

Based on the above research, the researcher integrated three theoretical frameworks and the conceptual framework proposed all variables related to this study. As shown in Figure 1, the conceptual framework shows the causal relationship between variables and aims to analyze the factors that affect Beijing students' willingness to use Rain Classroom.



**Figure1.** *Conceptual Framework*

**Note:** Constructed by the Author

This study aims to explore the factors that influence the behavioral intention to use the domestic LMS platform - Rain Classroom among undergraduates from three public universities in Beijing,

China, taking into account eight essential variables: task technology fit, peer influence, superior influence, perceived usefulness, perceived ease of use, subjective norms, attitudes, and behavioral intention to use. Furthermore, this study delves into the causal relationships between these variables to identify the determinants of behavioral intention to use.

According to the research aim and previous studies, conclude the hypothesis:

- H<sub>0</sub>1: Task technology fit has not significantly impacted perceived usefulness.
- H<sub>a</sub>1: Task technology fit has a significant impact on perceived usefulness.
- H<sub>0</sub>2: Task technology fit has not significantly impacted perceived ease of use.
- H<sub>a</sub>2: Task technology fit significantly impacts perceived ease of use.
- H<sub>0</sub>3: Peer influence has not significantly impacted subjective norms.
- H<sub>a</sub>3: Peer influence has a significant impact on subjective norms.
- H<sub>0</sub>4: Superior influence has not significantly impacted subjective norms.
- H<sub>a</sub>4: Superior influence has a significant impact on subjective norms.
- H<sub>0</sub>5: Perceived usefulness has a significant impact on attitude.
- H<sub>a</sub>5: Perceived usefulness has a significant impact on attitude.
- H<sub>0</sub>6: Perceived ease of use has a significant impact on attitude.
- H<sub>a</sub>6: Perceived ease of use has a significant impact on attitude.
- H<sub>0</sub>7: Attitude has not significantly impacted behavior intention to use.
- H<sub>a</sub>7: Attitude has a significant impact on behavior intention to use.
- H<sub>0</sub>8: Subjective norm has not significantly impacted behavior intention to use.
- H<sub>a</sub>8: Subjective norm has a significant impact on behavior intention to use.

## Methodology

The purpose of this study is to investigate the behavioral intention to use Beijing undergraduate students on the LMS platform - Rain class. The students are from the Beijing Union University (BUU), the Beijing City University (BCU), and the Beijing Institute of Graphic Communication (BIGC). This study used quantitative methods to collect data on students' intentions.

### Research Instrument

The research used quantitative analysis and questionnaires to collect the data. The questionnaire consisted of three main parts: screening questions, demographic information, and measuring all variables using a five-level Likert scale.

### Data Collection and Analysis

After assessing the content's validity and the reliability assessment's consistency, 500 questionnaires were distributed to undergraduate students at the three target universities, and the statistical tools SPSS and AMOS were used. In addition, the evaluation of discriminant validity was carried out using Confirmatory Factor Analysis (CFA), which also involved the extraction of average variance (AVE), computation of composite reliability (CR), determination of factor load, and assessment of T-value. Subsequently, Structural Equation Modelling (SEM) was employed to examine the hypothesis outcomes and explore the direct, indirect, and comprehensive impacts of correlations among the variables.

### Sample Size and Sampling Strategy

Fifty-six thousand four hundred-seven undergraduate students at the three target universities once again had three months or more previous experience using rain classes and ultimately comprised





the sample. A sample of 550 participants was selected, of which 500 were deemed valid after verification. Based on the proportion of the total population, the sample size consisted of 254 BUU students, 205 BCU students, and 91 BIGC students.

## Results and Discussion

### Demographic Information

Table 3 summarizes the detailed information of 500 respondents, of which 82.4% are from freshman and sophomore year students. The reason is that the undergraduate course focuses on the first and second grades of the undergraduate course, detailed in Table 3.

**Table 3** *Demographic Information*

Demographic Information (n=500)		Frequency	Percentage
Gender	Male	268	53.6%
	Female	232	46.4%
Grade	Freshman	277	55.4%
	Sophomore	135	27.0%
	Junior	56	11.2%
	Senior	32	6.40%
University	BUU	250	64.0%
	BCU	189	21.0%
	BIGC	61	8.60%

### Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is a statistical technique used to evaluate the measured properties of a potential variable, test the absolute fit of a hypothesized factor structure, and examine the relationship between a potential variable and an observed metric<sup>8</sup>

The CFA is used to determine whether the number and load pattern of each observed variable is consistent with theoretical predictions derived from the robustness of the hypothesis (Brow,2015). include chi-square Value to Degree of Freedom (CMIN/DF), Goodness of Fit Index (GFI), include Chi-Square Value to Degree of Freedom (CMIN/DF), Goodness of Fit Index (GFI), Adjust Goodness of Fit Index (AGFI), and Root Mean Square Error of Approximation (RMSEA) (kline,2015). According to the criteria shown in Table 4 and the Practical values of this study, it can be confirmed that all the goodness-of-fit indicators used in the CFA evaluation are valid.

**Table 4** *Goodness of Fit for Confirmatory Factor Analysis*

Index	Criterion	Source	Practical values
CMIN/DF	<3	Hair et al. (2010)	2.057
GFI	>0.90	Bagozzi & Yi (1988)	0.912
AGFI	>0.80	Sica & Ghisi (2007)	0.889
CFI	>0.90	Bentler (1990)	0.976
NFI	>0.90	Bentler& Bonnet (1980)	0.954
TLI	>0.90	Bentler& Bonnet (1980)	0.971
RMSEA	<0.05	Pedroso et al. (2016)	0.046

**Note:** Constructed by the Author



**Table 5** *Confirmatory Factor Analysis Result, Composite Reliability (CR), and Average Variance Extracted (AVE)*

Variable	Factor Loading >0.5	S.E.	T-value >1.98 & p-value<0.5	CR (pc) >0.7	AVE (pv) >0.5
Task Technology Fit (TTF)	.907				
TTF1	.890	.028	30.943***	0.948	0.820
TTF2	.920	.028	33.724***		
TTF3	.906	.030	32.410***		
TTF4					
Perceived Usefulness (PU)					
PU1	.888				
PU2	.957	.028	36.499***	0.969	0.885
PU3	.950	.029	35.810***		
PU4	.967	.029	37.697***		
Perceived Ease of Use (PEOU)					
PEOU1	0.874				
PEOU2	0.897	.036	27.141***	0.903	0.699
PEOU3	0.794	.040	22.119***		
PEOU4	0.774	.041	21.229***		
Attitude (AT)					
AT1	.895				
AT2	.897	.033	27.783***	0.906	0.764
AT3	.828	.035	24.569***		
Behavior Intention to use (BITU)	.779				
BITU1	.942	.048	24.866***	0.951	0.829
BITU2	.967	.047	25.779***		
BITU3	.942	.049	24.900***		
BITU4					
Peer Influence (PI)					
PI1	.904				
PI2	.874	.038	26.207***	0.904	0.759
PI3	.834	.041	24.395***		
Superior Influence (SI)					
SI1	.815				
SI2	.873	.048	21.873***	0.885	0.720
SI3	.857	.047	21.469***		



Variable	Factor Loading >0.5	S.E.	T-value >1.98 & p-value<0.5	CR (pc) >0.7	AVE (pv) >0.5
Subjective Norm (SN)					
SN1	.960				
SN2	.957	.023	43.921***	0.926	0.809
SN3	.768	.035	24.386***		

\*\*\*=P<0.001, \*\*=P<0.01, \*=P<0.05

**Note:** Constructed by the Author

**Table 6** Discriminant Validity

Correlation	TTF	PU	PEOU	AT	BITU	PI	SI	SN
TTF	0.672							
PU	0.365	0.783						
PEOU	0.412	0.506	0.489					
AT	0.642	0.282	0.309	0.584				
BITU	0.370	0.511	0.438	0.298	0.687			
PI	0.249	0.285	0.298	0.164	0.394	0.576		
SI	0.323	0.401	0.422	0.253	0.455	0.508	0.518	
SN	0.386	0.526	0.415	0.399	0.543	0.330	0.422	0.654

**Note:** Constructed by the Author

### Structural Equation Model (SEM)

This study's structural equation model (SEM) was validated after CFA. An SEM method evaluates a specific set of linear coefficients to determine if the proposed causal explanation matches. SEM detection can observe the correlation between variables and potential variables, and can also estimate measurement errors, representing changes in observed variables that cannot be explained by potential variables (Brown, 2015). Table 6 shows that even after AMOS correction, the combined values of CMIN/DF, GFI, AGFI, CFI, NFI, TLI, and RMSEA are above the required standard. Therefore, it is proved that the fit of SEM meets the standard.

**Table 7** Goodness of Fit for Structural Equation Modeling

Index	Criterion	Source	Practical values
2/df (CMIN/df)	<5	Hair et al. (2010)	2.990
GFI	>0.85	Bagozzi & Yi (1988)	0.886
AGFI	>0.80	Sica & Ghisi (2007)	0.857
CFI	>0.80	Bentler (1990)	0.954
NFI	>0.80	Bentler & Bonnet (1980)	0.932
TLI	>0.80	Hooper et al. (2008)	0.946
RMSEA	<0.08	Hooper et al. (2008)	0.063

**Note:** Constructed by the Author



## Hypothesis Testing Results

Table 8 shows the interconnectivity of the individual items. Each hypothesis was tested using standardized path coefficients ( $\beta$ ) and T-values to determine the strength and significance of the relationship. The results show that all P values are less than 0.001, which proves that all hypotheses are valid. Research proves that task technology fit, peer influence, superior influence, perceived usefulness, perceived ease of use, attitude, and subjective norm have a particular influence on students' behavior and intention to use Rain Classroom.

**Table 8** Hypothesis Result of the Structural Equation Modeling

Hypotheses	Path	Standardized Path Coefficient ( $\beta$ )	T-Value	Tests Result
H1 <sub>a</sub>	PU ← TTF	0.301	8.206***	Supported
H2 <sub>a</sub>	PEOU ← TTF	0.425	9.703 ***	Supported
H3 <sub>a</sub>	AT ← PU	0.217	3.436 ***	Supported
H4 <sub>a</sub>	AT ← PEOU	0.243	4.360 ***	Supported
H5 <sub>a</sub>	SN ← PI	0.160	3.567***	Supported
H6 <sub>a</sub>	SN ← SI	0.458	9.350***	Supported
H7 <sub>a</sub>	BITU ← AT	0.183	4.910***	Supported
H8 <sub>a</sub>	BITU ← SN	0.479	11.913***	Supported

**Note:** \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$

**Note:** Constructed by the Author

The study confirmed all the proposed hypotheses and the significant relationships between the variables under the framework.

H1: The hypothesis relationship suggests a significant influence of Task Technology Fit on Perceived Usefulness. This is indicated by a standardized path coefficient ( $\beta = 0.301$ ), which holds substantial importance at  $p < 0.001$ , as represented by three asterisks. The statistical strength of this significance is further emphasized by a t-value of 8.206. Therefore, the empirical evidence supports this hypothesis, implying that an increase in Task Technology Fit will lead to an augmented Perceived Usefulness.

H2: The hypothesis relationship suggests a significant influence of Task Technology Fit on Perceived Ease of Use. This is indicated by a standardized path coefficient ( $\beta = 0.425$ ), which holds substantial importance at  $p < 0.001$ , as represented by three asterisks. The statistical strength of this significance is further emphasized by a t-value of 9.703. Therefore, the empirical evidence supports this hypothesis, implying that an increase in Task Technology Fit will lead to an augmented Perceived Ease of Use.

H3: The hypothesis relationship suggests a significant influence of Perceived Usefulness on Attitude. This is indicated by a standardized path coefficient ( $\beta = 0.217$ ), which holds substantial importance at  $p < 0.001$ , as represented by three asterisks. The statistical strength of this significance is further emphasized by a t-value of 3.436. Therefore, the empirical evidence supports this hypothesis, implying that an increase in Perceived Usefulness will lead to an augmented Attitude.

H4: The hypothesis relationship suggests a significant influence of Perceived Ease of Use on Attitude. This is indicated by a standardized path coefficient ( $\beta = 0.243$ ), which holds substantial

importance at  $p < 0.001$ , as represented by three asterisks. The statistical strength of this significance is further emphasized by a t-value of 4.36. Therefore, the empirical evidence supports this hypothesis, implying that an increase in Perceived Ease of Use will lead to an augmented Attitude.

H5: The hypothesis relationship suggests a significant influence of Peer Influence on Subjective Norms. This is indicated by a standardized path coefficient ( $\beta = 0.160$ ), which holds substantial importance at  $p < 0.001$ , as represented by three asterisks. The statistical strength of this significance is further emphasized by a t-value of 3.567. Therefore, the empirical evidence supports this hypothesis, implying that an increase in Peer Influence will lead to an augmented Subjective Norm.

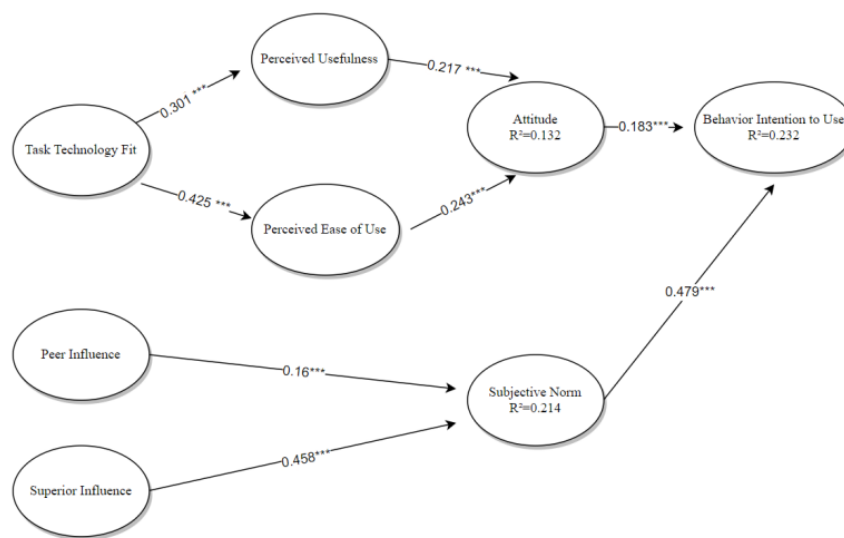
H6: The hypothesis relationship suggests a significant influence of Superior Influence on Subjective Norm. This is indicated by a standardized path coefficient ( $\beta = 0.458$ ), which holds substantial importance at  $p < 0.001$ , as represented by three asterisks. The statistical strength of this significance is further emphasized by a t-value of 9.35. Therefore, the empirical evidence supports this hypothesis, implying that an increase in Superior Influence will lead to an augmented Subjective Norm.

H7: The hypothesis relationship suggests a significant influence of Attitude on Behavior Intention to Use. This is indicated by a standardized path coefficient ( $\beta = 0.183$ ), which holds substantial importance at  $p < 0.001$ , as represented by three asterisks. The statistical strength of this significance is further emphasized by a t-value of 4.91. Therefore, the empirical evidence supports this hypothesis, implying that an increase in Attitude will lead to an augmented Behavior Intention to Use.

H8: The hypothesis relationship suggests a significant influence of Subjective Norms on Behavior Intention to Use. This is indicated by a standardized path coefficient ( $\beta = 0.479$ ), which holds substantial importance at  $p < 0.001$ , as represented by three asterisks. The statistical strength of this significance is further emphasized by a t-value of 11.913. Therefore, the empirical evidence supports this hypothesis, implying that an increase in Subjective Norms will lead to an augmented Behavior Intention to Use.

### Direct, Indirect, and Total Effects

This model further studies several parameters that affect students' intention to use and the relationship between parameters. The model shows that the attitude variance is 13.2%,  $R^2 = 0.132$ . The study found that perceived usefulness positively impacts attitude, which shows that the more useful Rain Classroom makes students feel when using it, the more positive students' attitudes towards its use will be. The most significant impact on attitudes is perceived ease of use. The easier it is to use Rain Classroom, the more positive students' attitudes towards its use will be. The variance of subjective norms is 21.4%, that is,  $R^2 = 0.214$ . This shows that peers, teachers, and schools positively impact students' intention to use Rain Classroom. Among them, the most obvious influence comes from teachers and schools. The final variance of behavioral intention to use is 23.2%,  $R^2 = 0.232$ . This shows that students' attitude towards Rain Classroom ultimately determines students' intention to use it. The more positive a student's attitude is, the more likely they will use Rain Classroom.



**Figure 2 : Path Diagram Analysis**

**Note:** \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$

**Note:** Constructed by the Author

## Conclusions

This study explores factors that affect the use of interest in the Rain Classroom in Beijing. The conceptual framework has eight hypotheses to detect the correlation between task technology matching, peer impact, superior influence, perceptual usefulness, ease of use, attitude, and subjective specification. To test, the study took 500 students from three target schools to participate in the questionnaire. To determine whether the data conforms to the framework built by the institute through verification factor analysis (CFA). The structural equation model (SEM) evaluates the relationship between the behavior intention to use and potential variables.

Research results of this article show that task technology fit has a positive impact on perceived usefulness and perceived ease of use. It shows that the degree of adaptability of technology will directly affect students' perception. Perceived ease of use has the most intuitive impact on attitude, while perceived usefulness also positively impacts attitude. In addition, peer and superior influence positively impact subjective norms, and the effect of superior influence is more significant. The final results show that subjective norms have a more positive impact on students' behavioral intention to use, and students' attitudes will also affect their behavioral intention to use Rain Classroom.

Among these, it is worth noting that although students' attitudes and subjective norms will impact their intention to use Rain Classroom, the influence of subjective norms is much more significant than that of attitudes. The factors that affect subjective norms mainly come from the influence of superiors. This shows that the requirements and hopes of schools and teachers will significantly increase students' intention to use Rain Classroom.

## Recommendations for Practice

Based on the statistical data and the research findings of this quantitative behavior intention to use investigation, the researchers put forward the following suggestions to help LMS platforms improve usage intention. First of all, in this article, the potential variable that has the most significant impact on students' behavioral intention to use is subjective norms. It can be seen that students in the three target colleges and universities are encouraged and expected to use Rain Classroom by positive



schools, teachers, and classmates. Therefore, creating an excellent online education atmosphere is necessary to encourage more students to participate in Rain Classroom learning actively.

Secondly, students' attitudes also positively affect their intention to use Rain Classroom. The more positive the students' attitude is, the higher their intention to use it will naturally be. According to this survey, two potential variables influence student attitudes: perceived usefulness and perceived ease of use. Both positively affect attitudes, with perceived ease of use being slightly higher.

Therefore, the researcher believes that in the subsequent teaching process, the operations should be appropriately simplified, and the Rain Classroom platform should also provide simple platform programs and practical manual help to students. Or use videos, pictures, and texts to inform students how to use Rain Classroom to preview before class, sign in during class, attend class, and ask questions after class. At the same time, it is also necessary to provide, in addition to the course itself, other videos, materials, etc., to assist learning so that students think that online topics are more valuable than traditional classes, and their attitudes will naturally be more positive.

Finally, task technology fit also affects perceived usefulness and ease of use, with a more noticeable impact on perceived ease of use. Therefore, Rain Classroom should try adapting to Chinese undergraduate courses. When students find that the platform has many videos and materials that are classified and adapted to the course, which can help them understand and complete homework after class, they will think that the Rain Classroom platform is very Easy to use and valuable. This will also indirectly affect their attitude towards and intention to use the platform.

After implementing these recommendations, students will be more adaptable to the domestic LMS platform and have more positive intentions in learning attitudes and usage.

### Limitations and Further Exploration

The research only focuses on the software Rain Classroom. Although the domestic LMS platform software can play a specific role in guiding and improving other software, it is more helpful to iterate the Rain Classroom software. Future research can study multiple software in parallel to understand the advantages and disadvantages of domestic online learning platforms to help domestic software develop better.

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