

Examining the Influence of Perceived Usefulness, Perceived Ease of Use, and Compatibility on Behavioral Intention toward IoT-based Smart Campus

Haiyan Cao^{1,2,*}, Md. Gapar Md Johar³, Jacqueline Tham²

¹School of Yonyou Digital and Intelligence, Nantong Institute of Technology, Nantong, 226001, China

²School of Graduate Studies, Post Graduate Centre, Management and Science University, Shah Alam, Selangor 40100, Malaysia

³Software Engineering and Digital Innovation Center, Management and Science University, Shah Alam, Selangor 40100, Malaysia

* Corresponding author

Abstract: As the rapid development of the Internet of Things and smart campus construction, the higher education environment is undergoing profound changes. The willingness of students to adopt smart campuses is not only determined by technical performance but also influenced by factors such as cognitive and user experience. Based on the Technology Acceptance Model and Innovation Diffusion Theory, the study constructed a research model with perceived usefulness (PU), perceived ease of use (PEU), and compatibility (CMP) as independent variables and behavioral intention (BI) as the dependent variable. A questionnaire survey was conducted among college students in Nantong City, Jiangsu Province, and a total of 753 valid samples were collected. Structural equation model was used to analyze the data. The results show that PU, PEU, and CMP all have a significant positive impact on BI.

Keywords: Smart Campus; Perceived Usefulness; Perceived Ease of Use; Compatibility; Behavioral Intention.

1. Introduction

As advanced technologies become more popular, the smart campus has emerged as an important concept for integrating technology into higher education [1]. Higher education institutions all hope to transition from digital campus to smart campus in order to become excellent universities [2]. In addition, the quality of a college is an important factor that students consider when choosing a university for further study. For example, the usefulness, ease of use, and compatibility of a range of equipment are key factors that students take into consideration [3].

There has been a lot of research on smart campus. In a study on the adoption factors of smart campus, Sneesl took stakeholders affiliated with universities in Iraq as the research subjects and used structural equation model (SEM) and artificial neural networks (ANN) to analyze the data. The results showed that technical factors affect the intention to adopt smart campus. However, the study did not report model fit indices (TLI, RMR, GFI, AGFI, CFI and RMSEA). It is suggested that the study be extended to other regions and that different methods be used for research [4]. El Khatib explored the application of information and communication technology in higher education and its impact on the future development of smart campus. When introducing advanced technologies, higher education institutions need to balance learning design with the innovative development of physical campus spaces, emphasizing the key role of intelligent design in improving educational quality and competitiveness. However, there are still challenges, especially in terms of technology adoption. To improve the quality of learning in smart campus, colleges should ensure that students have the skills to use relevant technologies effectively and pay attention to privacy and security issues [5].

In summary, although there has been a lot of research on smart campus, it has mostly focused on the implementation of

technology, with little research on the intention of students to use smart campus from a technological perspective. To fill this research gap, this study takes college students in Nantong City as the research object, constructs a research model of perceived usefulness, perceived ease of use, and compatibility, and uses behavior intention (BI) as the dependent variable. This paper aims to answer the following core research questions:

(1) Whether perceived usefulness significantly affect the intention of students in higher education institutions to use smart campus?.

(2) Does perceived ease of use importantly affect the intention of students in higher education institutions to use smart campus?.

(3) How does compatibility affect the intention of students in higher education institutions to use smart campus?.

2. Literature Review and Hypothesis Development

2.1. Hypothesis development

2.1.1. Perceived usefulness and behavioral intention

Perceived usefulness (PU) is one of the core concepts of the technology acceptance model (TAM) and is defined as “the extent to which an individual proposes to use a particular system to improve work or learning performance” [6]. In this study, perceived usefulness refers to the extent which the use of smart campus equipment can improve learning, living, or working efficiency. Research on smart learning environments by Fearnley indicated that PU has a greater impact on BI than perceived ease of use (PEOU), suggesting that users value the actual effectiveness of technology rather than simply ease of operation [7]. Masadeh found in the empirical study of the IoT teaching platform that PU not only directly positively affects BI, but also enhances indirect effects by improving learning motivation and participation [8]. Therefore, the study

proposes the following hypothesis:

H1: There is a significant relationship between Perceived usefulness and behavioral intention of IoT-Based Smart Campus.

2.1.2. Perceived ease of use and behavioral intention

Perceived ease of use (PEU) is one of the core concepts of the technology acceptance model (TAM) and is defined as “the degree to which an individual proposes that using a system will not require excessive effort” [6]. In this study, PEU refers to the degree to which students propose that smart campus equipment is simple to operate and easy to master. Criollo-C conducted a questionnaire survey of 120 engineering students at a university in Ecuador based on the TAM model to analyze the willingness to adopt emerging technologies in higher education. The study found that perceived ease of use and entertainment value are the main positive factors influencing the acceptance of technology by students [9]. Therefore, this study proposes the following hypothesis:

H2: There is a significant relationship between Perceived ease of use and behavioral intention of IoT-Based Smart Campus.

2.1.3. Compatibility and behavioral intention

Compatibility refers to the degree to which a particular technology or system matches existing values, past experiences, and current needs of users [10]. In Innovation Diffusion Theory (IDT), compatibility is proposed as one of the important factors affecting technology adoption, as it can significantly influence the attitude and willingness of users to accept new technologies [10]. In the research, compatibility

refers to the extent which the functions, platforms, interfaces, and services involved in smart campuses align with the existing usage habits, values, needs, or device environments of students. results from Lin et al. indicate that students with high self-efficacy and multiple self-regulation strategies in higher education perform better academically, while students lacking self-regulation strategies perform worse [11]. In other words, in terms of learning ability, students with higher self-efficacy may use more self-regulatory strategies in their studies and perform better in academic activities. Conversely, students with lower self-efficacy may exhibit a lack of self-regulation in their studies and achieve lower grades in academic activities. Therefore, it is hypothesized that:

H3: There is a significant relationship between Compatibility and behavioral intention of IoT-Based Smart Campus.

2.2. Research model

Based on the summary and integration of existing research results, and combined with the application characteristics of smart campus, the study constructed a research model, as shown in Figure 1. The research model sets three independent variables: perceived usefulness (PU), perceived ease of use (PEU), and compatibility (CMP), as well as one dependent variable—behavioral intention. The framework is primarily based on the Technology Acceptance Model (TAM) and the Innovation Diffusion Theory (IDT) to explore the mechanisms through which technological characteristics influence the adoption intentions of smart campuses.

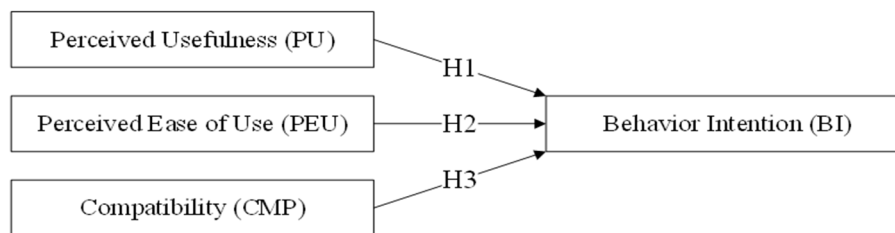


Figure 1. Research model

3. Methodology

The study used quantitative research methods to explore the relationship between perceived usefulness, perceived ease of use, and compatibility and behavioral intention toward smart campus adoption. The research design was based on a cross-sectional survey strategy, and data was collected through questionnaires.

The research subjects were college students in Nantong City, Jiangsu Province, as the group is highly relevant to the daily use of smart campus, therefore, it can provide effective data for the research.

Due to the large overall scale and widespread distribution across different institutions, the study employed stratified random sampling to ensure that the sample was representative in terms of gender, grade level, and major category.

4. Results

4.1. Reliability and validity test

In the study, the reliability and validity of the variables were examined using SEM method. As shown in Table 1.

4.1.1. Reliability analysis

To evaluate the internal consistency of the scale, this research used Cronbach’s Alpha coefficient for reliability testing. Generally, a Cronbach’s Alpha coefficient above 0.70 indicates that the scale has good internal consistency [12]. The results of the SPSS 26.0 analysis show that the Cronbach's Alpha coefficients for perceived usefulness (PU), perceived ease of use (PEU), compatibility (CMP), and behavior intention (BI) all exceed 0.70, as shown in Table 1, indicating that the measurement items for each construct perform well in terms of internal consistency and can measure the corresponding constructs relatively reliably.

4.1.2. Composite Reliability analysis

Composite reliability (CR) is used to further evaluate the reliability and consistency of each latent variable. Generally, a CR value greater than 0.70 is considered to indicate that the latent variable has high reliability [13]-[14]. The results calculated using AMOS 24.0 are shown in Table 4.1. The CR values for all constructs are above 0.70, indicating that the selected measurement indicators exhibit strong stability and reliability in explaining the latent variables.

Table 1. Table Reliability and validity test

Con.	Items	Unstd	S.E.	Z	P	Std	alpha	CR	AVE
PU	PU1	1				0.838	0.864	0.866	0.618
	PU2	0.933	0.041	22.719	***	0.754			
	PU3	0.953	0.043	22.069	***	0.737			
	PU4	0.992	0.04	24.996	***	0.811			
PEU	PEU1	1				0.884	0.898	0.900	0.695
	PEU2	0.875	0.037	23.891	***	0.729			
	PEU3	1.044	0.036	28.719	***	0.815			
	PEU4	1.007	0.03	33.74	***	0.896			
CMP	CMP1	1				0.826	0.875	0.876	0.639
	CMP2	1.003	0.042	24.164	***	0.799			
	CMP3	1.044	0.043	24.024	***	0.796			
	CMP4	1.026	0.044	23.258	***	0.776			
BI	BI1	1				0.881	0.936	0.938	0.685
	BI2	0.947	0.031	30.405	***	0.825			
	BI3	0.846	0.033	25.606	***	0.748			
	BI4	0.944	0.034	27.472	***	0.78			
	BI5	0.903	0.033	27.601	***	0.782			
	BI6	0.925	0.03	30.583	***	0.827			
	BI7	1.04	0.026	39.629	***	0.935			

4.1.3. Average variance extracted analysis

The Average Variance Extracted (AVE) is used to examine convergent validity, and its value should be no less than 0.50 to indicate that the latent variables can explain more than half of the variance in the measurement items [12][13][14]. The analysis results of this study are shown in Table 1. The AVE values for all constructs exceed 0.50, satisfied the requirements for convergent validity, indicating that the measurement items can effectively reflect the characteristics of their corresponding latent variables.

4.2. Modeling fit indices test

To test the overall fit of the structural equation model

Table 3. Measurement model assessment using model fit indices

	ChiSq/df	SRMR	RMSEA	GFI	AGFI	IFI	CFI	TLI
Test Value	2.23	0.02	0.04	0.96	0.94	0.98	0.98	0.97
Reference Value	≤	≤	≤	≥	≥	>	≥	≥
Sources	[20]	[21]	[22]	[23]	[24]	[21]	[12]	[25]

This study used AMOS 24.0 to test the fit of the constructed hypothetical model, with the results shown in Table 3. Chi-Square/df = 2.236, SRMR = 0.029, RMSEA = 0.041, GFI = 0.956, AGFI = 0.943, IFI = 0.982, CFI = 0.982, TLI = 0.979. Compared with the reference standards, these indices are within reasonable ranges. Therefore, the structural equation model in this study is feasible in terms of overall fit and can be used for subsequent path coefficient tests and hypothesis verification.

(SEM), this study referenced commonly used model fit evaluation metrics, including the chi-square/df ratio, standardized root mean square residual (SRMR), root mean square error of approximation (RMSEA), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), incremental fit index (IFI), comparative fit index (CFI), and Tucker-Lewis index (TLI). Generally, a Chi-Square/df value less than 3 indicates good model fit [12]; SRMR and RMSEA values should be less than 0.08 [15][16], GFI and AGFI should be greater than 0.95 and 0.9, respectively [17][18], and CFI, IFI, and TLI should all be no less than 0.90 [12][15][19].

4.3. Path hypothesis test

After verifying that the fit of the model reached an acceptable level, this study further tested the hypothesized paths to explore whether the relationships between the latent variables were significant. Path coefficients (Standardized Regression Weights), standard errors (S.E.), critical ratios (C.R.), and significance levels (p-values) were calculated using AMOS 24.0, with a significance level of 0.05. When the p-value is less than 0.05, it indicates that the path relationship is statistically significant.

Table 4. Hypothesis 1-3 results

Hypo	Path	Unstd.	S.E.	Z	P	Estimate	Results
H1	PU->BI	0.236	0.041	5.806	***	0.225	Supported
H2	PEU->BI	0.144	0.037	3.895	***	0.146	Supported
H3	CMP->BI	0.221	0.041	5.380	***	0.208	Supported

As shown in Table 4, the standardized path coefficient of perceived usefulness (PU) on behavior intention (BI) is 0.225,

$p < 0.001$, indicating that PU has a significant positive effect on BI, supporting hypothesis H1. The path coefficient of perceived ease of use (PEU) on BI is 0.146, $p < 0.001$, also showing a significant positive effect, supporting hypothesis H2; The path coefficient of compatibility (CMP) on BI is 0.208, $p < 0.001$, also showing a significant positive effect, supporting hypothesis H3.

5. Discussion

5.1. Findings

Based on the Technology Acceptance Model (TAM) and Innovation Diffusion Theory (IDT), this study combines the application characteristics of smart campus to explore the impact of perceived usefulness (PU), perceived ease of use (PEU), and compatibility (CMP) on behavior intention (BI). The results are as follows:

First, perceived usefulness has a positive effect on behavior intention, indicating that when students propose that the smart campus system can effectively improve learning efficiency and academic performance, they are more inclined to generate willingness to use it.

Second, perceived ease of use also significantly affects behaviour intention, indicating that when the smart campus platform is more concise and intuitive in terms of operation process, interface design and interactive experience, students are more willing to use the system.

Third, compatibility also has a significant positive effect on behaviour intention, indicating that if the smart campus system is compatible with students' existing learning methods, technical habits and equipment environment, it will be more easily accepted and adopted.

5.2. Theoretical contributions

First, this study combines the Technology Acceptance Model (TAM) with the Innovation Diffusion Theory (IDT) to construct a research model using three independent variables (perceived usefulness (PU), perceived ease of use (PEU), and compatibility (CMP)) and behaviour intention towards smart campuses as the dependent variable. As most literature focuses on a single theoretical model, the integrated perspective of this study not only enriches the theoretical basis of smart campus adoption research, but also provides empirical reference for cross-theoretical integration.

Second, this study verified the significant impact of PU, PEU, and CMP on behaviour intention (BI) in smart campus research, further confirming the applicability and explanatory power of TAM and IDT. This finding indicates that in an IoT-driven educational environment, perceived Usefulness, perceived ease of use, and compatibility remain the core factors driving adoption intentions. This not only expands the research boundaries of TAM in the context of higher educational smartification but also enhances the applicability of IDT in information technology adoption research.

5.3. Practical contributions

The study not only enriches the theoretical framework for research on the adoption of smart campus, but also provides practical suggestion for university administrators, educational policymakers, and technology developers.

First, the research results show that perceived usefulness (PU) has a significant positive impact on behavior intention (BI), which indicates that colleges should focus on the functional value and learning effectiveness of the system in the process

of promoting smart campuses. For example, in the promotion and training process, it can be shown through actual cases how the smart campus platform can improve learning efficiency, optimize the classroom experience, and enhance resource utilization, thus strengthening the motivation of students to use it.

Second, the significant role of perceived ease of use (PEU) indicates that student experience should be considered during technology development. In the design of smart campus systems, it is necessary to simplify operating procedures, optimize interface interactions, provide personalized services, and reduce student learning costs through new student training, online guidance, and instant help functions. It will directly improve the availability of the system and make students more likely to use it.

Finally, the importance of compatibility (CMP) means that smart campus should be fully compatible with existing learning methods, technical habits, and equipment environments of students. Higher educational institutions can gather feedback from users during the system development phase to make sure the platform works smoothly with common learning software, mobile devices, and network environments, reducing technical barriers.

5.4. Limitation

Although the study provides valuable empirical conclusions in the field of smart campus adoption, there are still some limitations that need to be addressed in future research.

First, the data for the study came from students at higher educational institutions in Nantong City, Jiangsu Province, and the sample was highly regional, which may affect the universal applicability of the results in other regions or cultural contexts. Therefore, the study conclusions should be applied with caution when extrapolated to other countries or regions, and it is suggested that future studies expand the sample scope to include more different types of higher educational institutions and cross-regional data.

Secondly, the independent variables in the research mainly focus on perceived usefulness, perceived ease of use, and compatibility. Although these variables cover important cognitive factors, they do not include important variables that may affect the adoption of smart campuses, such as emotional attitudes and security. In the future, the model variables can be expanded to improve interpretation.

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