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A Multi-Analytical Approach to Predict the Determinants of Cloud Computing Adoption in Higher Education Institutions

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Abstract: Cloud computing (CC) delivers services for organizations, particularly for higher education institutions (HEIs) anywhere and anytime, based on scalability and pay-per-use approach. Examining the factors influencing the decision-makers' intention towards adopting CC plays an essential role in HEIs. Therefore, this study aimed to understand and predict the key determinants that drive managerial decision-makers' perspectives for adopting this technology. The data were gathered from 134 institutional managers, involved in the decision making of the institutions. This study applied two analytical approaches, namely variance-based structural equation modeling (i.e., PLS-SEM) and artificial neural network (ANN). First, the PLS-SEM approach has been used for analyzing the proposed model and extracting the significant relationships among the identified factors. The obtained result from PLS-SEM analysis revealed that seven factors were identified as significant in influencing decision-makers' intention towards adopting CC. Second, the normalized importance among those seven significant predictors was ranked utilizing the ANN. The results of the ANN approach showed that technology readiness is the most important predictor for CC adoption, followed by security and competitive pressure. Finally, this study presented a new and innovative approach for comprehending CC adoption, and the results can be used by decision-makers to develop strategies for adopting CC services in their institutions.

Keywords: cloud computing; technology adoption; higher education institutions; SEM; neural network

1. Introduction

Cloud computing (CC) has emerged as a new technology and popular computing model to deliver access to a huge amount of data and computational resources by utilizing simple interface [1]. There are many characteristics of CC, including flexibility, cost-effectiveness, scalability, and collaboration, which make it crucial for higher education institutes, organizations, and users. According to a CC tracking poll IDC [2], 43% of HEIs had implemented or sustained CC by 2012. This number increased by 10% between 2011 and 2012, and the growth is estimated to increase in the next few years. Besides, the International Data Corporation stated that the industrial field, including the education sector, will witness an increase of $210 billion or about 23.8% in the amount of CC by 2019; hence, there will be an increase rate of 22.5% in five consecutive years to become $370 billion by 2022 [3]. It has been noted that cloud platforms, as well as ecosystems, will function as the launchpad for the drastic rise in the digital innovation pace and scale in the next five years. Additionally, CC is considered to be the fifth utility following the four main utilities, namely water, gas, telephone, and electricity [4]. In the education sector, institutions that provide education to degree-level, tertiary, and HEIs providers [5], will have to keep pace with technological advancement. In the past, investment in IT by these institutions has traditionally been expensive, yet the provided education services to the community are expected to be affordable and maintain excellent quality [6]. To rise to this challenge, HEIs must become more efficient through focusing on the delivery of excellent services, and they need to look for ways to maximize their resources in order to maintain providing excellent services [7]. Although HEIs need to deliver good standards of education through factual knowledge and more practical skills, they have a unique opportunity to graduate skillful and professional students, who are solution-focused and adept at problem-solving [5].

For higher education institutions, CC presents an ideal opportunity to lower their IT costs with increasing efficiency, which has a positive impact on their long-term sustainability. As suggested by Thomas [8], CC is not only a learning tool for HEIs but also an important platform in more general terms as it will encourage educators to improve their practice and encourage partnership in order to improve their productivity. Moreover, CC will be able to save both costs and energy output because the same cloud infrastructure can be utilized by a wide range of users in teaching, learning, and research [9]. Besides, the successful adoption of CC and delivery for cloud-based education services requires understanding of these processes from the side of HEIs [10,11].

Although CC suggests excessive aids to organizations, there are some challenges that might impact its adoption. Several studies on CC have been carried out in developed nations. Studies on CC in educational institutions in developing nations are scarce [12], especially in Malaysia [13,14]. The successful adoption of any novel technology such as CC does not depend only on universities and cloud service providers' support but also on users' willingness and intention to adopt and utilize these services [12,15,16]. Therefore, the adoption of any new technology depends on the innovativeness of the decision-makers. That is, the role of decision-makers plays an essential role because they are the main contributors to CC adoption, especially that they can support the required CC services and types in HEIs [17,18].

Many challenges are facing HEIs in sustaining the education process such as delivering affordable education services, improving education quality, increasing budgets and participants, and getting the requirement of infrastructure IT [19,20]. Therefore, HEIs keep struggling in managing their resources and improving their service [21]. CC is a favorable solution for HEIs that supports cost reduction and improves education quality [22]. Besides, the sustainability of HEIs can be achieved by providing the required infrastructure, software, and storage through CC adoption [21,23,24]. Thus, the emergence of CC and the advantages it provides can help bridge this technological gap. Generally, CC in HEIs is increasing in popularity, but it is still lagging behind the commercial, government, and other sectors [25]. Past literature has shown that productivity at the organizational-level increases significantly for organizations that have invested in ICTs for their operations [26]. Besides, the Coronavirus 2019 (COVID-19) pandemic affected HEIs not just in Wuhan, China where the virus originated but all other HEIs in 188 countries as of 6 April 2020. CC as a technology of the fourth industrial revolution (IR 4.0) could enable educational countermeasures to continue the education process despite the COVID-19 predicaments [27,28]. Therefore, CC in this case is not only an alternative option for HEIs but also an essential solution.

In the current study, the unit of analysis is the organization level because the primary focus is on decision-makers, who are responsible for CC adoption. Individuals are considered to be the observers for the phenomenon at the organizational level [29].

Besides, most of the prior studies have primarily focused on CC technology, costs, applications, security, and benefits in small and medium organizations [30]. However, a limited number of studies have focused on CC adoption and its usage in HEIs [3]. Furthermore, several studies have looked at

CC from different perspectives in various developing countries such as sub-Saharan Africa [30–32], Malaysia [33,34], and Saudi Arabia [18,35,36]. Other studies discussed CC implementation in academic libraries [37,38] and the enhancement of overall awareness regarding CC migration issues [18]. Moreover, organization-based studies have evaluated the readiness of HEIs to implement CCs [32,39,40], and other studies have examined the impacts of technology on HEIs [14,41].

Even though a substantial amount of consideration is given to the CC, few studies have been carried out to identify the influential factors in adopting CC in HEIs from the perspective of decision-makers [3,30]. Meanwhile, in spite of the efficiency and usefulness of advanced artificial neural networks (ANN) as a soft computing technique in identifying and ranking determinants in technology adoption [42], application of this technique in the context of CC remains mainly unexplored, especially in education atmosphere. Taking into consideration these points, the current study aimed to develop and test a proposed adoption model and to examine the key factors, influencing decision-makers' intention of CC adoption in Malaysian higher education institutions. Therefore, the key objectives of the current study are as follow:

To analyze the factors that influence the adoption of CC in HEIs.

To propose an appropriate model for evaluating the adoption of CC in HEIs, validated by using two analytical approaches (i.e., PLS-SEM and ANN).

To contribute to the body of knowledge on the organizational-level adoption, this research will first merge two well-established theories which are the Technology-Organizational-Environmental (TOE) framework [43] and the diffusion of innovations (DOI) [44], to fill the gap in previous literature. Drawing on the organizational level adoption theories, our research model is built on the TOE framework and DOI model which is in line with the objectives of this study. Furthermore, the research model constructs are grounded by the literature taking into account the context of the study. The study also implemented variance-based structural equation modeling (PLS-SEM) for assessing the factors impacting CC adoption, and a neural network is used for predicting how CC is adopted in HEIs. For this, the sequential multi-method research design, suggested by Scott and Walczak [45], was implemented as it is suitable for enabling a deeper understanding of the subject under investigation. In this study, PLS-SEM is applied for corroborating the validity of the causal relationships through the assessment of the goodness of the model's fit. Following this, PLS-SEM analysis of supported relationships along with PLS-SEM analysis of significant variables were utilized as the neural network structure inputs for estimating how CC is adopted in HEIs. Merging these two approached provides a significant benefit for utilizing a new method to evaluate CC adoption in which one method benefits help in balancing out the other method drawbacks [45].

Generally, we contribute to research in different ways. First, this research contributes to the body of knowledge within information systems (IS) field surrounding technology adoption. This study provided empirical literature within IS, especially CC, and it provided an extensive model that integrates the TOE framework and DOI model. Second, this study provided an assessment for CC adoption in HEIs, and more revitalization of the CC and intent of decision-makers to utilize CC in HEIs. Third, the DOI model and TOE framework incorporation improved the ability to explain the proposed model with 81% of the dependent variable's variance, which shows that the model's ability for prediction is powerful and remarkable. Fourth, this research used a hybrid approach for the integration of PLS-SEM and ANN to validate the proposed model and to give priority to the factors that impact CC adoption, through the identification of the relative importance of every factor. Conventional statistical approaches are valid and necessary; thereby, offering a powerful foundation in previous IS adoption studies. The suggestion of this research is the need to reinterpret past works on IS adoption through the combination of linear and non-linear approaches in order to provide outstanding strength to technology adoption. Fifth, since HEI is a promising market for cloud service providers, this study is remarkably impactful for cloud providers and technology practitioners as it will help in the recognition of the factors that influence the adoption of CC. Likewise, cloud providers need to provide a clear instruction or navigation system in guiding users in HEIs to operate the services smoothly, thereby increasing the assurance that cloud technology is used. Finally, the research results will help decision-makers with the assessment of cloud technology, organization, and environments during the decision of the adoption of CC. Furthermore, decision-makers may use this proposed framework for the investigation of other IT/IS adoption procedures.

The rest of this study is arranged as follows: Section 2 reviews previous studies on CC adoption. Section 3 presents the hypotheses of the study and discusses the model development. Section 4 highlights the research methodology and Section 5 explains the analytical approaches, including PLS-SEM and neural network. The discussion of the study is presented in Section 6, and Implications are presented in Section 7. Conclusion, limitations, and future research directions are discussed at the end of the study.

2. Literature Review

2.1. Cloud Computing Concept

The concept of CC does not have a single definition that has been accepted universally as there is still an ongoing discussion and debate about this term. This might be due to some parallels between other types of high-performance computing and CC, such as peer-to-peer computing, cluster computing, market and service-oriented computing, and grid computing [24]. As technology continues to make advancements, the debate around CC continues, and studying the existing literature does reveal some common characteristics for CC across the various available definitions [46].

According to the National Institute of Standards and Technology (NIST), CC is a model that allows wide-ranging, on-demand, network access to shared configurable computing resources such as services, storage, applications, and networks. These resources can be provided quickly and with little effort by either the provider or the customer [47] as they are essentially a way of integrating existing technologies, but provide them in a new way to help businesses make a fundamental change to their operations [48]. This is achieved by connecting existing technology, including software as a service (SaaS), utility computing, and grid computing [49]. Next-generation data centers that combined virtual services such as database, hardware, application logic, and user interface in a network was an objective for the application of cloud technology [50]. Crucially, these new data centers have allowed users to access their applications not only from a singular location but also from any place.

2.2. Cloud Computing Services and Deployment Models

According to [47], CC comprises a tripartite of services, infrastructure as a service (IaaS), platform as a service (PaaS) and software as a service (SaaS). The latter enables users to access applications via a cloud-based infrastructure. SaaS means that the infrastructure such as the servers, operating systems, and networks are essentially removed from the consumer, who no longer need to be concerned with this or with other issues such as data storage. To access the services, the customer uses either a direct interface, which is used for web-based emails such as Gmail, or a program interface such as Dropbox. Meanwhile, the IaaS model means that consumers can deploy and run the software, which they choose, through the provision of computing resources such as networks, storage, and processing. This can be achieved through varies softwares, which might be an application or even an entire operating system such as Microsoft Azure and Amazon Web Services, which are two examples of providers within this sphere. Finally, PaaS provides a platform for users to deploy applications on a broader cloud infrastructure and allows them to create and modify their applications by using libraries, services, and languages that have already been developed by a cloud platform provider such as Google App Engine or Heroku.

A description of the four deployment models in cloud technology applications is seen in [47], where these cloud types are named as private, community, public, and hybrid. The private cloud, as the name suggests, is used solely within one organization and its infrastructure may be either self-managed or operated by a third party [51]. This model is usually chosen when security issues are a concern for a particular organization, so in the academic sector, this may be due to ownership of certain resources or to cultivate an online community [51].

Concerning the community model, many institutions may use the same basic infrastructure that is hosted either by a third party or by one of the organizations that is part of the community. Organizations may consider this model to be an advantage either through shared costs and resources or because perceived risks are lessened when the model is shared [52]. This model may work well when used by cooperating organizations, or when institutions have a close relationship or are interlinked in some way but can be an issue in higher education sector where many similar institutions are essentially in competition with each other for students, funding and other resources.

The public cloud is probably the most popular form of cloud deployment and is managed by the provider of the service, and the most well-known providers are Microsoft One Drive, Dropbox, and Google Drive as well as those provided by Amazon. In the field of education, users such as students, lecturers and faculty staff will probably be familiar with the system, which is one of its advantages.

The final model of deployment is the hybrid cloud, which combines two or more models. Utilizing more than one model harnesses the benefits of each model and aims to mitigate the disadvantages of every single model as well as to provide a more flexible and wide-ranging approach.

2.3. Cloud Computing in HEIs

In the education environment, CC can provide both teachers and students with numerous advantages. Whether in education or research, the ability to store big data and to collaborate on projects and share materials is an attractive proposition [52]. Besides, because CC can be used remotely, users can take advantage of the ability to access these materials on any device at any time and from any place. HEIs and universities have chosen to bypass old-style IT set-ups and software systems in favor of CC, and they have been attracted to its efficiency and rapid implementation [21].

Collaborate approaches to learning are one of the key benefits that CC technology offers, which makes it an ideal choice for the institutions, looking for computer-based technologies to enhance more socially-oriented and cooperative learning styles [53]. Cloud computing also facilitates e-learning in human computing interaction as they are able to utilize facilities such as data access monitoring and storage through a cloud platform, which also provides its infrastructure [54].

Cloud computing is increasing in popularity in HEIs, although it is considered to be in its infancy in this sector of the market, as it is unable to surpass the commercial sector or government organizations [25]. However, it is increasingly becoming a necessary part of the educational offer rather than a choice, and this is due to the increasing competition in the higher education marketplace and the pressures on performance, student successes, and income [55]. HEIs can benefit from the CC features and surpass its limitations so that CC services can be accessible to the practicing educational community [56].

Table 1 illustrates how scientific contributors have discussed this subject from a range of perspectives and how they have attempted to capture the services that CC offers in the higher education sector. Despite this evidence, gaps in research are still clear at the organizational level [57], as many of the existing studies lack empirical findings about CC usage in HEIs [30,31]. This lack of evidence at the organizational level necessitates conducting further studies about CC adoption in HEIs and exploring in depth the factors that affect this process of adoption. Although Table 1 shows the previous literature on adoption of the CC in HEIs that includes the TOE, DOI, and technology acceptance model (TAM) models (TAM1, TAM3), this study is built on the organizational level theories (i.e., TOE and DOI) which is in line with the objectives of the study.

Table 1. The adoption of CC in HEIs: a summary of prior research studies.

Study	Title	Theory	Methodology	Country
[31]	"A cross-country model of contextual factors impacting CC adoption at universities in sub-Saharan Africa"	DOI theory and TAM	Quantitative research. A survey concerning university-level ICT experts as well as decision makers. 355 valid responses.	HEIs in sub-Saharan Africa
[30]	"Conceptualizing a model for adoption of CC in education"	DOI theory TAM	Conceptual Model	HEIs in sub-Saharan Africa
[58]	"The Effectiveness of Cloud-Based E-Learning towards Quality of Academic Services: An Omanis' Expert View"	N/A	Qualitative approach/Semi-structured interviews.	HEIs in Oman.
[18]	"An exploratory study for investigating the critical success factors for cloud migration in the Saudi Arabian higher education context"	N/A Success factors based on literature	Structured online questionnaire	HEIs in Saudi Arabia
[54]	"Using CC for E-learning systems"	LR		HEIs in Saudi Arabia
[24]	"Student perceptions of cloud applications effectiveness in higher education"	N/A	Survey	University in Southeast Michigan USA
[5]	"A conceptual model of e-learning based on CC adoption in higher education institutions"	DOI; FVM	Conceptual Model	HEIs in Oman
[59]	"Examining CC Adoption Intention in Higher Education: Exploratory Study"	TAM	A survey utilizing a questionnaire on paper.	Politehnica University of Bucharest, Romania.
[60]	"Investigating the structural relationship for the determinants of CC adoption in education"	TAM	A quantitative method/administer a survey	Universities in Thailand
[61]	"Cloud for e-Learning: Determinants of Its Adoption by University Students in a Developing Country"	TAM3	An empirical study and a survey questionnaire	Saudi Arabia
[62]	"Determinants and their causal relationships affecting the adoption of CC in science and technology institutions"	DOI	Focus group discussion and DEMATEL	Science and technology institutions, Taiwan
[35]	"CC adoption by HEIs in Saudi Arabia: an exploratory study"	TOE	Survey	HEIs in Saudi Arabia
[63]	"CC adoption and usage in community colleges"	TAM3	Virtual Computing Lab and focus groups concerning instructors as well as interviews of other stakeholders such as IT support staff and college administrators	Rural and urban community colleges, USA

2.4. Technology Adoption Theories

The adoption process refers to the decision-making individual (the adopter) or unit undergoing the process of taking a new product, service, or idea into account [44]. There are numerous phases involved in this process, and the outcome is the decision of whether the new item should be selected. According to [64], the decision is made by an entity regarding the adoption of a particular object and in a specific context. Moreover, various factors are affecting this decision, and in the present study, HEI is the entity while CC adoption is the object. After analyzing previous studies, it was found that many studies considered constructs influencing the CC adoption at an individual level ([24,59–61,63,65–77]); however, there was a dearth of material concerning this at the organizational level [31,32,35]. As mentioned above, the two most dominant hypotheses used for considering technology adoption from an organizational perspective are the TOE framework, and the DOI model [31,32,35,78–84].

2.4.1. TOE Framework

TOE framework can define the innovation process within an enterprise context because TOE considers three aspects of an enterprise, namely technology, organization, and environment, that affect the adoption of emerging technologies [43]. In this framework, technology refers to the internal and external technical knowledge of an organization, as well as the mechanization that may influence the adoption decision. Besides, the characteristics of the company, including its particular communications channels and resources, are under the organization aspects, while the external forces such as competition and the regulatory and market conditions sit within the environment aspect [43,85,86].

2.4.2. DOI Model

DOI theory uses five phases to explain how the innovation process works within an organization [25]. The five phases are knowledge, persuasion, decision, implementation, and confirmation [55]. This theory is broad-based and provides a persuasive explanation for the process of adopting innovation by any organization. By focusing on this process, DOI theory offers a complementary perspective because it focuses more on the technological aspects of the TOE framework, and the use of the two frameworks makes everyone has a complementary advantage.

The TOE framework and the DOI model are used widely to examine the adoption of technology at the organizational level [31,32,35,78–84]. We carry out an analysis of the adoption theories used in the literature. Table 2 shows that authors apply one or more theoretical models to build their research models. Nevertheless, it is not possible to apply a single theory to all types of innovations [87]. Therefore, an incorporated model of theories is desirable, to be used in deciding the adoption process of certain types of innovation.

Table 2. Mapping matrix of the model theories.

Theory/Model	**Definition**	**Justification**	**Limitation**	**Previous Studies**	
				IT Adoption (Dependent Variable)	***Source***
TOE	The aim of TOE framework [43] is to clarify the procedure for innovation adoption at the organizational level. It looks into three contexts that affect the use of an innovation in a firm—the organization, the technology, and the environment context.	TOE model has a wide power across a number of technological, industrial, and national/cultural contexts [88–90]. TOE framework can be applied in empirical research since new technologies are developed, especially when novel contexts for adoption can be identified [91].	TOE does not offer a robust model for relating the factors that affect the organizational acceptance decision making; instead, it gives a taxonomy for classifying adoption factors in their individual contexts. Researchers are advised to take a wider context into consideration in which improvement takes place [92].	Mobile supply chain	[93]
				Radio frequency identification (RFID)	[94–96]
				Green IT	[92,97]
				Interorganizational business process standards	[98]
				E-business	[86,99,100]
				SaaS	[101]
				Cloud computing	[102,103]
DOI	DOI theory [104] gives a detailed explanation on the diffusion of innovation within an organization. According to DOI theory, an innovation undergoes a number of stage procedures until it thrives in the firm [105].	DOI theory gives a broader standpoint on the diffusion incident and gives a good explanation on how new innovations are applied. Therefore, DOI enriches the technological context of the TOE framework, and thus gains value when applied in conjunction with the TOE framework [84].	It is not possible to apply a single theory to all types of innovations [87].	Internet	[106]
				E-procurement	[107]
				RFID	[108]
				E-business	[100,109]
				Cloud computing	[103]
TOE and DOI		DOI theory makes a wide standpoint available on the diffusion phenomenon, and it gives excellent explanations on how new innovations are chosen. Therefore, DOI enriches the technological context of the TOE structure, and thereby obtain value when applied in conjunction with TOE framework [84].		Benchmarking	[107]
				Collaborative commerce	[110]
				E-commerce	[79]
				Open source	[111]
				Digital transformation	[112]
TOE and INT		INT benefits TOE by enriching the environmental context of TOE framework [28–30], so it gains value when used in combination with the TOE structure [21].		Scope of ecommerce use	[113]
TOE, DOI and INT		A combination of DOI theory, TOE framework, and INT theory thus gives a theoretically solid basis to evaluate the technology, organization, and environment characteristics [84].		E-procurement	[63]
				SaaS diffusion in firms	[84]
TOE and ECM		It is imperative to incorporate not only technology-level factors from the IS continuance literature, but also new constructs and relationships that capture the complex nature of organization-level decisions [114,115].		Enterprise 2.0 post-adoption	[115]

2.5. Analysis Techniques

Statistical analysis has been an essential tool for researchers for more than a century to extend their ability to develop, explore, and confirm research findings. Statistical methods' applications have expanded recently with the advent of computer technologies [116]. In this section, we explain two analytical approaches, and why the purpose of their employment in this study.

2.5.1. Structural Equation Modeling

Structural equation modeling (SEM) is a second-generation multivariate data analysis method that is used to either explore or confirm theory [116]. There are two types of SEM—one is covariance-based, and the other is variance-based. CBSEM is used to confirm (or reject) theories. Variance-based structural equation modeling (i.e., PLS-SEM) is primarily used for exploratory research and the development of theories [116]. To validating the measurement and structural model, Variance-based structural equation modeling (PLS-SEM) was applied to the collected data with SmartPLS 3.0.

2.5.2. Neural Network

The neural network can be explained as a significant parallel distributed processor, consisting of simple processing units that are naturally inclined to store experimental knowledge and to provide access for use [117]. Moreover, a neural network is considered to be similar to the human brain and is capable of attaining new knowledge from its surroundings by implementing the learning process. Then, the synaptic weights store this acquired knowledge [117]. Following this, the learning algorithm uses sample data for altering the synaptic weights of the neural network in an orderly fashion in order to achieve the design objective [117]. Moreover, the neural network offers numerous benefits than traditional statistical methods. Such benefits include non-linear and linear neural networks to enable the assessment of non-compensatory decision processes, and it can help attain the input and output mapping without requiring specific distribution concerning the output or input [118]. Furthermore, the adaptivity of the neural network suggests that it is able to address the data generation process in terms of structural changes and that it is not difficult to re-train it according to environmental changes [118,119]. It has also been noted that neural networks surpass traditional compensatory models such as multiple, discriminant, and logistic regression analyses [118,119]. However, despite the fact that neural network has been implemented in studies in different fields such as economics [120], customer loyalty [121], wearable healthcare devices [122], and consumer choice [119,123], few studies have focused on its information systems applications [124]. Hence, the present study will first utilize PLS-SEM to determine the constructs that have strong relationships with the adoption of CC in HEIs, and then implement the non-compensatory neural network model for foreseeing the adoption of CC in HEIs according to the critical adoption variables.

3. Hypotheses and Model Development

A research hypothesis is defined as a "logically conjectured relationship between two or more variables expressed in the form of a testable statement" [125]. For this reason, the assumptions of the current study are discussed below.

3.1. Compatibility

In DOI theory, compatibility is the first variable that is expected to be able to foresee CC adoption. This is also called the extent to which an innovation matches the past practices, current values, and present needs of the potential adopter [104]. Moreover, compatibility examined how much innovation can conform to the existing systems. It has also been noted that the characteristics of a new technology innovation can impact potential innovation adopters. Further, DOI studies have accentuated how significant compatibility is when assessing the disposition of organizations for implementing new technology [104,126].

Several studies have examined compatibility as an important addition to the variance concerning IT managers' inclination to adopt CC [30,31,35,127,128]. Hence, the following hypothesis is devised:

Hypothesis 1 (H1). *Compatibility positively impacts CC adoption in HEIs.*

3.2. Competitive Pressure

Competitive pressure is the perceived pressure by the leaders of an institution when CC services help competitors to achieved substantial competitive advantage in teaching and learning effectiveness [115,129,130]. Literature has studied competitive pressure as a significant construct, affecting the use of CC in various contexts [100,112,115,131–133]. Therefore, the second hypothesis is as follows:

Hypothesis 2 (H2). *Competitive pressure positively influences CC adoption in HEIs.*

3.3. Complexity

Complexity refers to the perceived difficulty of the organization regarding comprehending and utilizing an innovation [134]. If the relevant innovation is deemed to be difficult to use, it reduces the possibility of adoption [104]. A meta-analysis study was conducted by Tornatzky and Klein [135] where they observed that compatibility and complexity formed the major attributes concerning technology innovation behavior. The DOI literature also highlights the importance of determining the complexity of organizations in their tendencies to implement new technologies [104,126].

Previous literature has studied complexity as the most significant construct, influencing CC adoption [30,31,35,127,128]. It is, therefore, hypothesized that:

Hypothesis 3 (H3). *Complexity negatively influences CC adoption in HEIs.*

3.4. Cost Savings

Cost savings refer to the decreased capital investment needed in an institution for IT service leased resources and hardware solutions [136]. The storage and delivery services provided by CC have significantly reduced the cost [137], which has made it a valuable solution in the current financial crisis to maintain the quality of services by the institutions [138]. Cloud computing technology is based on Internet technologies and cost-effectiveness as key distinguishing characteristics of CC [139] which can influence its adoption. Researchers found that perceived higher cost saving led to higher intention to adopt an innovation [140,141]. Based on the literature, it is postulated that:

Hypothesis 4 (H4). *Cost saving positively influences CC adoption in HEIs.*

3.5. Vendor Support

Top management literature suggests that IT service provider or vendor also plays a very important role in the decision of IT services adoption [142,143]. Vendor support in the case of CC services is far more crucial because cloud-based IT services from a capable vendor may enhance the internal capabilities of an organization [144]. Vendors provide cloud-based services, which can be dynamically priced and can be scaled up/down according to the requirements. This flexibility enables the client institution to develop and enhance their capabilities. However, only capable service providers will be able to provide these benefits. Therefore, it is hypothesized that:

Hypothesis 5 (H5). *Vendor support positively influences CC adoption in HEIs.*

3.6. Technology Readiness

Technology Readiness captures the internal technical resources of the organization [112]. A meta-analysis [145] asserted the technology readiness importance for IS adoption and impact. Mata, Fuerst [146] recommended technology readiness to be composed of technology infrastructure and IT skills.

Before adopting CC technology, it is important to know the readiness of an HEI. The HEI needs to promote the technology readiness of CC, and the Internet bandwidth should be sufficient for cloud access by all students and teachers. Instructional content should be ready to run on the cloud. Teachers and students need to have appropriate devices and an adequate internet connection to support the CC initiative [147].

Recent studies on CC adoption using DOI did find that technological readiness still has a significant impact on the adoption of CC [18,33,39,84,147]. Therefore, it is hypothesized that:

Hypothesis 6 (H6). *Technology readiness positively influences CC adoption in HEIs.*

3.7. Top Management Support

Top management support [18] refers to the top management's attitude regarding the concerned technology as well as the extent of support given to the adoption. In terms of a strategic perspective, the successful implementation of CC in HEIs depends on the capabilities of top leadership or management to drive the change from traditional deployment to CC through an official pro-cloud strategy [148]. The decision-makers' awareness and consensus are vital. Their support will ensure what cloud services are needed and what type of cloud deployment is best for HEIs settings. To do that, the decision-makers have to understand the benefits of cloud-based services, the value they can add to the educational services, and how to migrate to the CC environment [149]. Accordingly, it is hypothesized that:

Hypothesis 7 (H7). *Top management support positively influences CC adoption in HEIs.*

3.8. Security

Despite the boom in CC with new features and market access, security in CC remains the biggest problem hindering the adoption of CC services [31,37].

Security is one of the crucial technical problems concerning CC adoption. Cloud vendors are trying to simulate the classic principles of confidentiality, availability, and integrity, which are commonly found in physical systems for distributed, virtualized, and dynamic cloud systems that are accessed online [150]. Three service models are used in CC (SaaS, PaaS, and IaaS) and four deployment models (public, private, community, and hybrid), which require different levels of security for each model to protect the user's data [151]. Internet security vulnerabilities have been an issue for users for years, such as e-commerce and online banking. Hence, the importance of security in IT environment of HEIs is critical [148,152,153]. Because CC is based on Internet technology, the same security issues hinder its adoption. However, the advanced security algorithms used in CC have been identified as the main differentiators of CC [139] that can influence its adoption. Previous studies have considered security as an influencing factor in adopting CC services [31,33,37,38,147]. Accordingly, it is hypothesized that:

Hypothesis 8 (H8). *Data security negatively influences CC adoption in HEIs.*

3.9. Research Model

Based on the theoretical and conceptual background outlined previously, this research used a method that complements existing constructs in the DOI model through the lens of the TOE framework using constructs from the previous empirical literature on adoption research (see Table 2) to the context of IS adoption in HEIs. The importance of using these theoretical perspectives gives a theoretical basis to assess the task, organization, technology, and environment characteristics that affect CC adoption in HEIs, and this has received empirical support consistently [71,82–84,93,97,110,154,155]. To be able to include the various and wide list of factors from past search and filter them, we undertook a process of collaborating, matching, filtering, and consolidating for all the information and ideas from the past studies, discussed in the literature review [156,157]. Eventually, the most frequent factors were selected. Table 3 shows the mapping matrix of the related adoption theories and factors, obtained from previous literature.

Table 3. Mapping matrix of the model factors from TOE framework and DOI theory.

Model/ Theory	**Technology/ Dependent Variable**	**Source**	**Factors/Independent Variables**							
			Compatibility	*Complexity*	*Security*	*Technology Readiness*	*Cost Savings*	*Top mgmt. Support*	*Competitive Pressures*	*Vendor Support*
TOE	Cloud migration	[18]			×			×		
DOI and others	CC adoption	[30,31]	×	×	×	×	×			
TOE	Open systems	[158]		×						
TOE	Electronic data interchange	[159]				×	×			
TOE	E-business use	[85]				×				
DOI and TOE	E-business use	[112]	×	×	×	×	×			
TOE	E-business adoption	[100]				×				
TOE	E-business	[80]	×							
TOE	Knowledge management and enterprise systems	[81]	×	×				×		
DOI and TOE	Collaborative commerce	[110]	×	×				×		
DOI, TOE, and others	Internet utilization	[106]				×	×	×		
DOI, TOE, and others	Cloud-based services adoption	[144]						×		×
DOI and TOE	Benchmarking	[107]	×	×						
DOI	RFID	[108]		×				×		
TOE and others	E-business adoption	[86]				×				
TOE	E-commerce	[160]	×				×	×		
TOE	Internet/E-business	[109]	×	×				×		
TOE	RFID adoption	[161]	×	×			×	×		
DOI and TOE	CC adoption	[103]	×	×		×	×	×	×	
DOI	Internet-based purchasing application assimilation	[162]	×	×						
DOI	CC adoption	[163]	×	×						
TOE	CC adoption	[164]	×	×	×		×			
TOE	CC adoption	[165]	×	×			×	×	×	×
TOE	CC adoption	[102]	×	×		×	×	×	×	
DOI and others	CC adoption	[166]	×	×						
TOE and DOI	CC adoption	[84]	×	×	×	×	×	×	×	
TOE, DOI, and INT	SaaS diffusion in firms	[84]	×	×	×	×	×	×	×	
TOE and TAM	CC adoption	[167]	×	×		×			×	×
TOE and TAM	CC adoption	[167]	×	×				×	×	
TOE and TAM	CC adoption	[89]	×	×				×	×	
DOI and FVM	CC adoption	[82]	×	×	×	×	×	×		
FVM, TOE and DOI	Cloud ERP Adoption	[168]	×		×		×	×		
This study			**×**	**×**	**×**	**×**	**×**	**×**	**×**	**×**

We also formulated a related hypothesis to specify the purpose of the research, highlight future areas of research, and to consolidate knowledge relating to CC adoption. Figure 1 provides an overview of the research proposed model. The research model demonstrates that compatibility, complexity, security, technology readiness, cost savings, top management support, competitive pressure, and vendor support factors will have a significant relationship with the CC adoption in HEIs. The model is grounded at the organizational level of analysis [157], and the smallest unit of analysis is an individual of CC.

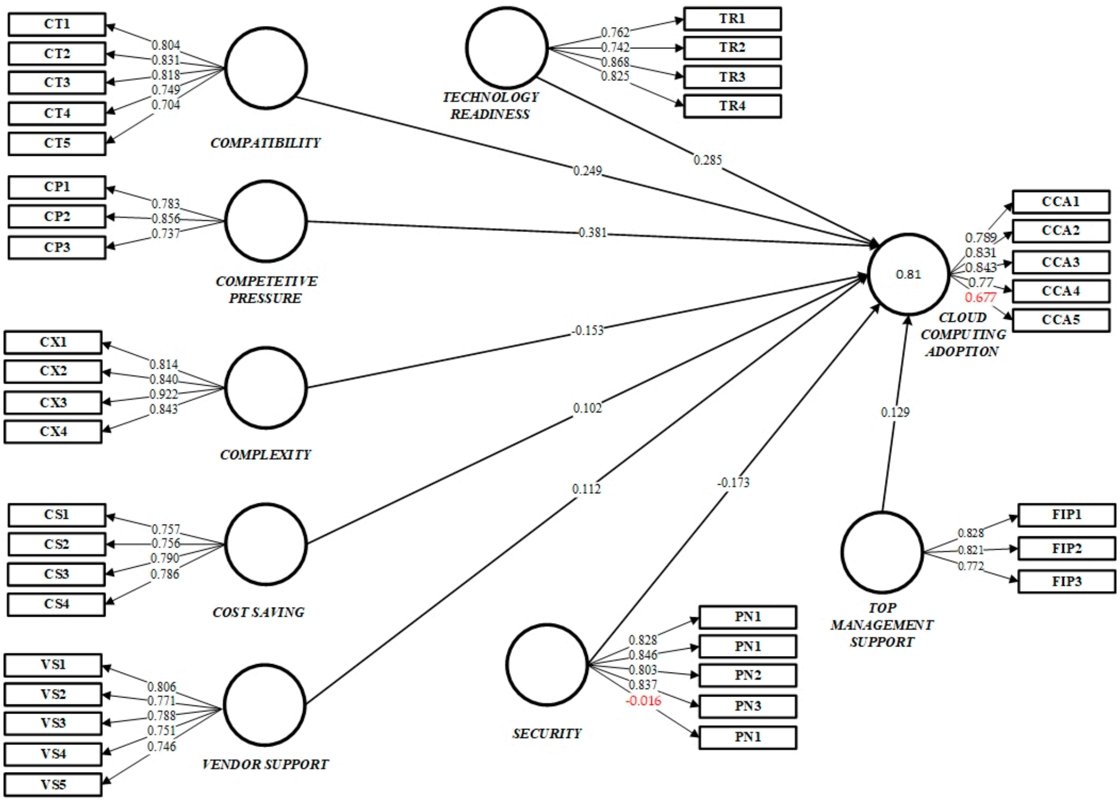

Figure 1. Proposed model.

4. Methodology

The proposed study applied two stages of analysis methods, namely variance-based structural equation modeling (PLS-SEM) and artificial neural networks (ANN). The reliability and validity of the measurement model and also hypotheses were tested by SEM, while the neural network was employed for the predictors and antecedents of CC adoption [45]. As indicated by Chan and Chong [169], to validate the relationship of hypotheses in behavioral and social science, PLS-SEM is frequently used; however, it is seldom integrated with other artificial intelligence algorithms. As PLS-SEM is employed for the linear model, it may often simplify the complications in making technology adoption decisions [170]. To solve this issue, the neural network method was used to recognize the non-linear relationships between predictors in the proposed research model. According to Chan and Chong [169], ANN helps to learn complex linear and non-linear associations between the factors of technology adoption and adoption decisions. Moreover, the ANN makes it possible to perform more precise anticipation in comparison to the general regression procedure [171]. However, some researchers applied a combination of ANN and PLS-SEM analysis in diverse adoption settings, such as CRM adoption Ahani, Rahim [172], CC Sharma, Al-Badi [66], and wearable healthcare devices and IOS adoption Chong and Bai [173]. Therefore, at the main phase, to find the factors that have an important influence on the adoption of CC, this study applied SEM. The ANN approach was employed in the second phase for predicting the CC adoption, based on the considerable factors resulted from the PLS-SEM analysis.

Sampling and Data Collection

Quantitative studies can utilize probability as well as non-probability sampling approaches. However, the non-probability sampling approach is mainly used for qualitative studies [174]. Generalizing the results driven from a small group of people to large groups is the key advantage of the quantitative research method. [175]. Daniel [174] declared that "in purposive sampling researcher purposely selects the elements because they satisfy specific inclusion and exclusion criteria for participation in the study." Purposive sampling is suitable for the initial phases of study where subjects have not much experience with a particular event under investigation [176]. Therefore, this study adopted a purposive sampling approach, and the target population of the study is the individuals who are related to the decision of adopting CC services in the institution (e.g., ICT directors, administrators, information technology officers, etc.) and can provide recommendations regarding the adoption of CC services. The summary of the respondent's characteristics in Table 2 shows that most of the respondents have advance or expert level in computer literature (i.e., 57.46% and 35.07% respectively) and 1–5 years or 6–10 years of experience in the field (i.e., 81.34% and 15.67% respectively). Face validity, content validity, and a pilot study were performed to ensure the validity and reliability of the questionnaire. For most scholars, a pilot study sample size of 20–40 is reasonable [177–182]. In this regard, our pilot study's reliability statistic was based on 30 online completed questionnaires. Structural equation modeling (SEM) was applied to the pilot data with SmartPLS 3.0 [116]. The results of a pilot study, conducted through a survey with ICT decision-makers, and based on the proposed conceptual model, indicate that the instrument is both reliable and valid, and so point the way towards further research. It is worth drawing attention to the fact that the questions were adapted from prior empirical literature that had been validated by previous researchers (see Appendix A). Data were collected online from May to July 2019. After three months, a total of 148 responses to the survey questionnaire were received by researchers. After data screening, some questionnaires with a missing value were excluded, and a total of 134 responses were found valid for the analysis. The demographic information of the respondents is presented in Table 4.

Table 4. Characteristics of the respondents.

Respondents Information		
	Frequency	**Percentage**
Computer literacy level		
Beginner	1	0.75%
Intermediate	9	6.72%
Advanced	77	57.46%
Expert	47	35.07%
Experience		
1–5 years	109	81.34%
6–10 years	21	15.67%
11–15 years	4	2.99%
More than 15 years	0	0
Job title		
Administrator	19	14.17%
Lecturer	13	9.70%
Teaching staff	3	2.38%
ICT director	26	19.40%
Chief information officer	11	8.21%
IT specialist	4	2.98%
Business analyst	2	1.49%
Researcher	53	39.55%
Associate professor	3	2.23%

5. Data Analysis and Results

This study applied two analytical approaches, namely variance-based structural equation modeling (PLS-SEM) and artificial neural network (ANN). First, the PLS-SEM approach has been used for analyzing the proposed model and extracting the significant relationships among the identified factors. The obtained result from PLS-SEM analysis revealed that factors identified significant in influencing decision-makers' intention towards adopting CC. Second, the normalized importance among those significant predictors was ranked utilizing the ANN. This section explains the data analysis and results in detail.

5.1. Analysis of PLS-SEM Results

A variance-based technique (i.e., PLS-SEM) was used to analyze the structural model, and this decision was made for several reasons: firstly, the partial least squares (PLS) method is effective for small-to-moderately-sized samples, and it provides parameter estimates even at reduced sample sizes [183,184]; secondly, PLS is viable for exploratory research [185], particularly when examining new structural paths in the context of incremental studies that extend previous models [186], or when the relationships and measures proposed are new or have not been extensively examined in prior literature [187,188]; and thirdly, the variance-based approach in PLS is effective for predictive applications. Therefore, since the study's objective was to identify the factors underlying CC adoption, PLS was a suitable choice [189].

5.1.1. Measurement Model Assessment

SEM is composed of two-step process measurement and structural model assessments. The measurement model assessment is the first step of the model assessment, to ensure that every construct is measured correctly. Reliability and validity are the primary requirement for measurement model assessment to measure the strength of the suggested model. According to Hair Jr, Hult [116], "for internal consistency of the measurement model composite reliability and Cronbach's α were applied." The validity of the constructs was evaluated by applying "average variance extracted (AVE)" and "cross-factor loadings." The reliability and validity results of the specified constructs were summarized in Table 5. As recommended by Hair Jr, Hult [116] for the reliability of the constructs, the value above 0.7 is a satisfactory score for the internal consistency of the survey. For all defined constructs, the results showed that composite reliability and Cronbach's α are above the satisfactory value of 0.7, which surpasses the suggested score, except CCA5 and VS5. Furthermore, the minimum score of 0.50 is considered to be an acceptable value of AVE for each construct [116]. As depicted in Table 5, the validity of scale items was above 0.5, which exceeded the threshold value. The next step after convergent validity verification is discriminant validity. The "discriminant validity" was evaluated by analyzing correlations between the constructs [190]. As revealed in Table 6, the Square root of AVE for defined constructs had a higher value in comparison to correlation co-efficient with other latent constructs. Therefore, "convergent and discriminant validity" was approved in the assessment of the measurement model [190]. Consequently, based on the above assessments, the validity and reliability of the constructs for the measurement model have been accepted and meet the recommended values.

Table 5. Constructs' reliability and validity.

Constructs	Items	OL (>0.7)	CA (>0.6)	CR (>0.7)	AVE (>0.5)
CC Adoption	CCA1	0.789	0.842	0.888	0.615
	CCA2	0.831			
	CCA3	0.843			
	CCA4	0.77			
	CCA5	0.677			
Compatibility	CT1	0.804	0.842	0.887	0.612
	CT2	0.831			
	CT3	0.818			
	CT4	0.749			
	CT5	0.704			

Table 5. *Cont.*

Constructs	Items	OL (>0.7)	CA (>0.6)	CR (>0.7)	AVE (>0.5)
Competitive pressure	CP1	0.783	0.71	0.836	0.63
	CP2	0.856			
	CP3	0.737			
Complexity	CX1	0.814	0.879	0.916	0.732
	CX2	0.84			
	CX3	0.922			
	CX4	0.843			
Cost saving	CS1	0.757	0.772	0.852	0.59
	CS2	0.756			
	CS3	0.79			
	CS4	0.768			
Vendor support	VS1	0.806	0.832	0.881	0.597
	VS2	0.771			
	VS3	0.788			
	VS4	0.751			
	VS5	0.746			
Technology readiness	TR1	0.762	0.812	0.877	0.642
	TR2	0.742			
	TR3	0.868			
	TR4	0.825			
Top Manager's support	TMS1	0.828	0.734	0.849	0.652
	TMS2	0.821			
	TMS3	0.772			
Security	SC1	0.828	0.74	0.829	0.55
	SC2	0.846			
	SC3	0.803			
	SC4	0.837			
	SC5	−0.016			

OL = Outer loading, CA = Cronbach's alpha, CR = Composite reliability, AVE = Average variance extracted.

Table 6. Fornell–Larckers criterion analysis construct.

	CC	CT	CP	CX	CS	VS	TR	TMS	SC
CCA	**0.784**								
CT	0.684	**0.783**							
CP	0.78	0.62	**0.794**						
CX	0.369	0.613	0.417	**0.856**					
CS	0.586	0.489	0.475	0.331	**0.768**				
VS	0.677	0.621	0.637	0.545	0.492	**0.773**			
TR	0.721	0.509	0.577	0.356	0.479	0.535	**0.801**		
TMS	0.669	0.549	0.615	0.36	0.486	0.643	0.474	**0.807**	
SC	0.547	0.569	0.682	0.4	0.499	0.535	0.509	0.521	**0.741**

Note: CC adoption (CCA); Compatibility (CT); Competitive pressure (CP); Complexity (CX); Cost saving (CS); Vendor support; Technology readiness (TR); Top manager's support (TMS); Security (SC).

5.1.2. Structural Model Assessment

In the PLS-SEM analysis, after analyzing the measurement model for getting approval for the reliability and validity of the defined constructs, the next step was the structural model assessment. In PLS-SEM as recommend by Hair Jr, Hult [116], for testing the predictive power of the structural model, researchers measured R-Square, and path coefficient between the constructs was used. Total predicted R^2 for the dependent variable (intention) is 0.81, which represents substantial coefficients of determination [116]. The result of the hypothesis testing and path coefficients for the structural model was measured, and the findings are shown in Table 7. The values for "$t = 3.091$" and "$p < 0.001$", "$t = 2.326$" and "$p < 0.01$", and "$t = 1.645$" and "$p < 0.05$" can be accepted for *t*-value at various significance levels [138]. The result of the hypotheses calculation by running bootstrapping shows that all the proposed CC adoption antecedent factors had a significant influence on it, except vendor support. Based on the analysis, CC adoption is positively influenced by compatibility ($\beta = 0.249$, *t*-value = 4.311, $p < 0.01$). Thus, this hypothesis supported. Competitive pressure ($\beta = 0.381$, *t*-value = 5.516, $p < 0.01$)

has positive significant influence on CC adoption. The complexity has a negative significant influence on CC adoption (β = −0.153, *t*-value = 2.887, $p < 0.01$); therefore, this hypothesis is also supported. Cost saving is another factor which had significant and positive influence on CC adoption (β = 0.102, *t*-value = 2.266, $p < 0.05$). However, vendor support (β = 0.112, *t*-value = 1.447, $p > 0.05$) does not have a significant influence on CC adoption, and this hypothesis is not supported. Furthermore, from the analysis, CC adoption is positively influenced by technology readiness (β = 0.285, *t*-value = 4.888, $p < 0.01$). The results indicated that the top manager's support has a positive and significant influence on CC adoption (β = 0.129, *t*-value = 1.978, $p < 0.05$). Meanwhile, from the analysis, it shows that CC adoption is negatively and significantly influenced by security (β = −0.173, *t*-value = 2.226, $p < 0.05$). It is clear from the result that among all the constructs, competitive pressure had the highest significant level and was the most significant factor that was selected and influenced the individuals' intention for the adoption of CC in higher education, followed by the technology readiness, which had higher significance in bootstrapping analysis. As depicted in Figure 2, the result of the proposed model showed that 81% of the variance in CC adoption can be described by the technological, environmental, and organizational factors (TOE) factors.

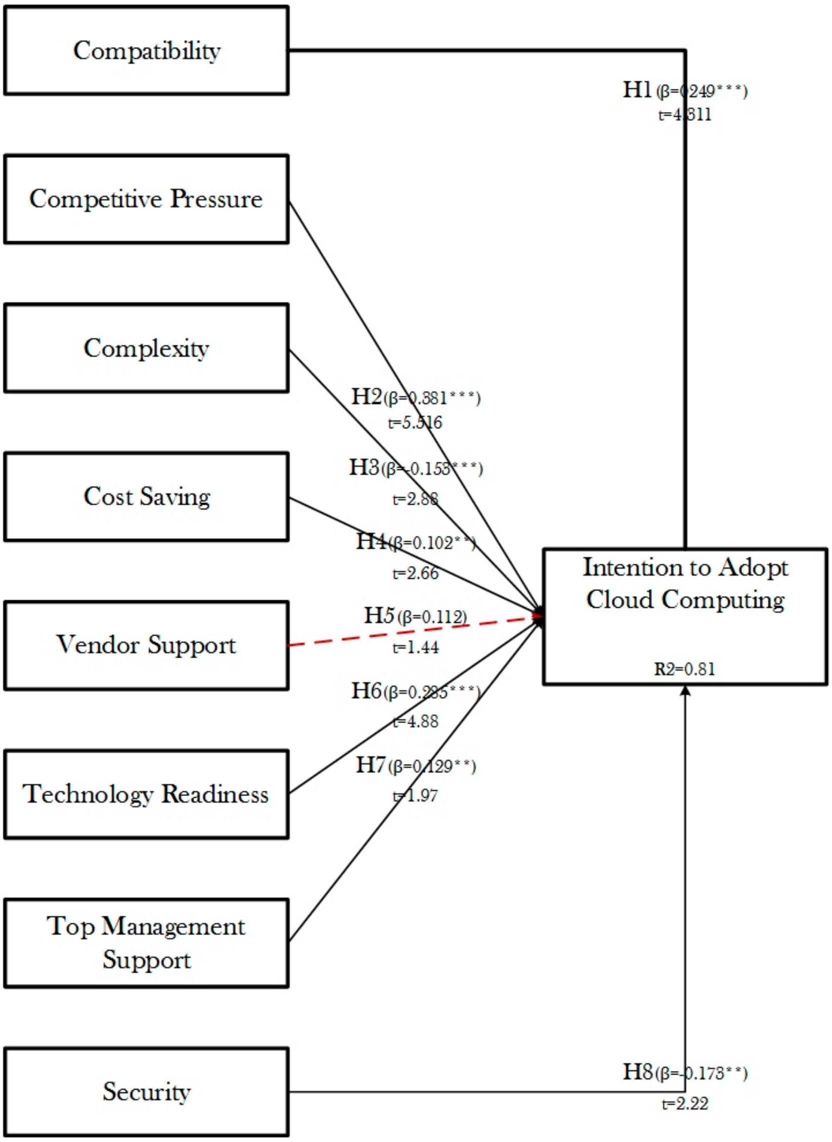

Figure 2. Results of structural model. Note: ** < 0.05, *** < 0.01.

Table 7. Summary of hypothesis tests.

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Value (|O/STDEV|)	*p* Values	Result
Compatibility -> CC adoption	0.249	0.243	0.058	4.311	0 ***	Supported
Competitive pressure -> CC adoption	0.381	0.375	0.069	5.516	0 ***	Supported
Complexity -> CC adoption	−0.153	−0.15	0.053	2.887	0.004 ***	Supported
Cost saving -> CC adoption	0.102	0.102	0.045	2.266	0.023 **	Supported
Vendor support -> CC adoption	0.112	0.117	0.077	1.447	0.148	NS
technology readiness -> CC adoption	0.285	0.277	0.058	4.888	0 ***	Supported
Top manager's support -> CC adoption	0.129	0.13	0.065	1.978	0.048 **	Supported
Security-> CC adoption	−0.173	−0.167	0.078	2.226	0.026 **	Supported

Note: ** < 0.05, *** < 0.01.

5.2. Analysis of Neural Network for Cloud Computing Adoption

The proposed study has combined the two analytical approaches, namely PLS-SEM as a statistical approach and neural network as an artificial intelligence technique. Multiple regression analysis (MRA) and PLS-SEM are considered to be a conventional linear statistical technique, which is used for identifying the linear relationship between variables and simplify the complex decision-making process [191]. To solve this issue, it is suggested to apply the artificial neural network, which can easily recognize the non-linear relationship. According to Chan and Chong [169], the advantage of using the neural network model is that it can learn complex linear and non-linear relationships between predictors and the adoption decision. Also, the ANN is more flexible and can give better prediction accuracy as compared to the linear model(s), and it may surpass the usual statistical technique (such as MRA) [172]. However, because of its "black-box" nature, ANN is not suitable for checking the hypothesis and determining the causal relationship [191]. Thus, this paper adopted a two-stages approach, similar to [66]. In the first stage of the study, the research model is tested, and the important hypothesized predictors are analyzed using SEM. The result of the PLS-SEM is then given as input to the model of ANN, which is employed to analyze the relative significance of each predictor variable in the second stage. Hence, the results of selected factors from Smart-PLS analysis were employed to improve ANN analysis. The applied ANN has three layers: "Input layer, hidden layer, and output layer". The hidden nodes have no direct connection with the outside world (thus the name "hidden") [192]. These nodes are responsible for performing computations and transferring information from the input nodes to the output nodes [193]. As depicted in Figure 3, seven independent substantiation factors, derived from PLS-SEM analysis, are considered as the input section for ANN; whereas one dependent variable (CC adoption) is considered as the output section of ANN (see Figure 3). Wang and Elhag [194] recommended that ANNs should be calculated by varying the number of hidden nodes from one to ten. To detect the hidden nodes (H1-H10 in Figure 3), researchers such as Ahani, Rahim [172] have recommended testing the ANN model by modifying the number of hidden nodes from one to ten. The proposed research has been applied to the 10 hidden nodes to create the relative significance of the predictors. The proposed study established ANN by using R programming, as it helps to simplify and give effective results. A multilayer perception training algorithm was applied for the preparation of the ANN model (see Table 8). Hence, 70 % of the data have been used as the train network model, and the remaining 30% of the data were used to test the proposed research model. Seven predicting factors, namely compatibility, competitive pressure, complexity, cost saving, technology readiness, security, and top management support, were tested. The factor "intention", which is the dependent variable in the proposed study, has been calculated in the output layer of the ANN model. The root-mean-square error (RMSE) was used to assess the precision of the ANN model that was developed [195] in both the training and testing datasets. As shown in Table 8, the average RMSE values of the training and testing procedures are relatively small at 0.1101 and 0.1022, respectively. Therefore, this confirms that there is an excellent model fit. Besides, the importance of variable is verified based on the number of non-zero synaptic weights connected to relevant hidden parts (see Table 8), which displays that the model has a high predicting accuracy, based on minor RMSE scores and it shows that the model is reliable in depicting the relationship between predictors and output.

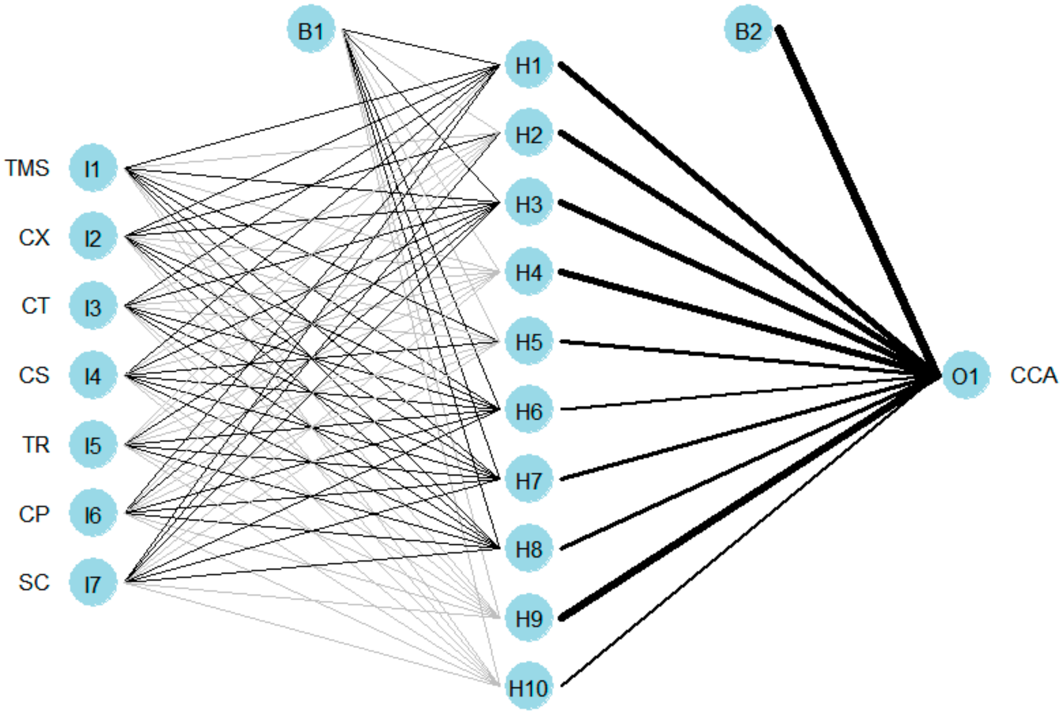

Figure 3. The anticipated ANN architect for 10 neurons. Note: CC adoption (CCA); Compatibility (CT); Competitive pressure (CP); Complexity (CX); Cost saving (CS); Technology readiness (TR); Top manager's support (TMS); Security (SC).

Table 8. RMSE values of artificial neural networks.

Network Configures	Testing	Training
ANN1	0.1174	0.0994
ANN2	0.1079	0.1004
ANN 3	0.1132	0.1013
ANN 4	0.1105	0.1015
ANN 5	0.1137	0.105
ANN 6	0.1054	0.1015
ANN 7	0.1069	0.1029
ANN 8	0.1124	0.1045
ANN 9	0.1066	0.1053
ANN 10	0.1141	0.0973
Average	0.1101	0.1022
Standard deviation	0.0034	0.0026

Therefore, all the factors are suitable for forecasting CC adoption as a dependent variable. The normalized importance is the ratio of the relative importance of each factor with its maximum relative significance, and it is stated in percentage form. Based on the PLS-SEM examination, just significant linear factors have been employed in the input parts of the ANN model. In this regard, just linear relationships have been checked. The normalized importance was calculated in the sensitivity analysis according to relative factor importance weights (see Table 9). The variable "technology readiness" resulted as the most significant factor in predicting the CC adoption, and "security" is the second important factor.

Table 9. Normalized importance of variables.

Variables	Importance	Normalized Importance
TMS	0.077	39.50%
CX	0.11	56.20%
CT	0.129	66.00%
CS	0.13	66.40%
TR	0.196	100.00%
CP	0.171	87.30%
SC	0.188	96.00%

Note: Compatibility (CT); Competitive pressure (CP); Complexity (CX); Cost saving (CS); Technology readiness (TR); Top manager's support (TMS); Security (SC).

6. Discussion

Our study examined the influence of eight constructs obtained from the literature. Our research model explained 81% of the dependent variable's variance, higher than other studies that examined the adoption of cloud computing (e.g., [31,196]). Sabi, Uzoka [196] study found that their model could explain only 43%, while Sabi, Uzoka [31] study found that their model could explain only 44.7%. The results of the previous studies and the current investigations are compared on variously considered factors.

According to the hypotheses test, compatibility has a positive and significant impact on CC adoption. The β, *t*-value, and *p*-value of the test result are 0.249, and 4.311 respectively, which is significant at the level of $p < 0.01$. These values demonstrate support for this hypothesis. Besides, the ANN output revealed that the variable "compatibility" is the fourth crucial factor in the prediction of the CC adoption. Hence, the adoption of CC is significantly affected by compatibility and H1 is supported. The result corroborates what was observed in past studies ([80,81,107,110,112]). According to this research, compatibility refers to the degree to which an innovation equates the previous practices, present values, and current needs of the likely adopter [104]. In addition, compatibility looked into the extent to which an innovation can attune to available systems.

The output of the measurement model shows that competitive pressure has a significant and positive impact on CC adoption. The β, *t*-value, and *p*-value of the test result are 0.381, 5.516, respectively, which is significant at the level of $p < 0.01$. These values demonstrate support for this hypothesis. Besides, the ANN output revealed that the variable "competitive pressure" is the third crucial factor in the prediction of CC adoption. Hence, the adoption of CC is significantly affected by competitive pressure. The result corroborates what was observed in past studies ([100,112,115,131–133]). According to this research, competitive pressure refers to the pressure observed by the leaders of an institution concerning the competitors' attainment of remarkable competitive advantage through CC services, such as the effectuality of teaching and learning ([115,129,130]).

The stipulation of hypothesis H3 is that complexity possesses a negative impact on CC adoption. According to [134], complexity shows the observed difficulty of an institution in understanding and using innovation. If a useful innovation appears difficult to be utilized, then there will be a reduction in the likelihood of adoption [104]. As portrayed in the results of the current study, there is a significant effect of complexity on CC adoption in HEIs, because the β, *t*-value, and the *p*-value of complexity are −0.153, 2.887 respectively, which is significant at the level of $p < 0.01$. Therefore, complexity has a significant effect on CC adoption in HEIs. This result is in line with previous studies [30,31,35,127,128].

The output of the measurement model shows a positive impact on cost saving with CC adoption. The β, *t*-value, and *p*-value of the result are 0.102, 2.266 respectively, which is significant at the level of $p < 0.05$. These values support the hypothesis that cost saving has a significant effect on the adoption of CC in HEIs. This result supports the findings of previous studies ([82–84,102,103,106,112,159–161,164,168]).

According to this research, cost savings is the reduced capital investment required in an institution for IT service in terms of leased resources and hardware solutions [136].

The stipulation of hypothesis H5 is that vendor support has a positive impact on the adoption of CC in HEIs. According to [142,143], vendors or IT service providers are important in deciding the adoption of IT services. As shown in the results of this study, there is no significant impact of vendor support on CC adoption in HEIs, because β, *t*-value, and *p*-value of the result are 0.112, 1.447 respectively, which is not significant as $p > 0.05$. Hence, H5 significance was unconfirmed, and the output of vendor support was insignificant, which might be due to the indicators utilized in measuring this factor being feeble. Accordingly, the study output is suggesting that further studies need to focus on the selection of powerful indicators of this construct.

The output of this measurement model shows a positive influence of technology readiness on CC adoption. The β, *t*-value, and *p*-value of the result is 0.285, 4.888, respectively, which is significant at the level of $p < 0.01$. These values demonstrate support for this hypothesis. Besides, the ANN output revealed that the variable "technology readiness" is the second crucial factor in the prediction of the CC adoption in HEIs. Therefore, the adoption of CC is significantly affected by technology readiness. The result corroborates what was observed in past studies [18,33,39,84,147]. According to this research, technology readiness secures the internal technical resources of an organization [112]. Before the adoption of CC technology, the readiness of the institution needs to be determined. That is, HEIs must facilitate the readiness of CC technology so that the internet bandwidth needs to be adequate for student and teacher cloud accessibility.

The output of this measurement model shows a positive influence of top management support on CC adoption (H7). The β, *t*-value, and *p*-value of the result are 0.129, 1.978 respectively, which is significant at the level of $p < 0.05$. These values demonstrate support for this hypothesis. Hence, the adoption of CC is significantly affected by top management support. This result is in line with the findings of past studies [81–84,102,103,106,108–110,160,161,168]. According to this research, the attitude of top management is important in terms of the technology involved and the degree of support provided for the adoption [18]. The knowledge and agreement of decision-makers are crucial. When they provide the necessary support, it will facilitate the needs of cloud services and the appropriate cloud deployment for HEIs settings.

Hypothesis H8 stipulates that security possesses a negative impact on the adoption of CC in HEIs. According to [31,37], security in CC is still the most remarkable challenge in adopting CC services. Security is a critical technical problem when it comes to adopting CC. Cloud vendors are making attempts towards the simulation of the typical principles of confidentiality, availability, and integrity usually within physical systems for distributed, virtualized, and dynamic cloud systems that users access online [150]. As shown in the results of this study, there is a significant impact of security on CC adoption in HEIs as the β, *t*-value, and *p*-value of the result are −0.173, 2.226 respectively, which is significant at the level of $p < 0.05$. Therefore, H5 significance was confirmed, and the output of security was significant.

7. Implications

7.1. Theoretical Contribution

This study provided empirical literature within IS, especially CC, and it provided an extensive model that integrates the TOE framework and DOI model. Also, this study provided an assessment for CC adoption in HEIs, and more revitalization of the CC and intent of decision-makers to utilize CC in HEIs.

The DOI model and TOE framework incorporation improved the ability to explain the proposed model. The proposed model was able to explain 81% of CC adoption variation, which shows that the model's ability for prediction is powerful and remarkable. Hair, Ringle [197] maintained that the R^2 values of 0.75, 0.50, or 0.25 for endogenous variables show significant, moderate, or weak coefficients of determination. This study extends the original TOE framework regarding CC as well as the generalizability; hence, this model is useful in the assessment of the intent to adopt any other innovation. This study was able to test whether the scales utilized in the survey instrument are valid and reliable.

In conclusion, this research used a hybrid approach for the integration of PLS-SEM and ANN to validate the proposed model and to give priority to the factors that impact CC adoption, through the identification of the relative importance of every factor. PLS-SEM determines linear association and ANN determines nonlinear association among predictors and target variables. According to the claim by past scholars, ANN is more accurate in prediction than PLS-SEM [45,66,169]. However, this study recognized that conventional statistical approaches are valid and necessary; thereby offering a powerful foundation in previous IS adoption studies. The suggestion of this research is the need to reinterpret past works on IS adoption through the combination of linear and non-linear approaches in order to provide outstanding strength to technology adoption.

7.2. Practical Implications

7.2.1. Implications for Practitioners and Cloud Providers

HEIs are a promising market for cloud service providers. Hence, this study is remarkably impactful for cloud providers and technology practitioners as it will help in the recognition of the factors that influence the adoption of CC. The research results show the essentiality of compatibility, competitive pressure, complexity, cost saving, security, technology readiness, and top management support in adopting CC in HEIs. CC is a new technology and remains thought-out as disruptive. HEIs still lack awareness of the benefits of using cloud services, especially in developing nations. Hence, cloud providers need to consider a variety of approaches in increasing the understanding of HEIs for this technology via workshops and seminars. There is a need to emphasize functional utilities and simple interfaces in the design of cloud services for HEIs towards easy usage of these services, even with little technological knowledge. Likewise, cloud providers need to provide a clear instruction or navigation system in guiding users in HEIs to operate the services smoothly, thereby increasing the assurance that cloud technology is used.

7.2.2. Implications for Decision-Makers

This study emphasizes that top management and ICT department support are important in adopting CC at the HEIs. Likewise, it was discovered that enhancing situations like technology readiness and security with the process in place is the impactful antecedent of adopting CC in HEIs. Hence, there is a need for decision-makers to concentrate on the development of these organizational resources towards gaining the highest merits of cloud services. Besides, top managers pay more attention to the assessment of cloud technology and its assimilation into IT infrastructure effectively and efficiently. In summary, the research results will help decision-makers with the assessment of cloud technology, organization, and environments during the decision of the adoption of CC. Furthermore, decision-makers may use this proposed framework for the investigation of other IT/IS adoption procedures.

8. Conclusions, Limitations and Future Research Directions

This current study utilized the notion of adopting CC in HEIs and likewise assessed how the research model created from the DOI mode and TOE framework correlates. This study demonstrates that there is consistency between the proposed model and the data. Apart from the direct influence of vendor support on the intention of adopting CC, the basic factors on decision-makers' intention have a significant influence on the adoption of CC in HEIs. The study outputs have theoretical effects on the identification of the factors influencing the decision-makers' intention to adopt CC and the crucial function of managerial awareness and competitive edges in the research model. The results of the current study affirmed that technology readiness is the most remarkable factor that determines the intention to adopt CC. Therefore, the results suggest that technology readiness has a remarkable and direct correlation regarding the adoption of CC in HEIs. Therefore, the results of the study were able to demonstrate that the theories are useful for pro-environmental behavior and to forecast the intention of adopting CC. Besides, the research model is useful for the improved explanation of the intention of decision-makers in adopting CC.

This study has some limitations that will bring about the focus of subsequent research. First, data were collected only in Malaysia. Therefore, subsequent studies can use data from other nations for the validation of the results in the current study. Second, the development of the model in this study was carried out using some critical factors within TOE framework dimensions; hence, future studies may include other critical factors within the three major dimensions. Third, one-time cross-sectional data was used in testing the model, so subsequent studies may work on the validation of the model introduced here with longitudinal data within some time. Fourth, this study tried the investigation of CC adoption in HEIs, based on the context of decision-makers; hence, subsequent studies can pay attention to the context of the cloud provider for a wider comprehension of the intention to adopt CC. Finally, this study looked into only the intent of an organization in adopting CC from the perspective of HEIs. Future studies can use the evaluation of the post-adoption phase, and the successful establishment of this common technology.

A world with current modern technologies that keep evolving requires organizations and individuals to keep adapting to the evolved technologies. Thus, researchers are required to always remain ahead of these innovations by investigating future technologies. In this regard, the fourth industrial (IR 4.0) revolution provides a dialectical, intricate, and intriguing opportunity to higher education (HE 4.0), in which the society would be changed for the better. Education in the IR 4.0 era (Education 4.0) is driven by biller technologies as artificial intelligence (AI), augmented reality (AR), internet of things (IoT), big data analysis, CC, and mobile devices, which can promote a way of teaching, research, and service and change the work area from task-centered to human-based [198]. To the best of the researchers' knowledge, no empirical study has been revealed on the adoption and use of HE 4.0. Therefore, further investigations on the adoption and use of HE 4.0 may gain the attention of the researchers.

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Appendix A

Table A1. Factors' Items and Definition.

Factors	Definitions		Measurement Items		
	Definition	Source(s)	Items	Adapted Source	Previous Studies
CC Adoption (CCA)	The intention to adopt cloud computing services in higher education institutions.		**(1 = Strongly Disagree to 7 = Strongly Agree)** **CCA1.** My institution intends to continue using our cloud computing solutions rather than discontinue. **CCA2.** My intentions are to continue using our cloud computing service rather than use any alternative means (traditional software). **CCA3.** If I could, I would like to *discontinue* my use of our cloud computing service. (**reverse coded**).	[199]	[114,115]
Compatibility (CT)	The extent to which the value of the cloud computing is consistent with existing values, beliefs, and the needs of a potential adopter.	[44,103,165,200]	**CT1.** The continuous use of cloud computing will be compatible with all aspects of my institution work. **CT2.** The continuous use of cloud computing fits well with the way I like to work at the institution. **CT3.** The continuous use of cloud computing is completely compatible with my current work requirements at the institution. **CT4.** It is easy to integrate cloud computing with our other existing systems (e.g., LMS, Finance, ERP, CRM, SCM, etc.). **CT5.** Cloud computing is compatible with our culture and values.	[83,94,112,160]	[31,84,133,134,161]
Complexity (CX)	The degree of difficulty to understand, use, or continue using the cloud computing.	[44,103,201]	**Cx1.** The continuous use of cloud computing requires a lot of mental effort. **Cx2.** The continuous use of cloud computing is frustrating. **Cx3.** The continuous use of cloud computing is too complex. **Cx4.** The skills needed to continue using cloud computing are too complex for the users.	[83,126]	[31,94,133]
Security (SC)	The degree to which cloud computing is appropriate for HEIs systems security requirements.	[44,202,203]	**SC1.** The confidentiality and security of my institution data are guaranteed when using cloud computing solutions. **SC2.** In case of damage, present liability law is clear about who will bear the liability. **SC3.** The cloud computing service provider will not exploit contractual loopholes (i.e., incomplete contracting) to the detriment of my institution. **SC4.** The institution's data stored on cloud computing is secure. **SC5.** The institution's data will be adequately protected through cloud computing systems. **SC6.** Cloud computing providers have stronger security systems to safeguard the institution's data.	[204]	[83,84,112,205,206]
Technology Readiness (TR)	The technological characteristics available in the institution, such as the IT professionals and the IT infrastructure.	[83,85]	**TR1.** My institution knows how cloud computing can be used to support our operations. **TR2.** The technology infrastructure of my institution is available to support cloud computing for continuous use. **TR3.** My institution is dedicated to ensuring that the users are familiar with cloud computing. **TR4.** My institution has good knowledge of cloud computing.	[93]	[83,84]

Table A1. *Cont.*

Factors	Definitions		Measurement Items		
	Definition	Source(s)	Items	Adapted Source	Previous Studies
Cost saving (CS)	Cloud computing creates an opportunity for innovation, reduces infrastructure costs, decreases energy consumption, and lowers maintenance expenditures.	[84,207,208]	**CS1.** Cloud computing is more effective than the alternative. **CS2.** Cloud computing saves time and effort. **CS3.** Institutions can avoid unnecessary cost and time by continuous use of cloud computing.	[93]	[83,84]
Top Management Support (TMS)	The vision, support, and commitment provided to foster the desired environment for the continuous adoption of cloud computing in HEIs.	[83,209]	**TMS1.** Top management is likely to take risk involving the continuous use of cloud computing. **TMS2.** Top management actively participates in establishing a vision and formulating strategies for the continuous use of cloud computing. **TMS3.** Top management communicates its support for the continuous use of cloud computing.	[93]	[83,84]
Competitive Pressure (CP)	The pressure perceived by an institution's leaders that competitors have achieved substantial competitive advantage by using cloud computing services (for example, in terms of teaching and learning effectiveness).	[114,129,130]	**CP1.** More and more institutions are conducting teaching activities and communication through cloud computing. **CP2.** More and more institutions are conducting knowledge management and sharing though cloud computing. **CP3.** More and more institutions are conducting project and learning management though cloud computing.	[85,112]	[114]
Vendor Support (VS)	Refers to the supplier activities that can significantly influence the probability to continue using cloud computing	[210]	**VS1.** Vendors actively market cloud computing. **VS2.** There is a service level agreement (SLA), guaranteed by the vendor. **VS3.** There is adequate technical support for cloud computing provided by vendors. **VS4.** Support is easily available from cloud computing vendors during implementation. **VS5.** Training for cloud computing is adequately provided by vendors.	[160,167,211]	[134,167]

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