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Adoption of IoT-Based Smart Campuses Based on an Extended Technology Acceptance Model: The Mediating Role of Behavior Intention

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Abstract. As the digital transformation of higher education continues to deepen, Internet of Things (IoT) technology provides crucial support for the development of smart campus and service innovation. However, the level of actual adoption of smart campus among students in higher educational institutions remains heterogeneous. This study introduces a compatibility construct to extend the Technology Acceptance Model (TAM), focusing on examining the influence mechanisms of perceived usefulness, perceived ease of use, and compatibility on behavioral intention and the adoption of smart campus. This study adopted a questionnaire-based approach to collect data, distributing 783 questionnaires to students in Nantong City, Jiangsu Province. A total of 753 valid responses were collected, with a response rate of 96%. Employing SPSS 26.0 and AMOS 24.0, the research conducted reliability and validity tests with structural equation modeling analysis. Research findings indicate that perceived usefulness, perceived ease of use, and compatibility all significantly promote behavioral intention. Furthermore, behavioral intention has a significant positive impact on the adoption of smart campus. Additionally, mediation analysis reveals that behavior intention plays a mediating role in the adoption of IoT-Based smart campus. This study contributes in two key areas: Theoretically, it extends the application of TAM research to the context of IoT-Based smart campus, providing new empirical evidence for understanding technology adoption mechanisms in educational digitization. Practically, it offers valuable insights for the development, functional optimization, and user adoption of smart campus initiatives in higher education institutions.

Keywords: Technology Acceptance Model, Smart Campus Adoption, Behavior Intention, Internet of Things

1. Introduction

With the rapid advancement of next-generation information technologies, innovations such as the Internet of Things (IoT), big data, cloud computing, and artificial intelligence are profoundly reshaping the operational models and governance structures of higher education (He et al., 2024). Against the backdrop of advancing initiatives like "Digital China", "Smart Education" and higher education informatization strategies, the Smart Campus has emerged as a vital vehicle for universities' digital transformation. By enabling intelligent sensing and coordinated control across diverse scenarios such as teaching, research, administration, and services, it facilitates efficient resource allocation and comprehensive enhancement of educational service quality. This approach is recognized as a key pathway to driving high-quality development in higher education institutions (Wu et al., 2023).

In contrast to traditional campus, Smart Campus emphasizes a core architecture centered on the perception layer, network layer, and application layer. Through application scenarios such as smart classrooms, online learning platforms, campus ID cards, and intelligent management systems, it enables real-time perception of teaching activities, precise analysis of learning behaviors, and intelligent decision-making for campus operations (Cavus et al., 2022). Therefore, its successful implementation depends not only on the perfection of technical infrastructure but also on the understanding, attitude, and willingness to use relevant technologies and systems among end users, especially college students. However, in actual implementation, many universities still face the issue of prioritizing construction over usage. Smart campus systems often suffer from low utilization rates, idle functions, or even resistance. This reality underscores the importance of systematically exploring IoT-based smart campus adoption mechanisms from a user perspective (Blakong et al., 2025).

In the field of information adoption research, the Technology Acceptance Model (TAM) and its extensions are widely used to explain users' acceptance behavior toward new technologies. TAM posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEU) are core factors influencing users' Behavioral Intention (BI), which in turn determines actual usage behavior (Davis et al., 1989; King & He, 2006). This study introduces the Compatibility (CMP) variable based on TAM theory to better explain users' adoption decisions in complex technological environments. Empirical research indicates that when new technologies enhance learning or work performance, are operationally straightforward, and align with users' existing habits and needs, users are more likely to form positive usage intentions and translate them into actual adoption behaviors.

Although existing research has explored smart campus adoption from various perspectives, it still presents the following shortcomings. First, most existing research focuses on either single technological dimensions or overall perception factors, with limited systematic integration of technology-specific factors and user behavioral mechanisms. Particularly in IoT-based smart campus scenarios, there is a lack of in-depth analysis on the combined effects of PU, PEU, and CMP. Second, some studies directly examine the impact of influencing factors on the adoption of smart campus technologies, overlooking the potential mediating role of behavioral intention. In fact, users' perceptions and evaluations of technology often do not directly translate into actual usage; instead, they require mediation through the psychological mechanism of behavioral intention. Third, in terms of research subjects, there is still relatively limited empirical research targeting university students as the core user group, particularly in second-tier cities like Nantong, Jiangsu Province, where relevant empirical evidence remains insufficient.

Based on the limitations of existing research, this study draws upon Technology Acceptance Theory to focus on the adoption of IoT-based smart campuses. It constructs and validates a comprehensive research model encompassing technology-specific factors, behavioral intention, and adoption behavior. Specifically, this study selects perceived usefulness (PU), perceived ease of use (PEU), and compatibility (CMP) as key technological factors to examine the direct influence of these factors on student behavior intention (BI) and the adoption of IoT-based smart campuses (ASC). It also focuses on analyzing the mediating role of behavior intention between technological factors and smart campus adoption. Through this research framework, this study aims to reveal the intrinsic mechanism of IoT-Based Smart Campus adoption, which involves "technology cognition—behavioral intention—actual adoption".

This study provides the following theoretical and practical significance. Theoretically, this study introduces compatibility into the IoT-based smart campus research context based on the TAM model and systematically examines the mediating effect of behavioral intention, thereby enriching research perspectives in the adoption of smart campuses and educational information systems. Practically, the findings assist educational administrators and software developers in more accurately identifying key factors influencing smart campus adoption, providing empirical evidence for optimizing system design, enhancing user experience, and promoting the sustainable development of smart campuses.

In summary, this study explores the adoption of IoT-based smart campuses by introducing behavior intention as a mediating variable within a technology specific framework. It constructs and validates a systematic research model to provide valuable theoretical support and practical insights for smart campus development and digital transformation in higher education.

2. Literature Review

2.1 Smart Campus

With the rapid advancement of information technology, higher education is transiting through a key phase of evolution from digital campus to smart campus. The concept of the Smart Campus originates from the Smart City philosophy, representing its concrete manifestation within the university setting. Existing research generally holds that a smart campus is not a single technological system, but rather a comprehensive intelligent ecosystem underpinned by information technology and centered on the needs of faculty and students. Research over the past five years has defined smart campuses from diverse perspectives. One category emphasizes technological attributes, defining smart campuses as systems that achieve comprehensive perception, interconnection, and intelligent management of campus environments, equipment, and services through technologies such as the Internet of Things (IoT), cloud computing, big data, and artificial intelligence (Polin et al., 2023). Another category focuses on user experience and service orientation, highlighting that the essence of smart campuses lies in providing students and faculty with efficient, convenient, and personalized learning, management, and lifestyle services, thereby enhancing educational quality and campus governance (Silva-da-Nóbrega et al., 2022). Synthesizing these perspectives, a smart campus can be defined as: an integrated system that leverages next-generation information technologies like IoT to systematically consolidate teaching, management, and service resources within higher education institutions. This integration aims to achieve intelligent campus operations, personalized services, and scientific decision-making. This definition establishes the conceptual foundation for subsequent exploration of smart campus adoption behaviors and their influencing factors.

The realization of smart campuses relies on the deep integration of multiple information technologies, with IoT technology considered its core foundation. By deploying sensors, smart terminals, and network devices, classrooms, laboratories, libraries, and public facilities across campuses can be perceived and monitored in real time, supporting data collection and intelligent management (Zhang et al., 2022). Building upon this foundation, cloud computing and big data platforms provide unified data storage, processing, and analytical capabilities for smart campuses, enabling cross-system integration of teaching data, management data, and behavioral data. In recent years, artificial intelligence technologies have been progressively introduced into smart campus scenarios. These technologies are applied to learning behavior analysis, intelligent recommendations, and decision support, thereby enhancing the intelligence level of campus services (Hu & Li, 2024). Functionally, smart campuses typically comprise modules such as intelligent teaching systems, campus management systems, learning support platforms, and integrated service systems. These components collectively form a highly integrated information environment, whose complexity and system compatibility directly influence students' user experience and adoption willingness toward the smart campus system.

At the practical application level, smart campuses have extensively permeated multiple domains within higher education institutions, including teaching, management, and services. In teaching, smart campuses support blended learning and personalized education through smart classrooms, online learning platforms, and learning analytics systems, thereby enhancing student engagement and learning outcomes (Al-Emran et al., 2025). In campus management, smart campus systems are deployed for academic administration, resource scheduling, security monitoring, and energy management. Research indicates that intelligent management systems effectively improve campus operational efficiency, reduce management costs, and enhance campus security levels (Cavus et al., 2022). Furthermore, smart campuses provide convenient lifestyle services through integrated campus cards, mobile campus applications, and comprehensive online service platforms. These applications not only enhance student satisfaction with campus services but also influence their perception of the overall value of smart campuses (Gupta et al., 2022).

Although significant progress has been made in smart campus development, current research indicates that it still faces multifaceted challenges. On one hand, smart campus systems often feature high technical complexity, with issues of system compatibility and usability potentially reducing user willingness to adopt them. On the other hand, data privacy and information security concerns have increasingly become key factors constraining the further promotion of smart campuses, as user apprehensions about data security may influence their adoption behavior (Gill et al., 2022). From a developmental perspective, smart campus research has gradually shifted from a technology-oriented approach toward a user-centered perspective in recent years, placing greater emphasis on students' and teachers' perceptions, attitudes, and behavioral responses toward smart campus systems. Scholars widely agree that the future success of smart campuses depends not only on technological maturity but also on users' subjective perceptions of their usefulness, ease of use, and convenience (Silva-da-Nóbrega et al., 2022). Therefore, it is necessary to systematically explore the influencing factors of smart campuses from a user adoption perspective, providing a theoretical basis for subsequent research grounded in the Technology Acceptance Model (TAM).

2.2 TAM

The Technology Acceptance Model (TAM) is one of the most influential theoretical frameworks in the fields of information systems and educational technology. It is widely used to explain users' acceptance and adoption behaviors toward new technologies (Davis, 1989; Venkatesh & Davis, 2000), as illustrated in Figure 1. TAM originated from the Theory of Reasoned Action (TRA), whose core principle lies in explaining behavioral decision-making processes through individual rational cognition. Building upon this foundation, Davis (1989) proposed TAM specifically for information system usage contexts. By simplifying users' perceptions of technology into several key psychological variables, he constructed a theoretical model capable of effectively predicting technology acceptance behavior.

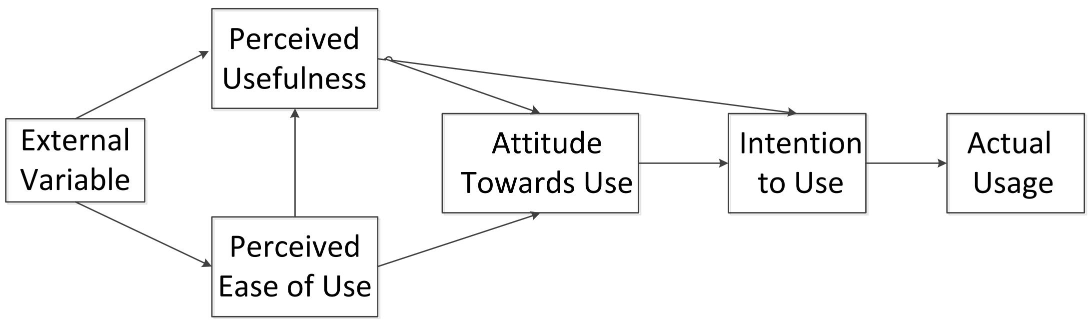

Fig. 1: Technology acceptance model

TAM has gained extensive empirical validation across diverse technological contexts due to its concise structure, clear logic, and strong explanatory power, proving particularly applicable to research on smart campus, IoT systems, and educational informatization (Kai et al., 2026). In the complex system environment of smart campuses, which heavily rely on information technology, students' subjective perceptions and behavioral intentions toward the system are considered key factors influencing the successful implementation of technology. Therefore, TAM provides a solid theoretical foundation for exploring adoption behaviors in IoT-based smart campuses. Compared to other behavioral theories, one of the most notable features of TAM is its high degree of contextual adaptability and operational utility.The model does not emphasize complex psychosocial processes but focuses on users' most direct cognitive judgments when encountering new technologies. This theoretical design enables TAM to be repeatedly validated across diverse technological contexts, gradually evolving into a foundational theoretical framework for technology adoption research. Studies over the past five years continue to widely adopt TAM as the core theoretical basis for analyzing user technology acceptance behavior. Particularly against the backdrop of emerging information technologies and digital services, TAM demonstrates robust theoretical vitality and explanatory power (Wei et al., 2025).

The fundamental theoretical framework of TAM posits that user adoption of technology is primarily determined by two core cognitive variables: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). These variables influence Behavioral Intention (BI), which in turn affects actual usage or adoption behavior.Perceived Usefulness (PU) refers to the extent to which users believe using a technology can enhance their learning or work performance;Perceived Ease of Use (PEOU) refers to the extent to which users perceive the process of using the technology as effortless, understandable, and straightforward;Behavioral Intention (BI) reflects the subjective willingness to use or continue using the technology in the future. Extensive research indicates that PU and PEOU are the most stable and explanatory factors in predicting user technology adoption behavior. Furthermore, PEOU not only directly influences BI but also indirectly affects adoption intention by enhancing PU (Kim et al., 2025).

Although TAM has demonstrated strong explanatory power in technology adoption research, as technological systems grow increasingly complex, scholars have gradually recognized that relying solely on core constructs may prove insufficient to comprehensively explain users' adoption decision-making processes. Consequently, expanding TAM by incorporating external variables has become a significant developmental direction in technology acceptance studies (Kim et al., 2025). Specifically, compatibility is a key concept derived from innovation diffusion theory that has been widely applied to broaden the explanatory framework of TAM. Compatibility typically refers to the degree of alignment between a new technology and a user's existing values, usage habits, experiences, and current systems. Within information systems research, compatibility is recognized as a significant contextual factor influencing the formation of user cognition and attitudes (Nasywahasna et al., 2025).

Research over the past five years indicates that incorporating compatibility into the TAM framework enhances the model's ability to explain complex technological systems, particularly in IoT systems, smart service platforms, and multi-system integration environments. By introducing compatibility variables, researchers can better understand psychological evaluation processes among users encountering new technologies, rather than being limited to the functional or operational characteristics of the technology itself (Kim et al., 2025).

In the field of educational technology, TAM has been widely applied to study user acceptance behaviors toward technologies such as online learning platforms, learning management systems, and intelligent teaching tools (Davis, 2025; Oulahsene, 2025). Existing research indicates that TAM and its extended models effectively explain technology acceptance behaviors among students and faculty within smart campus environments (Marian-Vladut et al., 2025). Furthermore, recent research trends have shifted from focusing solely on technological functionality toward greater emphasis on user experience and contextual usage. This evolution has deepened TAM's application in smart campus studies while driving the continual advancement of the model within educational informatization research.

In summary, the Technology Acceptance Model (TAM) serves as a classic theory in information systems research, providing a solid theoretical foundation for understanding users' technology adoption behavior. The core constructs demonstrate strong stability and explanatory power across diverse technological environments. By incorporating extended variables such as compatibility, TAM can better adapt to complex application scenarios like smart campus.

2.3 Research Model and Hypotheses Development

2.3.1 Research Model

This study conducted a systematic analysis of smart campus adoption among students in higher educational institutions based on the Technology Acceptance Model (TAM), integrating the application context of smart campus and IoT technologies. Within smart campus environments, information systems typically exhibit high integration, multi-scenario applications, and continuous usage orientation. Relying solely on the core constructs of traditional TAM is insufficient to fully explain user adoption behavior. Therefore, this study extends the TAM theoretical framework by introducing a compatibility external variable, proposing the research model shown in Figure 2.

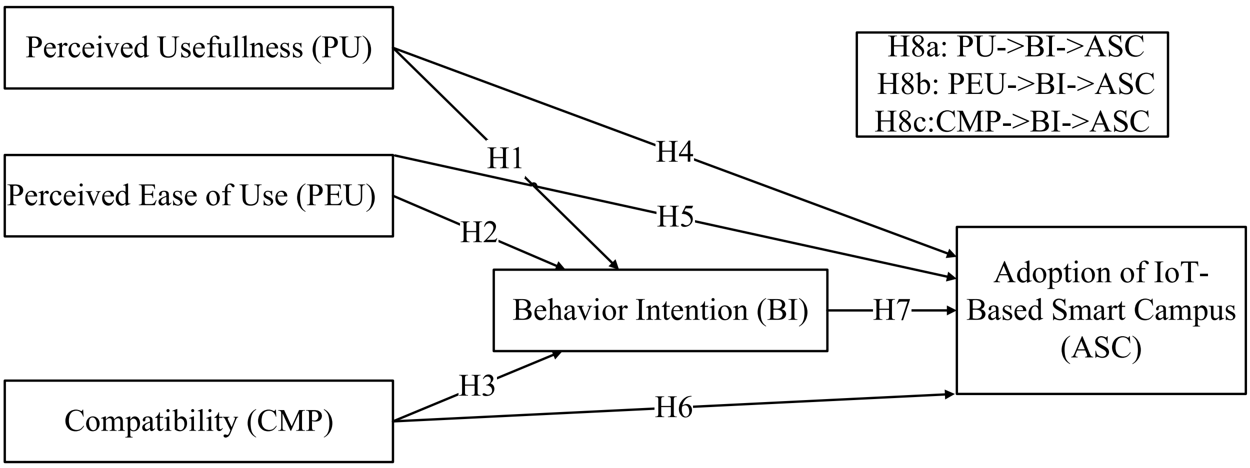

Fig. 2: Research model

The research model primarily consists of three independent variables: perceived usefulness, perceived ease of use, and compatibility. The mediating variable is behavioral intention, while the dependent variable is the adoption of smart campus systems. This study considers behavior intention as the key mediating variable between external factors and the adoption of smart campus. On the one hand, perceived ease of use, perceived usefulness, and compatibility may directly influence students' adoption behavior toward smart campuses. On the other hand, these factors may also indirectly affect adoption behavior by influencing students' behavioral intentions. This dual-path structure helps reveal the complexity of smart campus adoption mechanisms more comprehensively. Overall, while maintaining the core logical consistency of TAM theory, this study integrates the technological characteristics and educational application scenarios of smart campuses to construct a comprehensive research framework encompassing both direct and mediating effects. This framework provides a theoretical foundation for subsequent hypothesis development and empirical analysis.

2.3.2 Hypotheses Development

Perceived Usefulness (PU) is a core construct in the Technology Acceptance Model, referring to the extent to which users believe a technology can enhance their learning or work performance. According to the Technology Acceptance Model and its extended research, when users perceive that technology can deliver tangible benefits, their behavioral intention to adopt that technology significantly increases. In recent years, this relationship has been repeatedly validated in smart campus and IoT application contexts. For instance, Al-Emran et al. (2020) found in their smart learning system study that perceived usefulness significantly and positively influenced students' behavioral intentions; Deng et al. (2021) confirmed in IoT educational applications that perceived usefulness is a key predictor of user adoption intent; Furthermore, Alrasheedi et al. (2023) demonstrated through empirical research on smart campus systems that students' recognition of system usefulness significantly increases their willingness to use it. Therefore, this study proposes Hypothesis H1.

H1: The link between perceived usefulness and behavior intention

Perceived Ease of Use (PEU) refers to the degree to which users believe a system can be used without excessive effort. The Technology Acceptance Model (TAM) posits that the easier a system is to use, the greater the likelihood users will form positive behavioral intentions. In recent years, multiple empirical studies have validated the significant influence of perceived ease of use on behavioral intentions within the contexts of IoT and smart campuses. For instance, Nikou and Economides (2021) found in their study of digital learning systems that perceived ease of use significantly enhances students' behavioral intentions. Park et al. (2022) confirmed in their research on smart education platforms that operational convenience is a key factor in predicting user willingness to use. Furthermore, Zhang et al. (2024) demonstrated in their empirical study of IoT-enabled smart campuses that perceived ease of use can significantly boost students' usage intentions. Therefore, this study proposes Hypothesis H2.

H2: The link between perceived ease of use and behavior intention

Compatibility refers to the degree of alignment between new technology and existing values, usage habits, and needs of users. In studies extending the Technology Acceptance Model (TAM), compatibility is recognized as a significant technology-specific factor influencing users' adoption intentions. Recent research in IoT and smart systems contexts has confirmed that stronger compatibility between technology and users' established habits correlates with greater usage intentions. For instance, Talukder et al. (2020) found compatibility significantly and positively influenced behavioral intention in an IoT technology adoption study; Rahi et al. (2022) noted compatibility enhances user willingness to use in a smart service system study; furthermore, Li and Yu (2023) validated compatibility's significant promotional effect on student behavioral intention in a smart campus study. Therefore, this study proposes Hypothesis H3.

H3: The link between compatibility and behavior intention

In addition to indirectly influencing adoption behavior through behavioral intentions, some studies indicate that perceived usefulness may also directly impact actual adoption behavior. In IoT and smart campus contexts, when users explicitly perceive that a system can enhance learning efficiency or campus service quality, their actual usage behavior is more likely to occur. Wong et al. (2021) found in smart campus research that perceived usefulness directly influences system adoption. Al-Fraihat et al. (2022) confirmed in online learning system studies that perceived usefulness significantly predicts actual usage behavior. Furthermore, Huang et al. (2024) reached similar conclusions in IoT education system research. Therefore, this study proposes Hypothesis H4.

H4: The link between perceived usefulness and adoption of iot-based smart campus

Perceived ease of use not only influences behavior intention but may also directly promote technology adoption by reducing perceived technical complexity. Related studies indicate that in IoT and smart systems, the easier a system is to use, the more likely users are to engage in sustained and practical usage. Venkatesh et al. (2020) expanded the model to demonstrate that perceived ease of use directly influences usage behavior. Chao (2022) found in a smart campus system study that operational simplicity significantly impacts system adoption. Furthermore, Sun et al. (2024) confirmed this relationship in their research on IoT educational applications. Therefore, this study proposes Hypothesis H5.

H5: The link between perceived ease of use and adoption of iot-based smart campus

Compatibility is considered a key antecedent variable influencing the actual adoption of technology. When a technological system can seamlessly integrate into users' existing learning and lifestyle patterns, its likelihood of adoption significantly increases. Subsequent empirical studies of Rogers' theory demonstrate that compatibility plays a direct role in IoT adoption. Cruz-Jesus et al. (2021) confirmed in smart technology adoption studies that compatibility significantly influences usage behavior; Nikou et al. (2023) noted in IoT system research that high compatibility promotes actual adoption; furthermore, Chen et al. (2024) also found a significant positive impact of compatibility on adoption behavior in the context of smart campuses. Therefore, this study proposes Hypothesis H6.

H6: The link between compatibility and adoption of iot-based smart campus

Behavioral intention is widely regarded as the most direct variable for predicting actual technology adoption behavior. TAM, UTAUT, and their extended models all emphasize the decisive role of behavioral intention in determining actual usage behavior. A meta-analysis by Dwivedi et al. (2020) demonstrated that behavioral intention significantly predicts usage behavior across diverse technological contexts. Salloum et al. (2021) confirmed behavioral intention's significant influence on actual usage in smart learning system research. Furthermore, Zhou et al. (2023) similarly identified behavioral intention as a crucial antecedent to adoption behavior in IoT smart campus studies. Therefore, this study proposes Hypothesis H7.

H7: The link between behavior intention and adoption of iot-based smart campus

According to the Technology Acceptance Model theory, users' cognitive evaluations of technology typically influence their actual adoption behavior through behavioral intention. In recent years, numerous studies have validated the mediating role of behavioral intention in IoT and smart system contexts. For instance, Tarhini et al. (2021) found that behavioral intention mediates the relationship between perceived factors and usage behavior in smart learning research; Alam et al. (2022) confirmed the significant mediating effect of behavioral intention in IoT technology adoption studies; Furthermore, Xu et al. (2024) validated the mediating mechanism of behavioral intention between technology-specific factors and adoption behavior in smart campus research. Therefore, this study proposes Hypothesis H8.

H8a: Behavior intention mediates the relationship between perceived usefulness and adoption of iot-based smart campus

H8b: Behavior intention mediates the relationship between perceived ease of use and adoption of iot-based smart campus

H8c: Behavior intention mediates the relationship between compatibility and adoption of iot-based smart campus

3 Methodology

3.1 Scale Design

This study adopts the Technology Acceptance Model (TAM) as its theoretical foundation to measure university students' adoption toward smart campus. The measurement instruments in this study are primarily based on established research findings from relevant domestic and international fields, with revisions tailored to the context of smart campus and IoT applications. The measurement items for perceived usefulness and perceived ease of use primarily draw from the research of Davis (1989) and Venkatesh et al. (2003). They are used to gauge students' subjective perceptions regarding the smart campus system's effectiveness in enhancing learning efficiency, operational convenience, and user experience. The compatibility variable references the findings of Wu and Wang (2005), focusing on reflecting the degree of alignment between the smart campus system and students' existing learning methods, technology usage habits, and campus information systems. The measurement items adopted for smart campus adoption draw from information system adoption and smart education-related research (Ifenthaler & Schumacher, 2016), evaluating students' overall acceptance of IoT-based smart campus services. In the scale design process, each latent variable employed multi-item measurement approaches. Items were contextualized based on university smart campus application scenarios to enhance the scale's applicability and comprehensibility. All items were measured using a five-point Likert scale, where 1 indicates "Strongly Disagree" and 5 indicates "Strongly Agree." Prior to formal investigation, the scale's validity and clarity were verified through expert review and pre-testing, establishing a robust measurement foundation for subsequent empirical analysis (Viera et al., 2025).

3.2 Data Collection

The data for this study were collected from students at higher education institutions in Nantong City, Jiangsu Province. To enhance sample representativeness, a stratified random sampling method was employed for the questionnaire survey (Aoyama, 1954). The survey was distributed online via the an online survey platform, inviting students to participate voluntarily. A total of 783 questionnaires were collected. After data cleaning, 753 valid questionnaires were retained, yielding an effective response rate of approximately 95%. The sample covered different genders, grade levels, and academic disciplines, effectively reflecting the overall characteristics of the college student population.

3.3 Research Method

This study employs quantitative research methods to conduct an empirical analysis of students in higher educational institutions. Quantitative research methods can characterize relationships between variables in structured data formats, making them suitable for research domains such as technology acceptance and information system adoption (Sneesl et al., 2023). These methods are particularly well-suited for systematically testing theoretical models and their path relationships. During data analysis, SPSS 26.0 software was first used for sample data preprocessing and statistical analysis, including descriptive statistics of sample characteristics, reliability analysis of scales, and validity testing to ensure the reliability and validity of measurement tools. Subsequently, AMOS 24.0 was employed to construct a structural equation model, evaluate the overall model fit, and test path relationships among latent variables to validate research hypotheses.

4 Results

4.1 Descriptive Statistical Analysis of Samples

To understand the basic characteristics of the sample, this paper conducted a descriptive statistical analysis of the valid questionnaires collected. The analysis primarily describes the sample structure in terms of gender, grade level, major background, and school distribution, as shown in Table 1.

In terms of gender distribution, male students accounted for 50.6% and female students for 49.4%, indicating a relatively balanced overall ratio without significant gender bias. This suggests that the sample possesses good representativeness in its gender structure, which enhances the robustness of subsequent empirical analysis results.

In terms of grade distribution, the sample covered multiple stages including undergraduates, master's students, and doctoral students. Undergraduate students represented the largest proportion, primarily sophomores and juniors. This group typically possesses extensive experience using campus information systems and demonstrates a high level of awareness regarding smart campus services. Additionally, graduate and doctoral students also constituted a significant portion of the sample, reflecting the usage needs of senior students for smart campus systems in their academic and research activities. Overall, the sample distribution across different academic stages was reasonably balanced, reflecting the multi-tiered characteristics of the university student population.

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 South	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

In terms of academic backgrounds, the sample encompasses multiple disciplines including education, science and engineering, humanities and social sciences, as well as arts and physical education. Among these, students majoring in education and science and engineering constitute a relatively higher proportion, closely tied to the widespread application of smart campus systems in teaching management, learning support, and experimental practice. This diverse disciplinary distribution facilitates examining university students' adoption of smart campus systems from varied academic perspectives, thereby enhancing the generalizability of research findings.

In terms of institutional distribution, the sample originates from multiple higher education institutions in Nantong City, Jiangsu Province, encompassing both undergraduate universities and higher vocational colleges. The sample size distribution across institutions is relatively dispersed, avoiding concentration in any single institution, thereby demonstrating strong institutional diversity. This multi-institutional sample structure helps mitigate the potential influence of a single institutional context on research findings, enhancing the external validity of the study's conclusions.

In summary, the sample for this study exhibits a reasonably balanced and diverse distribution across gender, grade level, major, and institution, effectively reflecting the overall profile of university students in Nantong. This provides a reliable data foundation for subsequent empirical analysis of smart campus adoption behaviors.

4.2 Reliability and Validity Test

To examine the reliability and validity of the research scale, this study conducted a systematic analysis of the measurement model using SPSS 26.0 and AMOS 24.0. It primarily evaluated the measurement quality of the scale in terms of internal consistency reliability and convergent validity, As shown in Table 2.

Table 2: Reliability and validity test

Constructs	Items	Unstd.	S.E.	Z	P	Std.	Alpha	CR	AVE
PU	PU1	1				0.838	0.964	0.866	0.618
	PU2	0.934	0.041	22.719	***	0.754			
	PU3	0.954	0.043	22.075	***	0.737			
	PU4	0.992	0.040	24.999	***	0.811			
PEU	PEU1	1				0.884	0.898	0.866	0.694
	PEU2	0.875	0.037	23.89	***	0.729			
	PEU3	1.045	0.036	28.723	***	0.815			
	PEU4	1.008	0.030	33.752	***	0.896			
CMP	CMP1	1				0.827	0.875	0.876	0.639
	CMP2	0.998	0.041	24.158	***	0.797			
	CMP3	1.04	0.043	24.045	***	0.794			
	CMP4	1.026	0.044	23.394	***	0.778			
BI	BI1	1				0.881	0.936	0.938	0.685
	BI2	0.946	0.031	30.363	***	0.824			
	BI3	0.847	0.033	25.672	***	0.749			
	BI4	0.946	0.034	27.558	***	0.781			
	BI5	0.904	0.033	27.694	***	0.783			
	BI6	0.926	0.030	30.678	***	0.828			
	BI7	1.039	0.026	39.537	***	0.933			
ASC	ASC1	1				0.823	0.92	0.921	0.627
	ASC2	0.985	0.038	25.925	***	0.805			
	ASC3	0.788	0.039	19.961	***	0.665			
	ASC4	1.083	0.041	26.434	***	0.816			
	ASC5	0.861	0.037	23.102	***	0.743			
	ASC6	0.949	0.038	25.087	***	0.787			
	ASC7	1.045	0.035	29.959	***	0.886			

For internal consistency reliability, Cronbach's alpha coefficient and composite reliability (CR) were employed for assessment. Results indicate that Cronbach's α coefficients for perceived usefulness (PU), perceived ease of use (PEU), compatibility (CMP), behavioral intention (BI), and smart campus adoption (ASC) all exceed 0.70, ranging from a minimum of 0.875 to a maximum of 0.964, demonstrating strong internal consistency (Nunnally, 1979). Regarding composite reliability (CR), all constructs exceeded 0.70. Data revealed a minimum CR of 0.866 and a maximum CR of 0.938, meeting the commonly accepted threshold for latent variable reliability in academic research (CR $\geqslant$ 0.70) (Bagozzi & Yi , 1988). This further confirms the stable and reliable measurement outcomes of each scale.

Regarding convergent validity, assessment was conducted using standardized factor loadings and Average Variance Extracted (AVE). All items exhibited significant standardized factor loadings on their respective latent variables, with most loadings exceeding 0.70. This indicates that the measurement items adequately reflect the characteristics of the latent variables. The AVE values for each construct exceeded 0.50, ranging from a minimum of 0.618 to a maximum of 0.694. This satisfies the criterion for convergent validity (AVE ⩾ 0.50) (Fornell & Larcker, 1981), indicating that the latent variables explain a substantial portion of the variance in their measured items and that the scales exhibit good convergent validity.

In summary, the scales developed in this study meet recommended standards across multiple metrics, including Cronbach's α, composite reliability (CR), and average variance extracted (AVE). The measurement model demonstrates high reliability and validity, providing a robust data foundation for subsequent path analysis and hypothesis testing within the structural equation model.

4.3 Discriminant Validity

To examine the discriminant validity among latent variables in the scale, this study employs the criterion proposed by Fornell and Larcker (1981), as shown in the table. This method assesses discriminant validity by comparing the square root of the average variance extracted (AVE) for each latent variable against its correlation coefficients with other latent variables. If the square root of the AVE for each latent variable exceeds its correlation coefficient with other latent variables, it indicates conceptual independence among latent variables and confirms the scale possesses good discriminant validity (Fornell & Larcker, 1981).

Table 3: Discriminant validity test

	ASC	BI	CMP	PEU	PU
ASC	**0.792**				
BI	0.573	**0.828**			
CMP	0.416	0.389	**0.799**		
PEU	0.4	0.359	0.565	**0.833**	
PU	0.41	0.41	0.643	0.657	**0.786**

As shown in Table 3, the five variables which are Adoption of Smart Campus (ASC), Behavioral Intention (BI), Compatibility (CMP), Perceived Ease of Use (PEU), and Perceived Usefulness (PU)—exhibited average variance extracted root squares of 0.792, 0.828, 0.799, 0.833, and 0.786, respectively. All these values exceeded the respective correlation coefficients between each variable and the other latent variables. This indicates that the concepts measured by each latent variable are clearly distinguishable, and the items accurately reflect the characteristics of their respective latent variables without being confounded by other latent variables.

Specifically, the correlation coefficient between Adoption of Smart Campus (ASC) and Behavioral Intent (BI) is 0.573, which is lower than the square root of the average variance extracted (AVE) for ASC, 0.792; The correlation coefficient between Compatibility (CMP) and Perceived Ease of Use (PEU) is 0.565, also below their respective mean square root of variance extracted: CMP at 0.799 and PEU at 0.833.

Comparisons among all latent variables meet the criterion, further indicating the scales demonstrate good conceptual independence and measurement accuracy.

In summary, the scales developed in this study demonstrate strong discriminant validity. These scales not only effectively distinguish between latent variables but also provide a reliable measurement foundation for subsequent structural equation modeling and path analysis. This finding aligns with previous research on information systems and technology acceptance, further validating the scientific rigor and practical applicability of the adopted scales.

4.4 Modeling Fit Indices Test

To verify the overall fit of the structural equation model, this study examined the model's fit indices, including χ^2/df (Chi-square / degrees of freedom), P-value, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA), as shown in Figure 3.

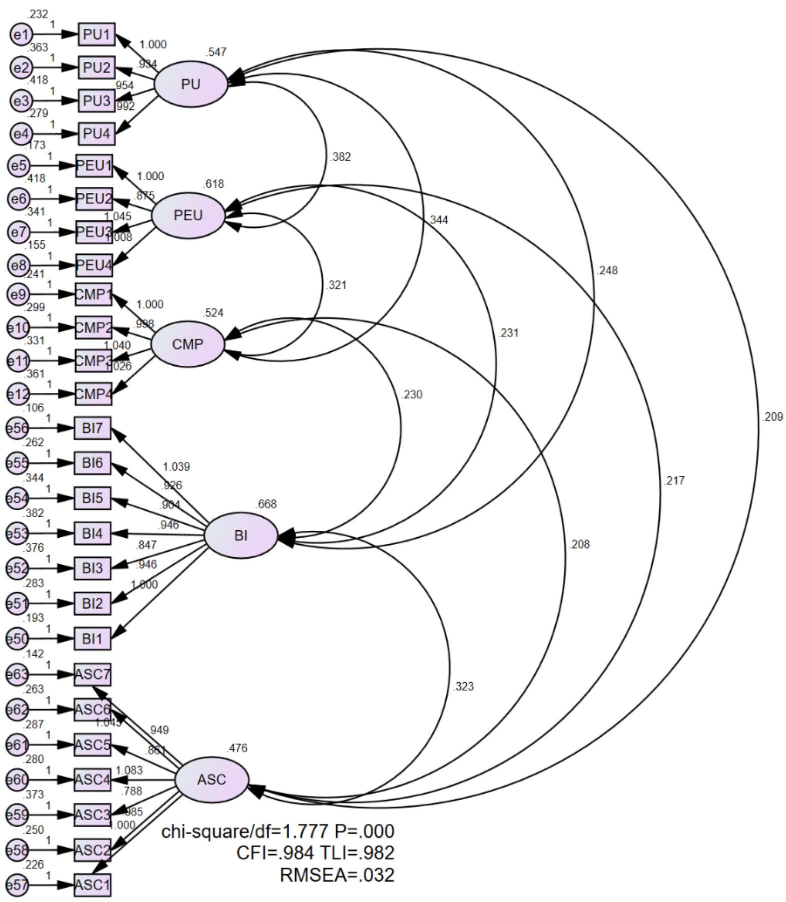

Fig. 3: Measurement Model

The results show that the model's χ^2/df is 1.777, below the recommended threshold of 3 (Bagozzi & Yi, 1988), indicating overall good model fit. The P-value is 0.000, which is normal and acceptable given the large sample size. Other fit indices further validate the model's excellent fit. CFI and TLI were 0.984 and 0.982, respectively, both exceeding the recommended standard of 0.90 (Bagozzi & Yi , 1988; Kline, 2005), indicating excellent model fit in both comparative and non-normative fit metrics. RMSEA was 0.032, significantly below the judgment threshold of 0.08 (Browne, M.W. and Cudeck, 1993), suggesting minimal model error and ideal fit. In summary, the structural equation model constructed in this study demonstrates overall good fit and reliability, reasonably reflecting the structural relationships among latent variables. Therefore, the model can be considered to have sufficient fit, providing a solid foundation for subsequent path analysis and hypothesis testing, ensuring the scientific validity and credibility of the structural equation analysis results.

4.5 Path Hypothesis Test

This study employs path analysis based on structural equation modeling to examine the direct effects of perceived usefulness, perceived ease of use, and compatibility on behavioral intention and smart campus adoption, as well as the direct role of behavioral intention in smart campus adoption, as illustrated in Figure 4. According to statistical standards for structural equation modeling, a P-value less than 0.05 is generally considered statistically significant (Fisher, 1925). The path estimation results are presented in Table 4.

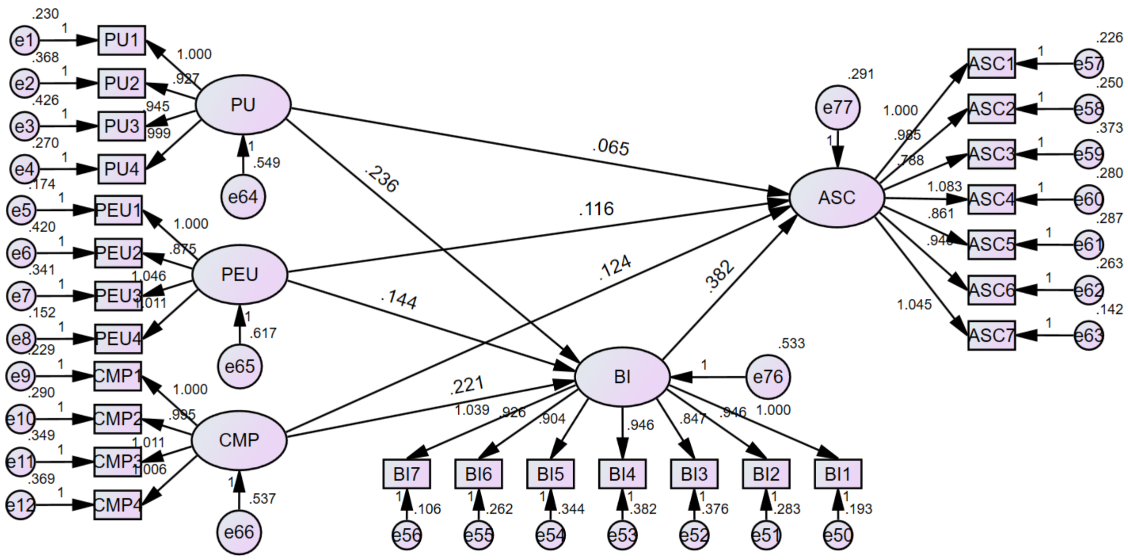

Fig. 4: Structural Models

Table 4: Hypothesis 1-7 results

Hypothesis	Path	Unstd.	S.E.	Z	P	Estimate	Results
H1	PU->BI	0.236	0.041	5.807	***	0.226	Supported
H2	PEU->BI	0.144	0.037	3.898	***	0.146	Supported
H3	CMP->BI	0.221	0.041	5.392	***	0.208	Supported
H4	PU->ASC	0.065	0.032	2.069	0.039	0.074	Supported
H5	PEU->ASC	0.116	0.029	4.043	***	0.14	Supported
H6	CMP->ASC	0.124	0.032	3.901	***	0.14	Supported
H7	BI->ASC	0.382	0.033	11.752	***	0.456	Supported

The results indicate that perceived usefulness significantly influences behavioral intention, with a P-value less than 0.001, supporting Hypothesis H1. Perceived ease of use significantly influences behavioral intention, with a P-value less than 0.001, validating Hypothesis H2. Compatibility significantly influences behavioral intention, with a P-value less than 0.001, supporting Hypothesis H3.

Regarding smart campus adoption, perceived usefulness significantly and directly influences adoption behavior, with a P-value of 0.039, supporting hypothesis H4. The direct effect of perceived ease of use on adoption behavior is significant, with a P-value less than 0.001, validating hypothesis H5. The direct effect of compatibility on adoption behavior is significant, with a P-value less than 0.001, supporting hypothesis H6. Furthermore, behavioral intention exhibits the most significant direct effect on smart campus adoption behavior, with a P-value less than 0.001, validating hypothesis H7.

In summary, all direct paths in the structural equation model reached statistical significance, indicating that perceived usefulness, perceived ease of use, and compatibility all positively influence college students' behavioral intentions. Simultaneously, these factors and behavioral intentions exert a significant positive effect on the adoption of smart campus systems. The overall path analysis results validate the validity of the research model, providing reliable data support for subsequent discussions and research conclusions.

4.6 Mediating Effects Test

To further examine the mediating effect of behavior intention, this study employs the Bootstrap method for mediation analysis. By conducting 1,000 repeated samples, 95% confidence intervals were constructed to test the indirect effect, direct effect, and total effect, as shown in Table 5. When the confidence interval for the indirect effect does not include zero, it indicates a significant mediating effect (Preacher & Hayes, 2008).

Table 5: Hypothesis 8 results (bootstrap)

Path relationship	Point estimate	Product of coefficient		Bootstrap 1000 times 95% CI			
				Bias-corrected		Percentile	
		SE	Z-value	Lower	Upper	Lower	Upper
PU->BI->ASC	0.09	0.024	3.75	0.045	0.14	0.044	0.139
PU->ASC	0.065	0.043	1.511628	-0.017	0.147	-0.017	0.147
PU->ASC	0.156	0.047	3.319149	0.063	0.247	0.069	0.25
PEU->BI->ASC	0.055	0.02	2.75	0.019	0.096	0.019	0.096
PEU->ASC	0.116	0.036	3.222222	0.045	0.19	0.042	0.188
PEU->ASC	0.171	0.04	4.275	0.094	0.249	0.093	0.247
CMP->BI->ASC	0.084	0.019	4.421053	0.053	0.124	0.052	0.123
CMP->ASC	0.124	0.04	3.1	0.046	0.206	0.045	0.205
CMP->ASC	0.209	0.039	5.358974	0.132	0.285	0.135	0.286

The results indicate that within the perceived usefulness path, perceived usefulness exerts a significant indirect effect on smart campus adoption through behavioral intention. The estimated indirect effect is 0.090, with both the lower and upper bounds of the 95% confidence intervals (Bias-corrected and Percentile) not containing zero. This confirms that behavioral intention plays a significant mediating role between perceived usefulness and smart campus adoption. Meanwhile, the direct effect of perceived usefulness on smart campus adoption was insignificant, with its 95% confidence interval containing zero. However, the total effect was significant, indicating that behavioral intention fully mediates this path.

In the perceived ease of use pathway, perceived ease of use exerts a significant indirect effect on smart campus adoption through behavioral intention, with an indirect effect estimate of 0.055 and a 95% confidence interval that does not include zero. Simultaneously, perceived ease of use also exhibits a significant direct effect on smart campus adoption, with its confidence interval not containing zero. The overall effect is significant, indicating that behavioral intention partially mediates the relationship between perceived ease of use and smart campus adoption.

In the compatibility pathway, compatibility significantly mediates the indirect effect on smart campus adoption through behavioral intention, with an estimated indirect effect of 0.084. Both the Bias-corrected and Percentile confidence intervals exclude zero. Concurrently, compatibility exerts a significant direct effect on smart campus adoption, and the total effect also reaches statistical significance. This indicates that behavioral intention partially mediates the relationship between compatibility and smart campus adoption.

In summary, behavior intention plays a significant mediating role between perceived usefulness, perceived ease of use, compatibility, and the adoption of smart campuses. Specifically, behavior intention acts as a full mediator in the perceived usefulness pathway and as a partial mediator in the perceived ease of use and compatibility pathways. This finding further validates the applicability of the Extended Technology Acceptance Model in the smart campus context and reveals the critical role of behavior intention in the adoption mechanism of smart campuses.

5 Conclusion

5.1 Theoretical Contributions

This study makes significant theoretical contributions to the fields of smart campuses and technology acceptance theory. First, building upon the traditional Technology Acceptance Model (TAM), this paper introduces compatibility as a crucial technology-specific factor, thereby constructing an extended model for the adoption of IoT-based smart campuses. Compared to traditional information systems, IoT-based smart campuses exhibit characteristics such as high system integration, complex application scenarios, and strong technological convergence. Incorporating compatibility into the analytical framework facilitates a more comprehensive explanation of the alignment between smart campus systems and students' existing learning styles, usage habits, and technological experiences, thereby expanding TAM's explanatory power within the smart campus context.

Second, this study empirically verified the mediating role of behavioral intention between technology-specific factors and the adoption of IoT-based smart campuses. Existing research has primarily focused on the direct impact of factors such as perceived usefulness and perceived ease of use on adoption behavior, while relatively limited attention has been paid to exploring their underlying mechanisms. The findings reveal that perceived usefulness, perceived ease of use, and compatibility do not directly influence smart campus adoption behavior. Instead, they exert indirect effects through the key psychological variable of behavioral intention. This deepens our understanding of the underlying mechanisms in the smart campus adoption process and provides new empirical evidence for expanding the path relationships within the Technology Acceptance Model.

Finally, this study conducted an empirical investigation into the adoption behavior of IoT-based smart campuses among university students, thereby enriching the relevant literature in the fields of smart education and educational informatization. Existing technology acceptance research has predominantly focused on commercial or organizational information system applications, while empirical studies on smart campuses in higher education remain relatively scarce. By adopting a higher education perspective and applying technology acceptance theory to the IoT smart campus context, this paper further expands the scope of relevant theoretical applications within the educational domain.

5.2 Practical Contributions

This study offers multifaceted implications for practical implementation. First, for administrators overseeing smart campus development in higher education institutions, the findings indicate that perceived usefulness, perceived ease of use, and compatibility are key factors influencing students' behavioral intentions. Therefore, as universities advance IoT-based smart campus initiatives, they should prioritize the effectiveness and usability of service functions. Ensuring that smart systems tangibly enhance learning efficiency, information accessibility, and campus management effectiveness will strengthen students' perception of the value delivered by smart applications. Second, regarding the design and development of smart campus systems, the study reveals that students' perceptions of system usability and operational experience significantly influence their adoption levels. Consequently, software developers and technical service providers should optimize user interfaces, enhance system response speeds, and improve cross-platform compatibility. This reduces operational costs, enables students to enjoy a seamless experience during use, and promotes sustained system adoption. Furthermore, the significant impact of compatibility highlights that universities must prioritize integration with existing teaching methods, curriculum systems, and campus life habits when deploying IoT technologies. Through scenario adaptation, learning resource consolidation, and the establishment of information exchange mechanisms, the smart campus ecosystem can be seamlessly integrated into students' daily learning and living contexts.

Finally, this study validates the mediating role of behavior intention in the adoption of smart campus technologies, which offers valuable insights for universities during project implementation. Higher education institutions must not only provide smart infrastructure but also enhance interest and psychological acceptance through training seminars, usage guidance, and promotional campaigns of students. This fosters positive behavior intention, thereby advancing smart campus development from merely "having technology" to achieving "active utilization and tangible value." In summary, this study offers actionable pathways for smart campus construction and promotion within the context of educational digital transformation. It provides practical guidance for policymakers, administrators, and technology providers.

5.3 Limitation

Although this study has achieved certain theoretical and practical outcomes in the field of IoT-based smart campus adoption, several limitations remain that require further refinement in subsequent research. First, the data in this study originates from a sample of students at a specific university, exhibiting geographical and demographic limitations. The sample structure is relatively homogeneous, failing to encompass diverse roles such as faculty and administrators. Consequently, the externalizability of the research conclusions may be constrained. Future research should expand the sample scope to include participants from different regions, multiple types of universities, or diverse roles to enhance the universality and explanatory power of the findings. Second, the cross-sectional questionnaire approach used in this study only reflects static relationships between variables and fails to capture the dynamic process of behavioral intentions and actual adoption behaviors over time. Subsequent studies may consider employing longitudinal tracking data or experimental designs to explore the evolutionary mechanisms of smart campus adoption behavior in greater depth.

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