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Factors Affecting the Adoption of IoT-Based Smart Campus: An Investigation Using Analytical Hierarchical Process (AHP)

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Abstract: The advancement of technology is making university campuses smarter every single day. Despite the benefits of these advanced technologies, the literature concerning the adoption of smart campuses is significantly lacking increased knowledge to provide effective smart campus solutions. This study aims to prioritize the adoption factors of an IoT-based smart campus. The study applied an analytical hierarchical process (AHP) on 25 factors drawn from the literature. The factors were classified into technology specific factors (TSF), organizational specific factors (OSF), environmental specific factors (ESF), and end-user specific factors (USF). Based on the results obtained, the most significant contributing factors were government support, privacy concerns, social influence, facilitating conditions, and service collaboration, whereas the least significant contributing factors were enjoyment, availability, reliability, mobility, and compatibility. Moreover, based on the global ranking computation, 12 factors from the OSF, ESF, and USF categories appeared to be more significant than TSF. The findings of this study could help university administrators, manufacturers, and policy-makers to understand the critical factors of smart campuses in order to improve the adoption and utilization of these solutions effectively.

Keywords: smart campus; IoT; AHP; adoption; technology specific factors; organizational specific factors; environmental specific factors; end-user specific factors

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Citation: Sneesl, R.; Jusoh, Y.Y.; Jabar, M.A.; Abdullah, S.; Bukar, U.A. Factors Affecting the Adoption of IoT-Based Smart Campus: An Investigation Using Analytical Hierarchical Process (AHP). *Sustainability* **2022**, *14*, 8359. https://doi.org/10.3390/su14148359

Academic Editor: Fernando Almeida

Received: 14 June 2022
Accepted: 4 July 2022
Published: 8 July 2022

1. Introduction

The smart campus is a buzzword used to describe the application of advanced technological tools to improve the administrative and teaching activities of universities [1]. Existing studies concerning the adoption factors of smart campuses have concluded that they are still emerging [2], although there are various solutions to different aspects of smart campuses. For example, to support successful and sustainable smart campus transitions, Ref. [3] used systems thinking analysis and further analyzed the systems thinking of a smart campus [4] based on the strength, weakness, opportunity, and threat (SWOT) model. Furthermore, Ref. [5] explored stakeholders' perceptions of smart campus criteria, while [6] suggested a novel smart campus method that focuses on the Internet of Things (IoT) in order to illustrate the concept of smart campuses through the IoT. Moreover, Ref. [2] investigated the IoT adoption factors with a view to identifying the factors that could be applicable for the adoption of an IoT-based Smart Campus.

In this context, the goal of the present study is to assess the factors influencing the adoption of smart campuses as presented in [2]. In order to accomplish this, this study applies and replicates the analytical hierarchical process (AHP) used by [7,8] to prioritize the factors influencing employee adoption of e-government and cloud computing in order to examine the adoption factors of an IoT-based smart campus. The aim of this replication in the context of IoT-based smart campuses is to evaluate the factors and confirm the potential of these factors for the success of smart campus initiatives, given that the study of smart campus adoption is still emerging.

It may appear logical to claim that a replication study cannot be considered new or important knowledge [9]. This study, on the other hand, is predicated on the assumption that replication in scientific research is a valuable strategy that can show scholars whether certain insights are acceptable in circumstances other than those anticipated in the initial study, rather than merely the result of specific circumstances not repeated in other studies [10]. According to [11], replicating scientific investigations is a good strategy for improving dependability and credibility while expediting discoveries. This study aims to demonstrate the critical role of technology adoption factors in helping administrations, policy makers, manufacturers, and researchers to develop and provide smart campus solutions that ease the administrative and teaching activities of the universities. However, evidence on how technology adoption factors shape stakeholder perceptions of smart campuses and how their knowledge influences their decision to adopt smart campus solutions, regardless of whether they were directly affected by these solutions, remains unanswered. As a result, this study prioritizes the factors that lead to the adoption of IoT-based Smart Campus solutions. Therefore, the following research questions (RQ) are addressed in this study:

- RQ1: Do technology adoption factors influence IoT-based Smart Campus adoption?
- RQ2: To what extent are technology adoption factors a significant influence on the adoption of IoT-based Smart Campus solutions?

This study adds three new insights to the existing body of knowledge. First, while the intentional use of smart solutions in universities has received a great deal of attention from academics and practitioners, there has not been very much research on the factors underpinning its success from an information systems standpoint. Second, as stakeholders' association with smart devices grows, this research may help administrators and policy makers to understand the perception of smart campus users in planning the implementation of smart campus solutions effectively. Third, the study methodology is founded on AHP, which aids in understanding of how technology adoption factors influence smart campus adoption. As a result, the research is structured as follows: Section 2 presents a review of the literature; Section 3 discusses the research methodology; Section 4 presents and discusses the study's results; Section 5 discusses the research contributions and future work; and Section 6 concludes the study.

2. Literature Review

There are various factors for the adoption of smart campuses, as identified by the systematic review of [2], which identified 112 potential IoT-based smart campus adoption factors from the literature. After duplicate and thematic analysis, 52 adoption factors were classified into technology specific factors (TSF), organizational specific factors (OSF), environmental specific factors (ESF), and end-user specific factors (USF). Thus, classifications according to these factors were carried out in accordance with the existing studies [8,12–14]. Nevertheless, this study is distinguished from the extant literature based on the fact that the 52 factors identified previously by [2] were not analysed by any scientific method. Therefore, to affirm the incremental contribution of this study, the AHP technique was adopted to investigate these factors. Notably, in order to avoid complexity, the 52 factors were subjected to further analysis to select the more significant factors for the adoption of smart campuses. After objective analysis, 25 factors were utilized for the AHP analysis, as presented in Tables 1–4. These factors were selected by avoiding bias through selection technique [15]. Specifically, this study applied the concept of selection strategy in selecting the factors. The selection technique is expressed in Equation (1) as

$$f = f_1, f_2, f_3 \ldots f_n > 1 \tag{1}$$

where f is a factor and n is a number of factors. Accordingly, if f is greater than 1, then f is a significant factor, and therefore selected for the AHP analysis. This technique is repeated until none of the factors can satisfy the criteria. Studying the adoption of smart campuses could contribute to the current knowledge about the success of smart solutions in universities. Based on a discussion of existing studies, 25 factors that may impact the adoption of IoT-based Smart campuses have been identified. As shown in Tables 1–4, these 25 factors are classified into four major categories: (1) technology specific factors, (2) organizational specific factors, (3) environmental specific factors, and (4) end-user specific factors.

Table 1. Technology Specific Factors.

Sub Factors	Source	Description
Reliability	[13,14,16,17]	The potential that IoT-based products will malfunction and fail to offer the intended services or functionality. The IoT products and services will always work properly as predicted.
Availability	[13,18,19]	The degree to which IoT devices will provide users with real-time connectedness to information and services.
Compatibility	[8,12,13,16,20–25]	The extent to which an IoT product is viewed as being compatible and consistent with users' current values, requirements, and previous experiences; IoT products suit users' lifestyles and are significantly important to them.
Mobility	[18,20,26]	IoT or smart devices can allow users to access information at any time. The ability to allow users to access information without the constraints of time or space.
Functionality	[17,27]	Refer to whether or an IoT device can execute a given task by offering the necessary features and functions. Perceived usefulness refers to whether the system's functionality can meet its requirements.
Security concerns	[8,17,19,20,22,25,26,28–30]	The extent to which users believe that the use of IoT products and service are free from any risk and that IoT and smart devices are secure.
Enjoyment	[19,24,25,31–33]	The degree to which the activity of utilizing IoT devices is judged to be joyful, with or without any performance repercussions coming from the usage.
Cost	[8,12,14,21,25,31,32,34]	The cost per unit that a consumer pays when they use IoT devices, such as purchase, installation, maintenance, and repair of components forming the IoT system.
Value	[20,30–33,35–37]	The user's assessment of the IoT or smart device's benefits vs. the device's cost is called its value. The value guides the individual's decision and appraisal of behavioral options.
Effective quality	[8,18,34,36,38,39]	Users' perception and impression of IoT devices prior to any other cognitive appraisal and evaluation of its consequences or their potential interactions with it or the quality of products or services.
Ease of use	[14,18–20,23–25,28,31,33,34,38–46]	The extent to which a person believes that implementing IoT products and services or smart systems will be effortless.
Usefulness	[18,19,22–26,31–35,38–44,46–49]	The extent to which an individual believes that utilizing an IoT product or a smart device will assist them in improving job performance or that incorporating IoT products and services into their daily activities will improve their performance.
Trust	[17–19,25,29,30,33,37,38,43,49]	Users' willingness to rely on something such as an IoT product, service, or smart gadget to perform an action is referred to as trust.

Table 2. Organizational Specific Factors.

Sub Factors	Source	Description
Facilitating condition	[19,44]	The result of external and internal circumstances. Users' views about the presence of necessary resources for undertaking a specific activity are referred to as external conditions. However, internal conditions refer to a user's assessment of their own personal skills to complete and effectively perform tasks.
Propagation	[1]	The provision of the model is to be replicated conveniently at various levels.
Service collaboration	[38]	The collaboration of responsibility or authority in government procedures and activities between governmental and non-governmental entities. Hence, an increase in citizen–government collaboration has the potential to affect smart technology adoption.

Table 3. Environmental Specific Factors.

Sub Factors	Source	Description
Social influence	[17,19,31,32,37,44]	The influence or behavior of others can impact an individual's attitudes, beliefs, or conduct. Individual social network is the idea that other people's thoughts and assessments of a product can influence an individual's decision concerning that product.
Government support	[14,21,48]	The government's ability to implement a number of steps to foster a favourable impression of IoT products and services among the general public.
External pressure	[13,21,48]	The degree to which a company's adoption of IoT products and services are influenced by competitors, business partners, or environmental factors.

Table 4. End-users Specific Factors.

Sub Factors	Source	Description
Self-efficacy	[14,27,36,37]	The expectation of self-assessment about achievements; that is, an individual's belief and executed behaviors to achieve the performance of an end.
Privacy concern	[12–14,16,19,22,26,29,33,35,43,50]	The ability to choose which personal information should be shared with others.
Domain-specific knowledge	[27,51]	Encompasses users' knowledge and understanding about technological solutions, product, or services, that is, the state of knowing and being informed of the benefits of IoT devices.
Satisfaction	[36,52]	Individual evaluation or usage of a technological system can result in emotional pleasure obtained as a result of fulfilling the user's needs or desires, which is referred to user satisfaction.
Innovativeness	[14,23,24,26,37,51]	The ability to embrace any modern technology or service if it is deemed new and innovative. Personal innovativeness refers to an individual's willingness to adopt new technologies or the degree to which a user adopts a technology compared to others.
Habit	[19,44]	The degree to which a user performs a specific activity automatically or instantly as a result of previous experiences.

3. Methodology

The AHP is a multiple-criteria decision-making (MCDM) technique that is commonly used to make judgments when numerous criteria or factors are present [53]. Although the AHP was designed to solve complicated MCDM problems, it has been used by numerous academics in a variety of domains, including decision-making, planning and development, allocation, selection, and ranking or prioritizing [7,8,54]. The authors of [55] used the AHP to assess employees' performance based on a variety of parameters. In [56], the authors used the AHP to rate employees based on a variety of performance-related factors. The authors of [54] prioritized factors that focused on a coordinated supply chain through AHP.

The AHP technique was utilized by [57] to determine and prioritize functional strategies such as human resource, marketing, and financial management in small and medium firms from Pakistan's automobile parts manufacturing sector. Fuzzy AHP was used by [58] to determine the most important factors influencing the development and diffusion of e-government among government employees in Iran. Moreover, selection of open source-based EMR software packages was evaluated through the integration of AHP and TOPSIS [59]. Using AHP, [60] prioritized the factors influencing the adoption of social media platforms among personnel from the public sector. Furthermore, the prioritization of factors that influence the adoption of e-government was crafted using AHP [7]. A study conducted in Saudi Arabian universities [61] investigated factors affecting the academic integrity of electronic learning through the integration of Delphi and AHP. Similarly, Ref. [8] prioritized the critical factors of cloud computing adoption with AHP. Additionally, a selection framework for hiring software programmers applicants was conducted with integrated AHP and TOPSIS [62].

The AHP methodology mostly divides an MCDM problem into at three levels: (1) objective, (2) criteria, and (3) decision alternatives [53]. The AHP creates a hierarchical model of these three levels. Each level is guided by the objectives of evaluating the criteria, comparing the choice alternatives for each criterion, and ranking these alternatives [63]. Accordingly, to rank the criteria or factors, the AHP employs expert pair-wise comparisons. According to [53], judgments concerning the factors are represented by "how one element dominates another in relation to a certain attribute". In general, the MCDM based on AHP consists of the following phases, as shown in Figure 1:

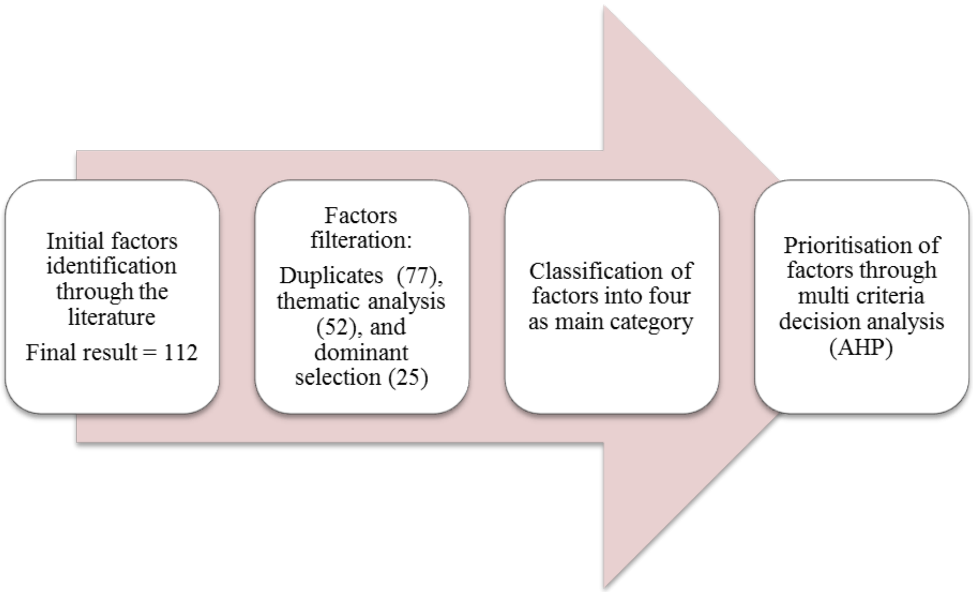

Figure 1. Smart Campus Factors: Identification and AHP Process.

3.1. Problem Structure and Hierarchy Process Model Development

This phase entails developing an acceptable AHP model hierarchy comprised of the aim, criteria or factors, sub-criteria or sub-factors, and alternatives. As this study is focused on evaluating factors relating to IoT smart campuses, the AHP hierarchy consisted of purpose, category, and factors. Consequently, the purpose of this research is to prioritize the elements impacting the adoption of IoT-based smart campuses. This aim (purpose) is positioned at the top of the hierarchical architecture (level 1). Level 2 includes the main category of the factors, whereas Level 3 includes the factors that may influence expert decisions to adopt IoT-based smart campuses. Figure 2 depicts the hierarchical model. The AHP model contains no choice options, because the goal of the study is solely to prioritize the components. However, the most significant factors obtained through the AHP analysis are ranked according the factors' weights.

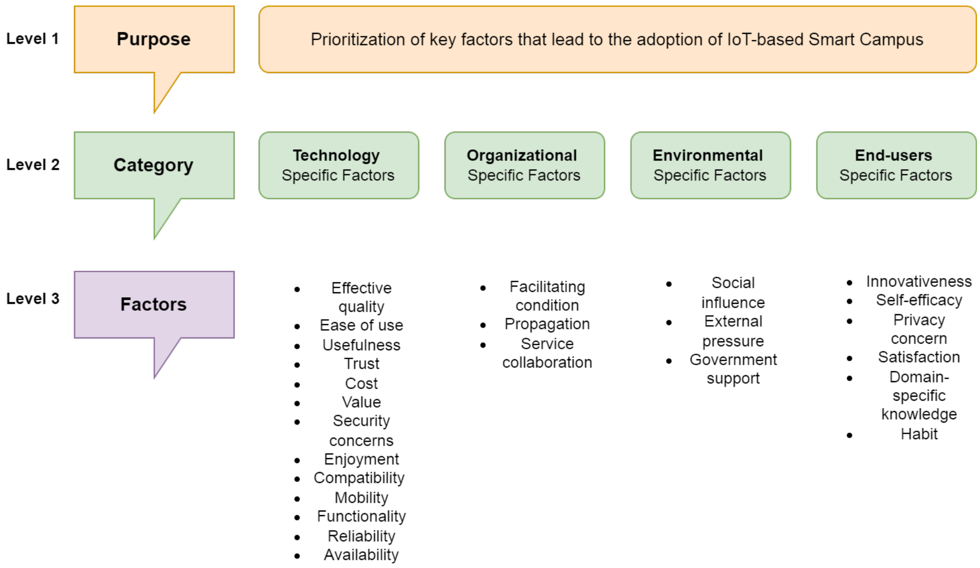

Figure 2. The AHP Hierarchy for Prioritizing Factors Influencing IoT-based Smart Campus Adoption.

3.2. Data Collection from Experts

During this phase, academicians and industry experts working on smart campus models, smart devices, or IoT provide data on pair-wise comparisons of numerous main factor, categories, and factors of IoT-based smart campuses. A nine-point scale [53] was employed for assigning the relative scores to the pair-wise comparisons among the various factors (see Table 5). Because AHP is not a statistical method, a statistically meaningful sample size is not necessarily required [64]. In addition a representative sample is not required with AHP, because the unit of analysis focuses on the decisions made and does not consider who made the decisions [65]. Many distinct examples of AHP research used a small sample size, as opposed to conventional surveys and statistical analysis where high sample sizes are advised [65]. Moreover, Ref. [66] further noted that the AHP technique is typically applied to investigate persons who are considered knowledgeable about the topic of research interest; therefore, a large sample size is not required.

Table 5. Relative Importance Scale of the AHP.

Intensity of Importance	Definition
1	Equally important
3	Moderately important
5	Strongly important
7	Very strongly important
9	Extremely strongly important
2, 4, 6, 8	Intermediate values (Reaching compromise values between 1, 3, 5, 7, 9)

Accordingly, over 70 experts from various institutions and industries were contacted to provide their perspectives on the significance of the factors impacting the adoption of IoT-based smart campuses. While twelve experts responded, only eleven responses were analysed due to consistency problems. Each expert had over five years of expertise with smart devices, IoT applications, technology adoption, and advanced technological solutions applied to improve the environment and peoples' way of life. Table 6 contains the experts' background information. A questionnaire (Appendix A) containing all the main factor categories as well as their corresponding factors was prepared based on a pair-wise comparison judgment using Saaty's nine-point scale. Accordingly, descriptions of all of the categories and factors were communicated to the expert respondents while the questionnaires were being administered. The study received fifteen responses, of which four responses were excluded due to incompleteness and consistency problems (refer to Section 3.3.4 for more clarification). Therefore, eleven responses were recorded and analyzed as valid data that met the consistency requirement.

Table 6. Expert Profile.

SN	Affiliation	Specialization	Experiences
1	Department of Information, Technology College of Computer, Qassim University, Kingdom of Saudi Arabia.	Human computer interaction, information systems, interactive systems, and identity management systems.	13
2	Computer Science Department, University of Hong Kong.	Computer science, security and privacy.	35
3	Département de génie mécanique, Université Laval, Pavillon Adrien-Pouliot, Canada.	Mechanical engineering.	
4	Pamplona University, Colombia; Francisco de Paula Santander University, Colombia.	Smart university, computer communications (networks), information security, and virtual education.	
5	Imam Abdulrahman Bin Faisal University.	Computer science, artificial intelligence, and information systems.	28
6	8 years as a public real estate management professional, 5 years as a PhD researcher in TU Delft University Netherlands.	Public real estate management, smart building technologies, smart campus tools, IoT and decision-making.	13
7	Permanent Lecturer in the Unniversitas Kristen Maranatha (UKM), School of Information Technology, Indonesia.	Computer science and information systems.	20
8	Covenant University, Department of Computer and Information Science Nigeria Ota, Nigeria.	Virtual reality, e-government, and information technology.	7
9	Chief Information Officer, at the SKC&C in Korea.	Technology Management.	
10	The Center for Wireless Communications at the University of Oulu, Finland.	Convergent IoT Communications for Vertical Systems.	15
11	Department of Management Information System, Cyprus International University. Nicosia, Cyprus.	Education consulting and management information systems.	6

3.3. Computation of Normalized Priority Weights

The following steps were taken to determine normalized weights:

3.3.1. Building Pair-Wise Comparison Matrices of the Factors

Pair-wise comparisons were performed to determine which factors outweighed the others [53,67]. The judgments obtained from calculation are presented as integers. If the xth element is greater than the yth element, the integer is placed in the xth row and yth column of the comparison matrix, and therefore its corresponding reciprocal is entered in the yth row and xth column of the matrix. Accordingly, if the elements or factors being compared are equal, a value of one is applied to both places. As a result, each comparison matrix $C = C_{xy}$, where C_{xy} is a square matrix of order n (n = number of factors compared) with reciprocate elements, as shown in Equation (2). Moreover, the AHP questionnaire matrix is presented in Appendix A.

$$C_{xy} = \frac{1}{C_{xy}}; x, y = 1, 2, 3, \ldots, n \tag{2}$$

3.3.2. Constructing Aggregate Comparison Matrices of the Factors

The aggregated judgment for each item of the comparison matrix is obtained by aggregating the replies collected from the experts on the pair-wise comparisons of factors categories and factors using the geometric mean technique [53,67]. The aggregated comparison matrix A for a certain characteristic is defined as $A = [A_{xy}]$, where A_{xy} is the geometric mean of the judgments of N decision makers, computed as shown in Equation (3):

$$a_{ij} = \left(\prod_{i=1}^{n} \right)^{1/N} \tag{3}$$

3.3.3. Calculating Priorities or Relative Weights of the Factors

For each category (main factor) and sub-factor, a normalized matrix N is generated to calculate the priority. The normalized matrix N is constructed based on the corresponding comparison matrix A as follows (Equation (4)):

$$N = [n_x], \text{where} \quad n_{xy} = \frac{a_{xy}}{\sum_{x=1}^{n} a_{xy}} \tag{4}$$

The priority (weights) for each factor are then derived by averaging the elements of each row N. Accordingly, the priority vector $W = [wi]$ is a column matrix of order $nx1$, as shown in Equation (5):

$$w_x = \frac{\sum_{y=1}^{n} n_{xy}}{n} \tag{5}$$

3.3.4. Validating the Result of all Comparison Matrices through Consistency Tests

The result of the comparison matrices was validated through consistency testing. This is because people are frequently inconsistent in their responses to questions. Hence, it is critical to evaluate the levels of consistency in the comparison matrices. This helps researchers to validate the predicted priority vectors. To achieve this, the consistency ratio (CR) was utilized as the measurement index in pair-wise comparisons. If CR is less than or equal to 0.10 ($CR \leq 0.10$), the amount of inconsistency in the comparison matrix A is deemed acceptable, and therefore the ranking results is acceptable [53]. Nevertheless, if the CR is greater than 0.10 ($CR > 0.10$), the ranking results is considered unacceptable. Hence, if such an instance were found, the decision maker should repeat the evaluation process [7,8]. A matrix A is considered to be consistent if and only if the matrix under evaluation has met the following conditions (see Equation (6)):

$$AW =_n W \tag{6}$$

The problem in Equation (3) is considered to be an Eigenvalue problem. The larger Eigenvalue λmax is considered to be greater than or equal to n [53]. The matrix A is more consistent if the λmax is closer to n. Hence, the consistency (CR) related to a comparison matrix A can be tested by the following steps. First, calculate $\lambda(max)$ using Equation (7)

$$AW = \lambda_{max} W \tag{7}$$

$$CR = \frac{CI}{RI} \tag{8}$$

where CI (consistency index) is given by Equation (9)

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{9}$$

and RI is the random index. Note: Different number of criteria (n) correspond to different values of random index [53] cited in [7], as shown in Table 7.

Table 7. Table of random index (RI).

N	1	2	3	4	5	6	7	8	9	10	11	12	13
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.58	1.56

3.3.5. Calculating Global Weights of All Factors

Equation (3) is used to compute the local weights for the main category and factors of IoT-based smart campus adoption. The global weights obtained for the main category are equal with their local weights. However, the global weights obtained for the factors are computed as indicated in Equation (10):

$$GWSF = LWSF \times GWCMF \tag{10}$$

where *GWSF* is the global weight of the factors, *LWSF* is the local weight of the factors, and *GWCMF* is the global weight of the corresponding main category.

4. Results and Discussion

Microsoft excel 2016 (MS EXCEL) was used to analyze the data obtained through the AHP questionnaire and matrix presented in Appendix A. The responses gathered from the experts on the pair-wise comparisons of various categories and factors were aggregated using the geometric mean approach, based on Equation (3). Hence, Tables 8–12 present the comparison matrices, weights, and CR for all of the hierarchical model's factors. The result revealed no consistency issues from the responses, as the values of the CR are smaller than the threshold value (0.10). Similarly, the findings indicated the consistency of the comparison matrices, and therefore, the weights or priorities are acceptable. Figure 3 breaks down the precise computations used to determine the weights and CR values for all the factors, both main and subfactors.

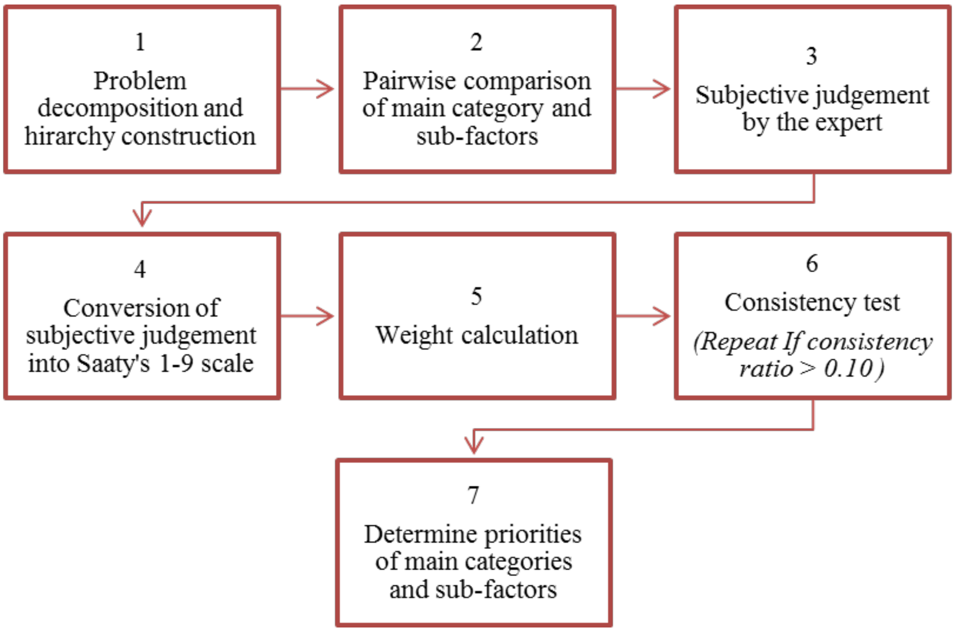

Figure 3. Breakdown for Determining Consistency Ratio.

First, Table 8 shows that end user specifics factors ($weight = 0.33$) rank first among the four primary categories, followed by environmental specific factors ($weight = 0.29$), organizational specific factors ($weight = 0.20$), and technology specific factors ($weight = 0.18$). Furthermore, the consistency test indices suggest that the consistency index (0.0020054), relative importance (0.90), and consistency ratio ($0.002228 < 0.10$) of the main category are acceptable. This shows the significance of the main factors to determine the success of adopting smart campuses.

Table 8. Results for Main Factors.

Factor Category	TSF	OSF	ESF	USF	Weight	Consistency Test
TSF	0.18	0.19	0.16	0.19	0.18	$\lambda max = 4.00602$
OSF	0.19	0.21	0.21	0.21	0.20	CI = 0.0020054
ESF	0.32	0.28	0.28	0.27	0.29	RI = 0.90
USF	0.31	0.33	0.35	0.33	0.33	CR = 0.002228 < 0.10

The findings obtained for organizational specific factors show that factors related to users' attentiveness, such as satisfaction, capacity to use new innovations, self-efficacy, concerns as a result of privacy, domain-specific knowledge, and habits are critical to improving IoT-based smart campus adoption. Technology that satisfies users and makes them feel knowledgeable and confident will lead to users being more at ease dealing with smart and IoT devices, making them more likely to adopt IoT-based smart campuses. The second most important factor influencing the adoption of IoT-based smart campuses is found to be environmental specific factors. The environmental aspects of smart campus applications have a significant impact on user readiness. The success of a smart campus may face greater challenges if users encounter environmental setbacks such as support from social tiers, external pressure, or a lack of government support. The third major component that may influence the adoption of IoT-based smart campuses has been identified as organization specific factors. Hence, users may strengthen their intention to adopt smart campus solutions if they are certain of receiving support. Technology specific factors are revealed to be the least relevant category influencing the adoption of IoT-based smart campuses. Different personnel have varying attitudes toward smart campus adoption. Thus, working with advanced technologies may be simple for certain staff, and quite challenging for others.

Second, the weight analysis of end user specific factors is shown in Table 9. According to the data, privacy concern ($weight = 0.34$) are judged to be the most relevant and important sub-factor, followed by satisfaction ($weight = 0.17$), self-efficacy ($weight = 0.16$), domain-specific knowledge ($weight = 0.13$), habit ($weight = 0.10$), and innovativeness ($weight = 0.10$). Furthermore, the consistency test indices suggest that the consistency index (0.006574853), relative importance (1.24), and consistency ratio ($0.0053023 < 0.10$) of the end user specific factors are acceptable. This shows the significance of the end user specific factors in determining the success of smart campus adoption. Therefore, the respondents' observed privacy concerns show that smart campus devices with insignificant privacy issues will attract more users than those with higher privacy concerns. Similarly, satisfaction, self-efficacy, domain-specific knowledge, habits, and innovativeness have an impact on willingness to adopt a smart campus, with satisfaction and self-efficacy slightly more important than others.

Third, the respondents view government support ($weight = 0.44$) to be more significant than social influence ($weight = 0.38$) and external pressure ($weight = 0.18$) among the two types of environmental specific factors (Table 10). Furthermore, the consistency test indices suggest that the consistency index (0.00860669), relative importance (0.58), and consistency ratio ($0.014839121 < 0.10$) of the environmental specific factors are acceptable. This shows the significance of environmental specific factors to determine success when adopting smart campuses. Hence, this study suggest that experts consider government support, such as financial and enabling policies, to be more significant with respect to embracing the concept of a smart campus. Although social influence is significant, it is slightly less so than government support. This shows that opinions from other individuals will influence the intention and adoption of smart campuses. Accordingly, external pressure is less significant as compared to government support and social influence.

Fourth, facilitating conditions ($weight = 0.44$) are determined to be more important than service collaboration ($weight = 0.34$) and propagation ($weight = 0.22$) among organisational specific factors (Table 11). Furthermore, the consistency test indices suggest that the consistency index (0.000329644), relative importance (0.56), and consistency ratio ($0.000588651 < 0.10$) of the organisational specific factors are acceptable. This shows the significance of the organisational specific factors in determining the success of smart campus adoption. Therefore, this study suggests that facilitating conditions can provide users with the necessary support for using smart campus applications and dealing with related challenges that could arise in the future. Moreover, seeking service collaboration and propagating smart campus solutions are less crucial according to the data. These findings are congruent with various sources in the technology adoption literature on the significance of these factors which have found that facilitating conditions favorably influence intentions to use technological applications [19,44].

Table 9. Results for End User Specific Factors.

Sub-Factor	Innovativeness	Self-Efficacy	Privacy Concern	Satisfaction	Domain-Specific Knowledge	Habit	Weight	Consistency
Innovativeness	0.10	0.10	0.11	0.09	0.07	0.10	0.10	$\lambda max = 6.03287$
Self-efficacy	0.15	0.16	0.16	0.15	0.15	0.17	0.16	$CI = 0.006574853$
Privacy concerns	0.3	0.34	0.35	0.4	0.34	0.32	0.34	$RI = 1.24$
Satisfaction	0.18	0.17	0.14	0.16	0.21	0.18	0.17	$CR = 0.0053023 < 0.10$
Domain-specific knowledge	0.17	0.14	0.13	0.10	0.13	0.13	0.13	
Habit	0.10	0.09	0.11	0.09	0.1	0.10	0.10	

Table 10. Results for Environmental Specific Factors.

Sub-Factor	Social Influence	Government Support	External Pressure	Weight	Consistency
Social influence	0.39	0.42	0.33	0.38	$\lambda max = 3.01721$
Government support	0.4	0.43	0.5	0.44	$CI = 0.00860669$
External pressure	0.21	0.15	0.18	0.18	$RI = 0.58$
					$CR = 0.014839121 < 0.10$

Table 11. Results for Organizational Specific Factors.

Sub-Factor	Facilitating Condition	Propagation	Service Collaboration	Weight	Consistency
Facilitating conditions	0.44	0.45	0.43	0.44	$\lambda max = 3.00066$
Propagation	0.21	0.22	0.22	0.22	$CI = 0.000329644$
Service collaboration	0.35	0.33	0.34	0.34	$RI = 0.56$
					$CR = 0.000588651 < 0.10$

Finally, within the technological specific factors (Table 12), the most important sub-factors are ease of use ($weight = 0.11$) and cost ($weight = 0.11$), followed by security concerns ($weight = 0.10$), usefulness ($weight = 0.09$), trust ($weight = 0.09$), value ($weight = 0.08$), effective quality ($weight = 0.07$), functionality ($weight = 0.07$), compatibility ($weight = 0.06$), mobility ($weight = 0.06$), reliability ($weight = 0.06$), availability ($weight = 0.06$), and enjoyment ($weight = 0.04$). Furthermore, the consistency test indices suggest that the consistency index (0.020888587), relative importance (1.56), and consistency ratio ($0.01339012 < 0.10$) of the technological specific factors are acceptable. This shows the significance of the factors to determining success when adopting smart campuses.

According to these findings, the ability of smart campus solutions to be easily used and the associated costs such as purchase, maintenance, etc., are critical for users working with smart campus applications. Users may become irritated if smart campus solutions are difficult to use and expensive. Moreover, security concern is the seventh-most important of the technological specific factors. This is due to expert comments to the effect that security is a non-negotiable feature any smart campus solution must have. Accordingly, other relevant factors include usefulness, trust, and the value to be derived from smart campus solutions.

The global weights and rankings of the 25 factors impacting IoT-based smart campus adoption are shown in Table 13. Accordingly, the top five factors considered crucial for the adoption of smart campuses are government support, privacy concerns, social influence, facilitating conditions, and service collaboration, whereas the least crucial factors include compatibility, mobility, reliability, availability, and enjoyment. As a result, universities and policy makers should prioritize these factors in order to increase the adoption of smart campuses.

Table 12. Results for Technology Specific Factors.

Sub-Factor	Effective Quality	Ease of Use	Usefulness	Trust	Cost	Value	Security Concerns	Enjoyment	Compatibility	Mobility	Functionality	Reliability	Availability	Weight	Consistency Test
Effective quality	0.07	0.08	0.07	0.11	0.05	0.07	0.07	0.07	0.08	0.06	0.07	0.06	0.07	0.07	$\lambda max = 13.25066$
Ease of use	0.09	0.11	0.12	0.13	0.09	0.12	0.14	0.08	0.1	0.09	0.12	0.1	0.09	0.11	$CI = 0.020888587$
Usefulness	0.09	0.08	0.1	0.1	0.08	0.1	0.08	0.07	0.07	0.11	0.1	0.09	0.11	0.09	$RI = 1.56$
Trust	0.06	0.08	0.08	0.09	0.14	0.07	0.1	0.09	0.11	0.11	0.1	0.09	0.11	0.09	CR = 0.01339012 $< 0.10\ \lambda$
Cost	0.15	0.12	0.12	0.07	0.11	0.13	0.13	0.07	0.13	0.11	0.08	0.1	0.09	0.11	
Value	0.08	0.07	0.07	0.11	0.06	0.08	0.07	0.1	0.09	0.08	0.07	0.1	0.09	0.08	
Security concerns	0.09	0.07	0.1	0.08	0.07	0.11	0.09	0.15	0.11	0.09	0.09	0.09	0.09	0.1	
Enjoyment	0.04	0.05	0.05	0.04	0.06	0.03	0.02	0.04	0.04	0.05	0.03	0.03	0.03	0.04	
Compatibility	0.06	0.07	0.08	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.09	0.07	0.07	0.06	
Mobility	0.08	0.07	0.05	0.05	0.06	0.06	0.06	0.04	0.06	0.06	0.09	0.06	0.06	0.06	
Functionality	0.06	0.06	0.06	0.06	0.1	0.08	0.07	0.09	0.05	0.05	0.07	0.11	0.06	0.07	
Reliability	0.07	0.06	0.06	0.06	0.06	0.05	0.06	0.08	0.05	0.06	0.04	0.06	0.07	0.06	
Availability	0.06	0.07	0.05	0.05	0.07	0.05	0.06	0.06	0.05	0.06	0.06	0.05	0.06	0.06	

Table 13. Local and Global Weights and Rankings.

Factors	Local Weight	Local Rank	Factors	Global Weight	Global Rank
Cost	0.10842	1	Government support	0.12732	1
Ease of use	0.10674	2	Privacy concern	0.11168	2
Security concerns	0.09507	3	Social influence	0.10790	3
Trust	0.09461	4	Facilitating condition	0.08999	4
Usefulness	0.09137	5	Service collaboration	0.06980	5
Value	0.08265	6	Satisfaction	0.05675	6
Effective quality	0.07059	7	External pressure	0.05139	7
Functionality	0.07041	8	Self-efficacy	0.05077	8
Compatibility	0.06309	9	Propagation	0.04403	9
Mobility	0.06244	10	Domain-specific knowledge	0.04358	10
Reliability	0.05971	11	Habit	0.03265	11
Availability	0.05727	12	Innovativeness	0.03179	12
Enjoyment	0.03763	13	Cost	0.01977	13
Facilitating condition	0.44152	1	Ease of use	0.01946	14
Service collaboration	0.34246	2	Security concerns	0.01733	15
Propagation	0.21601	3	Trust	0.01725	16
Government support	0.44423	1	Usefulness	0.01666	17
Social influence	0.37646	2	Value	0.01507	18
External pressure	0.17931	3	Effective quality	0.01287	19
Privacy concern	0.34130	1	Functionality	0.01284	20
Satisfaction	0.17344	2	Compatibility	0.01150	21
Self-efficacy	0.15514	3	Mobility	0.01138	22
Domain-specific knowledge	0.13319	4	Reliability	0.01089	23
Habit	0.09978	5	Availability	0.01044	24
Innovativeness	0.09715	6	Enjoyment	0.00686	25

Thus, we have fully revealed the factors most important to IoT-based smart campus adoption, using AHP to provide the local and global rankings of the 25 factors. These factors were evaluated for their capacity to influence the adoption of IoT-based Smart Campuses in different ways. The study observed that the technology specific factors were not found to be as significant as the another categories. The ranking of the factors in Table 13 is dominated by environmental specific factors, organizational specific factors, and end user specific factors.

5. Contribution and Future Work

5.1. Theoretical Contributions

This study reflects a desirable direction for study by examining the aspects that experts believe are vital for IoT-based smart campus adoption. The AHP analysis of the relative priority of these factors demonstrates the importance placed on each factor. This is crucial at this stage, as the smart campus is still emerging and studies concerning the adoption of this concept are lacking. Thus, proposing a suitable adoption model for a smart campus is required. The AHP has been helpful in the respect, as it helps in decision-making concerning different factors that could affect smart campus adoption.

Nevertheless, the AHP technique varies from prior scholars' analyses of advanced technological solutions such as IoT, smart devices, artificial intelligence, etc., which constitute the bigger picture of a smart campus. Most previous studies used multiple regression approaches or structural equation modeling to examine the relevant elements [16,20,25,28,32,33,38]. Although the beta coefficients acquired through multiple regression analysis can be stated as the relative weights of the components [7], their values are derived indirectly via testing. Furthermore, due to measurement mistakes in the independent and dependent variables, prediction errors between the real and predicted values of the dependent variable can occur.

Furthermore, collinearity issues between the independent variables may exist. As a result, these methodologies are incapable of providing precise information on these factors and their relative weights [68]. Moreover, previous studies used various theoretical models from the technology adoption literature to address various technological solutions supporting smart campuses. The value of this research lies in harmonizing those factors that are more relevant for smart campus users, whose technology use is mandated rather than optional. The current study included factors such as government support, privacy concern, social influence, facilitating condition, service collaboration, satisfaction, external pressure, self-efficacy, propagation, domain-specific knowledge, habit, and innovativeness.

5.2. Practical Implications

In a nutshell, these findings show that university administrators and decision-makers should take steps to increase smart campus adoption. Universities should provide adequate support to users of smart campus solutions to improve their technical abilities and enable them to use smart campuses comfortably. Similarly, the government should provide adequate support to universities through enabling policies and financial remuneration iin order to improve the adoption of smart campuses effectively. Users' privacy concerns should be managed appropriately in order to address privacy-related issues. The use of smart campus solutions should be promoted among users. User-associated factors such as self-efficacy, domain specific knowledge, habit, and innovativeness should be enhanced. Furthermore, universities should ensure that smart campus solutions are accessible quickly so that users may complete their responsibilities efficiently, thereby significantly enhancing user satisfaction.

5.3. Policy Recommendations

The entire society benefits from effective educational practices and policies. Government and educational stakeholders are required to support these practices. Therefore, this study found that while smart campuses are compelled to exist by choice or necessity and have a positive impact on the performance of educational sector, the elements that affect their adoption success have not been properly documented, which was the central focus of this study, that is, to prioritize adoption factors of IoT-based smart campus. Hence, this study discusses the following policy implications:

- Governments should encourage universities to increase their investments in smart campuses. For example, governments should support the education ministry and other relevant agencies with the funding and resources they need to support the implementation of smart campuses. This is because smart campus solutions remain extremely rare, particularly in poorer nations. Therefore, a particular government policy or support from developed nations may encourage smart campus implementation in developing and underdeveloped nations through progressive measures such as grants and financial assistance. Such regulations might elevate the smart campus in the minds of educational stakeholders, boosting student motivation for learning.
- According to [69], an IoT-based smart campus deployed sensing devices which are typically authority-operated, leaving students and employees with few options, as the surveillance system was installed everywhere. However, school executives and leaders have a greater obligation in today's data-driven environment to prioritize cybersecurity and refrain from violating user privacy [70]. To secure personal data while enabling a suitable level of context awareness, new laws, policies, and regulations must be implemented.
- Additionally, it is crucial that educational authorities at all levels identify and set data-related standards in accordance with their respective needs. It would be challenging for developers to accomplish data interoperability in the new information system without such standards. Hence, to ensure the success of the smart campus and to guide quick, robust, and organized innovation in smart education, there is an urgent need for a set of standards from a higher authority to support the development of the smart campus, preferably as part of a smart city plan.
- Moreover, there is a need for leaders in the educational environment to conduct environmental feasibility studies to foresee any upcoming issues that deserve more consideration in smart campus implementation. This will increase the capacity of the educational sector to keep track of developments occurring domestically, regionally, and globally. Hence, educational institutions will be able to innovate, minimize risk, and seize positive trends by creating and improving systems and efficient methods that identify, monitor, and analyze external changes.

Hence, the results of this study may offer policy makers relevant information and guidance for creating more effective support for smart campus initiatives. The findings of this study provide considerable evidence that can encourage the educational sector to take into account issues that are crucial for smart campus adoption.

5.4. Limitations and Future Work

This study's factors and classification were derived from the existing literature. Although the researchers attempted to collect many relevant factors and selected only 25 based on their frequency in the literature to avoid complexity, it is possible that a more complete hierarchy of factors can be constructed for future study, as the smart campus study area is developing and the factors influencing its adoption may change on a regular basis. Another disadvantage of this study's methodology is that the rating scale utilized in the AHP is conceptual. Thus, when performing pair-wise comparisons of diverse factors, there is the possibility of biased responses. As a result, while assigning relative rankings to various elements, extreme caution should be exercised.

Furthermore, several of the categories and factors chosen for the model may have interrelationships, such as privacy, security, and trust; habit and enjoyment; and domain-specific knowledge and self-efficacy. These interrelationships between the factors are not taken into account by the AHP method, which is a weakness of the current study. Hence, analytic network process (ANP) or using structural equation modelling (SEM) might be a better choice. As a result, this study can be extended by taking into account other characteristics that influence the adoption of smart campuses through ANP. Furthermore, future studies may conceptualizes a smart campus adoption model based on the significant factors derived from the AHP analysis for testing with a statistical regression-based method such as SEM.

Additionally, the expert respondents relied on in this study were distributed heterogeneously around the globe. Specifically, five experts worked in developed countries (Canada, the Netherlands, Finland, Cyprus, and South Korea), while six experts worked in developing countries (KSA, China, Columbia, Indonesia, and Nigeria). This contributes to another weakness of the study, as the expert responses were not analysed based on whether they worked in a developed or developing country. This is because governments in developing countries usually appear as a factor in technology adoption. Therefore, future studies could bridge this weakness, which is not within the scope of this paper, as this is a strong research gap that could contribute to the adoption of smart campuses in developing as well as under-developed nations. Furthermore, future research could collect data from Smart Campus users to provide more knowledge about the adoption factors of IoT-based smart campuses.

6. Conclusions

The smart campus has now been introduced as an evolutionary model for university campuses both by choice and by demand. However, despite its many benefits, the factors ensuring its adoption and success are lacking in the current literature. Universities, researchers, policy makers, and manufacturers are working hard to address these challenges. As a result, the goal of this study was to investigate and prioritize the elements that contribute to smart campus adoption. Based on the previously published literature about the adoption of IoT, this article identified 25 important factors, classified into technology specific factors, organizational specific factors, environmental specific factors, and end user specific factors. These factors were prioritized using the analytic hierarchy process. The study determined that the most significant contributing factors were government support, privacy concerns, social influence, facilitating conditions, and service collaboration, whereas the least significant contributing factors were enjoyment, availability, reliability, mobility, and compatibility. Furthermore, the results obtained from the global ranking suggest that twelve factors from among the organizational specific factors, environmental specific factors, and end user specific factors are more significant than any of the factors in the technology specific factors category. In addition, this study can offer policy recommendations and limitations for future research work. Specifically, this study provides theoretical and practical implications for the adoption of smart campuses.

Author Contributions: Data curation, R.S.; Formal analysis, R.S.; Funding acquisition, Y.Y.J. and M.A.J.; Investigation, R.S.; Methodology, R.S. and U.A.B.; Project administration, Y.Y.J. and S.A.; Supervision, Y.Y.J., M.A.J. and S.A.; Validation, R.S.; Writing—original draft, R.S.; Writing—review & editing, Y.Y.J., M.A.J. and S.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Ethical review and approval were waived for this study, due to REASON (approval was not required from the Institutional Review Board; the scope of the research does not fall under the category of studies mentioned in the Declaration and provisions from the Nuremberg Code of 1946 which pertain to the gathering of information as provided in the present set of guidelines).

Informed Consent Statement: Informed consent was obtained from all the experts involved in the study.

Acknowledgments: The authors would like to thank the Ministry of Higher Education and Universiti Putra Malaysia for all the support toward the success of this work.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. AHP Questionnaire

Introduction: The following tables present the comparison and proposition to be investigated in this study. Technology adoption factors are synthesized and categorized into technology-specific factors, organizational-specific factors, environmental-specific factors, and end-users-specific factors. Based on this, this study focuses on comparing each factor against the other factors. You are thus required to indicate your opinion on a scale of 1 to 9 (Appendix A), where a value closer to 1 indicates equal importance compared to other factors.

Table A1. Comparison among the Main Categories of Adoption Factors: How important are the following main categories in comparison?

Categories	**Technology Specific Factors**	**Organizational Specific Factors**	**Environmental Specific Factors**	**End-Users Specific Factors**
Technology Specific Factors				
Organizational Specific Factors				
Environmental Specific Factors				
End-Users Specific Factors				

Table A2. Comparison among the Technology Specific Factors: How important are the following adoption factors in comparison?

Adoption Factors	Effective Quality	Ease of Use	Usefulness	Trust	Cost	Value	Security Concerns	Enjoyment	Compatibility	Mobility	Functionality	Reliability	Availability
Effective quality													
Ease of use													
Usefulness													
Trust													
Cost													
Value													
Security concerns													
Enjoyment													
Compatibility													
Mobility													
Functionality													
Reliability													
Availability													

Table A3. Comparison among the Organizational Specific Factors: How important are the following adoption factors in comparison?

Adoption Factors	Propagation	Facilitating Condition	Service Collaboration
Propagation			
Facilitating condition			
Service collaboration			

Table A4. Comparison among the Environmental Specific Factors: How important are the following adoption factors in comparison?

Adoption Factors	Social Influence	Government Support	External Pressure
Social influence			
Government support			
External pressure			

Table A5. Comparison among the End Users Specific Factors: How important are the following adoption factors in comparison?

Adoption Factor	Innovativeness	Self-Efficacy	Privacy Concern	Satisfaction	Domain-Specific Knowledge	Habit
Innovativeness						
Self-efficacy						
Privacy concern						
Satisfaction						
Domain-specific knowledge						
Habit						

Table A6. Profile Information.

Date	
Name (Optional)	
Education	
Work Experiences	
Email	

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