The Impact of Social Influence and Facilitating Conditions on the Adoption of Smart Campus among Students of Higher Educational Institutions in Nantong: the Mediating Role of Behavioral Intention

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Abstract: - With the development of technology, the development of smart campuses has become a key direction for the development of information technology in higher educational institutions. To achieve smart campus development, it is essential to identify the key factors influencing the acceptance of smart campus initiatives among students. In the study, the research model with social influence and facilitating conditions as the independent variables, behavioral intention as the mediating variable, and adoption of smart campus as the dependent variable was constructed, and the research model was analyzed empirically by using structural equation modeling with the students of nine higher educational institutions in the area of Nantong City, Jiangsu Province. The results of the study show that (1) There was a strong positive effect of social influence and facilitating conditions on behavioral intention, and the influence factors are respectively 0.449 and 0.265. (2) Social influence and facilitating conditions not only directly affect students' adoption behavior but also play an indirect role through behavioral intention, and the proportions of the indirect effect are 57.9% and 23.5%, respectively.

Key-Words: - smart campus, social influence, facilitating conditions, behavioral intentions, adoption of smart campus, Higher Educational Institutions.

Received: June 7, 2025. Revised: August 22, 2025. Accepted: October 9, 2025. Published: June 23, 2026.

1 Introduction

With the rapid progress of technologies, including the Internet of Things, big data, and artificial intelligence, the construction of smart campuses has emerged as a key pathway for higher educational institutions to advance their digital transformation, [1]. The system of smart campus makes teaching, management, and learning more efficient and smarter through technical devices such as smart classrooms, online learning platforms, and virtual campus cards, [2]. However, in practical application, there are differences in the degree of adoption of smart campus systems by students, which directly affects the effectiveness of smart campus construction. Investigating the factors that influence the adoption of smart campus technologies by students has become a vital research focus, [3].

Although there are many theories related to technology adoption such as UTAUT, TAM, SCT and other theories, but UTAUT has a higher degree of explanation regarding the degree of acceptance intention, UTAUT theory is used in about 70% of the studies of user behavior intention and about 50% of the studies of user usage behavior, and it is one of the best methods to study the field of information technology acceptance at this time, [4].

It has been shown that social influence and facilitating conditions not only directly affect adoption behavior, but also indirectly through behavioral intention. However, research focusing on college students in Nantong City remains limited, particularly concerning empirical examinations of behavioral intention as a mediating mechanism, [5].

To bridge the identified gap, students enrolled in higher educational institutions in Nantong City are selected as the target group, and a research model is developed that includes social influence (SI), facilitating conditions (FC), and smart campus adoption (ASC), while treating behavioral intention (BI) as a mediator. The study aims to answer the core research questions below:

(1) Do social influence and facilitating conditions significantly affect student adoption behavior of smart campus in higher educational institutions?

(2) Does behavioral intention have a mediating effect in the role of social influence and facilitating conditions on the adoption of a smart campus?

2 Literature Review and Hypothesis Development

2.1 Basic Concept

2.1.1 Smart Campus

A smart campus is characterized as an updated higher education environment that incorporates advanced technologies, including the Internet of Things, artificial intelligence, cloud computing and big data. It not only focuses on the basic informatization system, but also includes functional modules such as smart classrooms, online learning platforms, and campus card services, [6].

Recent research suggests that there are still aspects of smart campus development that require critical scrutiny. Most studies emphasize IoT deployment, environmental monitoring, and automated management of resources, while comprehensive analyses of how these technologies effectively improve student learning, classroom interaction, and instructional practices are still scarce, [7].

Frameworks used to assess smart campuses are still in a relatively nascent and evolving stage. Polin et al introduced a conceptual framework that considers smart campuses as a scaled-down version of smart cities in higher education. Using the Delphi method, they developed a performance assessment system comprising four domains, 16 categories, and 48 indicators; however, these measures rely largely on expert judgment, and empirical testing is still limited, [8].

Studies on smart campus infrastructure and user experience have been growing, yet significant challenges persist. Evidence suggests that students tend to report higher satisfaction and engagement in universities with more advanced smart campus implementations, [9]. However, there are new management and security challenges that come with the rapid deployment of IoT devices, including privacy, cybersecurity, and interoperability challenges, [10]. Recent research has examined the use of 5G and IoT technologies in campus administration and educational services. However, the majority of studies remain focused on technical deployment or case-based analyses, with limited empirical evidence on student behavior and adoption intentions, [11].

Overall, research on smart campuses has gradually shifted from a purely technology-centered focus to include educational, managerial, and social responsibility perspectives. However, there remains a gap in empirical research that explores how students adopt these systems, in addition to the contributions of convenience, social influence, and individual user factors. It underlines the necessity of the present research to consider the specific context of students in Jiangsu Province and explore the main factors affecting the adoption of IoT-based smart campuses, helping to fill existing research gaps.

2.1.2 Selection of Constructs from the UTAUT Model

Venkatesh et al. introduced the UTAUT, which synthesizes eight established technology acceptance models and highlights four key factors influencing behavioral intention and system use: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), [12]. In this study, we concentrate on social influence and facilitating conditions, deliberately omitting performance and effort expectancy for specific reasons outlined below.

First, in Chinese higher education, the widespread maturity of smart campus technologies and students' familiarity with them diminishes the relevance of performance expectancy and effort expectancy. Core systems such as online learning platforms, virtual campus cards, and smart classrooms have been in place for several years, becoming an integral part of students’ daily learning activities, [13]. Consequently, the perceived levels of usefulness and ease of use show minimal differences, limiting their ability to explain notable differences in adoption intentions.

Second, the compatibility of sociocultural factors and infrastructure significantly influences students' behavioral decisions. Within the Chinese higher education context, peer norms, faculty expectations, institutional promotion, and the availability of adequate infrastructure and digital devices collectively form the core drivers of students' adoption of new technologies. The constructs of social recognition and enabling conditions reflecting societal acceptance and environmental support, respectively, best capture these characteristics, [4].

Finally, this study employs a simplified model emphasizing social and contextual determinants. Drawing on Hair, model simplification by retaining the most theoretically relevant constructs enhances estimation efficiency and interpretability without compromising explanatory power. Consequently, this research focuses on social influence and functional expectations to uncover the sociocultural mechanisms and technological enabling factors that most directly impact students' behavioral intentions and smart campus system adoption rates, [14].

In summary, excluding performance expectations and effort expectations is theoretically grounded and contextually justified. This approach enables a more focused analysis of how social influence and facilitating conditions jointly impact the adoption rate of IoT-based smart campus systems in Chinese higher education.

2.1.3 Social Influence

Social influence refers to the extent to which individuals are influenced by the opinions, attitudes, or behaviors of significant others around them (e.g., peers, teachers, family members, or leaders) when using new technologies, [12]. This study refers to the fact that students are often influenced by their teachers, peers, and schools, which affects their willingness to actively adopt smart campus facilities, [15].

2.1.4 Facilitating Conditions

Facilitating conditions refer to the resource support, technological infrastructure, and helpful environment available to individuals when using technological systems, [12]. Facilitating conditions of this study refer to the degree of convenience that some smart devices of the smart campus, such as smart classrooms, online learning platforms, and campus cards, bring to students in their studies and lives, [16].

2.1.5 Behavioral Intention

Behavioral intention refers to an individual's subjective inclination towards a behavior, reflecting the likelihood of engaging in that behavior in the future, [12]. In the study, behavioral intention refers to the intention to use the smart campus, [17].

2.1.6 Adoption of Smart Campus

Adoption behavior was declared as the willingness of students to actively use school-provided smart campus facilities in their studies and lives, including online learning platforms, virtual campus card, [5].

2.2 Hypothesis Development

2.2.1 Social Influence and Behavioral Intention

To enhance the effective adoption of a smart campus, it is crucial to examine the impact of social influence on the behavioral intention of individuals. Prior research consistently identifies social influence as a significant determinant of technology adoption. Based on this understanding, the study formulates the following hypothesis, H1:

H1: There is an important relationship between social influence and behavioral Intention of Smart Campus.

2.2.2 Facilitating Conditions and Behavioral Intention

According to the UTAUT theory, FC is regarded as an important dependent variable that influences the technology adoption intentions of users. When individuals perceive that the required technical support and operating environment are available, they will be more behaviorally inclined to try to continue using the system in question, [12]. A number of empirical investigations have demonstrated that facilitating conditions are positively associated with behavioral intention. Based on this evidence, the study puts forward the following hypothesis, H2:

H2: There is a meaningful relationship between facilitating conditions and the behavioral intention of the smart campus.

2.2.3 Social Influence and Adoption of Smart Campus

In educational technology research, social influence has been widely recognized as a major determinant of the adoption of smart campus, [18]. When applying the UTAUT model to investigate factors influencing IoT adoption in public universities, Almeterer proposed that peer influence affects the use and adoption of new technologies among students, [19]. Therefore, this study formulated Hypothesis H3:

H3: There is a strong correlation between social influence and the adoption of IoT-based smart campuses.

2.2.4 Facilitating Conditions and Adoption of Smart Campus

Facilitating conditions are generally considered significant as factors influencing both use intention and actual behavior, [12]. Based on research into IoT-enabled smart campuses, Sneesl found that facilitating conditions are among the critical driving forces for smart campus applications, [20]. Therefore, this study proposes the H4 hypothesis:

H4: There is a meaningful relationship between facilitating conditions and the adoption of IoT-based smart campus.

2.2.5 Behavioral Intention and Adoption of Smart Campus

There is a meaningful influence of BI on technology acceptance. The researcher has demonstrated that BI will noteworthy and positively affect the practical application of intelligent learning, [21]. Previous studies found that behavioral intention significantly affects e-learning adoption behavior, [22]. Therefore, the hypothesis H5 is proposed in the study:

H5: There is a meaningful relationship between the Behavior Intention of IoT-Based Smart Campus and the Adoption of IoT-Based Smart Campus.

2.2.6 Mediating Effect of Behavioral Intention of Smart Campus

Marikyan showed that most college students will further adopt smart service platforms only after forming a clear behavioral intention in a review of smart campuses, [23]. Previous research has showed that the effects of facilitating conditions and social influence on adoption behavior need to be transmitted through behavioral intention, which is a psychological mechanism, in an empirical study on the use of smart learning environments by university students, [24]. Use intention mediated the effect of social influence on actual usage, [25]. Previous studies examined the effect of social influence on e-learning adoption with behavioral intention as a mediating variable, [26]. Therefore, this study proposes hypotheses H6 and H7:

H6: BI mediates the relationship between Facilitating Conditions and ASC

H7: BI mediates the relationship between social influence and ASC.

2.3 Research Model

Based on the integrated findings from prior research and the application characteristics of smart campus, this study constructed the research model as shown in Figure 1. The model contains two independent variables, Social Influence (SI) and Facilitating Conditions (FC), one mediating variable, Behavioral Intention (BI), and one dependent variable, Adoption of Smart Campus (ASC).

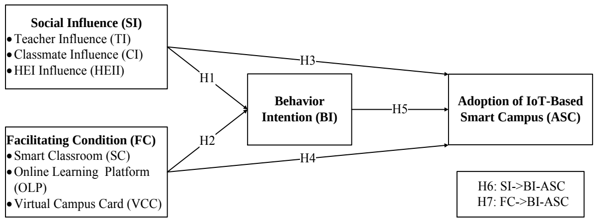

Fig. 1: Research Model
Source: created by the authors

3 Methodology

3.1 Scale Design

A questionnaire was designed to measure the adoption of smart campus among students. The questionnaire includes four variables, each of which is measured on a five-point Likert Scale, [27]. Each measurement question item is mainly based on national and international well-established scales, and Appendix provides detailed information on the variables and related references.

The questionnaire items in this study were adapted from several established domestic and international scales, with appropriate adjustments made based on the research context and characteristics of the study participants. To ensure the applicability and semantic accuracy of the scale content, three experts in higher education and information technology reviewed the draft questionnaire for content validity before formal distribution. Based on their feedback, certain item wording was revised and localized. Subsequently, a pretest involving 153 students of higher institutions in Nantong City, Jiangsu Province, provided preliminary validation of the questionnaire's reliability and validity. Preliminary test results indicated that Cronbach's α coefficients for all constructs exceeded 0.80, KMO values surpassed 0.8, and Bartlett's sphericity test was significant ($p<0.001$), demonstrating robust reliability and validity. Consequently, no revisions were made before formal data collection, building a strong foundation within the subsequent statistical analysis and hypothesis testing.

3.2 Data Collection

The study was conducted on students from nine higher education institutions in Nantong City, Jiangsu Province, with approximately 143,905 students. The questionnaires were drawn using a stratified random sample, and the questionnaire links were distributed online through Questionnaire Star, and students were invited to fill out the questionnaires voluntarily on campus, [28]. A total of 783 questionnaires were distributed. After excluding invalid responses, 753 valid questionnaires were ultimately obtained, resulting in a valid response rate of 95%. The sample encompassed students of various genders, grade levels, and academic backgrounds, ensuring a representative sample.

3.3 Research Method

The study takes a quantitative research approach to collect data through questionnaires and empirically analyzes the elements affecting the adoption of smart campuses among students in higher educational institutions using Structural Equation Modeling. SEM helps to deal with the relationship between multiple potential variables simultaneously and test hypotheses, and it applies to multidimensional and complex structured theoretical models, [29]. The questionnaire data were analyzed by SPSS 26.0 for sample descriptive statistics, reliability analysis and validity test. SEM was built using AMOS 24.0, and the research model was subjected to a goodness-of-fit test and path analysis to validate the research hypotheses.

4 Results

4.1 Descriptive Statistical Analysis of Samples

This study collected a total of 753 valid questionnaires and statistically analyzed the basic demographic characteristics of the study participants. The results are shown in Table 1.

The male proportion in the sample was 50.5%, while the female proportion was 49.4%, which indicates a balanced gender distribution within the sample, which can represent the overall characteristics of the student population in higher educational institutions. The sample covers all grade levels from undergraduate to PhD, but the proportion of undergraduates is 71%. There is a wide range of majors in the sample, with the highest percentage of majors in Education at 40.8%, followed by Science & Engineering at 34.3%.

Table 1. Demographic Profiles of Respondents (N=753)

Variable	Category	Frequency	Percent
Gender	Male	381	50.6
	Female	372	49.4
Grade	Freshman	89	11.8
	Sophomore	160	21.2
	Junior	161	21.4
	Senior	124	16.5
	Postgraduate First Year	78	10.4
	Postgraduate Second Year	62	8.2
	Postgraduate Third Year	47	6.2
	Doctoral	32	4.2
Profession	Arts & History	101	13.4
	Science & Engineering	258	34.3
	Arts & Sports	87	11.6
	Education	307	40.8
School	Nantong University	152	20.2
	Nantong Institute of Technology	133	17.7
	Nantong University Xinglin College	62	8.2
	Jiangsu Shipping College	67	8.9
	Jiangsu College of Engineering and Technology	76	10.1
	Jiangsu Vocational College of Business	70	9.3
	Nantong Vocational University	90	12
	Nantong College of Science And Technology	56	7.4
	Nantong Normal College	47	6.2

Source: created by the authors

4.2 Common Method Bias Test

In questionnaire-based research, data often originate from the same source, collected at the same time point from the same participants. That can result in a common method bias (CMB), thereby undermining the credibility of research findings. In order to assure the validity and reliability of the data in this study, the Harman single-factor test was used to detect common method bias. This method involves conducting an unrotated exploratory factor analysis (EFA) on all measurement items to judge if the proportion of total variance explained by a single factor is excessively high, thereby assessing whether there is a significant common method bias exists in the data.

The outcome of Harman's Single-Factor Test is shown in Table 2, which extracted four factors with eigenvalues greater than 1. The first factor explained 33.832%, which is lower than the 40% criterion,

[30]. This indicates no significant common method bias in the study, suggesting good discriminant validity of the questionnaire data.

Table 2. Results of Harman's Single-Factor Test

Component	Total	% of Variance	Cumulative %
1	12.856	33.832	33.832
2	3.669	9.654	43.486
3	3.406	8.964	52.45
4	2.119	5.576	58.026

Source: created by the authors

4.3 Reliability and Validity Test

In this study, structural equation modeling (SEM) was employed to examine the reliability and validity of each variable, which is presented in Table 3.

Table 3. Reliability and Validity of the Measurement Model

Constructs	items	Unstd.	S.E.	Z	P	Std.	Cronbach's alpha	CR	AVE
SI	TI	1				0.765	0.762	0.807	0.582
	CI	0.947	0.068	14.000	***	0.755			
	HEII	0.921	0.067	13.809	***	0.768			
FC	SC	1				0.777	0.780	0.827	0.615
	OLP	1.126	0.071	15.860	***	0.827			
	VCC	0.875	0.06	14.503	***	0.746			
BI	BI1	1				0.882	0.936	0.938	0.685
	BI2	0.945	0.031	30.377	***	0.823			
	BI3	0.848	0.033	25.742	***	0.75			
	BI4	0.945	0.034	27.624	***	0.781			
	BI5	0.902	0.033	27.662	***	0.782			
	BI6	0.925	0.03	30.734	***	0.828			
	BI7	1.037	0.026	39.597	***	0.933			
ASC	ASC1	1				0.822	0.920	0.921	0.628
	ASC2	0.986	0.038	25.903	***	0.806			
	ASC3	0.790	0.040	19.989	***	0.666			
	ASC4	1.086	0.041	26.462	***	0.817			
	ASC5	0.862	0.037	23.084	***	0.743			
	ASC6	0.95	0.038	25.042	***	0.787			
	ASC7	1.045	0.035	29.865	***	0.886			

Source: created by the authors

4.3.1 Reliability Analysis

For all constructs, the Cronbach's alpha coefficients exceed 0.7, as shown in Table 3, suggesting that the scales had good internal consistency, [31]. The Alpha coefficients for the dimensions of Behavioral Intentions (BI) and Adoption of Smart Campus (ASC) are 0.936 and 0.920, respectively, which are highly reliable. The remaining constructs, such as the sub-dimensions TI, CI, and HEII of SI and the sub-dimensions SC, OLP, and VCC of facilitating conditions (FC), also exceeded 0.75, which shows that the measurement instrument has good overall stability.

4.3.2 Composite Reliability Analysis

The combined reliability (CR) values for all constructs exceeded 0.85, this value exceeds the recommended threshold of 0.7 [32], indicating good interpretative power and construct consistency for each latent variable.

4.3.3 Average Variance Extracted Analysis

Each of the values of AVE is higher than 0.5, which meets the standard requirements [31], indicating that each measurement item can better reflect the latent variable to which it belongs and has strong convergent validity. In summary, this research employs scales that meet statistical standards for both reliability and validity, making it possible to proceed with subsequent structural equation modeling analysis.

4.3.4 Discriminant Validity

For the purpose of examining the discriminant validity between the constructs, the study was analyzed using the Fornell-Larcker criteria. This method demands that the square root of the average variance extracted (Square root of AVE) for each latent variable be higher than its correlation coefficients with other latent variables. As shown in Table 4. This indicates that the construct in this study has good discriminant validity.

Table 4. Discriminant Validity of the Constructs

Constructs	ASC	BI	FC	SI
ASC	0.792			
BI	0.573	0.828		
FC	0.538	0.436	0.784	
SI	0.467	0.543	0.548	0.763

Note: The diagonal values represent the square roots of the AVE, and the lower triangle shows the Pearson correlation coefficients.

Source: created by the authors

4.4 Modeling Fit Indices Test

To assess the integral fit of the structural equation model, several fit indices were evaluated in this study, including the chi-square degrees of freedom ratio (ChiSq/df), standardized root mean square of residuals (SRMR), root mean square error approximation (RMSEA), adjusted goodness-of-fit index (AGFI), value-added fit index (IFI), comparative fit index (CFI), and Tucker-Lewis Index (TLI), It is shown in Figure 2 that the AMOS simulation results are presented, and the model fit indices are listed in Table 5.

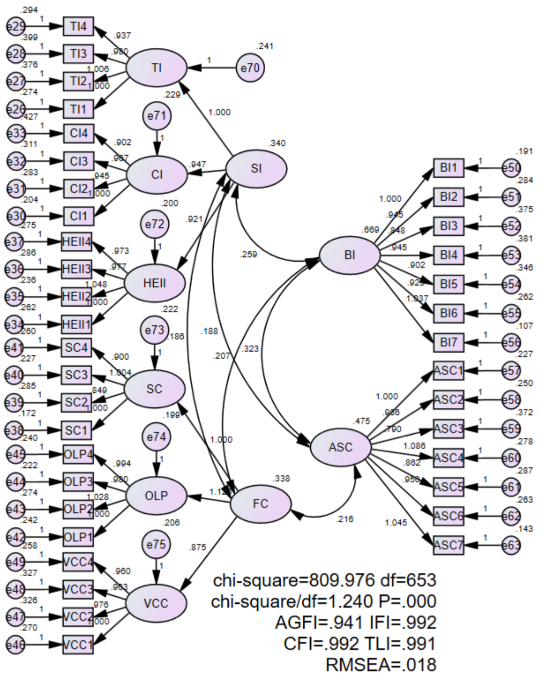

Fig. 2: AMOS Structural Model
Source: created by the authors

Table 5. Model Fit Indices for the Measurement Model

Compared Models	ChiSq/df	CFI	SRMR	IFI	RMSEA	AGFI	TLI
Test Value	1.240	0.9920	0.0278	0.9920	0.0180	0.9410	0.9910
Reference Value	≤3.000	≥0.900	≤0.080	>0.900	≤0.080	≥0.900	≥0.950
Sources	[31]	[32]	[33]	[33]	[34]	[35]	[36]

Source: created by the authors

In summary, all the fitting indices of the model are at or better than the recommended standards, especially RMSEA (0.018), SRMR (0.0278) and CFI/IFI/TLI are higher than 0.99, indicating that the model has an excellent fitting effect. Therefore, it can be confirmed that the structural equation model is suitable for testing the structural relationship between social influence, facilitating conditions, behavioral intention and adoption of smart campus.

4.5 Path Hypothesis Test

The study tested the proposed five path hypotheses (H1-H5), as shown in Table 6. The paths can be judged to be significant or not based on the P-value of less than 0.005, and the impact size of the paths can be judged based on the standardized coefficients, [37].

Table 6. Results of Direct Hypothesis Testing

Hypothesis	Path	Unstd.	S.E.	Z	P	Estimate	Results
H1	SI->BI	0.609	0.062	9.891	***	0.449	Supported
H2	FC->BI	0.358	0.054	6.683	***	0.265	Supported
H3	SI->ASC	0.143	0.049	2.925	0.003	0.125	Supported
H4	FC->ASC	0.377	0.046	8.161	***	0.333	Supported
H5	BI->ASC	0.324	0.035	9.185	***	0.385	Supported

Source: created by the authors

H1: Social influence has a significant positive effect on behavioral intention (β = 0.449, $p < 0.001$), suggesting that the support of teachers, peers, and higher education institutions positively contributes to the willingness of students to adopt a smart campus. H2: Facilitating conditions also have a significant positive effect on behavioral intention (β = 0.265, $p < 0.001$), indicating that the that the better the smart campus-related facilities (e.g., smart classrooms, online platforms, and one-card), the stronger the intention of students to use the facilities. H3: Social influences have a direct effect on the adoption of smart campus (β = 0.125, p = 0.003). H4:There is a remarkable direct effect of facilitating conditions (β = 0.333, $p < 0.001$), suggesting that students are more likely to actively use the smart campus system under conditions of complete infrastructure. H5: Behavioral intention has a significant positive effect on the adoption of smart campus (β = 0.385, $p < 0.001$).

4.6 Mediating Effects Test

To assess whether Behavioral Intentions serve as a mediator between Social Influences, Facilitating Conditions, and the adoption of a smart campus, the study applied a Bootstrapping analysis based on 1,000 iterations and a 95% confidence range. The findings are summarized in Table 7.

Mediating path of social impact (SI→BI→ASC): since the Bootstrap confidence interval (95%) does not contain 0: the bias-corrected confidence interval is [0.139, 0.277], and the percentile method confidence interval is [0.137, 0.272]. This suggests that the mediating effect is significant. Similarly, the direct effect remained significant. It indicates that behavioral intention plays a partial mediating role. The total effect was 0.340, and the indirect effect accounted for 57.9% of the total effect, indicating that behavioral intention was the main transmission path for SI to influence ASC.

Table 7. Results of Indirect Hypothesis Testing (Bootstrap)

Path relationship	Point estimate	Product of coefficient		Bootstrapping 1000 times 95% CI			
				Bias-corrected		Percentile	
		SE	Z-value	Lower	Upper	Lower	Upper
Indirect Effects							
SI→BI→ASC	0.197	0.034	5.794	0.139	0.277	0.137	0.272
Direct Effects							
SI→ASC	0.143	0.052	2.750	0.038	0.246	0.038	0.246
Total Effects							
SI→ASC	0.340	0.049	6.939	0.251	0.444	0.248	0.440
Indirect Effects							
FC→BI→ASC	0.116	0.026	4.462	0.070	0.177	0.069	0.174
Direct Effects							
FC→ASC	0.377	0.056	6.732	0.271	0.488	0.273	0.490
Total Effects							
FC→ASC	0.493	0.058	8.500	0.384	0.611	0.386	0.613

Source: created by the authors

Mediating path for facilitating conditions (FC→BI→ASC): Since the Bootstrap confidence interval (95%) did not contain 0, the bias correction interval was [0.070, 0.177] and the percentile interval was [0.069, 0.174], suggesting that the mediating effect was significant. Similarly, the direct effect was equally significant, and the percentage of the indirect effect amounted to 23.5%. It indicates that behavioral intention also plays a partial mediating role between FC and ASC.

5 Discussion

5.1 Findings

A structural equation model was constructed based on the UTAUT framework to examine the relationship between social influence, facilitating conditions, behavioral intention, and the adoption of a smart campus. The study employed path analysis and mediation effect testing using SPSS and AMOS software, which generated the following key findings:

First, social influences significantly and positively affect the behavioral intentions and adoption behaviors by students in higher educational institutions in Nantong city. Social influences (including teacher influences, peer influences, and higher educational institutions' influences) play a crucial part in the process of students adopting smart campus technologies. The path analysis results showed that social influence not only directly and significantly predicted behavioral intention ($p < 0.001$) but also had a notable direct effect on adoption behavior ($p = 0.003$).

Second, facilitating conditions well influence the behavioral intention and adoption of the smart campus by students in higher educational institutions in Nantong city. Facilitating conditions (including smart classrooms, online learning platforms, virtual campus cards) significantly and positively influenced behavioral intentions ($p < 0.001$) and adoption of smart campus ($p < 0.001$).

Third, behavioral intention plays a crucial mediating role between the independent variables and the adoption of a smart campus. Behavioral intention is not only an important transmission mechanism for the independent variables (SI and FC) to influence adoption behavior, but also has a significant positive effect on adoption behavior itself. The mediating path test further verified hypotheses H6 and H7, and behavior intention partially mediated the relationship between social influence and adoption of smart campus, suggesting that students are more likely to develop adoption intention in a positive social atmosphere, which can be transformed into actual behavior. At the same time, the relationship between facilitating conditions and behavioral adoption is partially mediated by behavioral intention. The better the technical support and resource base provided by the university, the more inclined students are to actively adopt the smart campus system.

In summary, the adoption of a smart campus is not entirely driven by external factors, but also by the internal subjective behavioral intention of students.

5.2 Theoretical Contributions

Based on the UTAUT theory and the application of smart campus technology in higher educational institutions, this study constructs a new research model with the following theoretical contributions:

First, this research develops the localized application of the UTAUT theory within the intelligent campus scenarios of Chinese higher education. Within China's higher education system, systematic empirical research on student adoption of IoT-based smart campus systems remains scarce. By using university students in Nantong City, Jiangsu Province, as the research sample, this study validated the applicability of social influence and facilitating conditions within the context of local educational culture and campus management systems. It revealed the interactive mechanisms between Chinese campus management models and student adoption behaviors, which leads to a richer cross-cultural explanatory power of UTAUT theory in the context of educational informatization.

Second, it clarifies how behavioral intention functions as a mediator in the adoption of smart campuses, deepening the theoretical understanding of Chinese university students regarding smart campus adoption. The findings indicate that within the higher education environment of China, characterized by strong collectivism and institutionalization, student adoption behaviors are driven not only by external conditions but also by intrinsic psychological motivations. This discovery enhances the explanatory power of UTAUT theory in localized educational contexts and provides a theoretical foundation for future multi-group analyses across institutions, disciplines, or populations.

Third, a detailed measurement framework based on smart campus characteristics was constructed. This study subdivided social influence into teacher influence, peer influence, and school organizational support, while breaking down enabling conditions into specific technological elements such as smart classrooms, online learning platforms, and campus card services. This dimensional design not only enhances the model's contextual relevance but also provides an operational measurement framework and validation pathway for subsequent research. Simultaneously, the findings reveal differential influences of various technological dimensions on student adoption processes, laying a theoretical foundation for future studies in other provinces.

5.3 Practical Contributions

This study not only expands the application of the UTAUT model at the theoretical level but also provides concrete and feasible suggestions and references for the construction and promotion of smart campuses in colleges and universities at the practical level. The major practical contributions are summarized in the following points:

First, it provides a basis for decision-making in the development of smart campuses in higher education institutions. The research results show that the adoption of smart campus by students is significantly influenced by two factors: social influence and facilitating conditions. In particular, encouragement from teachers and peers, promotion and support from the school, and the availability of smart facilities are important factors in promoting active use by students. Therefore, in the process of promoting the construction of a smart campus, higher education institutions should focus on the design of behavioral guidance and social incentive mechanisms to strengthen the demonstration effect within the higher education institutions.

Second, it provides a reference value for the priority of technological investment and resource allocation in higher educational institutions. Facilitating conditions such as smart classrooms, campus card, and online learning platform have a significant promotional effect on the behavioral intention and actual behavior of students. The research results show that the degree of infrastructure improvement is directly related to the final effectiveness of the system. Therefore, given limited resources, higher educational institutions should prioritize the improvement of smart service functions that are frequently used by students and provide a strong user experience, and optimize technology deployment strategies from the perspective of students.

Third, it provides data support for the development of smart campuses at local higher education institutions. A study based on questionnaire data from all higher education institutions in Nantong systematically analyzes key factors influencing smart campus adoption from the student perspective, offering real-world adoption insights for local universities. This provides practical references and data support for advancing regional educational informatization, evaluating smart campus projects, and formulating government policies.

5.4 Limitation

Although the research has achieved certain theoretical and practical outcomes in analyzing the mechanisms of smart campus adoption behavior, it still has some limitations that cannot be overlooked and require further refinement and expansion in subsequent research.

First, there are relatively limited model variables, not covering more psychological or technical factors. This study mainly constructs a research model based on the UTAUT theory. Although it includes core variables such as social influence, facilitating conditions, and Behavioral intentions, it does not consider potential factors, for example, technical factors and satisfaction. Future studies can introduce other psychological mechanisms or system characteristic variables to explore the factors influencing the adoption of smart campus more comprehensively.

Second, the data source is single and susceptible to self-reporting bias. This study collected data through self-administered questionnaires, and the answers of respondents may be affected by subjective bias or social expectations. In the future, combining multiple ways of gathering data, like the interview method and the observation method, can enhance the objectivity and reliability of the data, strengthening the robustness of empirical analysis.

Acknowledgement:
The authors gratefully acknowledge the financial support from Jiangsu Province Higher Education Informatization Research Major Project under Grant No. 2025JSETKT036; Nantong Institute of Technology Artificial Intelligence General Education Teaching Reform Research Special Project under Grant No. 2025JJG005; Research Project on Higher Education Teaching Reform at Nantong Institute of Technology.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Haiyan Cao: Conceptualization, software, formal analysis, investigation, resources, data curation, writing—original draft preparation, project administration, project administration; Md. Gapar Md Johar: methodology, validation, writing—original draft preparation; Jacquline Tham: formal analysis, investigation, visualization.

Sources of Funding for Research Presented in a Scientific Article or the Scientific Article Itself

The authors gratefully acknowledge the financial support from Jiangsu Province Higher Education Informatization Research Major Project under Grant No. 2025JSETKT036; Nantong Institute of Technology Artificial Intelligence General Education Teaching Reform Research Special Project under Grant No. 2025JJG005; Research Project on Higher Education Teaching Reform at Nantong Institute of Technology.

Conflict of Interest

The authors have no conflicts of interest to declare.

APPENDIX

Measurement items

Constructs	Varibles	Items	Items contents	Sources
SI	TI	TI1	When my teacher recommended using Smart Campus, I wanted to try it.	[15]
		TI2	When teachers frequently use the Smart Campus system, I am also more willing to use it.	
		TI3	I propose that teachers' evaluations of smart campuses are trustworthy.	
		TI4	I use Smart Campus to satisfy teachers' expectations of my use.	
	CI	CI1	My classmates think that I should use Smart Campus.	[15]
		CI2	When a high proportion of students use Smart Campus devices, I will also use them.	
		CI3	If my classmates propose a good feature, I will test it.	
		CI4	When deciding whether to use Smart Campus, I will consider my classmates' opinions.	
	HEII	HEII1	The school strongly promotes the use of Smart Campus technology.	[15]
		HEII2	The school provides clear guidelines for using the Smart Campus system.	
		HEII3	The university encourages students to participate in Smart Campus services.	
		HEII4	The school provides online human customer service for using the Smart Campus system.	
FC	SC	SC1	I think a smart classroom provides reliable education services to students.	[21]
		SC2	I propose that the provision of smart classrooms at my school will help to enhance my learning experience.	
		SC3	I think a smart classroom can help me to obtain high-quality education quality.	
		SC4	I believe that a smart classroom can help me obtain more knowledge and graduate following the university's policy.	
	OLP	OLP1	I find Online Learning Platform useful for studies.	[21]
		OLP2	Online Learning Platform increases learning productivity.	
		OLP3	Using the Online Learning Platform would make it easier to do my studies.	
		OLP4	Online Learning Platform allow me to accomplish class activities more quickly.	
	VCC	VCC1	The Virtual Campus Card service has improved the efficiency of my transactions on campus.	[28]
		VCC2	Virtual Campus Cards can ensure information security.	
		VCC3	Using the virtual campus makes living and learning more efficient.	
		VCC4	The virtual campus card platform can be used to query the required information.	
BI		BI1	Given the opportunity, I will use a smart campus for learning.	[29]
		BI2	I am willing to use a Smart Campus in the near future.	[29]
		BI3	I am open to using Smart Campus services if they are available.	[29]
		BI4	I intend to use a Smart Campus in the future.	[29]
		BI5	I will continue using Smart Campus to fulfil my future needs	[38]

Constructs	Varibles	Items	Items contents	Sources
		BI6	I will try to use Smart Campus services whenever possible.	[38]
		BI7	I plan to incorporate SmartCcampus services into my daily life.	[38]
ASC		ASC1	I plan to continue using the Smart Campus equipment.	[29]
		ASC2	I have already advised others of the smart campus service.	[29]
		ASC3	I actively use Smart Campus equipment for learning.	[29]
		ASC4	I frequently use Smart Campus equipment for learning.	[29]
		ASC5	I rely on Smart Campus.	[15]
		ASC6	I can operate the Smart Campus equipment proficiently.	[15]
		ASC7	The Smart Campus system has become an important tool for my learning.	[15]