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RESEARCH ARTICLE

Examining IoT-Based Smart Campus Adoption Model: An Investigation Using Two-Stage Analysis Comprising Structural Equation Modelling and Artificial Neural Network

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ABSTRACT The progress and evolution of technology have been rapidly transforming various aspects of our society and daily lives, including colleges and campuses into smarter environments compared to the past. Despite the numerous advantages offered by cutting-edge technologies, such as IoT-based smart campuses, academic research on their implementation suffers from a significant lack of comprehensive information necessary to deliver efficient smart campus solutions. Therefore, the focus of this study is to investigate the significance of IoT-based smart campus adoption from 14 proposed hypotheses. The researchers collected data from stakeholders affiliated with universities in Iraq, resulting in a dataset of 442 observations. To analyze the data, a two-stage approach was employed, consisting of structural equation modeling (SEM) and reevaluated with the artificial neural networks (ANN) method. The findings provide evidence supporting the significance of various constructs. In particular, the model demonstrates satisfactory predictive relevance, indicating its effectiveness in making accurate predictions or forecasts. The ANN analysis suggests that the model has predictive capabilities. Moreover, the study findings support the importance of perceived usefulness in technology-specific factors, facilitating conditions, and propagation in organizational-specific factors, government support, social influence, and external pressure in environmental-specific factors, as well as privacy concerns, self-efficacy, satisfaction, and domain-specific knowledge in end-user-specific factors. Four hypotheses related to perceived ease of use, service collaboration, habit, and innovativeness were rejected. Notably, the study identifies propagation as the most significant predictor in the ANN analysis. The conclusions of this study can be beneficial for university administrators, manufacturers, and policymakers in understanding the essential components of smart campuses to enhance the adoption and maximize the effectiveness of smart solutions.

INDEX TERMS Smart campus, IoT, adoption factors, smart education, higher education, SEM, ANN.

I. INTRODUCTION

In recent years, the rapid progress of Internet of Things (IoT) technologies has opened up new possibilities for transformative applications across multiple domains [1], [2], including the realm of higher education. Particularly, the notion of a "Smart Campus" appeared as a promising paradigm, harnessing IoT capabilities to enhance campus operations, improve resource management, and provide innovative services to students and faculty [3]. An IoT-based

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smart campus is described as the integration of IoT technologies and solutions in various aspects of a campus environment, such as education, administration, facilities management, and student services [3], [4], [5]. It involves the use of interconnected devices, sensors, and data analytics to improve operational efficiency, enhance safety and security, optimize resource utilization, and provide a seamless and personalized experience for students, faculty, and staff. The smart campus offers various benefits and functionalities services [3], [4] as summarised in Figure 1.

The IoT technologies can enhance the learning experience by enabling smart classrooms equipped with interactive displays, digital whiteboards, and connected devices [6]. Students can access educational resources, collaborate with peers, and receive personalized feedback. IoT-based tracking systems can also monitor attendance, analyze student engagement, and provide insights to improve teaching methodologies. Moreover, IoT devices and sensors can monitor the campus environment for potential risks, including surveillance cameras, access control systems, and fire detection sensors [3], [5], [7]. Specifically, devices like unmanned aerial vehicles (UAVs) have the potential to carry out surveillance and real-time monitoring, generating fresh information, as enlightened upon in the existing studies [8], [9], [10], [11], [12]. The real-time data collected from these devices can be analyzed to detect anomalies, raise alerts, and facilitate rapid response in case of emergencies in Campuses. Smart lighting systems can optimize energy consumption and enhance safety by automatically adjusting lighting levels based on occupancy and daylight.

In addition, the IoT-based solutions enable efficient management of campus infrastructure [3], which offers predictive maintenance to identify potential equipment failures and enable proactive maintenance, minimizing downtime [13]. IoT-based smart cards or wearables can serve as student identification, granting access to various campus facilities, such as libraries, labs, and dormitories [14]. Location-based services can provide real-time information about campus events, transportation options, and personalized notifications based on individual preferences [5], [15]. Furthermore, smart campus solutions can contribute to sustainable practices on a smart campus [3]. For example, smart grids and energy management systems optimize energy distribution and consumption, reducing carbon footprint. Environmental sensors can monitor air quality, temperature, and humidity, facilitating informed decisions for sustainable campus planning. Water management systems can monitor usage, detect leaks, and optimize irrigation in landscaping. Therefore, understanding the factors influencing Smart Campus adoption is crucial for educational institutions seeking to leverage these technologies effectively [16], [17], [18], [19].

To comprehensively investigate the factors influencing the IoT-based Smart Campus adoption intention, a robust analytical approach is required. This research paper presents multiple analysis methods, combining the power of Structural Equation Modelling (SEM) as well as Artificial Neural Networks (ANN) [20], [21], [22], [23], [24]. This integrated approach offers a more accurate insight into the complex dynamics underlying the adoption model and processes. In the first stage of the analysis, SEM is employed for the evaluation of the latent variables and observed variable relationships. SEM provides a statistical framework for testing theoretical models, enabling the assessment of the direct and indirect effects of various factors of IoT-based Smart Campus adoption. By capturing both the measurement as well as the structural models, the SEM offers a holistic view of the relationships among the constructs and enables the examination of hypothesized relationships.

Building upon the findings from the SEM stage, the second stage of analysis employs ANN to enhance the predictive power of the model. ANN leverages the principles of machine learning to evaluate and enhance the performance of predictive models by training neural network architectures. Through the ANN analysis, the importance of different predictors can be assessed, potentially uncovering hidden patterns and nonlinear relationships that may be missed by traditional statistical approaches. The integration of the two methods in this study contributes to a more robust and comprehensive investigation of the factors influencing the adoption of Smart Campus technologies. By combining the strengths of both approaches, we aim to provide valuable insights and practical implications for educational institutions embarking on Smart Campus initiatives. Understanding the drivers and barriers to adoption is essential for informed decision-making, resource allocation, and effective implementation strategies.

Hence, the central premise of this study revolves around exploring the significance of IoT-based smart campus adoption, a topic that has been gaining increasing attention in recent years due to rapid technological advancements and their implications for educational institutions. The novelty of this study comes from two key aspects; A) a holistic model for IoT-based Smart Campus adoption, and B) methodological design. This study believes that these elements collectively establish the novelty of the study and its potential to inform university administrators, manufacturers, policymakers, and researchers about the essential components of smart campuses.

A. HOLISTIC IOT-BASED SMART CAMPUS MODEL

The integration of factors from these four key themes results in a comprehensive and holistic framework that has not been extensively explored in the context of IoT-based smart campus adoption. While previous research might have focused on individual elements within these themes [3], [25], [26], [27], this study uniquely combines them through a systematic review process [17] and analytical hierarchical process [28] to provide a more complete understanding of the factors that collectively influence the adoption of smart campus solutions. This holistic approach reflects the intricate interplay between technology, organizational dynamics, environmental influences, and end-user perceptions empirically, thereby offering a richer and more nuanced perspective on

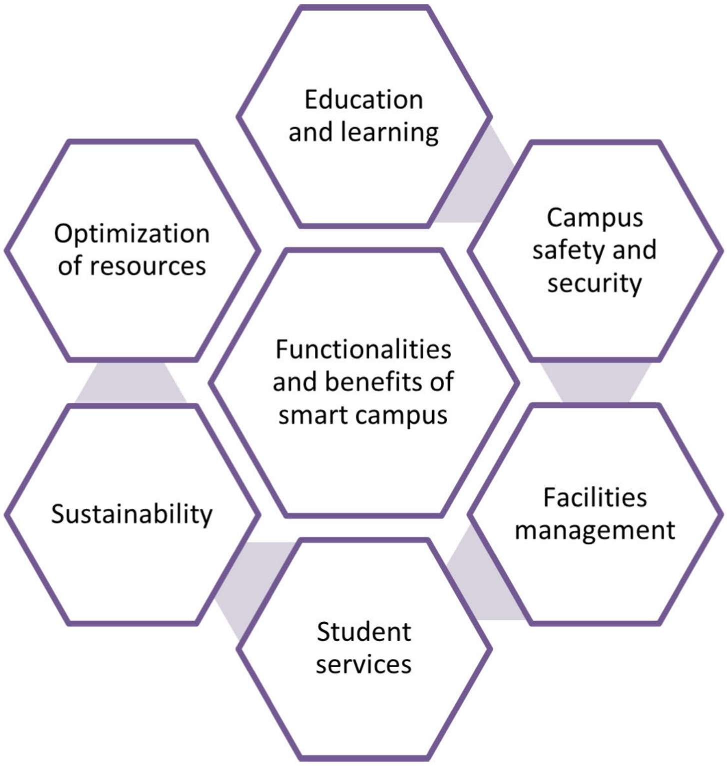

FIGURE 1. Summary of smart campus functionalities and benefits.

the adoption process. Notably, the integration of factors from diverse themes inherently brings together insights from multiple disciplines such as technology adoption, organizational behavior, environmental studies, and user experience. This interdisciplinary approach enriches the study's novelty by acknowledging the multifaceted nature of the topic. The incorporation of these different perspectives enables the study to contribute to a broader range of academic and practical domains, fostering a more holistic understanding of the challenges and opportunities presented by IoT-based smart campus adoption. Similarly, the incorporation of these four themes in the study's framework adds to its novelty by ensuring its applicability to various contexts. While the study focuses on universities in Iraq, the identified factors and their interrelationships can serve as a foundation for examining smart campus adoption in other regions and educational settings. This adaptability enhances the study's potential impact beyond its immediate context and strengthens its relevance to a wider audience.

B. METHODOLOGICAL DESIGN

Considering the fact that the concept of smart campuses and the integration of IoT technologies have been explored to some extent [3], [5], [6], [29], [30], [31], [32], this study takes a distinct approach by focusing on a specific geographical context - universities in Iraq, with empirical data. This contextualization is crucial as it acknowledges the diversity in adoption challenges and opportunities that may not be directly transferable from other regions. As such, the study fills a gap by providing insights into the adoption of smart campus solutions in a region that might have unique socio-cultural, economic, and technological factors.

Furthermore, the study's methodology adds to its novelty. The two-stage approach involving SEM followed by ANN analysis showcases a rigorous analytical process [33], [34], [35], [36], [37] that offers a comprehensive understanding of the factors influencing smart campus adoption. The ANN analysis, in particular, provides a predictive dimension to the study, enabling accurate forecasts and highlighting the potential of this approach for future research in similar domains. In addition, the empirical evidence collected from stakeholders affiliated with universities in Iraq, resulting in a dataset of 442 observations, further enhances the novelty of the study. The specific findings, including the identification of propagation [3] as a significant predictor, emphasize the importance of tailoring smart campus strategies to the local context. These elements collectively establish the novelty of the study and its potential to inform university administrators, manufacturers, policymakers, and researchers about the essential components of smart campuses for future consideration.

C. ORGANISATION OF THE PAPER

In this study, the aim is to contribute significantly to the ever-growing body of knowledge on the adoption of IoT-based Smart Campus, offering insights that can drive successful implementation and utilization of these transformative technologies in the higher education landscape.

Accordingly, the remaining part of the paper is structured as follows: Section II provides a review background of the relevant literature on IoT-based Smart Campus adoption as well discussion of the hypothesized model. Section III comprehensively describes the proposed research methodology, including data collection procedures, measurement instruments, and the analytical framework. Section IV presents the results and findings from the two-stage analysis, which covers data normality, measurement model, structural model, and ANN outcomes. Section V covers the result of the as well as implications for policy and practice for educational institutions. Finally, Section VI covers the conclusion of the study, which summarizes the key contributions and suggests avenues for future research.

II. LITERATURE OVERVIEW

The majority of existing technology adoption studies have primarily revolved around the realm of IoT applications [38], [39], [40], [41], [42], [43] with less emphasis on IoT-based Smart Campus. Table 1 presents the current literature concerning the IoT smart campus. Accordingly, there's been a notable scarcity of studies focusing on the adoption context of Smart Campus. This perspective not only encompasses the incorporation of IoT technologies but also addresses various facets of campus life, from educational enhancements to effective infrastructure management. As a result, the proceeding sections provide a succinct overview of the research landscape. This underscores the crucial gap in the existing literature, namely the limited exploration of the broader smart campus adoption concept and hypothesis development.

A. RESEARCH GAP AND MOTIVATIONS

The trends in smart campus research indicate a growing interest in leveraging IoT technologies, big data, and edge computing to enhance various aspects of campus life, from teaching and learning to infrastructure management. These trends demonstrate the potential for smart campuses to provide more efficient and user-centric services. While there are several noteworthy trends and areas of focus within the field. These trends provide valuable insights into the current state of research and the areas that require further exploration, especially highlighting the need for an integrated adoption model for IoT-based smart campuses, as presented in Table 1. For example, one of the focuses of the literature is proposing and experimenting with algorithms for smart campuses to improve features such as security, authentication, campus management, etc. [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54]. Other studies propose the criteria and indicators for successful smart campus initiatives [25], [55], [56], [57], [58], [59]. There is extensive literature on the theoretical or conceptual framework for smart campuses [56], [60], [61], [62], [63], and utilizing multi-decision criteria to investigate the factors for smart campuses [28], [64], and [65]. Specifically, several studies, e.g., [43], [66], have explored the implementation of IoT in the educational sector. This approach aims to enhance traditional teaching methods with IoT technologies, improving student engagement and learning outcomes. The concept of a campus edge computing network, using elements such as street lighting as IoT communication nodes, has gained traction in recent research [44]. Similarly, some existing papers, e.g., [45], [64], emphasize the importance of robust data acquisition, management, and storage systems in smart campuses. Additionally, addressing semantic interoperability issues is a critical aspect of IoT-enabled smart campuses, as highlighted by Reference [63]. These issues relate to the compatibility and seamless communication of various IoT devices and applications within the campus ecosystem.

Moreover, the integration of IoT and big data analytics has been explored in creating small-scale testing environments for smart city technologies within a university campus [47], [60]. This approach focuses on optimizing resource management and supporting strategic decisions for improving campus services and sustainability. Several studies [55], [57], [61] focus on defining criteria and KPIs for evaluating smart campuses. These criteria help in assessing the success, effectiveness, and decision-making of smart campus initiatives. In addition, a human-centered approach to smart campus development is evident in studies evaluating user experiences and satisfaction [50]. This approach emphasizes the importance of meeting user expectations and requirements. The analysis of the prior research revealed that, while existing studies provide valuable insights into various aspects of smart campuses, there is a noticeable gap in the literature regarding an integrated adoption model for IoT-based smart campuses. The existing research focuses mostly on implementation, but there is a need for an adoption model for the successful deployment of smart campuses. Therefore, an integrated adoption model for IoT-based smart campuses serves as a valuable resource for universities planning to embark on the journey toward a smarter campus, and proposing such a model is a novel and significant contribution to the literature. The model would provide a roadmap for the strategic deployment of IoT technologies, considering all relevant components and their interplay. By addressing this research gap, this study contributes to the development of a comprehensive framework that guides universities in creating truly smart campuses that benefit both students and faculty.

B. HYPOTHESIS DEVELOPMENT

The literature analysis conducted in earlier studies reveals that studies on technology adoption can be categorized into four primary classifications [17], [28], [70], [71], [72], [73], [74]. These classifications, as previously discussed [17], [28], encompass four broad themes: technology-specific factors (TSF), organizational-specific factors (OSF), environmental-specific factors (ESF), and end-user-specific factors (USF) are the key elements considered. In adoption

TABLE 1. Summary of smart campus existing studies.

Ref	Year	Paper summary	Focus/ contribution	Paper type/ method
[66]	2017	This paper introduces a model of the IoT and discusses the implementation of various IoT applications in a university campus, including IoT Flipped Classroom, IoT Entrance System, student feedback, IoT Orangery, and IoT heating system. The paper also includes feedback from students to assess the impact of implementing IoT-based Flipped Classroom compared to traditional educational approaches.	IoT-based Flipped Classroom	Implementation and student feedback
[44]	2018	This paper introduces a campus edge computing network that employs street lighting as IoT communication nodes, integrating various computing services. Neural network learning algorithms analyze networks and compute resource requirements for efficient resource allocation and load balancing.	Campus edge computing network	Implementation and experiment
[45]	2018	This paper focuses on the design of an underlying data acquisition network comprising rules, drivers, and online equipment management to enable the collection of various data types. The Hadoop distributed system is employed for data storage and management, and data models encapsulate services, ultimately providing a safe and accurate service to smart campus users.	Data acquisition network	Implementation and experiment
[63]	2019	This paper focuses on addressing semantic interoperability issues in IoT-enabled smart campuses by identifying requirements for a semantic model to facilitate seamless and heterogeneous communication.	Semantic interoperability	Conceptual-based ontology
[46]	2019	This paper outlines the University of Málaga's long-term dedication to Smart Campus development, covering infrastructure, management, research support, and learning initiatives.	IoT and telecommunication architecture	Implementation, case study
[47]	2019	The study explores the integration of IoT and big data in a traditional university campus to create a small-scale testing environment for smart city technologies. By collecting data through IoT devices and using big data analytics, the university campus serves as a prototype for optimizing resource management and sustainability in urban areas.	integration of IoT and big data	Prototype implementation
[61]	2020	This study proposes a strategic map for intelligent university development, which underlines the pivotal role of technology in shaping successful smart campus projects	Strategic maps	Qualitative, theoretical, or conceptual
[25]	2020	The study combines qualitative and quantitative methods to analyze perceptions and gather insights from stakeholders. The research results define and evaluate the criteria for a Smart Campus but also offer recommendations for the implementation of Smart Campuses in higher education settings.	Smart campus criteria	Qualitative and quantitative analysis
[55]	2020	This research addresses the need for a comprehensive set of Key Performance Indicators (KPIs) for smart campuses and smart microgrids, which creates a list of 74 relevant and measurable KPIs that are categorized into 15 service areas. The objective is to provide a mechanism for campus management to assess and enhance the smartness of their university campus and microgrid.	Key Performance Indicators (KPIs)	Qualitative analysis
[43]	2020	This paper discusses a smart campus system in Chinese colleges that use campus big data, including various features related to student consumption, location preferences, and activities, to classify students and determine subsidies. It tackles data imbalance issues with different processing methods and employs classification algorithms for improving student management efficiency and staff workload reduction.	Smart campus system	Implementation and experiment
[56]	2020	This study proposes a strategic framework for Smart Campus components. The framework centers on IoT and cloud computing, supported by eight main criteria and 25 sub-applications	Strategic framework	Theoretical or conceptual

TABLE 1. ***(Continued.)*** **Summary of smart campus existing studies.**

[48]	2021	This paper addresses disputes in smart city application acceptance by proposing SpecTalk, which demonstrates it feasibility and effectiveness in conforming IoT implementations to TAICS standards for smart campus applications.	SpecTalk	Implementation/ experiment
[49]	2021	This article discusses integrating IoT sensors to monitor indoor air quality and adjust Heating, ventilation, and air conditioning (HVAC) systems in educational buildings, aiming to maintain well-being and enhance learning performance through training an artificial neural network.	HVAC systems	Implementation and experiment
[50]	2021	This paper discusses the evaluation of user experiences using the MeCUE technique on the UMS HopIn! bus tracking app, part of the smart campus implementation at Universiti Malaysia Sabah. User evaluations reveal that the application met expectations, with most requirements fulfilled and a positive UX rating.	Bus tracking app	Implementation and experiment, case study
[60]	2021	This research explores existing IoT applications' capabilities and identifies the gaps in integrating IoT data into organizational decision-making processes. Through four case studies, it analyzes the decision-making processes and outlines the requirements for integrating IoT data into campus management for informed strategic decisions.	Requirements for integrating IoT data	Case study
[67]	2021	This study uses a systems thinking approach to identify SWOT factors affecting Smart Campus transitions. Data from a stakeholder workshop at the University of Technology were analyzed to create a causal loop diagram (CLD) highlighting the relationships between these factors.	Factors affecting Smart Campus transitions	Systems thinking approach
[58]	2021	This study examines stakeholders' perspectives on digital technologies and platforms for transitioning to smart campuses, focusing on a South African University of Technology. Data collected from staff and student representatives indicates a low level of awareness and utilization of digital technologies and platforms.	Perspectives on transitioning to smart campuses	Survey
[51]	2022	This paper presents an improved algorithm for wireless sensor networks in smart campuses.	Security algorithm	Experiment
[57]	2022	This paper explores the role of financial information in creating intelligent campuses within the context of smart cities. It identifies key principles and tactical approaches, highlighting IoT and cloud technology as essential infrastructure.	Framework with eight main criteria and 25 sub-applications	Survey
[52]	2022	This paper introduces a Smart Campus system using spatiotemporal authentication fingerprints from GPS and CCTV to detect unauthorized access, making it suitable for Smart Cities 2.0 universities.	Security system	Implementation and experiment
[28]	2022	This study prioritizes the adoption factors for IoT-based smart campuses using an analytical hierarchical process (AHP).	Prioritisation of adoption factors	Investigation using AHP
[64]	2022	This study defines criteria for a 'Smart Campus' using AHP analysis with input from students, faculty, administrative staff, and IT support personnel at a UAE-based institute. The study ultimately developed a decision support tool based on the Utility function model to assist decision-makers in choosing the optimal solution for smart campus transformation.	Decision support tool	Investigation using AHP
[59]	2022	This research conducted an importance-performance analysis (IPA) at a Brazilian university, confirming the importance of eight dimensions for evaluating a smart campus and providing priority insights for academic managers.	Dimensions smart campus evaluation	IPA analysis
[53]	2023	This study introduces a mathematical decision-making tool, based on the evidential reasoning (ER) approach and implemented in Python, to help universities prioritize smart campus solutions.	Mathematical decision-making tool	Implementation and experiment, survey and validation

TABLE 1. ***(Continued.)*** **Summary of smart campus existing studies.**

[65]	2023	The study introduces a Smart Availability Scale (SAS) for evaluating smart campus services through multi-criteria decision-making methods. The study provides guidance for stakeholders transitioning from traditional to smart universities.	Smart Availability Scale	Multi-criteria decision-making
[54]	2023	The paper discusses Universiti Utara Malaysia's adoption of IoT for creating a smart campus, with a particular focus on an IoT-based campus bus tracking system using LoRa technology.	Tracking system	Implementation and experiment, case study
[68]	2023	The study explores how technologies can be applied to smart campuses. It presents findings related to IoT-based drone systems for patrolling, cloud servers for energy monitoring, AI for campus placement predictions, and more.	Technologies application	Qualitative
[69]	2024	The paper proposes a feedback-driven concept drift detection and adaptation methodology for real-world data streams environmental sensors at the University of Oulu Smart Campus.	Architecture for drift detection system	Implementation and experiment, case study

studies, it is crucial to consider various aspects related to Smart Campus, such as the technology, organization, environment, and end users. These factors collectively contribute to the successful implementation and utilization of technological solutions. For example, technology-specific factors refer to the specific features and capabilities of the technology that are relevant to the users, which involves understanding the functionalities, ease of use, compatibility with existing systems, security measures, and any unique attributes that make the technology appealing and beneficial [74], [75]. Organizational-specific factors focus on the characteristics and resources of the organization, particularly in the context of higher education institutions, such as the organization's size, degree of centralization, formalization, human resources, managerial structure, availability of slack resources, and the level of employee linkages [74]. The environmental factors encompass the external factors that surround the organization, including the structure and size of institutions, competitive landscape, regulatory environment, and macroeconomic background [73], [74]. Finally, end-user factors focus on the personal features as well as characteristics of the users themselves, such as their knowledge, skills, attitudes, perceptions, and preferences towards technology play a significant role in determining their acceptance and effective use of the technology [73]. By considering these factors, higher institutions can develop strategies that address the diverse aspects influencing the adoption and effective use of technology. Hence, as presented in Figure 2, the hypothesized model for the adoption of IoT-based smart campuses based on these factors is conceptualized to illustrate the impact of TSF, OSF, ESF, and USF on the behavioral intention of IoT-based Smart Campus adoption (BISC).

1) TECHNOLOGY SPECIFIC FACTORS

The factors specific to technology encompass the perceived ease of use (PE) and perceived usefulness (PU) as defined in the Technology Acceptance Model (TAM) [76]. PE refers to an individual's subjective evaluation of the effort required to use a particular technology or system, while behavioral intention represents an individual's inclination to engage in a specific behavior [76], [77], [78], [79]. Understanding the impact of PE on behavioral intention is critical for predicting and promoting the adoption of IoT-based Smart Campus initiatives. Previous research conducted in various technological contexts has explored the relationship between PE and behavioral intention, providing valuable insights for the present study. The TAM sheds light on this relationship, asserting that PE significantly influences behavioral intention, suggesting that individuals are more likely to adopt a technology if they perceive it as easy to use. Numerous studies investigating the adoption of IoT-based technologies have applied TAM and consistently supported the influence of PE on behavioral intention [80], [81], [82], [83]. Additionally, the Unified Theory of Acceptance and Use of Technology (UTAUT) [84], integrates influential theories including TAM, and emphasizes the significance of PE in shaping behavioral intention. According to UTAUT, perceiving technology as easy to use leads to more positive intentions to adopt it. Research applying UTAUT in the context of IoT-based technologies consistently reveals a positive association between PE and behavioral intention [81], [82], [83], [85], [86]. Therefore, hypothesis 1 (H1) is suggested as follows:

- **H1:** There is a significant relationship between perceived ease of use and BISC.

Secondly, perceived usefulness (PU) refers to an individual's subjective evaluation of how using a specific technology or system will surely enhance their performance or productivity, while behavioral intention represents an individual's inclination to engage in a particular behavior [76], [78], [79], [87], [88], [89], [90]. Understanding the influence of PU on behavioral intention is crucial for predicting and promoting the adoption of Smart Campus initiatives. Similarly, the TAM offers a theoretical framework to explore the relationship

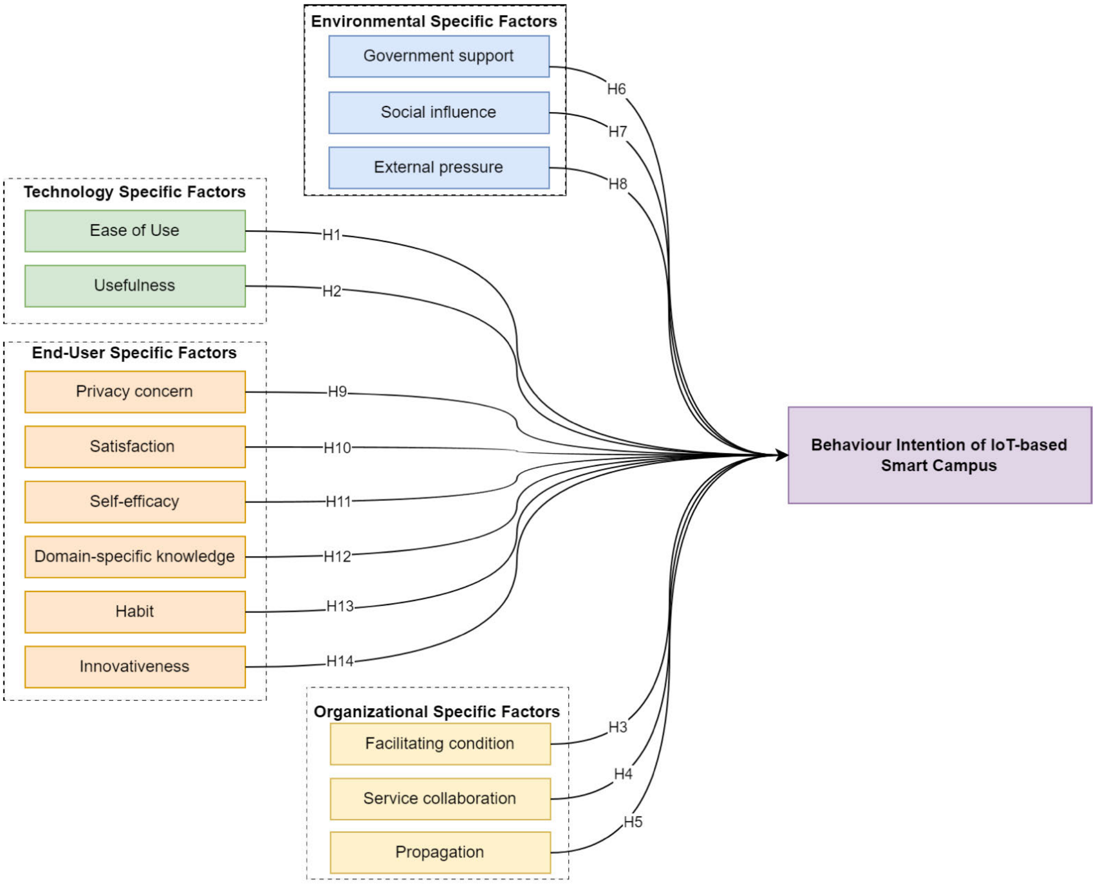

FIGURE 2. **Conceptual model and hypotheses.**

between PU and behavioral intention. TAM highlight that individuals or peoples are more likely to adopt a technology if they perceive the technology to be useful. Numerous studies have applied TAM to investigate the adoption of IoT-based technologies and consistently support a positive relationship between PU and behavioral intention [87], [88], [89], [90], [91]. Apart from TAM, other theoretical models and frameworks also contribute to understanding the relationship between PU and behavioral intention. Notably, the UTAUT suggests that when individuals perceive technology as useful, they are more likely to develop positive intentions to adopt it. Several studies applying UTAUT in the context of IoT-based technologies have also found a positive relationship between PU and behavioral intention [87], [88], [89], [90]. This study specifically focuses on the adoption of IoT-based Smart Campus initiatives, highlighting the significance of PU in driving behavioral intention. Therefore, this study suggests hypothesis 2 (H2) as follows:

- **H2:** There is a significant relationship between perceived usefulness and BISC.

2) ORGANIZATIONAL SPECIFIC FACTORS

The organization-specific factors comprise facilitating conditions (FC), service collaboration (SC), and propagation (PG). Firstly, FC refers to the resources, support, and infrastructure available to individuals that facilitate the adoption and use of a technology or system [78], [84], [86], [92]. Understanding how FC influences behavioral intention is essential for promoting the successful implementation of IoT-based Smart Campus initiatives. The UTAUT also sheds light on the facilitating condition-behavioral intention relationship. UTAUT suggests that FC are critical determinants of individuals' intentions to use technology. When individuals perceive that the necessary conditions for using technology are in place, their behavioral intention to adopt and use the technology increases. Studies applying UTAUT in the context of IoT-based technologies environments have similarly found a positive association between FC and behavioral intention [78], [86], [92]. In the specific context of IoT-based Smart Campus adoption, research has emphasized the importance of FC in shaping behavioral intention. Hence, this study of IoT-based technologies and Smart Campus environments can be impacted by FC. Thus, this study posits hypothesis 3 (H3) as follows:

- **H3:** There is a significant relationship between facilitating conditions and BISC.

Secondly, service collaboration refers to the cooperation and interaction among different stakeholders, such as students, faculty, staff, and administrators, in utilizing and contributing to IoT-based Smart Campus services and applications [81]. Understanding how service collaboration influences behavioral intention is crucial for promoting effective implementation and utilization of IoT-based solutions for Smart Campus. Research specific to IoT-smart devices adoption highlights the importance of service collaboration in shaping behavioral intention [81]. In this study, increased collaboration and partnership between various entities (e.g. government organizations, non-governmental organizations, etc.) with the aim of sharing responsibility, authority, or support in governmental processes as well as actions, has a positive impact on smart adoption, including the adoption of smart campuses. Therefore, hypothesis 4 (H4) is proposed as follows:

- **H4:** There is a significant relationship between service collaboration and BISC.

Thirdly, propagation refers to the spread and dissemination of information, knowledge, and awareness about IoT-based Smart Campus initiatives among relevant stakeholders, such as students, faculty, staff, and administrators [3]. Understanding how propagation influences behavioral intention is crucial for effectively promoting and encouraging the adoption of IoT-based Smart Campus solutions. Existing studies specific to IoT-based Smart Campus adoption highlights the importance of propagation. For example, the emphasis on propagation especially to replicate smart campus was highlighted strongly in the prior study [3]. In this study, propagation has been suggested as one of the factors influencing the adoption of IoT-based Smart Campus technologies. Hence, hypothesis 5 (H5) is posited as follows:

- **H5:** There is a significant relationship between propagation and BISC.

3) ENVIRONMENTAL SPECIFIC FACTORS

Environmental-specific factors encompass three key constructs, which include government support (GS), social influence (SI), and external pressure (EP). Government support refers to the initiatives, policies, funding, and resources provided by government entities to promote and facilitate the technologies and services of Smart Campus adoption [73], [87], [93]. Understanding how government supports influences behavioral intention is crucial for promoting the successful implementation and widespread adoption of IoT-based Smart Campus solutions. Accordingly, the presence of government support plays a significant role in shaping individuals' behavioral intention by providing a conducive environment and resources for IoT-based Smart Campus adoption [93]. Several studies have highlighted the impact of government support on behavioral intention [73], [87], [93]. Government support can take various forms, including policy initiatives, funding schemes, infrastructure development, and regulatory frameworks. These measures create an enabling environment and provide the necessary resources and incentives for stakeholders to adopt IoT-based Smart Campus solutions. Hence, hypothesis 6 (H6) is suggested as follows:

- **H6:** There is a significant relationship between government support and BISC.

Secondly, social influence refers to the impact of social interactions, norms, and the opinions of others on an individual's decision-making and behavior [86], [94], [95]. Therefore, understanding how social influence affects behavioral intention is crucial for promoting and facilitating the successful adoption of IoT-based Smart Campus solutions. The prominent Theory of Planned Behavior (TPB) [79], emphasizes the role of subjective norms in shaping behavioral intention. Subjective norms represent an individual's perception of the social pressures and expectations regarding a specific behavior. In the context of IoT-based Smart Campus adoption, subjective norms capture the influence of peers, colleagues, and the institutional community on an individual's behavioral intention. Studies applying TPB in the context of technology adoption have consistently found that subjective norms significantly influence behavioral intention [83], [85], [86], [92], [94], [95]. Therefore, this study highlights the significance of SI as a driver of behavioral intention among stakeholders in IoT-based smart campuses. As a result, this study proposed hypothesis 7 (H7) as follows:

- **H7:** There is a significant relationship between social influence and BISC.

In addition, external pressure refers to the influence exerted on individuals or organizations by external factors, such as regulatory bodies, industry standards, market demands, and stakeholder expectations [88], [93]. Hence, understanding how external pressure influences behavioral intention is crucial for effectively promoting and facilitating the adoption of IoT-based Smart Campus solutions. In the context of IoT-based Smart Campus adoption, external pressure captures the influence of external factors and stakeholders on individuals' behavioral intentions. Studies applied in technology adoption contexts have found that external pressure significantly influences behavioral intention [72], [87], [88], [93]. Therefore, the literature supports a relationship between external pressure and behavioral intention in the context of IoT-based Smart Campus adoption. As a result, hypothesis 8 (H8) is proposed as follows:

- **H8:** There is a significant relationship between external pressure and BISC.

4) END-USER SPECIFIC FACTORS

The end-user factors (ESF) encompass the personal features or characteristics of the users. These factors cover privacy concerns (PC), satisfaction (SF), self-efficacy (SE), domain-specific knowledge (DK), habit (HB), and innovativeness (IN). Firstly, privacy concern refers to individuals' worries or apprehensions regarding the collection, disclosure, and use of their personal information in the context of IoT-based Smart Campus technologies and services [89], [92], [96]. Therefore, understanding how privacy concern influences behavioral intention is crucial for addressing privacy-related challenges and promoting the successful adoption of IoT-based Smart

Campus solutions. Privacy concerns have emerged as a critical factor influencing individuals' behavioral intention to adopt IoT-based Smart Campus initiatives [89]. As the collection and utilization of personal data become more prevalent in educational settings, stakeholders become increasingly concerned about the potential risks associated with privacy breaches and unauthorized access to their information. Several studies have examined the impact of privacy concerns on behavioral intention in the context of IoT Smart technologies [71], [72], [73], [82], [89], [90], [92], [96], [97], [98], [99], [100]. The educational institutions and policymakers play a crucial role in addressing privacy concerns and shaping individuals' behavioral intention. The privacy concerns can be addressed through various strategies and measures to enhance individuals' trust and confidence in IoT-based Smart Campus initiatives. Therefore, this study proposed hypothesis 9 (H9) as follows:

- **H9:** There is a significant relationship between privacy concerns and BISC.

In the context of satisfaction and behavioral intention of smart campus relationships. Satisfaction refers to an individual's subjective evaluation of their experience, benefits, and overall fulfillment derived from using IoT-based Smart Campus technologies and services [101], [102]. Existing research has highlighted the importance of user satisfaction as a key element for achieving success in the field of information technology (IT) [103], [104], [105]. Within technology adoption studies, SF consistently emerges as a prominent factor due to its substantial influence on adoption behavior, as demonstrated in the literatures [106], [107], and [108]. Hence, understanding the influence of satisfaction on behavioral intention is crucial for ensuring the long-term success and sustainability of IoT-based Smart Campus solutions. Numerous studies have examined the impact of SF on behavioral intention in the context of technology adoption [101], [102]. Existing research consistently demonstrates a relationship between SF and behavioral intention, suggesting that individuals who are satisfied in terms of their previous and current experience are more likely to continue using and adopting the technology. Therefore, this study proposed hypothesis 10 (H10) as follows:

- **H10:** There is a significant relationship between satisfaction and BISC.

Thirdly, self-efficacy refers to individuals' belief in their own ability to successfully perform a specific task or behavior [73], [102], in this case, the adoption and usage of IoT-based Smart Campus technologies and services. Thus, understanding the influence of self-efficacy on behavioral intention is crucial for promoting individuals' confidence and motivation to adopt IoT-based Smart Campus solutions. Nevertheless, the literature consistently demonstrates a relationship between self-efficacy and behavioral intention in technology adoption contexts services [73], [95], [102], [109]. When individuals possess a high level of self-efficacy, they believe in their ability to overcome challenges, learn new technologies, and successfully adopt and utilize them. This confidence influences their intention to engage in the behavior. Therefore, individuals with higher self-efficacy are more likely to have stronger intentions to adopt and utilize IoT-based Smart Campus technologies and services. As a result, this study deposited hypothesis 11 (H11) as follows:

- **H11:** There is a significant relationship between self-efficacy and BISC.

The domain-specific knowledge refers to individuals' understanding and expertise in a particular subject or domain, in this case, the knowledge related to IoT-based Smart Campus technologies and their application in educational settings [109], [110]. Understanding the influence of domain-specific knowledge on behavioral intention is crucial for promoting individuals' competence and confidence in adopting and using IoT-based Smart Campus solutions. Various studies have explored the impact of domain-specific knowledge on behavioral intention in the context of technology adoption [109], [110]. The studies suggest a relationship between domain-specific knowledge and behavioral intention. This indicates that individuals with a higher level of insight as well as more knowledge in the IoT-based Smart Campus technologies are very likely to have a stronger intention to adopt and utilize these technologies. Therefore, hypothesis 12 (12) is suggested as follows:

- **H12:** There is a significant relationship between domain-specific knowledge and BISC.

Furthermore, habit refers to the automatic and repetitive behaviors that individuals develop over time, often driven by their previous experiences and established routines [86], [92]. Hence, understanding the influence of habit on behavioral intention is essential for identifying the factors that shape individuals' adoption patterns and promoting the sustained use of IoT-based Smart Campus technologies. Research examining the impact of habit on behavioral intention in technology adoption contexts [86], [92], has provided valuable insights into the relationship between habit and behavioral intention. The studies consistently demonstrate a relationship between habit and behavioral intention [86], [92]. This indicates that individuals with a strong habit of using technology are more likely to have a higher intention to adopt and utilize IoT-based Smart Campus solutions. Therefore, this study suggests that the extent to which users perform a particular behavior automatically or instinctively as a result of experience influences their behavioral intention to adopt IoT-based smart campus technologies. As a result, this study proposed hypothesis 13 (H13) as follows:

- **H13:** There is a significant relationship between habit and BISC.

Finally, innovativeness refers to individuals' propensity to adopt and embrace new technologies and innovations [110], [111], [112]. Similarly, understanding the influence of innovativeness on behavioral intention is crucial for identifying the factors that shape individuals' readiness to adopt and utilize IoT-based Smart Campus technologies. Existing research that investigated the impact of innovativeness on behavioral intention in technology adoption contexts, has provided valuable insights to suggest a relationship between innovativeness and behavioral intention [73], [90], [95], [110], [111], [112]. These studies suggest that individuals with a higher degree of innovativeness are more likely to have a stronger intention to adopt and utilize IoT smart technologies. Therefore, this study highlights that the willingness to accept IoT-based smart technology or service can influence users' behavioral intentions. Thus, this study posits hypothesis 14 (H14) as follows:

- **H14:** There is a significant relationship between innovativeness and BISC.

III. METHOD

This study proposes and analyzes a model that focuses on the adoption of IoT-based smart campuses. To achieve this objective, the study employs confirmatory factor analysis through the use of PLS-SEM, which stands for partial least squares structural equation modeling. In order to lay the groundwork for this research, a systematic literature review (SLR) of existing literature on technology adoption was conducted, focusing on identifying the influencing factors of IoT smart devices. The literature review conducted by Ref erence [17] provides a comprehensive list of influencing factors related to smart campus applications and implementations. To further evaluate the identified influencing factors and to facilitate the selection of the factors objectively, the researchers utilized an Analytical Hierarchy Process (AHP) [28], which is a widely recognized multi-criteria decision-making technique [70], [113]. By employing AHP, the study systematically evaluated and prioritized various factors involved in the selection process. This allowed for a structured and rigorous analysis, enabling the selection of the most suitable options based on their relative importance and performance according to the defined criteria [70]. This process involved classifying and ranking 25 technology adoption factors according to the influencing factors identified in Sneesl [28], a conceptual model consisting of 14 factors was developed to examine the proposed model. Furthermore, the model was then analyzed using PLS-SEM. It is worth mentioning that previous studies [24], [90], [95], [111], [114] have also utilized this approach. The proposed research method consists of three phases, as depicted in Figure 3, which are discussed in the proceeding subsections. The current study provides a further discussion of the chosen method.

A. PHASE 1: LITERATURE REVIEW THROUGH SLR

The literature review was conducted following the guidelines of SLR as reported in previous SLR studies [115], [116], [117]. The SLR process was divided into four stages, as depicted in Figure 3 (see Sneesl [17] for more detail). Nevertheless, in the first stage, a comprehensive search for relevant research articles was conducted. Keywords identified from the existing literature were used to generate a query for searching research articles. The second stage involved the screening of articles based on their titles and abstracts, which excluded articles that are not relevant from further reading. Following the title and abstract screening, the selected articles underwent a more detailed evaluation based on criteria for inclusion and exclusion. Accordingly, the inclusion criteria strictly comprised papers indexed in JCR or Scopus and articles that incorporated technology acceptance or adoption theories. After applying these criteria, a final 108 articles remained for full-text reading and analysis. Finally, 59 articles were read in full. Accordingly, the literature reading and data extraction identified and collated various technology adoption factors. This study made a significant finding by identifying a total of 112 factors, which were classified into four themes [17] (see Figure 2). However, to ensure accuracy and avoid redundancy, duplicate factors were identified and filtered, resulting in a refined set of 77 factors. Further refinement was achieved through a second round of duplicate filtering using thematic analysis, which ultimately yielded 52 factors.

B. PHASE 2: RANKING OF FACTORS THROUGH AHP

In order to delve deeper into the 52 factors identified in a previous study [17], the AHP technique was employed in Reference [28]. The purpose was to simplify the analysis and focus on the most crucial factors for the implementation of smart campuses. Initially, an objective analysis was conducted using the frequency technique, which helped narrow down the selection to 25 factors for the subsequent AHP analysis [28]. The AHP methodology involves breaking down the decision-making problem into three levels, namely the objective, criteria, and alternatives [113]. By applying the AHP in the aforementioned study [28], the study was able to identify and determine the most significant contributing factors for the successful adoption of smart campuses. The AHP technique played a crucial role in systematically evaluating and prioritizing the identified factors, providing valuable insights for decision-makers and stakeholders involved in implementing smart campuses. Hence, the application of the AHP technique proved instrumental in identifying the key factors that contribute to the successful implementation of smart campuses. Notably, the global ranking of the factors suggested that twelve factors from various categories led to the conceptualization of the IoT-based smart campus model proposed in this study.

C. PHASE 3: EMPIRICAL STUDY

In this stage, two preliminary activities were performed before the data collection for the empirical study. These activities are briefly discussed which comprise instrumentation such as expert evaluation and pilot test. Moreover, the PLS-SEM analysis and artificial neural network analysis (ANN) methods are discussed accordingly.

1) INSTRUMENTATION THROUGH EXPERT REVIEW

Based on the literature for technology adoption for IoT and smart devices [82], [83], [85]. The instrument for this

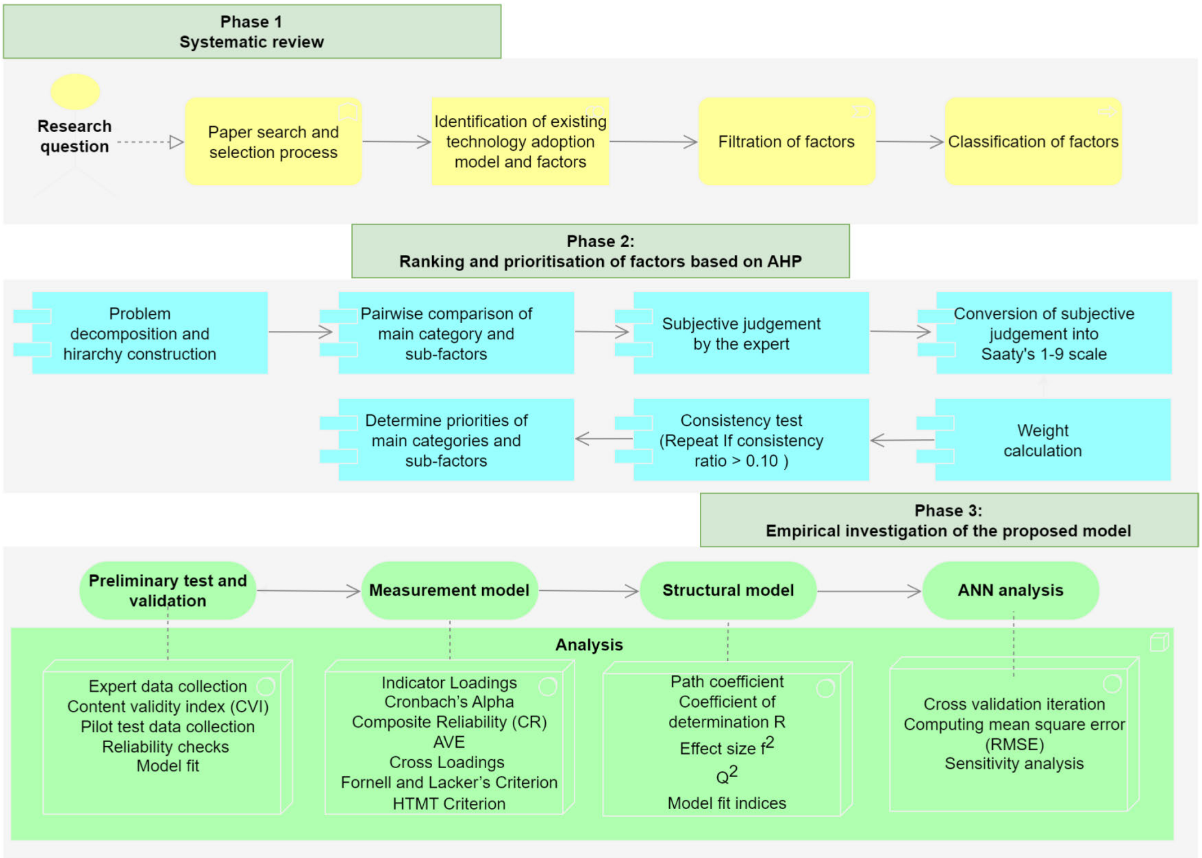

FIGURE 3. Proposed research methodology.

study is developed, adapted, or adopted in accordance with academic research practice. Then, an expert review document was created for early content validity from a group of expert panels in the information systems, smart campus, IoT, and smart technologies fields. This involves seeking expert opinions in the relevant field of study [118], [119]. By incorporating expert judgments and recommendations, the proposed model is further validated by five experts. 14 factors were derived from technology adoption literature and AHP, as factors affecting the adoption intention of Smart Campus. The expert evaluation form was designed according to the classification of the factors proposed previously [17], [28]. The expert evaluation form was designed in such a way that the responses provide a valuable report on the content, face, and construct validity of the proposed model. Accordingly, the expert review form indicates the rating of each factor based on a 4-point Likert scale. Moreover, the form is divided into key sections. PART A covered the participant information. PART B: covered the construct and face validity of the IoT-based Smart Campus adoption model as well as a text box for experts to provide comments. Finally, PART C covered the content validity for each construct as well as the items. Accordingly, the expert response was evaluated through the content validity index (CVI) with a modified kappa statistical coefficient. By following these content validity recommendations and employing appropriate statistical measures like the CVI and kappa statistics, the reliability, as well as validity of the research items, are ensured for subsequent analyses.

2) PILOT TEST DESIGN

The pilot test, often considered a crucial component of a good research design, plays a significant role in evaluating the research instrument's effectiveness [120]. Its purpose, as a preliminary investigation, is to test the viability and significance of the research instrument before conducting a full-scale study [120], [121]. In this study, after the instrument passes the content validity test is then adopted for the pilot test. The pilot test questionnaire includes multiple-choice questions and sections. The first section focuses on participant demographics which covers years of experience in the university. Accordingly, the validity of the instrument is thoroughly investigated, which is done to determine the instrument's reliability in order to ascertain the effectiveness of the items associated to each construct. To evaluate the instrument's reliability of the variables as well as the correlation between the variables, Cronbach's alpha and regression models were employed. Hence, the direct effect was tested through percentile bootstrapping (5000 samples) [122] using SPSS 24 with 35 participants. The decision to employ these indexes and analysis methods was influenced by their widespread use in the literatures [123],

[124], and [125]. In particular, Cronbach's alpha was utilized to verify the item's reliability, which ranged from 0.7 to 0.9, an indication that the reliability of the research instrument is acceptable [126].

3) SURVEY PROCEDURE

Staff from all the public universities in Iraq were the target participants in this study. Detailed demographic information about the participants is recorded in Table 2. The survey questionnaire was translated into the Arabic language of the target participants. The Arabic version of the questionnaire can be accessed through an electronic medium, particularly Google Forms, to collect the data. It can be found at the following link: online survey for a smart campus. Nevertheless, the survey questionnaire is presented in the Appendix. Accordingly, the survey methodology played a pivotal role in data collection and analysis. This study meticulously designed the data collection process, targeting a representative sample of participants from all the universities in Iraq. The survey instrument, a structured questionnaire tailored to the study's objectives about a smart campus, was crafted with precision to ensure that it would be easily understood by the participants. The questionnaire structure and content were fine-tuned to ensure it gathered the necessary data. As mentioned earlier, the study conducted a pilot test to refine the survey instrument before its full deployment, which is an essential step in optimizing the survey's effectiveness. The data collection procedure, primarily administered through online platforms, incorporated ethical considerations such as informed consent and data privacy statements. Throughout the survey, ethical considerations remained paramount, ensuring participant anonymity and adherence to ethical guidelines and regulations. To maintain data quality and reliability, rigorous data validation and quality control processes were in place. Statistical analysis was conducted to derive meaningful insights from the collected data, as discussed in the proceeding section. This transparent and well-documented survey procedure underpins the credibility and validity of our research findings.

4) DATA ANALYSIS PROCEDURE

After the data collected is completed, the analysis section covers the data screening procedures, measurement assessment, structural models, and ANN analysis. The data screening was specifically used to check the multicollinearity issues and common method bias (CMB). Additionally, the reflective measurement models deal with the models' reliability and validity, by analyzing the different types of tests via composite reliability (CR), convergent and discriminant validity, while the structural models test the hypotheses through path analysis, and model fit and prediction capacities through coefficients of determination (R^2), model fit indices, and F-test statistics (F^2).

Choosing an appropriate statistical model to analyze survey research has remained a challenge for researchers.

TABLE 2. Demographic distribution of the respondents.

Gender distribution	Male	266 (60.2%)
	Female	176 (39.8%)
Age Distribution	Less than 18	0 (0%)
	18 to 24 years	14 (3.2%)
	25-34 years	81 (18.3)
	35-44 years	155 (35.3%)
	45 years above	192 (43.4%)
Educational background	Doctoral degree	195 (44.1%)
	Master's degree	114 (25.8%)
	Bachelor's degree	97 (21.9%)
	Diploma	36 (7.9%)

Covariance-based structural equation modeling (CB-SEM) has traditionally been the dominant approach [127], but the PLS-SEM has gained popularity in recent years [127], [128]. In the current study, the proposed model was evaluated using SmartPLS 4.0 program, which employed the PLS-SEM method [127]. The model was computed using the bootstrapping method with 10000 samples [129]. PLS-SEM, a variance-based approach, accounts for all the variance and uses the sum of the variance to estimate model parameters. This choice is guided by the literature recommendation, which is suitable for testing the theoretical framework and predicting outcomes [127].

Finally, to assess the predictive capacity of the model, an ANN was employed. ANN modeling tool simulate human-like neural systems and learn the behavior of the agent under investigation [34]. To enhance the performance of neural networks, their learning capabilities can be trained [33], [35]. For the ANN analysis, SPSS v24 was utilized, following previous studies [20], [21], [22], [23], [24]. Specifically, an ANN using a feed-forward back-propagation algorithm was employed to estimate the relative significance of the independent variables against the dependent variable through the Multilayer Perceptron (MLP) method. A tenfold cross-validation procedure was performed on the dataset, resulting in 10 ANN models. Accordingly, the training phase utilized 70% of the data, while the remaining 30% was used to assess the projected fitness of the trained network, thereby minimizing the risk of overfitting.

IV. RESULT

The structural assessment model plays a crucial role in analyzing the relationships and dynamics among variables within a research study [130]. Hence, the structural model allows this study to assess and predict the outcome variable. It examines the causal relationships to determine the strength and significance of the variables [131]. The structural assessment model aids in understanding how different factors interact and influence the outcome variable under investigation. Utilizing SEM, researchers can assess the overall fit of a given model and evaluate the significance and effect sizes of the hypothesized relationships [131]. These techniques provide insights into the complex relationships between variables, contributing to a deeper understanding of the underlying mechanisms and supporting evidence-based decision-making [132]. In this study, the assessment of the IoT-based smart campus model employed in the current study is presented, which includes the measurement model, path analysis, and the assessment of model fit and effect sizes. In addition, the assessment of ANN analysis was covered in this section. By applying these techniques, we aim to gain insight on the relationships between variables and their impact on IoT-based smart campus adoption.

A. DATA NORMALITY

Before examining the proposed model, the collected data underwent several normality tests to assess whether any normality issues were present. Firstly, the data was subjected to Harman's single factor test, a commonly used method for evaluating common method bias (CMB) [133]. The test was conducted on all variables to determine the presence of CMB. The findings revealed that after rotating 79 factors, one factor accounted for approximately 26.75% of the variance. This value is below the established threshold of 50% ([133], [134], [135]. Consequently, it can be inferred that the data does not exhibit any concerns related to CMB. Secondly, the Bartlett Sphericity test was employed to examine whether the correlation matrix was formed by two or more independent sources. The obtained result yielded a significance level of 0.00, the data collected from universities staffs to determine their behavioral intention to use IoT-based smart campus, follows a normal distribution. Additionally, the Kaiser-Meyer-Olkin (KMO) measure of sample adequacy was also utilized to check the normality, resulting in a satisfactory value of 0.897 for the total correlation matrix (commonly referred to as "marvelous"). By considering these normality coefficients, it can be concluded that there are no normality issues present in this study, indicating that the model can be further analyzed.

B. MEASUREMENT MODEL ASSESSMENT

After assessing the data for normality issues and obtaining satisfactory results, the next step involved subjecting the data to a reliability test to determine the convergent validity techniques. The result obtained for convergent validity analysis revealed that all item loading's exceeded 0.500, specifically ranging from 0.556 to 0.918, as depicted in Table 3 and Table 4. These results indicate that the items and their related constructs exhibit a significant degree of variance [127], [136]. However, it was observed that a few item loading values significantly impacted the reliability and validity coefficients, such as Cronbach's alpha, coefficients A and C, and average variance extracted (AVE). Consequently, these items were systematically eliminated one at a time, resulting in the removal of a total of 15 items (PU1, GS2, GS3, GS6, PC4, PC5, PC7, SF6, SF7, DK5, PG1, FC6, FC7, FC8, and BISC1). The reliability metrics for the latent variables of the model are summarized in Table 3. Moreover, Cronbach's alpha values ranged from 0.714 to 0.937, all exceeding the recommended threshold of 0.70, indicating a strong level of item reliability. Additionally, to demonstrate composite reliability, the CR-rho_a coefficient should surpass 0.7, and in this study, it ranged from 0.747 to 0.971. Similarly, the composite reliability (CR-rho_c) values were also higher than 0.700, ranging from 0.818 to 0.955. Furthermore, all AVE metrics were greater than 0.500, with values ranging from 0.534 to 0.841 [127], [136]. Therefore, the reliability test results, along with the convergent validity techniques, provide evidence that the measurement model employed in this study is robust and accurately captures the underlying constructs of the data.

The discriminant validity of the measures was assessed by comparing the indicator loadings of each construct to the others. As depicted in Table 4, the results indicate that all indicators loaded at or above the loading of the other constructs, demonstrate significant discriminant validity. Furthermore, the loadings of each indicator on its corresponding construct were significantly greater and more significant than the loadings of the indicators on the other variables in the sample, further supporting the presence of discriminant validity. In addition to the cross-loading analysis, the Fornell-Larcker criterion was utilized to evaluate the discriminant validity of the measurement model, as presented in Table 5.

The Fornell and Larcker criterion is widely recommended for assessing the degree of shared variance among constructs [137], [138]. While it does not provide a definitive measure of differences between constructs, it is commonly employed due to its extensive use in the literature [131], [138], [139]. The Fornell and Larcker criterion was applied to evaluate discriminant validity. Accordingly, discriminant validity is evaluated by comparing the square roots of the AVE and the correlation coefficients between the constructs. Accordingly, the results obtained for the Fornell and Larcker criterion (see Table 5), indicates that the AVE values for all constructs exceed the threshold value, a criterion satisfied by this study findings [137]. Furthermore, the Fornell-Larcker index requires two criteria to establish discriminant validity. Firstly, the square root of each construct's AVE must be greater than its correlation with another construct. Secondly, each item must load disproportionately on the construct with which it is most closely correlated [136], [137]. Based on the Fornell-Larcker index results, all values are statistically significantly larger than the correlated constructs, indicating acceptable discriminant validity.

Moreover, the Heterotrait-Monotrait Ratio of Correlation (HTMT) was employed as a method to assess the correlation ratios between constructs [131]. HTMT is used to measure discriminant validity among variables [138]. In HTMT, a value of 0.90 or higher suggests a lack of discriminant validity, while a value below 0.85 is considered acceptable for demonstrating discriminant validity between two variables. Additionally, the HTMT method evaluates the average correlation of indicators among constructs in the model [138], [140]. It is worth noting that the HTMT confidence interval should not include a value of one (1), as a value close

TABLE 3. Item loadings and reliability measures.

Construct	Items	Loadings	Cronbach's alpha	CR-rho_a	CR-rho_c	AVE
Behavioural intention of SmartCampus	BISC2	0.835	0.820	0.825	0.877	0.592
	BISC3	0.840				
	BISC4	0.821				
	BISC5	0.758				
	BISC6	0.556				
Domain-specific knowledge	DK1	0.918	0.937	0.952	0.955	0.841
	DK2	0.895				
	DK3	0.934				
	DK4	0.921				
External pressure	EP1	0.842	0.761	0.761	0.862	0.676
	EP2	0.830				
	EP3	0.793				
Facilitating condition	FC1	0.798	0.831	0.843	0.880	0.594
	FC2	0.730				
	FC3	0.786				
	FC4	0.760				
	FC5	0.780				
Government support	GS1	0.779	0.746	0.747	0.854	0.662
	GS4	0.852				
	GS5	0.809				
Habit	HB1	0.804	0.883	0.891	0.914	0.680
	HB2	0.851				
	HB3	0.798				
	HB4	0.843				
	HB5	0.827				
Innovativeness	IN1	0.779	0.774	0.777	0.870	0.690
	IN2	0.862				
	IN3	0.849				
Privacy concern	PC1	0.831	0.714	0.759	0.818	0.534
	PC2	0.604				
	PC3	0.652				
	PC6	0.809				
Ease of use	PE1	0.789	0.814	0.819	0.870	0.574
	PE2	0.780				
	PE3	0.732				
	PE4	0.677				
	PE5	0.803				
Propagation	PG2	0.813	0.856	0.864	0.902	0.698
	PG3	0.872				
	PG4	0.858				
	PG5	0.798				
Usefulness	PU2	0.791	0.826	0.826	0.885	0.657
	PU3	0.788				
	PU4	0.840				
	PU5	0.822				
Service collaboration	SC1	0.702	0.790	0.800	0.864	0.615
	SC2	0.828				
	SC3	0.773				
	SC4	0.826				
Self-efficacy	SE1	0.880	0.849	0.863	0.894	0.631
	SE2	0.884				
	SE3	0.804				
	SE4	0.748				
	SE5	0.627				
Satisfaction	SF1	0.814	0.929	0.971	0.946	0.778
	SF2	0.912				
	SF3	0.912				
	SF4	0.893				
	SF5	0.875				
Social influence	SI1	0.812	0.880	0.882	0.913	0.678
	SI2	0.839				
	SI3	0.868				
	SI4	0.861				
	SI5	0.731				

to 1 indicates a lack of discriminant validity [140]. The correlations among the constructs based on the HTMT are presented in Table 6. The results indicate that all values obtained for the constructs in this study were below the threshold of 0.85, suggesting that discriminant validity is achieved in the measurement models. Consequently, the

TABLE 4. Crossloadings of measurement items.

	BISC	DK	EP	FC	GS	HB	IN	PC	PE	PG	PU	SC	SE	SF	SI
BISC	0.835	0.331	0.454	0.346	0.457	0.441	0.456	0.602	0.355	0.498	0.355	0.390	0.397	0.073	0.264
	0.840	0.299	0.397	0.303	0.432	0.339	0.388	0.544	0.279	0.423	0.307	0.304	0.341	0.009	0.237
	0.821	0.325	0.416	0.295	0.427	0.354	0.391	0.476	0.306	0.530	0.296	0.405	0.361	0.042	0.192
	0.758	0.259	0.354	0.276	0.375	0.273	0.362	0.453	0.218	0.454	0.254	0.413	0.364	0.097	0.267
	0.556	0.764	0.293	0.524	0.343	0.385	0.339	0.469	0.389	0.452	0.244	0.329	0.686	0.262	0.472
DK	0.467	0.918	0.278	0.471	0.285	0.294	0.435	0.443	0.429	0.424	0.174	0.300	0.686	0.340	0.503
	0.365	0.895	0.239	0.444	0.242	0.230	0.370	0.392	0.336	0.390	0.123	0.235	0.645	0.276	0.489
	0.501	0.934	0.315	0.488	0.327	0.285	0.438	0.504	0.402	0.440	0.183	0.299	0.646	0.285	0.504
	0.537	0.921	0.314	0.520	0.365	0.362	0.433	0.514	0.434	0.468	0.239	0.323	0.659	0.364	0.555
EP	0.381	0.240	0.842	0.222	0.271	0.383	0.402	0.384	0.159	0.331	0.215	0.455	0.207	0.014	0.202
	0.401	0.218	0.830	0.183	0.314	0.386	0.480	0.395	0.123	0.380	0.207	0.443	0.223	0.074	0.224
	0.452	0.312	0.793	0.305	0.313	0.354	0.378	0.410	0.196	0.436	0.105	0.446	0.341	0.097	0.271
FC	0.314	0.353	0.213	0.798	0.229	0.329	0.259	0.476	0.380	0.379	0.121	0.296	0.387	0.228	0.402
	0.310	0.306	0.219	0.730	0.449	0.350	0.247	0.499	0.340	0.383	0.143	0.337	0.326	0.245	0.417
	0.444	0.549	0.251	0.786	0.362	0.358	0.374	0.548	0.507	0.440	0.248	0.324	0.627	0.281	0.460
	0.361	0.332	0.236	0.760	0.292	0.421	0.170	0.491	0.337	0.411	0.165	0.271	0.420	0.249	0.503
	0.293	0.447	0.194	0.780	0.331	0.310	0.121	0.549	0.334	0.357	0.148	0.222	0.512	0.224	0.559
GS	0.485	0.223	0.362	0.334	0.779	0.434	0.311	0.426	0.293	0.672	0.226	0.330	0.343	0.150	0.252
	0.414	0.253	0.320	0.358	0.852	0.392	0.309	0.445	0.270	0.459	0.231	0.396	0.277	0.154	0.349
	0.391	0.361	0.192	0.363	0.809	0.303	0.288	0.433	0.341	0.397	0.201	0.309	0.308	0.237	0.339
HB	0.464	0.261	0.440	0.377	0.468	0.804	0.446	0.561	0.312	0.547	0.241	0.528	0.367	0.160	0.346
	0.391	0.183	0.342	0.310	0.435	0.851	0.350	0.461	0.260	0.480	0.241	0.420	0.355	0.210	0.277
	0.310	0.237	0.328	0.368	0.249	0.798	0.279	0.388	0.240	0.382	0.125	0.349	0.279	0.258	0.289
	0.375	0.334	0.380	0.429	0.402	0.843	0.329	0.546	0.181	0.483	0.137	0.413	0.353	0.229	0.414
	0.383	0.324	0.365	0.422	0.335	0.827	0.289	0.489	0.235	0.408	0.155	0.366	0.331	0.185	0.357
IN	0.401	0.318	0.472	0.121	0.238	0.275	0.779	0.310	0.273	0.346	0.298	0.427	0.230	0.176	0.187
	0.429	0.414	0.393	0.276	0.323	0.383	0.862	0.390	0.397	0.415	0.315	0.369	0.304	0.221	0.312
	0.439	0.411	0.411	0.380	0.365	0.381	0.849	0.465	0.381	0.440	0.230	0.539	0.409	0.325	0.433
PC	0.614	0.421	0.434	0.467	0.348	0.538	0.443	0.831	0.329	0.525	0.256	0.419	0.485	0.190	0.423
	0.355	0.251	0.394	0.510	0.450	0.383	0.331	0.604	0.293	0.400	0.137	0.503	0.276	0.195	0.335
	0.346	0.402	0.285	0.662	0.467	0.352	0.256	0.652	0.279	0.415	0.185	0.330	0.346	0.175	0.452
	0.567	0.412	0.312	0.428	0.387	0.455	0.326	0.809	0.230	0.402	0.182	0.342	0.411	0.262	0.445
PE	0.291	0.364	0.161	0.448	0.332	0.215	0.323	0.289	0.789	0.325	0.383	0.171	0.444	0.373	0.380
	0.263	0.338	0.069	0.399	0.251	0.158	0.184	0.224	0.780	0.309	0.486	0.037	0.469	0.289	0.408
	0.331	0.219	0.205	0.222	0.196	0.293	0.462	0.218	0.732	0.317	0.527	0.171	0.296	0.261	0.258
	0.289	0.306	0.163	0.458	0.342	0.189	0.304	0.351	0.677	0.332	0.213	0.181	0.300	0.246	0.384
	0.356	0.436	0.133	0.401	0.289	0.264	0.304	0.342	0.803	0.262	0.422	0.229	0.427	0.234	0.388
PG	0.435	0.332	0.286	0.498	0.579	0.445	0.330	0.471	0.388	0.813	0.201	0.320	0.438	0.221	0.341
	0.561	0.444	0.445	0.491	0.490	0.455	0.465	0.523	0.375	0.872	0.244	0.430	0.453	0.188	0.332
	0.552	0.419	0.368	0.376	0.605	0.481	0.363	0.472	0.381	0.858	0.254	0.414	0.515	0.163	0.338
	0.502	0.371	0.455	0.372	0.479	0.511	0.450	0.517	0.213	0.798	0.134	0.520	0.420	0.134	0.340
PU	0.316	0.160	0.198	0.116	0.273	0.159	0.268	0.229	0.408	0.237	0.791	0.177	0.177	0.026	0.101
	0.331	0.204	0.181	0.245	0.234	0.209	0.264	0.268	0.469	0.202	0.788	0.238	0.335	0.163	0.218
	0.298	0.168	0.137	0.160	0.178	0.193	0.313	0.171	0.427	0.193	0.840	0.166	0.193	0.061	0.040
	0.296	0.115	0.160	0.196	0.188	0.163	0.248	0.181	0.443	0.181	0.822	0.179	0.169	0.051	0.049
SC	0.320	0.241	0.388	0.414	0.334	0.444	0.344	0.443	0.143	0.404	0.177	0.702	0.244	0.234	0.253
	0.402	0.262	0.392	0.198	0.351	0.415	0.363	0.400	0.064	0.402	0.187	0.828	0.231	0.052	0.115
	0.363	0.235	0.450	0.317	0.237	0.398	0.477	0.394	0.206	0.401	0.171	0.773	0.318	0.119	0.212
	0.416	0.264	0.481	0.291	0.405	0.366	0.495	0.427	0.261	0.391	0.205	0.826	0.242	0.192	0.198
SE	0.456	0.619	0.254	0.541	0.262	0.289	0.297	0.452	0.428	0.457	0.190	0.229	0.880	0.214	0.540
	0.531	0.608	0.263	0.482	0.353	0.340	0.349	0.465	0.425	0.447	0.242	0.253	0.884	0.189	0.488
	0.432	0.603	0.247	0.562	0.255	0.276	0.368	0.411	0.416	0.413	0.177	0.314	0.804	0.270	0.493
	0.392	0.540	0.212	0.415	0.342	0.328	0.214	0.390	0.336	0.437	0.217	0.239	0.748	0.270	0.487
	0.400	0.470	0.290	0.392	0.314	0.419	0.271	0.382	0.408	0.424	0.261	0.272	0.627	0.212	0.429
SF	0.065	0.241	0.054	0.232	0.162	0.267	0.189	0.228	0.257	0.111	0.092	0.078	0.208	0.814	0.374
	0.147	0.359	0.058	0.294	0.177	0.179	0.261	0.248	0.329	0.198	0.055	0.167	0.323	0.912	0.450
	0.099	0.282	0.024	0.239	0.180	0.204	0.241	0.210	0.337	0.200	0.068	0.154	0.256	0.912	0.399
	0.109	0.279	0.083	0.315	0.207	0.254	0.267	0.280	0.337	0.192	0.137	0.175	0.217	0.893	0.431
	0.102	0.342	0.123	0.324	0.241	0.229	0.314	0.270	0.344	0.195	0.082	0.214	0.226	0.875	0.433
SI	0.335	0.504	0.299	0.531	0.337	0.434	0.338	0.507	0.434	0.395	0.099	0.269	0.545	0.401	0.812
	0.280	0.471	0.145	0.471	0.261	0.282	0.298	0.410	0.435	0.283	0.152	0.103	0.475	0.378	0.839
	0.318	0.502	0.226	0.532	0.356	0.306	0.275	0.483	0.369	0.315	0.060	0.225	0.499	0.387	0.868
	0.280	0.482	0.232	0.514	0.307	0.359	0.334	0.443	0.450	0.364	0.117	0.146	0.542	0.447	0.861
	0.313	0.343	0.256	0.435	0.296	0.293	0.309	0.440	0.277	0.291	0.112	0.232	0.455	0.347	0.731

TABLE 5. Fornell-Larcker criterion matrix.

	BISC	DK	EP	FC	GS	HB	IN	PC	PE	PG	PU	SC	SE	SF	SI
BISC	0.770														
DK	0.518	0.917													
EP	0.504	0.316	0.822												
FC	0.458	0.527	0.292	0.771											
GS	0.535	0.338	0.366	0.432	0.813										
HB	0.474	0.325	0.456	0.462	0.469	0.825									
IN	0.510	0.460	0.510	0.317	0.374	0.419	0.831								
PC	0.670	0.511	0.484	0.667	0.536	0.601	0.470	0.730							
PE	0.409	0.441	0.196	0.504	0.370	0.302	0.424	0.378	0.758						
PG	0.618	0.473	0.469	0.517	0.641	0.566	0.484	0.593	0.405	0.836					
PU	0.384	0.202	0.210	0.222	0.271	0.224	0.337	0.265	0.540	0.251	0.811				
SC	0.481	0.320	0.546	0.379	0.425	0.512	0.537	0.528	0.216	0.507	0.236	0.784			
SE	0.562	0.718	0.319	0.604	0.384	0.413	0.381	0.531	0.509	0.548	0.273	0.328	0.794		
SF	0.125	0.348	0.077	0.322	0.219	0.248	0.292	0.281	0.367	0.209	0.095	0.185	0.287	0.882	
SI	0.373	0.561	0.286	0.606	0.381	0.410	0.378	0.559	0.477	0.403	0.130	0.243	0.613	0.477	0.824

TABLE 6. Heterotrait-Monotrait Ratio of Correlation (HTMT).

	BISC	DK	EP	FC	GS	HB	IN	PC	PE	PG	PU	SC	SE	SF	SI
BISC															
DK	0.582														
EP	0.631	0.365													
FC	0.540	0.580	0.357												
GS	0.674	0.402	0.472	0.547											
HB	0.543	0.350	0.549	0.535	0.556										
IN	0.637	0.535	0.668	0.375	0.487	0.494									
PC	0.835	0.612	0.657	0.915	0.772	0.732	0.618								
PE	0.491	0.498	0.242	0.604	0.478	0.344	0.522	0.504							
PG	0.733	0.519	0.570	0.609	0.786	0.641	0.589	0.760	0.490						
PU	0.462	0.221	0.268	0.256	0.341	0.254	0.423	0.334	0.653	0.295					
SC	0.598	0.367	0.703	0.476	0.550	0.609	0.684	0.729	0.269	0.617	0.290				
SE	0.673	0.807	0.392	0.703	0.481	0.478	0.465	0.665	0.618	0.646	0.324	0.408			
SF	0.150	0.361	0.100	0.357	0.266	0.289	0.337	0.344	0.422	0.230	0.111	0.228	0.321		
SI	0.439	0.614	0.340	0.706	0.471	0.459	0.453	0.706	0.569	0.463	0.157	0.294	0.712	0.523	

constructs can be considered distinct and unrelated to each other, thus supporting the validity of the model.

C. STRUCTURAL MODEL ASSESSMENT

The structural assessment model employed in the current study is presented in this section, which includes the path analysis, and the assessment of model fit and effect sizes. By applying these techniques, this study aims to gain insight into the relationships between the variables. Hence, the results of the research hypotheses are visually presented in Figure 4, and further details and explanations are provided in Tables 7, 8, and 9.

1) R-SQUARE AND EFFECT SIZE

In general, a low or moderate coefficient of determination (R-square; R^2) suggests that the endogenous variables in the model have relatively weak to moderate explanatory power. Additionally, in most cases, the values of Q-square (Q^2) obtained from blindfolding algorithms tend to be lower than the values of R^2 [127]. According to the result (see Table 7), the model was able to explain a significant amount of variation in respondents' perceptions of the behavioral intention regarding IoT-based smart campus ($R^2 = 0.632$). This indicates that the model accounts for 63.2% of the explanatory capability. Moreover, the research model also showed significant results and variation for the behavioral intention of IoT-based smart campuses ($Q^2 = 0.351$). These results show that the research model successfully captures and explains a considerable portion of the variance in respondents' behavioral intention related to IoT-based smart campuses. The Q^2 value further indicates that the model's predictive power is meaningful, providing additional support for the research findings.

Moreover, the effect sizes of the endogenous variables for the research model are summarized in Table 7. This measures the magnitude or strength of the relationship between variables and helps determine the practical significance of the findings. According to prior studies [141], [142], effect sizes can be categorized as small, medium, or large, or very small, very large, and huge effect sizes, providing a measure of practical significance in the interpretation of research findings. Similarly, previous studies in the field of technology adoption have reported effect sizes in the range of very small to small [143], [144]. In this case, the effect sizes are categorized as very small, small, or no effect. Based on the table, most of the endogenous variables show very small effect sizes. Variables such as DK, EP, FC, GS, IN, PG, PU, SF, and SI have effect sizes ranging from 0.010 to 0.022, indicating a very small impact on the behavioral intention of IoT-based smart campuses. These

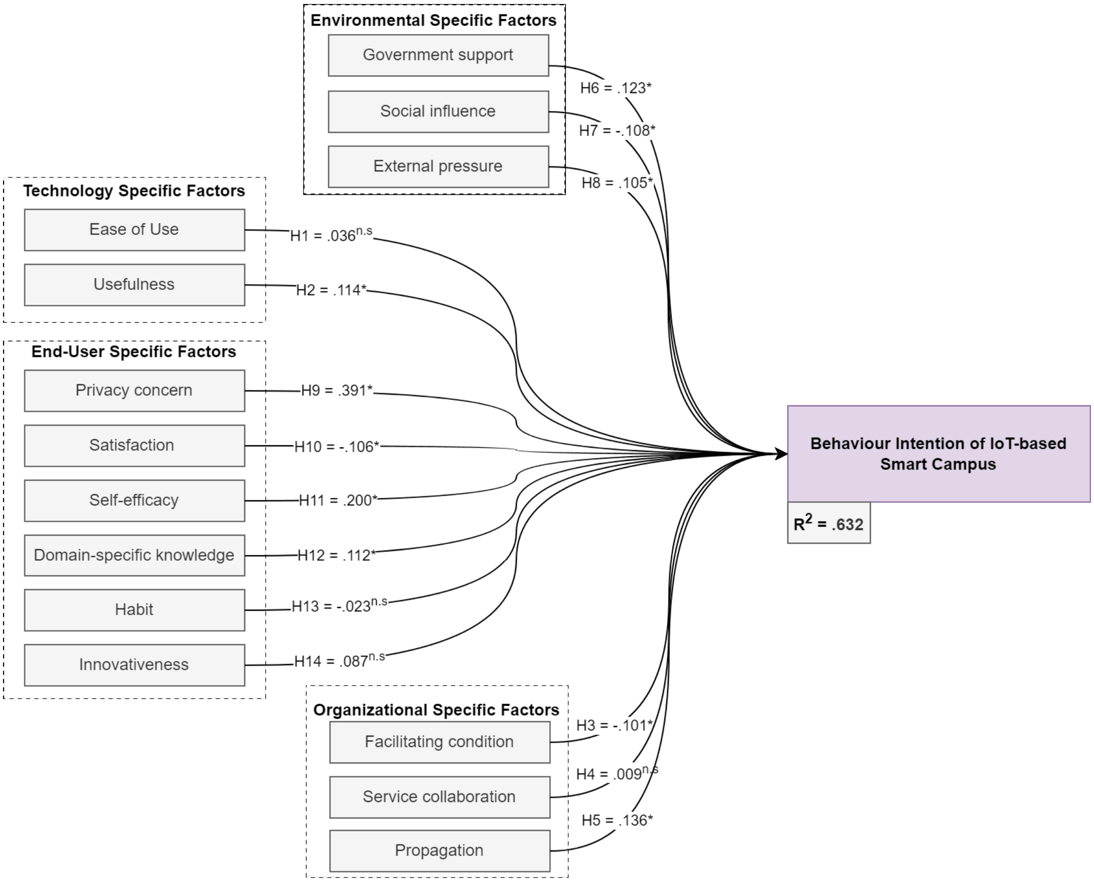

FIGURE 4. Proposed structural model of IoT-based smart campus adoption intention.

variables, while statistically significant, have relatively weak practical significance in explaining the variance in behavioral intention. On the other hand, the variable PC (privacy concern) shows a small effect size of 0.147. Although it is categorized as small, it indicates a relatively stronger impact compared to the other variables. This suggests that privacy concern has a slightly more substantial influence on behavioral intention in the context of IoT-based smart campus adoption. Additionally, the variables HB, PE, SC, and SE have effect sizes close to zero, indicating no significant impact on behavioral intention. These variables do not contribute meaningfully to the variance in behavioral intention in the context of the research model.

2) MODEL FIT

There are several model fit indices that were recommended in the literature to examine and assess the goodness-of-fit of the saturated model and the estimated model (Hair et al. [127] and Henseler et al. [138]) of the proposed IoT-based Smart Campus adoption model. The model fit indices include SRMR (Standardized Root Mean Square Residual), d_ULS (d-value based on unweighted least squares), d_G (d-value based on geodesic distances), and Chi-square, as presented in Table 8. Firstly, both the saturated model and the estimated model have the same SRMR value of 0.077. A lower SRMR value indicates a better fit, and since the SRMR values are the same for both models, it suggests that the estimated model fits the data reasonably well. Secondly, similar to the SRMR, the d_ULS values are the same for both the saturated model and the estimated model (12.331). A lower d_ULS value indicates a better fit, and since the values are the same, it suggests that the estimated model provides a comparable fit to the saturated model. Thirdly, the d_G values are identical for both the saturated model and the estimated model (3.970). A lower d_G value indicates a better fit, and since the values are the same, it suggests that the estimated model is comparable to the saturated model in terms of fit. Finally, Chi-square is a traditional measure used to evaluate the fit of a structural equation model [139]. However, it is known to be sensitive to sample size, and in large samples, even minor model misspecifications can lead to a significant Chi-square value. In this case, both the saturated model and the estimated model have the same Chi-square value of 9061.057. Hence, based on these fit indices, the estimated model provides a reasonably good fit to the data, as indicated by the comparable values to the saturated model.

3) HYPOTHESIS TESTING

The hypothesized relationship was assessed through the path coefficient, which is presented in Table 9. Similarly, Table 9

TABLE 7. PLS Measures (R Square and F Square).

Endogenous variables	R^2	R^2 Adjusted	Q^2	Endogenous variables	BISC	Comment
Behavior intention of IoT-based Smart Campus adoption	0.632	0.620	0.351	DK	0.014	Very small
				EP	0.017	Very small
				FC	0.011	Very small
				GS	0.022	Very small
				HB	0.001	No effect
				IN	0.010	Very small
				PC	0.147	Small
				PE	0.002	No effect
				PG	0.020	Very small
				PU	0.022	Very small
				SC	0.000	No effect
				SE	0.038	Very small
				SF	0.022	Very small
				SI	0.013	Very small

TABLE 8. Model fit indices of the Proposed Model.

Coefficients	Saturated model	Estimated model
SRMR	0.077	0.077
d_ULS	12.331	12.331
d_G	3.970	3.970
Chi-square	9061.057	9061.057

also contains results for t-values and p-values, indicating that the hypothesis is examined statistically. Firstly, the result of the structural model examines the multicollinearity in the data through the variance inflation factor (VIF). Accordingly, the result observed that the VIF values are significantly less than 5. This shows that multicollinearity is not a concern in this study [127]. Remarkably, this supports the CMB results, as well as the KMO and Bartlett's test of sphericity under the normality test. Hence, it is now statistically practical to discuss the outputs obtained for the formulated research hypotheses.

The technology specifics factors that were derived from TAM have two constructs; PE and PU which are H1 and H2. The finding shows that hypothesis 1 was not supported, as there was an insignificant relationship between PE and behavioral intention of IoT-based smart campuses (t = 0.697, p = 0.486). Hypothesis 2 is supported, with a positive relationship between PU and behavioral intention of IoT-based smart campuses (t = 2.609, p = 0.009). In the organizational-specific factors, results were obtained for H3, H4, and H5, which stated that FC has a statistically significant impact on the behavioral intention of IoT-based smart campus (t = 2.157, p = 0.031), service collaboration is not significant on the behavioral intention of IoT-based smart campus (t = 0.199, p = 0.842), and propagation has a statistically significant impact on behavioral intention of IoT-based smart campus (t = 2.724, p = 0.006).

In addition, the findings of this study support all the hypotheses for the environmental specifics factors; H6, H7, and H8. The result shows that government support, social influence, and external pressure have a statistically significant impact on the behavioral intention of IoT-based smart campuses (t = 2.474, p = 0.013; t = 2.209, p = 0.027; t = 2.271, p = 0.023). In the end-user-specific factors, six hypotheses were tested. The result shows that the impact of privacy concern, self-efficacy, and domain-specific knowledge was positive and significant on the behavioral intention of IoT-based smart campus, indicating support for H9, H11, and H12 (t = 7.714, p = 0.000; t = 3.779, p = 0.000; t = 1.981, p = 0.048), and satisfaction is negative and significant on the behavioral intention of IoT-based smart campus, indicating support for hypothesis H10 (t = 2.803, p = 0.005). However, the impact of habit and innovativeness on the behavioral intention of IoT-based smart campuses was not significant (t = 0.602, p = 0.547; t = 1.917, p = 0. 0.055), rejecting support for H13 and H14. Table 8 summarised the hypotheses test and the corresponding outcome.

D. ANN RESULT AND ANALYSIS

The ANN analysis allows for the prediction of outcomes based on complex relationships and patterns in the data. This captures non-linear relationships and interactions among variables, making it a powerful tool for forecasting and predicting smart campus adoption. By training the neural network on a dataset, the model learns the underlying patterns and makes accurate predictions on new, unseen data. Accordingly, a specific number of hidden neurons were created. These neurons were then activated using the hyperbolic tangent activation function, which is commonly used to introduce non-linearity and capture complex patterns in data. On the other hand, the output layers of the model were activated using the sigmoid activation function, which maps the output values between 0 and 1, often used in binary classification tasks. To evaluate the predictive accuracy of the ANN model, the researchers employed the root mean square error (RMSE) metric. RMSE calculates the average difference between the predicted and actual values, providing a measure of the model's performance in terms of the error between the predicted and observed data points. The calculation of RMSE was performed for each network within the ANN model. The selection of the hyperbolic tangent and sigmoid activation functions, along with the use of RMSE as an evaluation metric, is supported by previous studies (References [21], [23], and [35]). These studies likely

TABLE 9. PLS structural model results and hypotheses test.

Hypotheses	Relationships	Path Coefficients	SE	T statistics	P values	Decision
H1	PE ->BISC	0.036	0.035	0.697	0.486	Not Accepted
H2	PU ->BISC	0.114	0.116	2.609	0.009	Accepted
H3	FC ->BISC	-0.101	-0.100	2.157	0.031	Accepted
H4	SC ->BISC	0.009	0.011	0.199	0.842	Not Accepted
H5	PG ->BISC	0.136	0.141	2.724	0.006	Accepted
H6	GS ->BISC	0.123	0.120	2.474	0.013	Accepted
H7	SI ->BISC	-0.108	-0.107	2.209	0.027	Accepted
H8	EP ->BISC	0.105	0.107	2.271	0.023	Accepted
H9	PC ->BISC	0.391	0.391	7.714	0.000	Accepted
H10	SF ->BISC	-0.106	-0.103	2.803	0.005	Accepted
H11	SE ->BISC	0.200	0.198	3.779	0.000	Accepted
H12	DK ->BISC	0.112	0.107	1.981	0.048	Accepted
H13	HB ->BISC	-0.023	-0.025	0.602	0.547	Not Accepted
H14	IN ->BISC	0.087	0.088	1.917	0.055	Not Accepted

TABLE 10. Root-mean-square error (RMSE) values for training and testing.

Network	RMSE (Training)	RMSE (Testing)	RMSE difference
1	0.175	0.177	0.002
2	0.151	0.176	0.025
3	0.165	0.147	0.018
4	0.142	0.186	0.043
5	0.157	0.169	0.012
6	0.145	0.165	0.020
7	0.179	0.160	0.018
8	0.162	0.175	0.013
9	0.150	0.181	0.031
10	0.140	0.149	0.010
Mean	0.157	0.169	0.019
SD	0.01351285	0.01300188	0.011685675

Input Neurons: PG, SC, IN, SE, EP, GS, PU, SI, SF, PE, HB, DK, FC, and PC; SD=Standard deviation.

demonstrated the effectiveness of these choices in similar analysis scenarios or data domains. Table 10 presents the RMSE values for the ANN model, indicating an average RMSE of 0.485 for the training data and 0.499 for the testing data. These values suggest that the error is small, demonstrating the model's satisfactory prediction power. A smaller RMSE indicates a more precise fit and forecast of the data, indicating higher predictive accuracy. Furthermore, the number of hidden neurons with non-zero synaptic weights in the ANN model was utilized to estimate the significance of the factors in the model. Accordingly, Figure 5 provides a visual representation of one of the 10-fold cross-validation iterations of the ANN model based on Reference [145] guidelines.

ANN analysis allows for the identification of important features or variables that contribute significantly to the predicted outcomes. By calculating the relative importance or weights of the input variables, it provides insights into the factors that have the most influence on the dependent variable. This information can be valuable in understanding the key drivers and making informed decisions. Accordingly, after establishing the predictive relevance of the ANN model, a sensitivity analysis was conducted to assess the predictive potential of the exogenous variables in relation to the endogenous variables [35], [146]. The relative importance of each exogenous variable was calculated, and the normalized relative values were derived, as displayed in Table 11. Notably, when examining the 14 factors using the NN models, propagation emerged as the most influential predictor in the model, with a normalized relative value of 81.14%. The results also revealed that service collaboration (77.91%), innovativeness (73.23%), self-efficacy (72.12%), external pressure (71.29%), government support (60.97%), perceived usefulness (59.95%), and social influence (59.93%) were all significant predictors of IoT-based smart campus adoption, albeit with varying degrees of importance. The table presents the comprehensive relevance of each variable. Overall, ANN analysis offers a robust and versatile approach to understanding, predicting, and modeling complex systems, making it a valuable tool in various fields, including IoT-based smart campus models. It provides insights into the relationships between variables, identifies important predictors, and enables accurate predictions, ultimately enhancing decision-making and understanding of the system under investigation.

V. DISCUSSION

This study conducts empirical studies that explore the perceptions, attitudes, and behaviors of key stakeholders (such as faculty and administrators) towards IoT-based smart campus solutions. The study employs quantitative research methods (survey questionnaires) to collect data on the identified factors and their relationship with the adoption of smart campus solutions. The model was validated through statistical analysis techniques such as structural equation modeling (SEM). The study provides insights into the specific relationships and strengths of the factors influencing the behavioral intention to adopt IoT-based smart campus solutions. Specifically, 14 hypotheses were tested in this study (10 were supported and 4 were rejected); the findings of the study are discussed accordingly.

Firstly, the factors under the technology-specific factors, derived from TAM suggest that the relationship between perceived ease of use and behavior intention of IoT-based

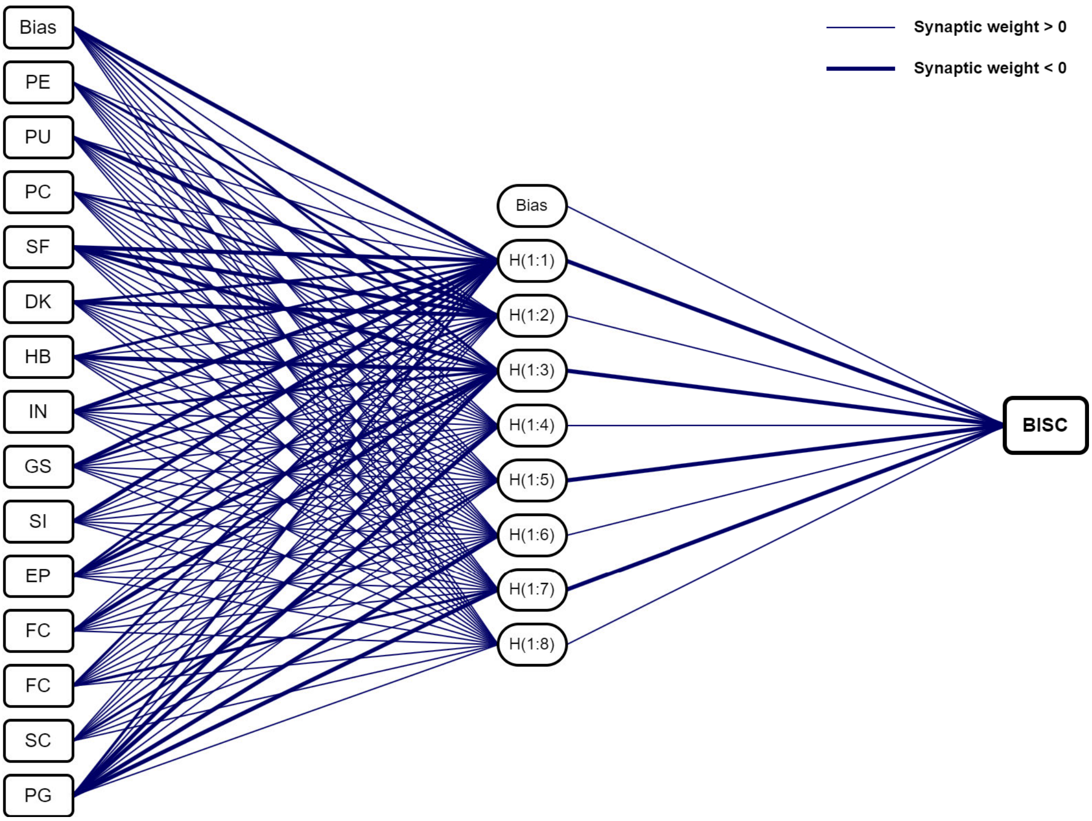

FIGURE 5. ANN Model. Notes*: Hidden layer activation function: Hyperbolic tangent; Output layer activation function: Sigmoid; Input neurons: PG, SC, IN, SE, EP, GS, PU, SI, SF, PE, HB, DK, FC, and PC.

TABLE 11. Sensitivity Analysis: Independent Variable Relative Importance.

Networks	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	Mean (AVG)	Normalized RI (AVG)
PG	0.117	0.11	0.125	0.108	0.098	0.04	0.088	0.121	0.092	0.068	0.0962	81.14%
SC	0.113	0.07	0.106	0.082	0.075	0.105	0.072	0.091	0.109	0.092	0.0913	77.91%
IN	0.153	0.09	0.064	0.082	0.059	0.115	0.078	0.102	0.068	0.065	0.0875	73.23%
SE	0.097	0.13	0.068	0.049	0.113	0.092	0.069	0.069	0.078	0.084	0.085	72.12%
EP	0.093	0.05	0.062	0.105	0.065	0.072	0.113	0.087	0.099	0.082	0.0825	71.29%
GS	0.044	0.09	0.112	0.074	0.074	0.055	0.056	0.071	0.068	0.07	0.0709	60.97%
PU	0.072	0.06	0.049	0.051	0.083	0.073	0.095	0.084	0.067	0.063	0.0699	59.95%
SI	0.065	0.08	0.053	0.083	0.07	0.065	0.058	0.082	0.045	0.096	0.0692	59.93%
SF	0.075	0.06	0.08	0.055	0.057	0.064	0.049	0.068	0.058	0.063	0.0633	53.80%
PE	0.048	0.08	0.042	0.043	0.06	0.081	0.066	0.055	0.07	0.054	0.0594	51.37%
HB	0.03	0.05	0.082	0.096	0.059	0.043	0.06	0.033	0.062	0.07	0.0586	50.99%
DK	0.044	0.06	0.075	0.062	0.066	0.064	0.068	0.036	0.041	0.068	0.058	50.35%
FC	0.024	0.05	0.034	0.061	0.062	0.068	0.079	0.055	0.075	0.055	0.0564	49.42%
PC	0.025	0.04	0.048	0.05	0.059	0.061	0.05	0.045	0.066	0.071	0.0517	45.49%

Input Neurons: PG, SC, IN, SE, EP, GS, PU, SI, SF, PE, HB, DK, FC, and PC; RI=Relative importance.

Smart Campus adoption is not statistically significant. This finding support existing studies [98], [112], [114], [147] but contradict others [81], [111], [148], [149], [150], [151], [152], [153] whose found a significant impact of ease of use. Accordingly, it can be concluded that the study did not find support for a significant relationship between perceived ease of use and behavior intention of IoT-based Smart Campus adoption. However, the study suggests that the relationship between perceived usefulness and behavior intention of IoT-based Smart Campus adoption is statistically significant. This finding supports existing studies on the significance of usefulness on IoT-related devices [81], [98], [100], [111], [112], [114], [147], [149], [150], [151], [152], [153], [154], [155], [156]. Although, this relation is not supported by the work of [148]. Nevertheless, based on this study's findings, it can be concluded that the study found a significant relationship between perceived usefulness and behavior intention of IoT-based Smart Campus adoption. This suggests that individuals' perception of the usefulness of IoT-based Smart Campus technologies influences their intention to adopt and use them. These results contribute to the understanding of the factors that drive behavior intention in the context of IoT-based Smart Campus adoption.

Secondly, in organizational factors, the study suggests that the relationship between facilitating conditions and behavior intention of IoT-based Smart Campus adoption is statistically significant, which is supported by the existing literatures [86], [109], and [150]. This suggests that the availability of facilitating conditions may hinder or negatively influence individuals' intention to adopt and use IoT-based Smart Campus technologies. Overall, these findings contribute to the understanding of the role of facilitating conditions in shaping behavior intention in the context of IoT-based Smart Campus adoption. Also, the relationship between propagation and behavior intention of IoT-based Smart Campus adoption is statistically significant. Accordingly, the finding of this study emphasized the significance of propagation, as highlighted by [3], with empirical evidence. Therefore, This suggests that the extent to which information about the benefits and advantages of IoT-based Smart Campus adoption is spread and communicated (propagation) positively influences individuals' behavior and intention to adopt and use these technologies. However, the finding suggests that the relationship between service collaboration and behavioral intention of IoT-based Smart Campus adoption is not statistically significant. This finding does not support existing work regarding the influence of service collaboration for the study of IoT service orchestration in Smart Government [81]. This study finding implies that in the context of IoT-based Smart Campus adoption, service collaboration may not have a significant impact on individuals' behavior and intention to adopt and use these technologies.

Thirdly, the finding suggests that the relationship between government support, social influence, and external pressure with behavior intention of IoT-based Smart Campus adoption is statistically significant. This finding suggests that the level of support and initiatives provided by the government positively influence individuals' behavior and intention to adopt and use IoT-based Smart Campus technologies. This study collaborates with Reference [73], who found that government policy significantly influences embracing the Smart-Home revolution. Accordingly, this study implies that government policies, funding, and regulations that promote the adoption and implementation of these technologies can have a significant impact on individuals' intention to adopt and utilize them. These results highlight the role of government support in fostering the adoption of IoT-based Smart Campus technologies.

Similarly, the finding suggests that social influence, such as opinions, recommendations, and perceptions of others, has a significant impact on individuals' behavioral intention to adopt and use IoT-based Smart Campus technologies. This finding supports existing studies on the significance of social influence [109], [150] as well as subjective norm [152] on IoT adoption. However, a study by Reference [86] found social influence not significant for the IoT-Based Smart Meter adoption. According to the findings of this study, it implies that when individuals perceive a higher level of social influence against the adoption of these technologies, their behavioral intention to adopt and utilize them decreases. In addition, this finding suggests that external pressures, such as regulations, policies, or institutional mandates, play a significant role in influencing individuals' behavioral intention to adopt and use IoT-based Smart Campus technologies. This finding does not support existing literature on the influence of external pressure for a study regarding Smart factory adoption for small and medium enterprises [87]. It implies that when individuals perceive a higher level of external pressure to adopt these technologies, their behavioral intention to adopt and utilize them increases. These results highlight the importance of external factors and institutional context in shaping individuals' intention to adopt IoT-based Smart Campus technologies. Overall, the findings emphasize the importance of organizational-specific factors in shaping the adoption of IoT-based Smart Campus technologies.

Furthermore, the findings of the end-user-specific factors suggest support for privacy concerns, satisfaction, self-efficacy, and domain-specific knowledge. The finding indicates that individuals' concerns regarding privacy in the context of adopting and using IoT-based Smart Campus technologies play a significant role in shaping their behavior intention. This result supports existing literature regarding the impact of privacy and trust in a study about Google Glass adoption [149] as well concern for privacy [73], [89], [92], [96], [98], [100], [156], [157]. This highlights the importance of addressing privacy concerns when promoting the adoption of IoT-based Smart Campus technologies. Nonetheless, the findings emphasize the need to address privacy concerns and ensure data protection in the implementation of IoT-based Smart Campus technologies. Similarly, the study highlights the importance of addressing user satisfaction in the implementation of IoT-based Smart Campus technologies as is also significant in this study, which supported the existing work on the IoT technology such as near field communication (NFC) customer satisfaction and loyalty [102]. It implies that organizations and institutions should focus on enhancing user satisfaction by providing reliable, user-friendly, and efficient technologies and services. This emphasizes the need for continuous improvement, user feedback, and responsive support mechanisms to ensure high levels of user satisfaction, ultimately driving positive behavior intention and successful implementation of these technologies on campus.

In addition, the study finding indicates that individuals' self-efficacy, their belief in their own ability to adopt and use IoT-based Smart Campus technologies, has a significant impact on their behavioral intention. Similarly, this finding supports existing studies about the impact of self-efficacy for IoT-related devices [102], [109], [156]. This suggests that when individuals have higher levels of self-efficacy, they are more likely to have a positive behavior intention toward adopting and utilizing these technologies. These results highlight the importance of self-efficacy in shaping individuals' behavior intention and adoption of IoT-based Smart Campus technologies. Moreover, the finding indicates that individuals' domain-specific knowledge, expertise, and understanding of the specific domain related to IoT-based Smart Campus technologies, have a significant impact on their behavioral intention. Similarly, this finding supports existing studies about the positive impact of this construct [110], [158]. Accordingly, the finding of this study suggests that when individuals possess higher levels of domain-specific knowledge, they are more likely to have a positive behavior intention toward adopting and utilizing smart campus technologies.

However, the relationship between habit and behavior intention of IoT-based Smart Campus adoption is not statistically significant. Likewise, the relationship between innovativeness and behavior intention of IoT-based Smart Campus adoption is not statistically significant. Specifically, the finding indicates that habit, defined as the automatic and routine behaviors individuals develop, does not play a significant role in shaping their behavior intention to adopt and utilize IoT-based Smart Campus technologies. The habit, as part of the cluster of individual factors, was found to be significant in IoT technologies adoption [92] as well as in the study of IoT-Based Smart Meter [86]. This study suggests that individuals' behavior intention is not strongly influenced by their existing habits when it comes to adopting smart campus technologies. Also, the finding of the study suggests that individuals' level of innovativeness, which refers to their willingness to adopt new technologies and embrace change, may not have a strong influence on their behavioral intention to adopt and utilize IoT-based Smart Campus technologies. This result supports existing literature regarding the insignificant influence of innovativeness on behavioral intention [95], [148]. However, some studies [73], [111] found innovativeness as a driving factor in smart home technology adoption.

Nevertheless, it is important to note that although the impact of perceived ease of use, service collaboration, habit, and innovativeness on the behavioral intention of IoT-based smart campuses are not statistically significant, it does not necessarily imply that these variables have no influence at all. Other factors and variables in the model may have a more dominant impact on behavior intention, overshadowing the role of ease of use, service collaboration, habit, and innovativeness in this specific context. Nevertheless, the findings obtained from SEM analysis support the earlier study regarding the significance of perceived ease of use, habit, and innovativeness, which have lower ranking compared to other factors [28]. Further research and analysis may be needed to explore additional variables or factors that might explain the behavior intention of IoT-based Smart Campus adoption more comprehensively. These findings suggest that perceived ease of use, service collaboration, habit, and innovativeness, may not be a strong predictor in this context, and other factors such as perceived usefulness, and other external influences may play a more prominent role in shaping individuals' behavior intention towards adopting IoT-based Smart Campus technologies.

Additionally, the analysis of predictive power validates the findings of the structural model regarding the fit of the proposed model, revealing that the overall predictive capability of the model is relatively adequate. Based on the ANN analysis, the RMSE was small, suggesting that the model demonstrates strong predictive ability. Subsequently, the sensitivity analysis conducted using ANN identified propagation as the most influential predictor in the model, followed by service collaboration and innovativeness, in this order. This order of importance associated with variables may appear contradictory to the results obtained from the path coefficient analysis, which suggested that the impact of service collaboration and innovativeness lacked significance. Nevertheless, it is worth noting that the core principle underlying ANN is to enhance the performance and learning capabilities of neural network (NN) models [33], [35]. Consequently, the utilization of ANN analysis has effectively improved the significance of other variables, potentially revealing a meaningful association between service collaboration and innovativeness on the outcome of IoT-based smart campus adoption intention.

A. PRACTICAL IMPLICATIONS

The findings of this study suggest several important implications for university administrators and decision-makers aiming to enhance smart campus adoption. First and foremost, universities should provide adequate support to users of smart campus solutions. This support may come in the form of training programs and resources to improve users' technological abilities and familiarity with smart campus technologies, enabling them to use these solutions comfortably and effectively. Additionally, government support is crucial in promoting smart campus adoption. Governments should develop enabling policies and provide financial incentives to universities, facilitating the implementation and integration of smart campus solutions. Such support can significantly contribute to the successful adoption and implementation of smart campus initiatives.

Secondly, addressing users' privacy concerns is another vital aspect to consider. Universities and administrators should develop robust privacy policies and mechanisms to protect users' personal information and ensure compliance with relevant data protection regulations. By effectively managing privacy-related issues, universities can foster trust and confidence among users, encouraging their active participation and engagement in the smart campus environment. Moreover, promoting the use of smart campus solutions among users is essential. Universities should create awareness campaigns, highlighting the benefits and advantages of using smart campus technologies. By showcasing the positive impact and value of these solutions, users can be motivated to embrace and utilize them more readily.

Additionally, attention should be given to factors associated with users, such as self-efficacy, domain-specific knowledge, habit, and innovativeness. Efforts should be made to enhance these factors through targeted interventions,

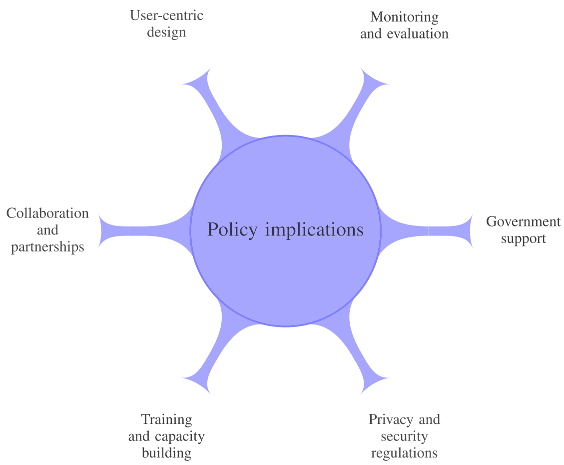

FIGURE 6. Summary of policy recommendations.

training programs, and continuous learning opportunities. By empowering users and building their confidence, universities can drive higher levels of smart campus adoption and engagement. Lastly, universities should ensure that smart campus solutions are easily accessible and user-friendly. Quick and convenient access to these technologies enables users to fulfill their responsibilities efficiently, leading to enhanced satisfaction and overall positive experiences with the smart campus environment. By implementing these recommendations, universities can pave the way for successful smart campus adoption, fostering a technologically advanced and innovative educational environment that benefits both the institutions and their users.

B. POLICY IMPLICATIONS

Based on the findings of the study, several policy recommendations can be made to promote the adoption of IoT-based smart campus solutions in higher education institutions. These recommendations aim to address the identified factors that influence adoption and create an enabling environment for the successful implementation of smart campus initiatives, as illustrated in Figure 6. Firstly, governments should provide strong support to universities in the form of policies, funding, and infrastructure development. This support can encourage universities to invest in smart campus solutions and ensure their effective implementation. Governments can establish dedicated funding programs for universities to adopt and implement smart campus technologies, as well as provide regulatory frameworks to facilitate the integration of IoT-based solutions in higher education institutions. Secondly, policy frameworks should be established to address privacy concerns related to the collection and use of personal data in smart campus environments. Clear guidelines and regulations should be developed to ensure data protection, user consent, and secure data management practices. This can help build trust among users and alleviate privacy concerns, ultimately fostering greater adoption of smart campus solutions.

Thirdly, higher education institutions should prioritize training programs and capacity-building initiatives to enhance the technological abilities of users and stakeholders. Workshops, seminars, and training sessions can be organized to educate students, faculty, and staff on the benefits and functionalities of smart campus solutions. This can improve their skills and confidence in utilizing these technologies, leading to increased adoption and usage. Moreover, collaboration among universities, industry stakeholders, and technology providers is essential to drive smart campus adoption. Policy recommendations should encourage universities to establish partnerships with technology companies, start-ups, and other relevant organizations. These collaborations can facilitate the development of innovative solutions, knowledge sharing, and resource pooling, thereby accelerating the adoption of smart campus technologies.

In addition, policy frameworks should emphasize the importance of user-centric design principles in the development and implementation of smart campus solutions. Solutions should be intuitive, user-friendly, and tailored to the specific needs and preferences of the higher education community. User involvement in the design and evaluation process should be encouraged to ensure that the solutions meet their expectations and requirements. Furthermore, it is crucial to establish mechanisms for ongoing monitoring and evaluation of smart campus initiatives. Policy recommendations should encourage universities to regularly assess the effectiveness and impact of implemented solutions. This can help identify areas for improvement, address any challenges or issues that arise, and ensure continuous enhancement of the smart campus environment. Hence, by implementing these policy recommendations, higher education institutions and policymakers can create a supportive ecosystem for the adoption of IoT-based smart campus solutions. These recommendations address key factors identified in the study and can pave the way for a more technologically advanced and innovative higher education landscape.

VI. CONCLUSION

This study was conducted to examine the factors that influence the adoption of smart campus solutions. The study is important in this area to adapt and customize the factors identified in the literature to the specific context of Iraq's higher education system. The insights from the literature inform the development of a comprehensive framework for IoT-based Smart Campus. Considering the lack of existing studies on the relationship between factors of IoT-based smart campuses and the adoption of smart campus solutions in Iraq's higher education, this study proposes a theoretical foundation for Smart Campus adoption. The component of the conceptualized framework was screened through duplicate screening, thematic analysis, frequency techniques, and AHP. Furthermore, the study employed structural equation modeling based on PLS-SEM to analyze the collected data and examine the relationships between the identified factors and the adoption of smart campus solutions.

TABLE 12. Survey instrument.

Factors	Items	Ref
USF: Privacy concern	I am concerned that smart campus services are collecting too much information from me.	[160], [161]
	I am concerned that smart campus services will use my information for other purposes.	[160], [161]
	I am concerned that smart campus services will share my information with other parties.	[160], [161]
	I am concerned that smart campus services does not protect the privacy of my information.	[160], [161]
	The smart campus collecting my personal data without my permission concerns me.	[73]
	The information gathered by smart campus can be tracked, analyzed, and misused.	[73]
	I fear using an IoT-based smart campus service due to the loss of my data and privacy.	[73]
USF: Satisfaction	I am very satisfied with the manufacturer of smart campus services.	[101]
	The manufacturer of smart campus services meets my expectations.	[101]
	The manufacturer of smart campus services fits my needs/wants.	[101]
	I am very satisfied with the smart campus services.	[102]
	I feel very good about the smart campus services.	[102]
	I am very happy about the smart campus services.	[102]
	I am very pleased with the smart campus services.	[102]
USF: Self-efficacy	I have sufficient knowledge to use the IoT-based smart campus by myself.	[73]
	I will be able to operate the various IoT-based devices inside a smart campus although I have never used them before.	[73]
	Adopting IoT-based smart campus services is entirely within my control.	[73]
	I have the capacity and ability to use smart campus services.	[73]
	No one can stop me from using IoT-based Smart Campus if I wish.	Developed by the study
USF: Domain-specific knowledge	I have enough information about the services of IoT-based Smart Campus.	[109]
	I have enough information about the advantages of using IoT-based Smart Campus.	[109]
	I have enough information about the ways of opening an IoT-based Smart Campus.	[109]
	I have enough information about the operation of IoT-based Smart Campus.	Developed by the study
	I have enough information about the disadvantages of using IoT-based Smart Campus.	Developed by the study
USF: Habit	Choosing Smart Campus Service to access building has become automatic to me.	[162]
	Using Smart Campus to perform some tasks in the university is natural to me.	[162]

TABLE 12. ***(Continued.)*** **Survey instrument.**

	When I need to access a facility, using Smart Campus services is an obvious choice for me.	[162]
	I am beginning to think that using Smart Campus service is habitual for me.	Developed by the study
	I think that I will develop a habit of using Smart Campus devices and services regularly.	Developed by the study
USF: Innovativeness	Living experiences in an IoT-based smart campus is different from a traditional campus.	[73]
	The concept of an IoT-based smart campus is unique.	[73]
	The services offered by IoT-based smart campus are new and rewarding.	[73]
TSF: Ease of Use	The main purpose of Smart Campus services is clear and understandable.	[76], [78], [163]
	I think that learning to use the Smart Campus system would be very easy for me.	[76], [78], [163]
	With the Smart campus system, it would be easy for me to avoid difficulty in doing some work.	[76], [78], [163]
	I would find it simple to use Smart campus solutions in my school.	[76], [78], [163]
	Instructions of Smart Campus are easy to follow.	[76], [78], [163]
TSF: Usefulness	Using the Smart campus system would make me feel better about myself.	[76], [78], [164]
	By using Smart campus solutions, I would hope to be helping my school and society.	[76], [78], [164]
	The use of Smart campus services would increase my peace of mind and I would be relaxed.	[76], [78], [164]
	I think that using Smart Campus services allows me to complete transactions more quickly.	[76], [78], [164]
	I think that using Smart campus services would enable me to conduct tasks more quickly and save time.	[76], [78], [164]
ESF: Government support	I think that there is top management support for using IoT-based Smart Campus.	[87]
	I think that there is enough employee involvement in information technology.	[87]
	I think that there is efficient information technology investment to support IoT-based smart campuses.	[87]
	I think that the government plays a significant role in framing policies encouraging smart campus use.	[73]
	Limited campaigning and publicity about IoT smart campus result in overall ignorance among the public.	[73]
	I believe that government support contributes to successful IoT-based smart campus adoption by providing a friendly and suitable environment.	[93]
ESF: Social influence	I believe that using IoT Smart campus can improve my social status.	[164]
	I think people who use IoT Smart campus have higher reputations than those who do not use IoT Smart campus.	[164]

TABLE 12. *(Continued.)* Survey instrument.

	I think that using IoT smart campus will make people respect me more.	Developed by the study
	I think that people who use smart campuses are more intelligent and smart.	Developed by the study
	People will think that I am smart and intelligent when they see that I am using IoT smart campus.	Developed by the study
ESF: External pressure	I think that external pressure such as competition will drive the university to implement an IoT smart campus.	[93]
	I think that IoT smart campuses will help universities maintain competitiveness with other universities.	[93]
	I think that prospective students will make universities implement IoT-based smart campuses.	Developed by the study
OSF: Facilitating condition	I have the necessary resources to use IoT-based smart campus services.	[78]
	There is an availability of a specific person (group) to assist with IoT-based smart campus usage difficulties.	[78]
	I have the necessary knowledge and information to use IoT-based smart campus.	[78]
	IoT-based smart campus is compatible with other technologies I use.	[78]
	The internet facilities I have fully meet the needs to use IoT-based smart campus.	Developed by the study
	I have adequate and effective workshops and training to familiarize myself with the IoT-based smart campus.	Developed by the study
	My university promotes the use of IoT-based smart campuses sufficiently.	Developed by the study
	Support services and infrastructure give me more confidence to use IoT-based smart campus.	Developed by the study
OSF: Service collaboration	I think that human involvement is purposeful toward individual value creation regarding IoT-based smart campus services goal attainment.	[81]
	I think that service collaboration between government and private agencies is important for continued business success for IoT-based smart campuses.	[81]
	I think that service collaboration is strongly committed to a shared mission for IoT-based smart campus.	[81]
	I think that citizens are involved in government operations by actively evaluating the available information and notifying of shortcomings of IoT-based smart campuses.	[81]
OSF: Propagation	I think that replication will enable many universities to implement smart campuses.	Developed by the study
	I think that IoT-smart campus solutions can be replicated conveniently.	Developed by the study
	I think that the cost of replicating smart campus solutions is reduced significantly.	Developed by the study
	I think that the ability to propagate IoT-based smart campus services will make smart campus widely implemented.	Developed by the study
	I think that replicating smart campus solutions is easier than installing new solutions.	Developed by the study
	I will continue to use IoT smart campus rather than any conventional system.	[81]

TABLE 12. ***(Continued.)*** **Survey instrument.**

	I intend to continue using IoT smart campus if a positive commitment is shown by the government towards the IoT smart campus.	[81]
	If the services offered by the government are trustworthy, I will be using the IoT smart campus more precisely.	[81]
	My participation in IoT smart campus is a way to respond to government calls to action regarding service innovation.	[81]
	I am likely to access a university facility with an IoT smart campus system.	[165]
	In my daily life, I will continue to use IoT smart campus services.	[164]

The findings of this study provide insights into the specific factors that influence the adoption of smart campus solutions in Iraq's higher education context. Specifically, significant factors include perceived usefulness, government support, social influence, privacy concern, facilitating conditions, satisfaction, self-efficacy, external pressure, propagation, and domain-specific knowledge. However, factors such as perceived ease of use, service collaboration, habit, and innovativeness were not significant based on the findings of this study. Nevertheless, this study is not without limitations. The model fit reported in this study is based on PLS-SEM model fit indices. Since CB-SEM was not utilized in this study, the model fit indices for CB-SEM (TLI, RMR, GFI, AGFI, CFI, or RMSEA) could not be reported. Consequently, it raises the question of why the researcher did not use CB-SEM in the first place to estimate and evaluate the model fit when assuming common factor models for all constructs in the PLS path model. It is important to note that the literature on PLS-SEM about model fit differs from CB-SEM, which is a full information method, while PLS-SEM is not [159]. Therefore, reporting CB-SEM model fits (TLI, RMR, GFI, AGFI, CFI, or RMSEA) is not considered in this study. As a result, future research could replicate the study using a different method, particularly CB-SEM, to analyze the model.

APPENDIX A

Refer to Table 12.

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