



Factors Affecting University Students' Behavioral Intention to Use Teaching Application

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Received 09/07/2024

Revised 12/07/2024

Accepted 12/08/2024

Abstract

Background and Aim: Blended learning has become a prominent approach for improving educational and training efforts. The Rain classroom is a widely utilized electronic learning platform in China. This study explored the factors that affected student behavioral intentions regarding the Rain Classroom applications. The latent variables investigated in the study include perceived usefulness (PU), performance expectancy (PE), attitude to use (ATT), virtual classroom quality (VCQ), instructor characteristics (IC), social influence (SI), and behavioral intentions (BI). The objective of the research is to determine the extent to which each variable influences the use of the Rain Classroom applications.

Materials and Methods: The research study conducted at Zhanjiang University of Science and Technology in China aimed to investigate the factors affecting the use of the Rain Classroom. The survey, which involved a sample of 500 students, utilized structural equation modeling (SEM) and confirmatory factor analysis (CFA) to analyze the collected data.

Results: The findings of the data analysis revealed that all the factors influencing behavioral intention were statistically significant, and the hypotheses were duly corroborated. Notably, performance expectancy (PE) emerged as the most influential determinant of behavioral intentions (BI) towards the adoption of the Rain Classroom.

Conclusion: The findings of this study have underscored the significant role of key factors in shaping behavioral intentions to utilize the Rain Classroom. The analysis conducted unveiled that the performance expectancy and the user's attitude towards the application were pivotal factors in determining the willingness of individuals to adopt and engage with the application.

Keywords: Teaching application factors; University students; Behavioral intentions

Introduction

The rapid progress of information and communications technology (ICT) has significantly reshaped education on a global scale. With society becoming increasingly technology-driven, ICT has been integrated into all aspects of human life, leading to significant developments in the field of education (Vidakis & Charitakis, 2018). Blended learning has become a prominent approach for improving educational and training efforts. Blended learning offers a unique and dynamic educational experience for students. This approach not only enhances student engagement and motivation but also provides educators with valuable data and insights into individual student progress, allowing for personalized instruction and targeted interventions (Riffell & Sibley, 2005). To advance the goal of China's education informatization development, the concept of "Internet + education" is widely utilized, deeply integrating information technology into education and teaching. An increasing number of new technologies are being applied to the field of education. Parveen & Zamir (2020) claimed that new technologies are not only in Online courses online courses are shining brightly, and more and more information technologies are beginning to enter traditional classrooms to help with teaching.

It is essential to understand the potentials and challenges that come with blended learning (Parveen 2020). Numerous hybrid e-learning initiatives often fall short of attaining their intended learning and teaching objectives due to the utilization of unsuitable technology, inadequate instructor qualities, or insufficient attention and support from the organization. (Engelbrecht, 2005; Selim, 2007). Despite its popularity among domestic researchers and teachers, the Rain Classroom lacks global recognition compared to similar online learning platforms like Google Meet or Microsoft Teams. There has been limited research conducted on the implementation and utilization of Rain Classroom. Its primary aim is to enhance the overall educational experience before, during, and after class, ultimately maximizing the effectiveness of teaching and learning (Zeng, 2016). The Extended Unified Theory of Acceptance and Use



of Technology Model (UTAUT2) and the Technology Acceptance Mode (TAM) have been widely employed by researchers (Kwak, Seo & Ahn, 2022). However, only a few researchers have attempted to apply the UTAUT paradigm to Rain Classroom.

Current studies on Rain Classroom have not fully explored all the essential factors that could significantly influence students' behavioral intentions. Therefore, identifying the variables that impact students' behavioral intentions towards Rain Classroom remains a crucial task. Among these challenges, the behavioral intentions of learners and teachers are significant. Therefore, a thorough investigation is necessary to evaluate the students' willingness to use teaching applications for the educational process.

A key element in the effective integration of educational technology is students' behavioral intention to use teaching applications. This goal is a reflection of students' willingness to interact with digital tools, which is impacted by how beneficial and user-friendly they find the applications to be. The Technology Acceptance Model (TAM), as proposed by Davis (1989), holds that users' acceptance and subsequent use of technology are primarily determined by perceived usefulness and perceived ease of use. Students are more likely to accept and make effective use of a teaching application when they feel that it will improve their learning and is user-friendly. To fully realize the advantages of educational technologies—like more individualized instruction and easier access to resources—this adoption is essential. Additionally, by comprehending the behavioral intentions of students, educators, and developers can create more user-friendly and effective teaching applications. Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT), which added elements such as social influence and enabling conditions to the TAM. These elements highlight how crucial peer pressure and a positive learning environment are in influencing students' intentions to use educational apps. A more conducive learning environment can be fostered and overall educational outcomes can be improved by considering these factors when developing more engaging and supportive educational tools that cater to students' needs and preferences.

The Rain classroom is a widely utilized electronic learning platform in China, providing intelligent terminals for seamless teacher-student connectivity. To effectively introduce Rain Classroom in higher education, it is essential to ensure its acceptance. It is essential to comprehend and recognize the primary factors that impact the adoption of Rain Classroom.

Objectives

The present research endeavors to elucidate the extent to which various factors, including social influence (SI), performance expectancy (PE), perceived usefulness (PU), virtual classroom quality (VCQ), instructor characteristics (IC), and attitude to use (ATT), contribute to shaping students' behavioral intention (BI) towards the utilization of the Rain Classroom.

Literature review

Perceived Usefulness

Perceived Usefulness (PU) is the measure of an individual or group's belief in a technology's ability to improve their work performance. The acceptance and use of a new system by users depends on their perception of its potential to enhance their job performance. According to Ladyshevsky's (2004) findings, students primarily focus on e-learning due to its perceived usefulness (PU). Perceived usefulness is a widely acknowledged factor influencing attitudes and usage of products and services.

H1: Perceived usefulness (PU) has a significant influence on attitudes to use in the adoption of the Rain Classroom.

Attitude to Use

Attitude to use (ATT) is a comprehensive evaluation of an individual's capacity to execute a particular behavior. It can be deduced that users' perspectives on technology are their subjective opinions, regardless of whether they are positive or negative (Azhari & Usman, 2021). Acceptance Model (TAM) underscores the correlation between attitude and intention, indicating that attitude plays a crucial role as an evaluative predisposition towards behavior. Azhari and Usman (2021) also stated that the impact of technology usage can be observed through the emotions that follow. These emotions may range from positive feelings such as comfort, pleasure, and a sense of being assisted, to negative feelings such as boredom.

H2: Attitudes to use (ATT) have a significant influence on Behavioral Intention (BI) in the adoption of the Rain Classroom.

Instructor characteristics

Instructor characteristics play a crucial role in creating an effective e-learning environment. These characteristics, such as timely response, technical knowledge, confidence, and innovativeness, enable instructors to encourage students to engage and learn. Alrousan et al. (2022) emphasized the importance of instructors possessing a deep understanding and motivation to effectively utilize e-learning technologies to enhance students' learning experiences. Many prior research studies have found that the traits of educators are essential in determining the perceived value of their instruction.

H3: Instructor characteristics (IC) have a significant influence on Perceived usefulness (PU) in the adoption of the Rain Classroom.

Virtual classroom quality

Virtual classroom quality refers to the degree to which technology offers a suitable learning environment for students. This encompasses aspects such as user interface design, reliability, usability, and service quality (Alrousan et al., 2022). According to Pham et al.'s (2019) research, the quality of online learning, particularly its functionality, usability, and media presentation of course materials, is crucial for its successful adoption by students.

H4: Virtual classroom quality (VCQ) has a significant influence on Perceived usefulness (PU) in the adoption of the Rain Classroom.

Performance expectancy

Performance expectancy, as defined by Venkatesh et al. (2003), denotes an individual's perception of how using a system will enhance their study or work performance. It is a key factor that influences users' perceptions of the usefulness and effectiveness of a technology. Therefore, technology developers need to focus on improving performance expectancy to increase the likelihood of technology acceptance (Chen, 2022). This refers to the belief that utilizing the system would result in improved student performance.

H5: Performance Expectancy (PE) has a significant influence on students' Behavioral Intention (BI) in the adoption of the Rain Classroom.

Social influence

Social influence, as defined by Venkatesh et al. in 2003, pertains to an individual's recognition of the significance of their actions considering the views and judgments of others. The opinions and recommendations of family, relatives, and colleagues can significantly influence an individual's decision to use a technology. Venkatesh et al. (2003) have provided evidence that social influence directly affects how individuals recognize and adopt new solutions. This finding highlights the importance of understanding the role of social factors in the acceptance and utilization of innovations.

H6: Social Influence (SI) has a significant influence on students' Behavioral Intention (BI) in the adoption of the Rain Classroom.

Behavioral intention

Behavioral intention or use is the extent to which an individual is inclined or motivated to engage in a particular behavior, as defined by Davis et al. (1989). This concept plays a significant role in determining the uptake and adoption of new technologies. It is important to understand individuals' intentions and motivations when it comes to embracing and incorporating these advancements into their lives. The TAM and UTAUT models have established that a person's Behavioral Intention significantly affects their actual behavior. This suggests that the more determined one is to carry out a specific action, the higher the likelihood of it being executed.

Conceptual Framework

A conceptual framework serves as a foundational academic research tool, derived from the examination of precedents, as illustrated in Figure 1. This study encompasses seven variables: Social Influence, Instructor Characteristics, Virtual Classroom Quality, Performance Expectancy, Perceived Usefulness, Attitude to Use, and Behavioral Intention.

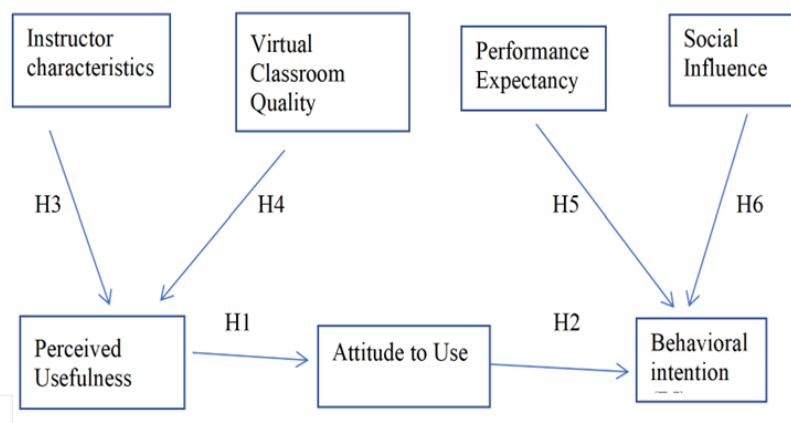


Figure 1 Conceptual Framework

Methodology

Research Instrument

The research utilized a quantitative methodology and a descriptive technique to establish the relation between technology acceptance and student behavioral intention to use the Rain Classroom at Zhanjiang University of Science and Technology in China. To effectively generalize results, an online survey-based questionnaire was employed to gather data from first-year college students. 30 scale items, derived from earlier studies, were employed to assess the latent variables. The seven variables were PE(5items), SI(4items), BI(5items), PU(3items), VCQ(5items), IC(5items) and AU(3items). Each item in the study was assessed using a five-point scale, which spanned from 1 = Strongly Disagree to 5 = Strongly Agree.

The researcher diligently sought the expertise of three professionals from related fields to assess the validity of the items before dissemination. The evaluation process employed the Item-Objective Congruence (IOC) index, which yielded scores of 0.67 or higher, thereby confirming the validity of the questionnaire items. In addition, the internal consistency reliability was assessed with 30 students for the pilot test, the measurement scales were assessed for reliability using Cronbach's alpha coefficients, with all values exceeding 0.90, indicating a satisfactory level of reliability for exploratory research (Hair et al., 1998).

Population and Sample: Studying population is essential for all first-year students who have studied the outline of modern Chinese history from Zhanjiang University of Science and Technology in September 2022, A total of 5048 students used the blended learning mode supported by Rain Classroom, they are aged between 18 and 20. The purposive sampling technique and stratified quota sampling method have been utilized to select the population for this study. The quantitative section of the study included a sample size of 500 individuals from 2 different majors who were aforementioned students. One of the majors is English, and the other is Chinese education.

Table 1 Population and Sample Size

Major & class	English major class1	English major class2	English major class3	English major class4	Chinese education class1	Chinese education class2	Chinese education class3	Total
Class size	140	136	140	130	130	130	140	946
Sample	74(15%)	71(14%)	74(15%)	69(14%)	69(14%)	69(14%)	74(15%)	500

Data Collection Process: Before filling out the survey, participants were instructed to review the cover letter, which detailed the study's aims. They were assured that their involvement and responses would remain anonymous, confidential, and voluntary. Participants were also made aware of their right to



withdraw from the study at any point without facing any form of pressure or coercion. They were reminded that there were no correct or incorrect answers and were encouraged to provide their genuine opinions as objectively as possible. It was emphasized that agreeing to participate implied consent and that the data collected would be used exclusively for the study's purposes.

Data Analysis: The researcher, employing Jamovi and Amos software, successfully gathered 470 questionnaires with pertinent responses. Subsequent confirmatory factor analysis (CFA) was conducted to assess discriminant validity, average variance extracted (AVE), composite reliability (CR), factor loading, and t-values. Furthermore, a structural equation model (SEM) was employed to investigate the hypotheses and elucidate the interrelationships among the variables.

Results

Demographic Information

The survey was administered to a total of 500 students, all of whom responded. The demographic breakdown consisted of 230 male participants, accounting for 45.5% of the total, and 270 female participants, comprising 54.5% of the respondents. However, the analysis excluded 22 incomplete responses and 8 participants identified as multivariate outliers, resulting in a final sample of 470 valid data points for the study.

Table 2 Demographic Information of Samples

Variable	Category	Frequency	Percentage
Gender	Male	230	45.5%
	Female	270	54.5%
	Total	500	100%
Year of Study	Year 1	500	100%

Mean Values of the Variables: The mean, a statistical measure, represents the average score and reflects the central tendency of the participants' attitudes toward the variables under investigation. As shown in Table 3, the overall mean value across the seven variables in the study indicates the general strength of the participants' perspectives on the subject matter.

Table 3 Descriptive Analysis of Each Variable

Variable	Mean	Standard Deviation
Perceived Usefulness	3.75	1.312
Attitude to Use	3.71	1.339
Behavioral Intention	3.784	1.283
Instructor Characteristics	3.768	1.305
Virtual Classroom Quality	3.788	1.295
Performance Expectancy	3.762	1.281
Social influence	3.81	1.281

Confirmatory Factor Analysis (CFA)

The research findings demonstrated a favorable goodness-of-fit for the measurement model. The CMIN/DF ratio stood at 1.885, well below the recommended threshold of 5.00 (Awang, 2012). The goodness-of-fit index (GFI) attained a value of 0.905, exceeding the 0.85 criterion recommended by Sica and Ghisi (2007). Furthermore, the adjusted goodness-of-fit index (AGFI) reached a value of 0.885, surpassing the 0.80 criterion proposed by the same authors. Collectively, these indices indicated the acceptability and reliability of the measurement model.





The statistical summary presented in Table 4 demonstrated remarkable reliability, with the composite reliability (CR) value exceeding the recommended threshold of 0.70. Additionally, the average variance extracted (AVE) surpassed the 0.50 benchmark, indicating a satisfactory level of convergent validity. These compelling results validated the convergent and discriminant validity of the confirmatory factor analysis (CFA) findings, reinforcing the robustness and soundness of the underlying construct measurements.

Table 4: Factor Loading, AVE, and CR

Latent variables	Observation variable	Estimate	S.E.	P	CR>0.7	AVE>0.5
PU	PU1	0.838			0.89	0.73
	PU2	0.855	0.048	***		
	PU3	0.869	0.049	***		
ATT	ATT1	0.866			0.89	0.73
	ATT2	0.866	0.042	***		
	ATT3	0.830	0.041	***		
BI	BI1	0.843			0.917	0.688
	BI2	0.811	0.044	***		
	BI3	0.797	0.045	***		
	BI4	0.837	0.043	***		
	BI5	0.856	0.046	***		
IC	IC1	0.834			0.909	0.666
	IC2	0.813	0.048	***		
	IC3	0.769	0.045	***		
	IC4	0.841	0.048	***		
	IC5	0.820	0.047	***		
VCQ	VCQ1	0.834			0.906	0.658
	VCQ2	0.806	0.047	***		
	VCQ3	0.805	0.046	***		
	VCQ4	0.802	0.047	***		
	VCQ5	0.809	0.047	***		
PE	PE1	0.839			0.909	0.667
	PE2	0.809	0.045	***		
	PE3	0.824	0.043	***		
	PE4	0.806	0.047	***		
	PE5	0.805	0.046	***		
SI	SI1	0.830			0.898	0.688
	SI2	0.854	0.047	***		
	SI3	0.836	0.049	***		
	SI4	0.795	0.047	***		

Discriminant validity has been confirmed according to Fornell & Larcker (1981) when the square root of the Average Variance Extracted (AVE) is larger than the coefficient of any intercorrelated construct.



This was illustrated in Table 5, where the square root of the AVE for all constructs along the diagonal line exceeded the inter-scale correlations. Therefore, the discriminant validity was ensured.

Table 5 Discriminant Validity

	PU	ATT	BI	IC	VCQ	PE	SSI
PU	0.854						
ATT	0.589	0.854					
BI	0.57	0.591	0.829				
IC	0.632	0.684	0.651	0.816			
VCQ	0.559	0.609	0.559	0.641	0.811		
PE	0.633	0.679	0.622	0.723	0.624	0.817	
SI	0.579	0.641	0.553	0.657	0.585	0.655	0.829

Structural Equation Model (SEM)

In this section, the goodness of fit of the SEM model was evaluated through the assessment of six indices: CMIN/DF, GFI, AGFI, CFI, NFI, and RMSEA. The covariance matrix was corrected, and the goodness-of-fit results before and after the correction are summarized in Table 6.

Table 6 Goodness-of-Fit for Structural Model before and after Adjustment

Fit Index	Acceptable Criteria	Statistical Values	
		Before Adjustment	After Adjustment
CMIN/df	<5.00 (Awang, 2012)	4.491	2.39
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.765	0.883
AGFI	≥ 0.80(Sica & Ghisi, 2007)	0.727	0.861
NFI	≥ 0.80 (Bentler, 1990)	0.828	0.917
CFI	≥ 0.80 (Sharma et al., 2005)	0.857	0.950
TLI	≥ 0.80 (Wu & Wang, 2006)	0.844	0.944
RMSEA	<0.08 (Pedroso et. al., 2016)	0.091	0.055
Model Summary		Not in harmony with empirical data	In harmony with empirical data

Note: CMIN/DF=The Ratio of the Chi-Square Value to Degree of Freedom, GFI=Goodness of-Fit Index, AGFI= Adjusted Goodness-of-Fit Index, CFI=Comparative Fit Index, NFI=Normed Fit Index, RMSEA= Root-Mean-Square Error of Approximation.

Research Hypothesis Testing Result

The strength of association between the independent and dependent variables suggested in the hypothesis is determined by regression coefficients or standardized path coefficients. SPSS 26 and AMOS 26 software were used for path analysis in this study.

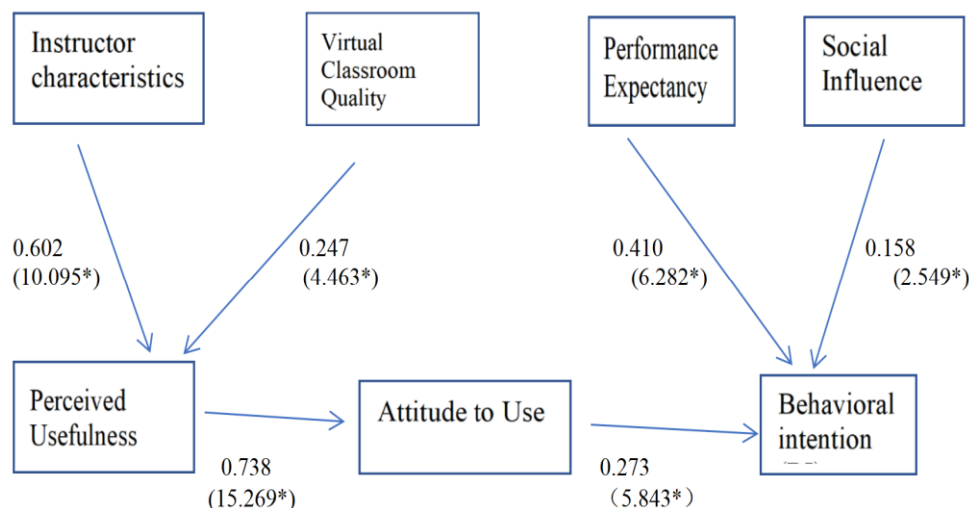


Figure2 Result of the Structural Model

Table 7 Hypothesis Testing Result of the Structural Model

Hypothesis	Standardized Coefficients (β)	t-value	Result
H1: ATT←PU	0.738	15.269*	Supported
H2: BI←ATT	0.273	5.843*	Supported
H3: PU←IC	0.602	10.095*	Supported
H4: PU←VCQ	0.247	4.463*	Supported
H5: BI←PE	0.410	6.282*	Supported
H6: BI←SI	0.158	2.549*	Supported

Note: ***= $p < 0.001$; **= $p < 0.01$; *= $p < 0.05$.

As shown in the data in Table 7 and Figure 2, six hypotheses are supported. The explanation of each hypothesis is presented in the following section.

The research findings presented suggest a compelling relationship between perceived usefulness and attitudes toward the use of the Rain Classroom. The standardized path coefficient of 0.738 and a t-value of 15.269 for the hypothesized path (H1) indicate a strong and statistically significant association between these two constructs. This underscores the pivotal role that the perceived usefulness of a technology plays in shaping individuals' attitudes and, ultimately, their inclination to adopt or utilize it.

The impact of attitude toward the use on behavioral intention to use the Rain Classroom application has been empirically demonstrated. The standardized path coefficient between these two variables is 0.273, with a t-value of 5.843 in H2. This suggests that when students hold a favorable impression of using the Rain classroom application, they are more likely to exhibit an intent or willingness to utilize the platform.

The strongest impact on perceived usefulness is Instructor characteristics. The standardized path coefficient of 0.602 and a t-value of 10.095 in H3 demonstrate a strong relationship between these two variables. This finding suggests that the attributes and qualities of the instructor, such as their expertise, teaching style, and engagement with students, play a crucial role in shaping the perceived usefulness of the learning experience.

Another impact on perceived usefulness is Virtual classroom quality (VCQ) with a standardized path coefficient of 0.247 and t-value of 4.463 (H4). This finding suggests that the quality of the virtual classroom environment, including factors such as the technology infrastructure, instructional design, and user



experience, plays a crucial role in shaping students' perceptions of the overall usefulness of the learning platform.

Performance Expectancy (PE) has been found to have a significant impact on behavioral intention, as evidenced by the standardized path coefficient of 0.410 and a t-value of 6.282 in hypothesis 5 (H5). This suggests that individuals' perceptions of the potential benefits and usefulness of the Rain Classroom play a crucial role in shaping their intention to use or adopt it.

Social Influence (SI) is another factor that impacts behavioral intention with a standardized path coefficient of 0.158 and a t-value of 2.549 (H6). This finding underscores the importance of the social environment in shaping individual behavior and decision-making processes.

Conclusions

This study aimed to comprehensively analyze the crucial factors influencing the behavioral intention of using the Rain Classroom in educational institutions in Guangdong, China. The researcher has proposed six hypotheses to address the research questions, examining whether perceived usefulness, attitude to use, instructor characteristics, virtual classroom quality, performance expectancy, and social influence have direct or indirect impacts on the behavioral intention to use the Rain Classroom. The determinants of the research were adapted from two core theories: the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and three theoretical frameworks from previous studies.

In the present investigation, a sample of 500 students was selected for examination. The validity and reliability of the research model were assessed through Confirmatory Factor Analysis (CFA), and the model was subsequently refined by the evaluation results.

The results indicated that performance expectancy was the strongest predictor of behavioral intention to use, compared to attitude to use. Undoubtedly, it is the responsibility of lecturers and instructors to ensure that the content provided within the educational system is of the highest caliber and consistently updated. By doing so, they can better cater to the needs and expectations of the students they serve.

The perceived usefulness of a particular educational tool or resource can be significantly influenced by the instructor's characteristics, compared to the VCQ, which means understanding these instructor-related factors can provide valuable insights into the design and implementation of effective learning environments, ultimately enhancing the overall educational experience for students.

Perceived usefulness (PU) was found to have the most significant direct impact on students' attitudes toward utilizing the Rain Classroom platform and an indirect effect on the BI.

In the present study, the findings have successfully addressed the research inquiries and aligned with the established objectives. The data collected and the subsequent analysis provides a comprehensive understanding of the research problem under investigation.

Discussion

Based on the results, it showed that performance expectancy was the strongest predictor of behavioral intention to use, compared to attitude to use. Lv et al. (2023) also claimed that a student's positive attitude towards the discussed system and their anticipation of improving academic performance will increase their likelihood of using Rain Classroom. These findings underscore the importance of understanding and addressing users' expectations and needs when designing and implementing new systems or technologies.

The perceived usefulness of a particular educational tool or resource can be significantly influenced by the characteristics and attributes of the instructor. Factors such as the instructor's expertise, teaching methodology, and overall engagement with students have been identified as key antecedents that contribute to the perceived usefulness of the educational material. The analysis revealed a positive and statistically significant relationship between the instructor characteristics aspect of learning and the perceived usefulness in the adoption of the Rain classroom. This supports the previous studies of Ahmed (2010), Alqahtani and Rajkhan (2020), and Hadullo et al. (2017) that instructors' characteristics have a direct effect on the perceived usefulness of their educational offerings, as this can have a profound influence on student satisfaction and learning outcomes.

The importance of perceived usefulness in shaping attitudes and usage behaviors towards products and services is a well-established concept. The findings presented suggest that students' willingness to utilize the Rain classroom platform is contingent on their perceived benefits of doing so. This aligns with

the conclusions drawn from previous research in this domain. This is supported by the study of Teo and Zhou (2014), Singh et al. (2021), Hargreaves et al. (2022), and Arteaga Sánchez et al.(2013).

Implications for Practice

The research findings presented in this study provide valuable insights into the factors influencing the behavioral intention of undergraduate students to utilize the Rain Classroom.

Firstly, these findings suggest that students' perceptions of the system's ability to enhance their academic performance, as well as their overall attitude and disposition towards using the platform, play a crucial role in shaping their intention to engage with the Rain Classroom. While certain factors may have a more substantial impact, the study also reveals that other variables can exert a more moderate or negligible influence on the students' behavioral intention.

Secondly, these findings underscore the complex and multifaceted nature of the factors that shape students' willingness to adopt and utilize educational technologies, such as the Rain Classroom, within the academic setting. The implications of this research can inform the development of strategies and interventions aimed at promoting the effective integration of the Rain Classroom and similar educational platforms into the learning experience of undergraduate students.

At last, as the developer, top management, and marketing practitioners seek to enhance the perceived usefulness and positive impressions of the Rain Classroom, it is essential to focus on the platform's qualities and performance. By addressing these significant factors, they can effectively encourage the usage of the Rain classroom and other online learning tools, which have become increasingly vital not only in the current digital age but also as an alternative to ensure continuous learning during disruptive events, such as the COVID-19 pandemic. This holistic approach to understanding and addressing students' perceptions and behavioral intentions can contribute to the successful integration and sustained utilization of the Rain Classroom within the teaching-learning process.

Behavioral Intention to Use the Rain Classroom

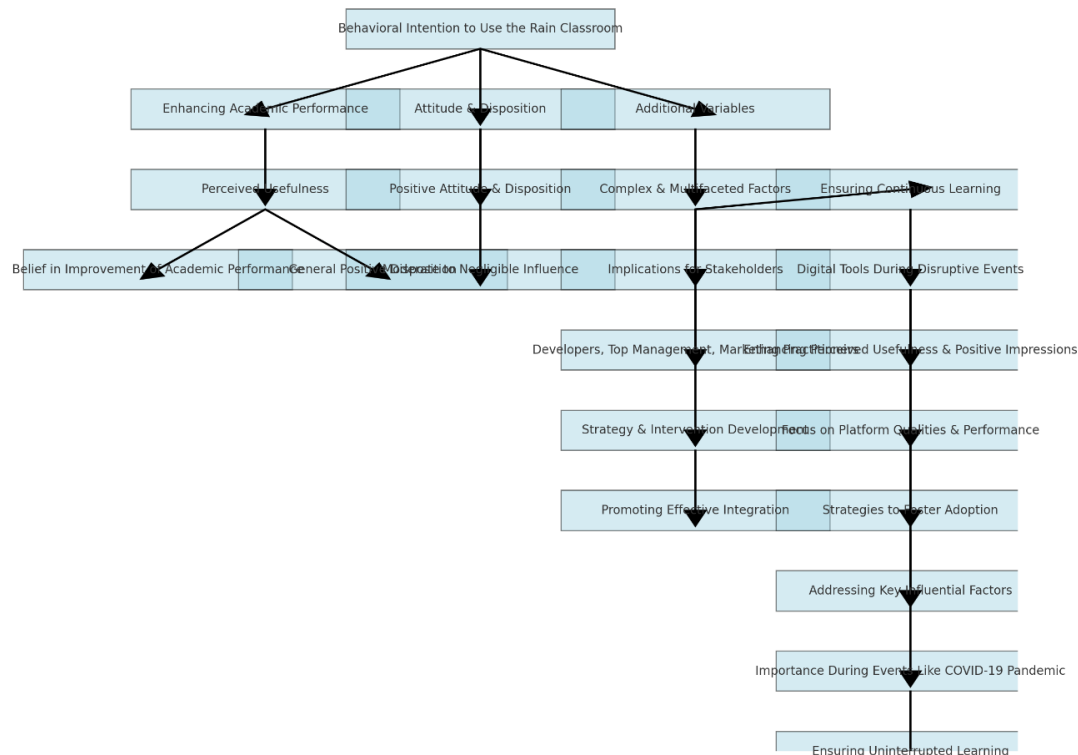


Figure 3 Behavioral Intention to Use the Rain Classroom



Recommendation

Firstly, the research focused solely on higher education institutions and collected data from selected locations in Zhanjiang University of Science and Technology, Guangdong, thereby restricting the scope and sample size of the analysis. Broadening the geographical reach and examining a more diverse range of educational settings could enhance the generalizability of the findings.

Secondly, the study centered on a single type of online learning platform, the Rain Classroom, whereas exploring a wider array of e-learning systems, such as Zoom and Massive Open Online Courses (MOOCs), as well as their varied applications, may uncover distinct patterns and shed light on the underlying factors influencing user behavior.

Thirdly, future studies may employ experimental methodologies to isolate and examine the causal relationships between specific quality factors and the dependent variable of behavioral intention, thereby enhancing the rigor of the research model.

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