



# The Factors Affecting the Continuous Use of Smarter Classroom by College Teachers in Liaoning Province

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## Abstract

**Background and Aim:** This study investigates the key factors influencing the adoption and continued use of smart classroom technology among higher education faculty members. Grounded in the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT2), and Expectation-Confirmation Model (ECM), this research examines the relationships between Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Social Influence (SI), Facilitation Conditions (FC), Personal Innovativeness in Information technology (PIIT), Satisfaction (SAT), and Continuance Intention (CI). Theoretically, it extends the application of technology adoption models in the higher education context by confirming the mediating role of satisfaction and the moderating influence of social and institutional factors. Practically, the findings offer actionable insights for policymakers, university administrators, and technology developers to design more user-friendly smart classroom systems, enhance faculty training, and develop policies that foster long-term engagement with technology-enhanced teaching. This study seeks to investigate the key elements impacting the adoption of smart classroom technologies among university educators, offering substantial value for advancing the integration of digital transformation outcomes in education.

**Materials and Methods:** A quantitative research design was employed, collecting data from university faculty members with experience using smart classrooms. The study was grounded in the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT2), and Expectation-Confirmation Model (ECM). Key variables examined included Perceived Ease of Use, Perceived Usefulness, Social Influence, Facilitation Conditions, Personal Innovativeness, Satisfaction, and Continuance Intention. The data were analyzed utilizing SPSS and AMOS software, with confirmatory factor analysis (CFA) and structural equation modeling (SEM) applied to evaluate construct validity, reliability, and inter-construct relationships.

**Results:** The findings reveal that PEOU and PU significantly influence faculty satisfaction, which in turn plays a mediating role in continued use intentions. Furthermore, SI and FC positively impact CI, emphasizing the importance of institutional support and peer collaboration in sustaining technology adoption. PIIT was also found to be a critical predictor of CI, highlighting the role of individual technological adaptability. This study provides both theoretical and practical contributions.

**Conclusion:** This research examined a sample of faculty members and identified the primary determinants of their engagement with smart classroom tools. Overall, this study achieved its objectives by verifying that Perceived Ease of Use, Perceived Usefulness, Social Influence, Facilitation Conditions, Personal Innovativeness, and Satisfaction are the key determinants of faculty members' willingness to continue using smart classrooms. These findings provide valuable insights for educators, administrators, and technology developers, offering practical guidelines for optimizing digital teaching strategies and institutional policies.

**Keywords:** Factors Affecting; Smart Classroom; College Teachers

## Introduction

The “China Education Modernization 2035” development strategy emphasizes the need to accelerate the modernization of education, placing greater demands on educational informatization. In response to this need, smart classrooms have emerged as a crucial component of modern educational reform. A smart classroom integrates advanced digital technologies, such as artificial intelligence, big data, and cloud computing, to enhance teaching effectiveness and student engagement. Despite the growing implementation of smart classrooms, there remains a gap in understanding their impact on learning





outcomes and instructional methods. Existing literature explores various aspects of educational technology, but further research is needed to assess how smart classrooms contribute to the broader goals of educational modernization. Therefore, this study aims to investigate the role of smart classrooms in achieving the objectives outlined in the “China Education Modernization 2035” strategy.

This study seeks to investigate the key elements impacting the adoption of smart classroom technologies among university educators, offering substantial value for advancing the integration of digital transformation outcomes in education.

A smart classroom is a typical materialization of the smart learning environment. It is a high-end form of multimedia and network classroom. It is a new type of classroom built with the help of Internet of Things technology, cloud computing technology, Blockchain technology, and intelligent technology. This new type of classroom includes tangible physical space. Invisible digital space is a new type of classroom that uses various intelligent equipment to assist in the presentation of teaching content, facilitate the acquisition of learning resources, promote classroom interaction, and realize situation awareness and environmental management functions. Smart classrooms aim to provide humane and intelligent interactive spaces for teaching activities; through the combination of physical space and digital space, the combination of local and remote, it improves the relationship between people and the learning environment and realizes the natural interaction between people and the environment in the learning space, promote personalized learning, open learning, and ubiquitous learning.

Smart classrooms supported by AI technology have the main features of data mining, intelligent analysis, and full-process evaluation. They use advanced technologies such as Artificial Intelligence(AI), big data, the Internet of Things, Massive open online courses (MOOC), Augmented Reality(AR), cloud computing, and the popularization of smart devices to provide teachers with comprehensive teaching data support, allowing teachers to use smart teaching. In the environment, precise teaching strategies and diversified teaching methods are used to help students achieve personalized learning and promote the improvement of students' higher-order cognitive abilities.

With the reform of higher education in China, teaching evaluation methods have been introduced. It no longer focuses solely on the learner's learning results but instead focuses on the learner's learning process.

With the broad application of the new generation of information technologies, such as in the education industry, the emergence of the smart classroom has a great impact on traditional education concepts, content, and methods (Li et al., 2018).

Previous studies on the smart classroom mainly focused on theoretical discussions, technical efficiency, construction, and application. The development of smart classrooms can be summarized in two stages. The first is a continuous innovation result of technology, and the second relates to the improvement of core literacy (Li et al., 2018).

There are a few studies on the behaviors of users of smart classrooms. Previous studies have mostly focused on teachers' willingness to adopt or use smart classrooms (Selim et al., 2020), but there is a lack of deeper research on teachers' switching intention from traditional to smart classrooms.

Most college teachers have not implemented smart classrooms in daily teaching practices, as they still regard smart classrooms as experimental. Therefore, how to improve the utilization rate of smart classrooms has become a practical problem that must be solved by Chinese universities to fully realize educational informatization. This study will provide data on the influencing factors of teachers' intention to use smart classrooms and further promote the correct use of smart classrooms by college teachers.

In recent years, the integration of technology into educational settings has become increasingly prevalent, with smart classrooms emerging as a prominent innovation in higher education institutions. Smart classrooms leverage advanced technological tools and resources to enhance teaching and learning experiences, offering potential benefits such as increased interactivity, flexibility, and access to educational resources. However, despite the potential advantages, the adoption and effective utilization of smart classrooms by university faculty members remain variable.





Understanding the factors influencing university faculty members' adoption and usage of smart classrooms is essential for optimizing their implementation and maximizing their benefits. This study aims to investigate the factors influencing university faculty members' usage of smart classrooms, focusing on seven key variables:

1. **Perceived Ease of Use:** The degree to which faculty members perceive smart classroom technology as easy to use and integrate into their teaching practices.
2. **Perceived Usefulness:** Faculty members' perceptions of the extent to which smart classrooms facilitate their teaching activities and enhance the learning experiences of students.
3. **Facilitation Conditions:** The external factors and resources that support or hinder faculty members' adoption and usage of smart classrooms, including technical support, training opportunities, and institutional policies.
4. **Social Influence:** The impact of social factors, such as colleagues' opinions, departmental norms, and institutional culture, on faculty members' decisions to adopt and use smart classrooms.
5. **Personal Innovativeness:** Faculty members' propensity to embrace and adopt innovative technologies and teaching methods, influencing their readiness to explore and experiment with smart classroom technology.
6. **Satisfaction:** Faculty members' overall satisfaction with the smart classroom experience, encompassing factors such as usability, functionality, and alignment with teaching goals.
7. **Continued Intention:** Faculty members' intention or willingness to continue using smart classrooms in their teaching practices over time, reflecting their long-term commitment to integrating technology into their pedagogical approaches.

By examining these seven variables, this study seeks to identify the key determinants of university faculty members' adoption and usage of smart classrooms and provide insights into strategies for promoting their effective implementation and utilization in higher education settings.

Despite the growing popularity of smart classrooms, there is limited research that comprehensively examines the interplay of these variables and their impact on smart classroom usage in higher education. Therefore, this study seeks to fill this gap by providing insights into the key determinants of smart classroom adoption and usage behavior among faculty and students in higher education institutions.

Understanding these factors is essential for educational policymakers, administrators, and technology developers to design and implement effective strategies for promoting the successful integration and utilization of smart classrooms in higher education environments. By identifying the factors that influence smart classroom usage, this research aims to contribute to the advancement of educational technology and the enhancement of teaching and learning experiences in higher education institutions.

## Objectives

This study aims to identify the factors affecting higher education teachers' intentions to use smart classrooms and to determine how these factors affect higher education teachers' intentions to use smart classrooms. This study examines the role of variables, such as Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Satisfaction (SAT), and Social Influence (SI), in shaping college teacher adoption of smart classrooms and continued use of smart classrooms.

## Literature review

### 1. Technology Adoption

**Perceived ease of use:** "Perceived ease of use" is a key concept in the Technology Acceptance Model (TAM), introduced by Fred Davis in 1989. This concept defines the degree to which a user believes that using a particular system or technology would be free of effort. Specifically, it describes the user's perception of how easy and intuitive the system is to use. Davis elaborated on this concept in his seminal paper, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology" (Davis, 1989).





**Perceived Usefulness:** Davis (1989). PU is defined as the degree to which a user believes that using a particular system will enhance their job performance. This concept is foundational to understanding user acceptance of technology, as it directly influences an individual's intention to use new technologies.

**Social Influence:** In the UTAUT model, Venkatesh et al. (2003) identified Social Influence as one of the four key determinants of behavioral intention to use technology. They proposed that Social Influence has a significant impact, especially in the early stages of technology adoption, where users rely heavily on the opinions and behaviors of others to guide their own usage decisions. The influence of peers, supervisors, or organizations can be particularly strong in environments where the technology in question is new or unfamiliar.

**Continued intention:** Continued intention refers to the likelihood that users will continue using a technology or system after their initial adoption. It is a critical concept in understanding long-term user engagement and technology adoption. Davis (1989).

## 2. Personal Factors

**Personal Innovativeness:** Personal Innovativeness is a key concept in the field of technology acceptance, particularly in understanding individual differences in the adoption and use of new technologies. Defined as the willingness of an individual to try out any new information technology, Personal Innovativeness reflects the degree to which a person is open to new experiences and is inclined to adopt novel technologies (Agarwal & Prasad, 1998a).

**Satisfaction:** Venkatesh and Davis (2000) extended TAM by incorporating additional variables and extending the model to TAM2. They confirmed that satisfaction is a critical component in the model, influencing users' behavioral intentions and adoption decisions. Their research illustrated that user satisfaction, influenced by perceived ease of use and usefulness, significantly affects users' likelihood to adopt and persist in using a technology.

## 3. Institutional Support

**Facilitation conditions:** Facilitating Conditions explain the environmental and organizational support factors that influence the use of technology (Thompson et al,1991). These conditions refer to the external resources or support that users perceive to help them successfully use new technology or systems, including infrastructure, technical support, training, and management support.

This study aims to address these research gaps by introducing new variables (e.g., switching intention) and extending existing models (e.g., TAM and UTAUT). Specifically, it will explore how personal innovativeness, satisfaction, and social influence jointly affect users' switching intention and continued intention while analyzing the moderating role of facilitating conditions in different organizational environments. Through these efforts, this study will provide new theoretical insights and practical guidance for the field of technology acceptance.

## Conceptual Framework

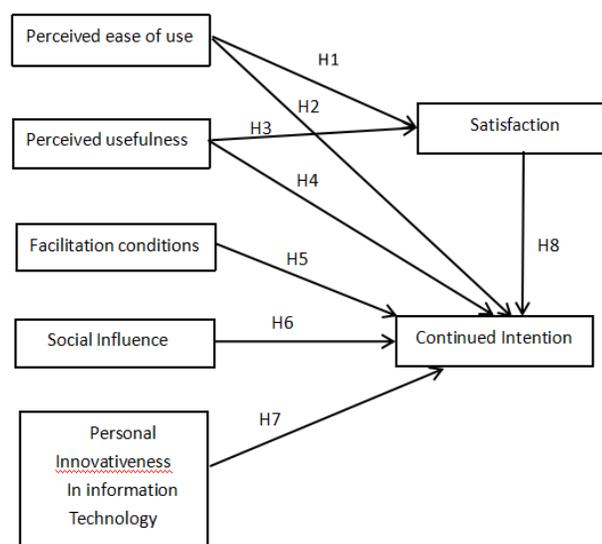
The conceptual framework of this study is constructed with support from existing theories and past empirical research. The conceptual framework encompasses all variables utilized in this study. Within this study's conceptual framework, there are causal relationships among 7 variables aimed at analyzing the factors influencing college teachers' use of smart classrooms. The first theoretical framework supports the study of the impact of social influence, facilitating conditions, and individual innovation on satisfaction and continuous intention. The second framework validates the influence of perceived usefulness and perceived ease of use on satisfaction and teachers' continuous intention. The third framework provides insights into the impact of social influence and facilitating conditions on continuous intention and behavior. The conceptual framework of this study comprises 7 independent variables, including one intermediate variable.

The conceptual framework of this study is based on seven variables. Hair et al. (2013) indicated that there are three types of variables: independent variables, intermediate variables, and dependent variables. Dependent variables are used to describe outcomes. Independent variables are defined as variables that may influence another variable (Clark, 2010). In this study, the independent variables are system quality,



information quality, service quality, and trust. Cooper and Schindler (2014) defined intermediate variables as variables that may influence the dependent variable. Intermediate variables may affect the dependent variable and are positioned between the dependent and independent variables (Gray, 2017). In this study, there is one intermediate variable, which is satisfaction. Dependent variables are defined as the target variables of the study (Jackson, 2006). O'Leary (2017) pointed out that dependent variables are the variables researchers attempt to investigate. This study has only one dependent variable, which is the intention to continue usage behavior.

The objective of this research is to investigate the factors influencing the usage of smart classrooms by college teachers. In terms of the conceptual framework, this study aims to explore eight relationships between variables. The first research question, perceived ease of use, is the independent variable, and satisfaction is the intermediate variable. The second relationship is between perceived ease of use and intention to continue usage. Perceived ease of use is the independent variable, and intention to continue usage is the dependent variable. The third relationship is between perceived usefulness and satisfaction. Perceived usefulness is the independent variable, and satisfaction is the intermediate variable. The fourth relationship is between perceived usefulness and intention to continue usage. Perceived usefulness is the independent variable, and intention to continue usage is the dependent variable. The fifth relationship is between facilitating conditions and the intention to continue usage. Facilitating conditions are the independent variable, and intention to continue usage is the dependent variable. The sixth relationship is between social influence and intention to continue usage. Social influence is the independent variable, and intention to continue usage is the dependent variable. The seventh relationship is between individual information technology innovation and intention to continue usage. Individual information technology innovation is the independent variable, and intention to continue usage is the dependent variable. The eighth relationship is between satisfaction and intention to continue usage. Satisfaction is the intermediate variable, and intention to continue usage is the dependent variable.



**Figure 1** Conceptual Framework

## Methodology

### Research design and analysis

The design of this study is survey research, which mainly uses questionnaire research methods to understand the opinions of college teachers, thereby studying the factors that influence the use of smart classrooms by college teachers. Based on established scales and previous studies, this study includes seven



variables: PEOU (4 items), PU (4 items), FC (4 items), SI (5 items), PIIT (4 items), SAT (4 items), and CI (3 items). A five-point Likert scale was used for evaluation. The questionnaire's validity and reliability were confirmed through S-CVI (Polit and Beck, 2006) and IOC testing. The distribution and data collection of the questionnaire were conducted via Questionnaire Star. Data analysis was conducted using CFA and SEM.

### **Population and Sample:**

The research objective of this paper is to select college teachers who have experience in using smart classrooms in universities with the same smart classroom construction modules and good results in using smart classroom projects.

In the research, the researcher employed for this study used a Structural Equation Model (SEM) Sample Size Calculator to determine the appropriate sample size. According to the calculation, the minimum recommended sample size is 247.

Purposive sampling was used to generate 500 samples from two colleges. However, because of the educational environment of colleges and universities, these teachers have common characteristics. The population of this study consists of university teachers who have used or have some understanding of smart classrooms. College teachers generally possess strong summarization and communication skills, allowing this group to more accurately express their understanding of the factors influencing usage. A purposive sampling method was employed to select a sample of 500 teachers.

### **Human Research Ethics:**

This study has developed an informed consent form tailored to the participants. The informed consent form includes relevant information about the study, such as its direction, objectives, methods, potential risks, and benefits. Emphasis is placed on the voluntary nature of participation in the informed consent form, and it is made clear to participants that they can withdraw at any time without facing any negative consequences. The process of informing participants about the informed consent form is documented, which is crucial for ensuring that participants fully understand the content of their involvement and freely consent to it.

### **Data Collection Process:**

This study rigorously designed the distribution and collection of questionnaires to ensure the effectiveness and integrity of the data collection process. The questionnaire forms were distributed online through the Questionnaire Star internet platform, which is a professional survey platform with powerful functionalities to ensure data security. The distribution of questionnaires was coordinated between the smart classroom construction company and the faculty departments of the universities. This study received strong support from the faculty departments of two colleges. The assistance of faculty departments in distributing questionnaires to university teachers can increase the participants' level of attention and ensure that responses are carefully considered. In summary, the precision of the measurements of the questionnaire data can be guaranteed.

### **Data Analysis:**

This research utilized advanced statistical tools, specifically SPSS and AMOS, for data analysis and hypothesis validation. The analytical approach, Structural Equation Modeling (SEM) to investigate the relationships among key variables, including Perceived Ease of Use, Perceived Usefulness, Facilitating Conditions, Social Influence, Personal Innovativeness in Information Technology, Satisfaction, and Continued Intention, in the context of university instructors' adoption of smart classroom technologies.

## **Results**

### **Demographic Information**

The participants in this study were 500 university teachers from two higher education institutions in Liaoning Province. Table 1 presents the demographic characteristics, including gender, age, and education level. The demographic data reveal a gender composition of 23.4% male and 76.6% female respondents. Regarding age distribution, the majority of respondents, 34.0% were 35 years old and below, while 30.2% were aged 35-45 years, 20.6% were aged 45-55 years, and 15.2% were 55 years and above. Regarding





education level, 53.8% held a bachelor's degree, 43.2% held a master's degree, and 3% held a doctoral degree.

**Table 1** Demographic Information of Samples

Variables	Category	Frequency	Percentage
<b>Gender</b>	Male	117	23.4%
	Female	383	76.6%
	Total	500	100%
<b>Age</b>	35 years old and below	170	34.0%
	35–45 years old	151	30.2%
	45 (excluding 45) – 55 years old	103	20.6%
	55 (excluding 55) and above	76	15.2%
	Total	500	100%
<b>Education Level</b>	Bachelor’s degree	269	53.8%
	Master’s degree	216	43.2%
	Doctoral Degree	15	3.0%
	Total	500	100%

**Mean Values of the Variables**

In the present investigation, participants' attitudes toward the measured variables were evaluated using a 5-point Likert scale (1= strongly disagree to 5= strongly agree) designed to assess the level of agreement. To ensure a systematic and standardized interpretation of the collected data, a set of predefined analytical criteria was established for the interpretation of mean scores across each measured variable.

**Table 2** Descriptive Analysis of Each Variable

	Mean	SD	Interpretation
<b>PEOU</b>	3.907	0.858	Agree
<b>PU</b>	3.866	0.836	Agree
<b>FC</b>	3.755	0.878	Agree
<b>SI</b>	4.234	0.748	Agree
<b>PIIT</b>	3.941	0.830	Agree
<b>Sat</b>	4.156	0.790	Agree





	Mean	SD	Interpretation
CI	3.783	0.886	Agree

**Normality Test**

When both the skewness and kurtosis values fall between -2 and 2, the distribution is generally considered to approximate normality (West, Finch, & Curran, 1995). From Table 3, it can be seen that the skewness and kurtosis of the scale data in this study fall within the range of -2 to 2, indicating that the data meet the requirements of normal distribution.

**Table 3** Normality of Data

		Skewness		Kurtosis	
		Statistic	Standard	Statistic	Standard
<b>PEOU</b>	PEOU1	-0.353	0.109	-0.320	0.218
	PEOU2	-0.191	0.109	-0.305	0.218
	PEOU3	-0.601	0.109	-0.192	0.218
	PEOU4	-0.521	0.109	-0.545	0.218
<b>PU</b>	PU1	-0.492	0.109	-0.331	0.218
	PU2	-0.297	0.109	-0.357	0.218
	PU3	-0.660	0.109	-0.132	0.218
	PU4	-0.026	0.109	-0.477	0.218
<b>FC</b>	FC1	-0.455	0.109	-0.211	0.218
	FC2	-0.329	0.109	-0.256	0.218
	FC3	-0.212	0.109	-0.284	0.218
	FC4	-0.647	0.109	0.183	0.218
<b>SI</b>	SI1	-0.528	0.109	-0.355	0.218
	SI2	-0.539	0.109	-0.110	0.218
	SI3	-0.434	0.109	-0.537	0.218
	SI4	-1.259	0.109	1.144	0.218
	SI5	-0.993	0.109	0.595	0.218
<b>PIIT</b>	PIIT1	-0.047	0.109	-0.452	0.218
	PIIT2	-0.875	0.109	0.340	0.218
	PIIT3	-0.550	0.109	-0.196	0.218
	PIIT4	-1.131	0.109	0.562	0.218
<b>Sat</b>	Sat1	-0.667	0.109	-0.194	0.218
	Sat2	-0.668	0.109	-0.412	0.218
	Sat3	-0.923	0.109	-0.048	0.218
	Sat4	-0.109	0.109	-0.813	0.218
<b>CI</b>	CI1	-0.221	0.109	-0.138	0.218
	CI2	-0.484	0.109	-0.239	0.218
	CI3	-0.553	0.109	-0.361	0.218





### CFA

CMIN/DF (1.953) is significantly lower than the threshold, indicating an excellent fit between the model and the data. RMSEA (0.052) values suggest minimal discrepancy between the observed and predicted covariance matrices; the observed value is significantly lower than the threshold, indicating a very close fit between the model and the data. The high values of GFI (0.925) exceed the threshold, indicating that the model explains a high proportion of the variance in the data. The high values of AGFI (0.908) exceed the threshold, confirming that the model fit remains strong. The high values of NFI (0.905) exceed the threshold, indicating that the model provides a significant improvement over the null model. The high values of CFI (0.951) indicate an excellent fit compared to the baseline model. The high values of TLI (0.943) exceed the threshold, confirming that the model fit remains strong even after accounting for model complexity.

**Table 4** Confirmatory Factor Analysis Fit Indices

Fit Index	Fit Index	Value
<b>CMIN/DF</b>	< 5.00 (Awang, 2012; Al-Mamary and Shamsuddin, 2015)	642.580/329 or 1.953
<b>GFI</b>	≥ 0.85 (Sica & Ghisi, 2007)	0.925
<b>AGFI</b>	≥ 0.80 (Sica & Ghisi, 2007)	0.908
<b>NFI</b>	≥ 0.80 (Wu & Wang, 2006)	0.905
<b>CFI</b>	≥ 0.80 (Bentler, 1990)	0.951
<b>TLI</b>	≥ 0.80 (Sharma et al., 2005)	0.943
<b>RMSEA</b>	< 0.08 (Pedroso et. al., 2016)	0.052
<b>Model Summary</b>		<b>Acceptable Model Fit</b>

### Convergent Validity

The factor loadings for all items corresponding to PEOU, PU, FC, SI, PIIT, Sat, and CI exceed 0.5, indicating that the items associated with each latent variable are highly representative. Additionally, the average variance extracted (AVE) for each latent variable is greater than 0.5, and the composite reliability (CR) exceeds 0.7, demonstrating that the convergent validity is ideal.

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

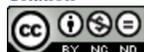
Latent Variables	Source of Questionnaire	Item Amount	Cronbach's Alpha	Factors Loading	CR	AVE
<b>PEOU</b>	Venkatesh et al. (2003)	4	0.855	0.742-0.789	0.856	0.597
<b>PU</b>	Venkatesh et al. (2003)	4	0.849	0.755-0.777	0.851	0.587
<b>FC</b>	Venkatesh et al. (2003)	4	0.824	0.650-0.771	0.834	0.559
<b>SI</b>	Venkatesh et al. (2003)	5	0.847	0.687-0.782	0.853	0.538
<b>PIIT</b>	Agarwal & Prasad (1998)	4	0.855	0.759-0.882	0.858	0.602
<b>SAT</b>	Bhattacharjee (2001)	4	0.829	0.703-0.779	0.832	0.554
<b>CI</b>	Bhattacharjee (2001)	3	0.836	0.775-0.812	0.837	0.631

### Discriminant Validity

From the table, it can be observed that the correlation coefficients between PEOU, PU, FC, SI, PIIT, Sat, and CI are all smaller than the corresponding square roots of the AVE. This indicates that the latent variables exhibit a certain degree of correlation while also maintaining a sufficient level of distinctiveness. In other words, the discriminant validity of the scale data is satisfactory.

**Table 6** Discriminant Validity

	PEOU	PU	FC	SI	PIIT	Sat	CI
<b>PEOU</b>	<b>0.773</b>						
<b>PU</b>	0.232	<b>0.766</b>					
<b>FC</b>	0.231	0.267	<b>0.748</b>				
<b>SI</b>	0.194	0.263	0.187	<b>0.733</b>			



	PEOU	PU	FC	SI	PIIT	Sat	CI
PIIT	0.274	0.137	0.220	0.132	<b>0.776</b>		
Sat	0.394	0.332	0.231	0.269	0.227	<b>0.744</b>	
CI	0.449	0.470	0.396	0.423	0.424	0.521	<b>0.794</b>

### Structural Equation Model

All fit indices exceed their respective thresholds, indicating that the model provides an excellent fit to the data. The low CMIN/DF (2.342) and RMSEA (0.052) values suggest a minimal discrepancy between the observed and predicted covariance matrices. The high values of GFI (0.903), AGFI (0.884), NFI (0.881), CFI (0.928), and TLI (0.920) confirm that the model explains a substantial proportion of the variance and outperforms baseline models. This analysis confirms that the structural equation model meets the highest standards of goodness-of-fit, ensuring its reliability and validity for academic research.

**Table 7** Fit Indices Results of the Structural Equation Model

Fit Index	Fit Index	Value
CMIN/DF	< 5.00 (Awang, 2012; Al-Mamary and Shamsuddin, 2015)	800.950/342 or 2.342
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.903
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.884
NFI	≥ 0.80 (Wu & Wang, 2006)	0.881
CFI	≥ 0.80 (Bentler, 1990)	0.928
TLI	≥ 0.80 (Sharma et al., 2005)	0.920
RMSEA	< 0.08 (Pedroso et. al., 2016)	0.052

**Model Summary** **Acceptable Model Fit**  
 Note: CMIN/DF 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.

### Hypotheses Testing

From the structural equation model (SEM) path coefficient table, it can be observed that: PEOU has a significant positive effect on Sat ( $\beta=0.347$ ,  $p < 0.001$ ), thus Hypothesis H1 is supported. PU has a significant positive effect on Sat ( $\beta=0.268$ ,  $p < 0.001$ ), thus Hypothesis H2 is supported. PEOU has a significant positive effect on CI ( $\beta=0.200$ ,  $p < 0.001$ ), thus Hypothesis H3 is supported. PU has a significant positive effect on CI ( $\beta=0.265$ ,  $p < 0.001$ ), thus Hypothesis H4 is supported. FC has a significant positive effect on CI ( $\beta=0.192$ ,  $p < 0.001$ ), thus Hypothesis H5 is supported. SI has a significant positive effect on CI ( $\beta = 0.252$ ,  $p < 0.001$ ), thus Hypothesis H6 is supported. PIIT has a significant positive effect on CI ( $\beta = 0.276$ ,  $p < 0.001$ ), thus Hypothesis H7 is supported. Sat has a significant positive effect on CI ( $\beta = 0.269$ ,  $p < 0.001$ ), thus Hypothesis H8 is supported.

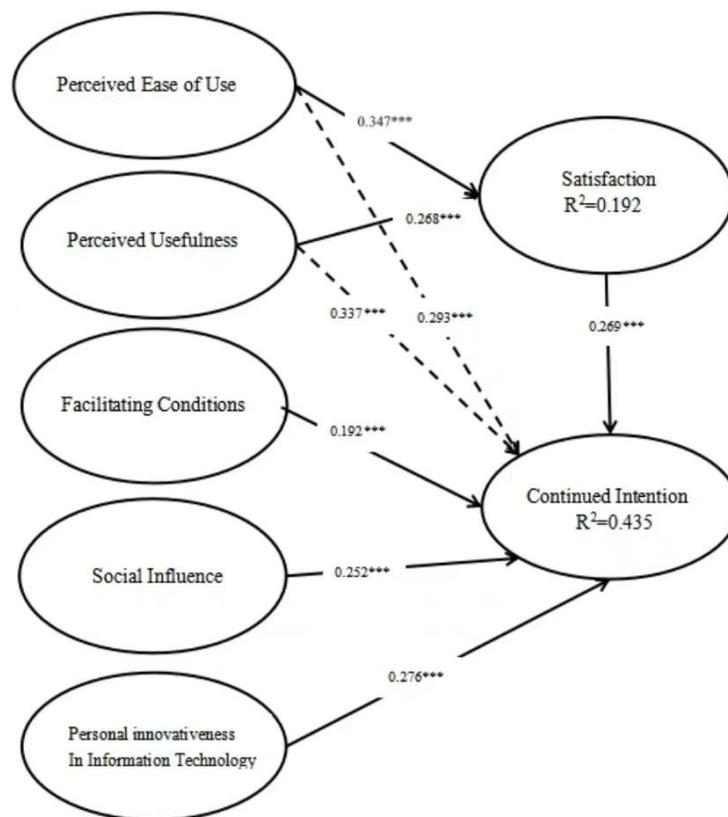
**Table 9** Fit Indices Results of the Structural Equation Model

	Hypothesis	Standardized path Coefficients ( $\beta$ )	t-value	Testing result
H1	PEOU->Sat	0.347	6.477***	Supported
H2	PU->Sat	0.268	5.145***	Supported
H3	PEOU->CI	0.200	3.943***	Supported
H4	PU->CI	0.265	5.278***	Supported
H5	FC->CI	0.192	4.142***	Supported
H6	SI->CI	0.252	5.294***	Supported
H7	PIIT->CI	0.276	5.809***	Supported
H8	Sat->CI	0.269	4.848***	Supported

### Direct, Indirect, and Total Effects

Through BOOTSTRAP testing ( $n = 5000$  resampling iterations), the following findings can be observed: When the dependent variable is Satisfaction (Sat), both Perceived Ease of Use (PEOU) and

Perceived Usefulness (PU) have direct effects on Sat, with standardized path coefficients of 0.347 and 0.268, respectively. The explanatory variables in the model demonstrate a certain degree of explanatory power for Sat, with an  $R^2$  value of 19.2%, indicating that PEOU and PU collectively explain 19.2% of the variance in satisfaction. When the dependent variable is Continuance Intention (CI), the following variables have direct effects on CI: PEOU, PU, Facilitating Conditions (FC), Social Influence (SI), Personal Innovativeness in IT (PIIT), and Satisfaction (Sat). Their respective path coefficients are 0.200, 0.265, 0.192, 0.252, 0.276, and 0.269. Additionally, PEOU and PU also exhibit indirect effects on CI through Sat, with indirect effect values of 0.093 and 0.072, respectively. The explanatory variables in the model collectively provide a certain degree of explanatory power for CI, with an  $R^2$  value of 43.5%, meaning that the predictors explain 43.5% of the variance in continuance intention.



**Figure 2** Path Diagram Analysis  
 Note: \*\*\*  $p < 0.001$

## Discussion

The research results found that Personal Innovativeness in IT (PIIT) significantly influenced Continuous Usage Intention ( $\beta = 0.276$ ,  $p < 0.001$ ), making it the strongest predictor of continuous usage intention. This suggests that teachers with higher levels of technological curiosity and adaptability are more likely to integrate smart classrooms into their teaching practices. This finding supports Rogers' (2003) Diffusion of Innovation Theory, which posits that early adopters play a crucial role in accelerating technology adoption. The study indicates that identifying and leveraging early adopters within institutions can facilitate broader teacher engagement with smart classroom technology. Technical support teams should be available to assist faculty members with troubleshooting and optimizing their use of smart classroom tools. Institutions should also establish policies that encourage faculty members to experiment with digital teaching methods and reward innovative practices in smart classroom integration.



Satisfaction (Sat) was found to mediate the relationship between PEOU, PU, and CI ( $\beta = 0.269$ ,  $p < 0.001$ ). Teachers who reported high satisfaction with smart classrooms were more likely to continue using them. This finding aligns with Bhattacharjee's (2001) ECM, which states that satisfaction is a critical determinant of continued technology use. The results suggest that institutions should prioritize initiatives that enhance user satisfaction, such as continuous professional development, user-friendly interfaces, and responsive technical support, to ensure long-term engagement. From the perspective of technology developers and policymakers, it is critical to consider faculty feedback when designing and refining smart classroom technologies. Developers should collaborate closely with educational institutions to understand the specific needs and challenges faced by educators in different teaching contexts. Customizing features to align with diverse instructional methods and user preferences can enhance user experience and adoption rates. Additionally, integrating AI-driven analytics and adaptive learning features can further personalize the smart classroom experience for both educators and students.

PU was found to be a strong predictor of continued intention ( $\beta = 0.265$ ,  $p < 0.001$ ). Teachers who perceived smart classrooms as beneficial for their teaching reported a higher likelihood of continued use. This is consistent with Bhattacharjee's (2001) Expectation-Confirmation Model (ECM), which posits that users who perceive long-term benefits from a system are more likely to continue using it. The study highlights that institutions should focus on demonstrating the tangible benefits of smart classrooms to sustain high levels of adoption. For faculty members, recognizing the pedagogical benefits of smart classroom technology is crucial in fostering long-term engagement. Educators should actively explore how these tools enhance student interaction, content delivery, and assessment strategies.

Regarding institutional support and facilitation conditions, universities should allocate sufficient resources to maintain and upgrade smart classroom infrastructure. Moreover, creating faculty communities or discussion forums where educators can share their experiences, challenges, and best practices can further strengthen their commitment to using smart classrooms.

The study's population is limited to university faculty members who have experience using smart classrooms, potentially limiting the applicability of the results to alternative educational settings or demographic groups. While efforts were made to ensure diversity in participant backgrounds and experiences, the results may not fully represent the perspectives of faculty members from different disciplines, institutional settings, or geographical regions. Therefore, careful consideration is warranted when generalizing the results to wider demographic groups.

## Conclusion

This study investigated the key factors influencing university faculty members' continued use of smart classroom technology. Using an empirical approach, this research examined a sample of faculty members and identified the primary determinants of their engagement with smart classroom tools.

A quantitative research design was employed, collecting data from university faculty members with experience using smart classrooms. The study was grounded in the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT2), and Expectation-Confirmation Model (ECM). Key variables examined included Perceived Ease of Use, Perceived Usefulness, Social Influence, Facilitation Conditions, Personal Innovativeness, Satisfaction, and Continuance Intention.

The data were analyzed utilizing SPSS and AMOS software, with confirmatory factor analysis (CFA) and structural equation modeling (SEM) applied to evaluate construct validity, reliability, and inter-construct relationships.

This study tested eight hypotheses regarding teachers' engagement with smart classroom technology. The results confirmed that PIIT, satisfaction, and perceived usefulness significantly influence teachers' satisfaction, with satisfaction acting as a mediator in the intention to continue using the technology. Additionally, social influence and facilitating conditions contribute to continued use, highlighting the importance of institutional support and peer collaboration. The findings are consistent with previous studies (Venkatesh et al., 2003; Bhattacharjee, 2001), reinforcing the relevance of these theoretical frameworks in the adoption of educational technology.

## Recommendation

This study provides valuable insights for educators, administrators, and technology developers, offering practical guidelines for optimizing digital teaching strategies and institutional policies. For educators and administrators, by identifying factors that influence faculty members' adoption and





satisfaction, institutions can design targeted training programs and support systems to enhance smart classroom integration. For technology developers, insights from this study can guide software developers in refining smart classroom features, ensuring usability, accessibility, and alignment with pedagogical needs. For policymakers, the study highlights the need for policies that support faculty training, infrastructure development, and long-term engagement with smart classroom technologies.

Future research could extend to university faculty members from different cultural backgrounds to explore how cultural variations influence attitudes, perceptions, and behaviors toward smart classroom adoption and continued usage. Investigating how educational policies influence the promotion and implementation of smart classroom technologies, and how policymakers can refine policies to support faculty engagement and technological advancements. Through these research directions, future studies can offer a more comprehensive understanding of smart classroom technology use in higher education and provide theoretical and practical insights for improving teaching quality and faculty engagement.

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