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Fog Computing Adoption for Higher Education Institutions: A Perspective of Multi-Analytical Structural Equation Modeling and Artificial Neural Networks

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Abstract

Fog computing is employed in widespread sectors; fog computing in higher education will probably enhance the operations of higher education institutions. However, the adoption of fog computing in this context is still in its early stages, and research in this area is limited. So, there appears to be a deficiency in the adoption of fog computing to enhance higher education institutions' operations. The current paper implements a quantitative methodology the data was gathered through a questionnaire, where 103 surveys were collected from academic and information technology staff at nine universities in Sana'a, Yemen. This study aims to build a conceptual framework to identify factors that affect in adoption of fog technology by higher education institutes and investigate them. where the current study utilizes the Technological, Organizational, and Environmental (TOE) framework as a basis for analysis. Nine factors have been tested in this study, where the factors relative advantage, Compatibility, Security, privacy, Technology Readiness, TOP management, Regulatory Policy, Competitive Pressure, and Socio-Culture have a positive effect. The proposed framework was empirically validated using multi-analytical structural equation modelling and artificial neural network (SEM-ANN) method. We identify the relative advantage of the first ranking (100%), Socio-Culture (67%), security (55%), compatibility (49%), privacy (45%), competitive pressure, and technology readiness are in the same ranking, with a score of 31%. Finally, the government regulation and top management support have (23%) and (29%), respectively, as the significant factors that affect in adoption of fog computing by higher education institutes.

Article Info

Keywords:
Fog Computing Adoption, Higher Education Institutions, TOE Framework, SEM, ANN

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1. INTRODUCTION

Cloud computing is considered a big switch in IT owing to the facilitation that improves organizations, but there are still some limitations to this technology [1]. Fog computing resolves the lack of cloud computing [2]. Fog computing is an extension of cloud computing that addresses limitations in cloud computing, such as delays in response time, security, privacy, mobility, and centralization [3, 4].

This technology was introduced by CISCO in January 2012. Fog Computing (FC) is an emerging distributed computing platform aimed at fetching computation close to its data sources, which can reduce the latency and cost of delivering data to a remote cloud Fog technology is an emerging decentral computing platform aimed at fetching computation at edge network, which can reduce the latency and cost of delivering data to a remote cloud, the fog computing can be collected and process sensitive amounts of data generated by IoT, offering real-time analysis and local decision-making for the current environment [5, 6].

The demand for fog computing in daily life has increased owing to the needs of our lives, such as health care, smart cities, and education. The characteristics of fog technology make it an enabler for various services, owing to its geographic coverage, proximity, bandwidth required, availability, and analysis of the collected data from a variety of devices [7, 8].

Fog computing is a decentralized computing platform that extends cloud computing to address the limitations of cloud technology, such as response delay, mobility, network overhead, security, and privacy. Storage and analysis of fog computing data near hardware improves the quality of service in the environment in which it is located, in real-time analysis applications [9, 10].

The Internet of Things collects sensitive data from the surrounding environment and sends it to fog computing for storage and analysis in real time. Further analysis can send data to cloud computing [11]. Fog computing can enhance daily operations in various sectors such as education. It improves fast computing and analysis through distributed computing, which means that better support can be provided efficiently to the education system and high-quality services that demand urgent decisions and actions [12]. The lack of expertise in information technology and training lecturers and other employees in institutions regarding the usage of fog technology are still the biggest challenges confronting universities [13].

As mentioned above, fog computing is a distributed computing platform that extends cloud computing to solve the limitations of cloud computing, such as response delay, mobility, network overhead, security, and privacy. Storage and analysis of fog computing data near endpoints improve the quality of service in the environment in which it is located in real-time analysis applications [9]. It works as an intermediary layer between the cloud computing and IoT layer applications [9]. It alleviates network congestion and systematically analyzes the collected information by relocating both data and storage to the end user [14].

Fog computing contributes to the increased heterogeneity of data across multiple formats as well as the diversity of devices and platforms utilized [2, 15]. Its layers can support deep data analysis using artificial intelligence and machine learning algorithms [16].

The primary goal of utilizing fog technology in the education sector is to enhance the protection of learning materials and other services provided to students [13]. Fog computing technology fits with organizations and has automation with machine-to-machine interactions. It is located between cloud technology and IoT devices to support local processing, secure data, and save privacy [2, 13]. In addition, one of the main goals of fog technology is to connect cloud computing and IoT. Therefore, fog technology is not just an extension of cloud computing; however, it is a broker system that connects the cloud with IoT to increase the flexibility of the system and privacy owing to close fog computing from the end user [17].

Fog technology can enhance learning efficiency and reduce the costs of education. It improves eLearning operations by providing benefits for teachers and students, as they interact in real time and access from anywhere at any time [18, 19]. Fog technology platforms are relatively modern; therefore, their adoption must be carefully planned and understood before their implementation. Fog technology is a network topology exchange, analysis, and storage of data in a local area and can transfer insensitive data to cloud computing for permanent storage, So Fog technology is not a variation for cloud computing but only comes to additional extend the computation, and communication facilities to end-users of the IoT network [20].

There is a lack of literature on fog technology to investigate the factors and build a theoretical framework for determining the factors that affect the adoption of fog technology by higher education institutes. Furthermore, there is no validation using two analytical methods (i.e., PLS-SEM and ANN) associated with developing countries, such as Yemen.

This study aims to build a TOE-based model for determining factors that affect the adoption of fog technology by higher education institutes in any country, generally, and in Yemen. The case study has been conducted at higher education institutions in the Republic of Yemen, and distributed to the chiefs of departments, Faculties of Computer Science and Technology, IT Managers/Director, staff of IT, Deans of the Computing/IT Faculties, and lecturers at Computing/IT Faculties at nine Yemeni universities. As a result of this study, new factors have been addressed in addition to many previous factors that affect the adoption of Fog Computing in the higher education institutions' sector.

The remainder of this paper is structured as follows: Section 2 presents the related work; Section 3 presents the research framework and hypotheses; Section 4 presents the research methodology; Section 5 presents the evaluation of results; Section 6 presents the ANN results; Section 7 presents a general discussion; and Section 8 outlines the conclusions, research contributions, recommendations, and future work.

2. LITERATURE REVIEW

2.1. Related Work

This section presents the most recent studies related to the main topic of this study. Authors in [2] reviewed and analyzed the variables that affect the intention to adopt fog computing by firms in general. They combined the two frameworks to define the key factors in the decision to adopt fog technology. They determine a group of factors have significant and influence positively on the decision to adopt fog technology (i.e., relative advantage, compatibility, awareness, cost-effectiveness, security, infrastructure, ease of use, usefulness, and location), group of factors no significant and negative influence on the decision to adopt fog computing (i.e., complexity, privacy, and information intensity) and other have significant and influence negative on the decision to adopt fog technology, they appeared the challenges that face adopt fog computing in organization. Most factors depend on similar studies implemented in cloud computing environments. Fog features are single and extend to the features of cloud computing, such as its near-to-user, distribution, and heterogeneous nature.

The authors of [7] addressed the factors that influence the adoption of fog computing in organizations. These factors focus on the target user, geographical distribution, main content generator, customer, data storage (temporary), large-scale distributed processing, latency tolerance, security, and fast responsiveness. They mentioned gaps in the adoption of fog technology in organizations, as organizations still depend on cloud computing owing to deployment flexibility for business applications.

The authors of [15] proposed a conceptual framework to analyze the factors that affect the intention to adopt fog computing for heterogeneous data analysis. The authors defined variables that can be employed to improve the quality of the results of data analysis, such as quality indicators, quality control, validity finding, and reliability outcome.

In [21], the authors compared fog computing with cloud and edge technologies. They concluded that fog technology introduces high performance to healthcare information systems due to characteristics such as decentralization, proximity to end users that enhance response time, support heterogeneity, etc. They discussed the issues and challenges that confronted fog computing when used in healthcare information systems, such as device integration, data management, Service Latency, security and violation of privacy of patients' data, scalability, and interoperability.

Authors in [22] presented a framework to determine readiness for adopting big data by Higher Educational Institutions in Namibia. This study may not be applicable to other countries, as technology adoption and implementation vary. Interviews and questionnaires were conducted with 345 respondents.

The authors of [23] proposed a conceptual framework to analyze the factors that affect the adaptation of cloud-based e-learning (CBEL) by Lebanese students. They combined three models: the TAM, UTAUT, and ISS. Four dependent factors have been proposed that affect behavioral intention: ease of use, relative advantage, social influence, and user satisfaction. Additionally, the attitude factor was used as a mediating variable that affected the dependent variable. The border of this study was four universities in Lebanon.

In [24], the authors discussed the factors that influence the adoption of cloud computing by the higher education sector. They used the UTAUT framework in addition to the trust factor. They analyzed effort expectancy, performance expectancy, social influence, and trust and found that these factors affect the intention of students to adopt cloud technology. Furthermore, facilitating condition factors have a very positive effect on actual use behavior. Moreover, moderate variables such as sex, age, experience, and voluntariness influenced the relationships hypothesized in the proposed study.

In [25], the authors proposed a framework called the Technology-Organization-Environmental and Quality Framework for adopting Cloud Computing (TOEQCC) by higher education institutes in Jordan. This framework is extended from the Technology Acceptance Model (TAM) by combining both the Technology-Organization-Environmental (TOE) and the Diffusion of Innovation. The findings analyzed nine motivators and barriers to the adoption of cloud computing by higher education institutes in Jordan: cost benefits, trialability, disaster recovery, scalability, HEI size, knowledge sharing, compatibility, ICT usage level, and security and privacy.

The authors of [26] incorporated seven technological determinants: service quality, perceived security, perceived privacy, perceived utility, trustworthiness, relative advantage, and perceived analytical ease. These seven technological determinants are incorporated into the model posited by the researcher in [26] to investigate how Saudi Arabian universities adopt mobile cloud computing.

Authors in [27] have developed and validated the Theory of Planned Behavior to Cloud Computing Services undertaken in 2017.

The study in [28] included 260 faculty members from Tabriz University of Medical Sciences, Iran. The primary factors that encourage and prevent applying cloud computing within academic institutions in developing countries, specifically Jordan, were investigated by the authors of [28] employing an interpretive framework and a qualitative research methodology.

Authors in [29] conducted a comprehensive analysis of the factors that impact organizational choices regarding the adoption of cloud-based solutions. Their study employed the technology-organization-environment (TOE) framework to examine these influential factors. This study analyzed and classified the factors that influence the adoption of cloud computing in organizations. The authors investigated stand-alone or integrated TOE with other adoption theories, and the objectives were to define cloud services and models, as well as identify theoretical frameworks or models for analyzing how organizations utilize cloud services.

In [30], the authors investigated and analyzed the factors affecting the adoption of cloud computing by HEIs in Yemen using the TOE model. Except for tribalist culture, which had a significant negative influence, the study concluded that the independent variables, such as relative advantage, reliability, compatibility, security, technology readiness, top management support, regulatory policy, and competitive pressure, all had significant positive impacts on the adoption of cloud computing. The study additionally found that tribalist culture moderates the relationship between compatibility, reliability, security, relative advantage, regulatory policy, and cloud computing adoption.

The authors in [31] addressed factors that influence the adoption of IOT-based E-Learning higher educational institutes (HEIs) and categorized factors into four groups: Individual, Organizational, Technological, and Environmental factors. They conducted a comparative analysis of factors that influence the adoption of IOT-based e-learning to determine which factors are prioritized to affect the development of higher education institutes.

In [32], the authors analyzed the improvement in the operation of fog computing adoption in the Saudi government sector, and developed a new comprehensive fog computing adoption model for Saudi Arabian public organizations (FCA-SAPO). Accordingly, this conceptual research model aims to develop a new comprehensive fog computing adoption model for Saudi Arabian public organizations (FCA-SAPO) to enhance Fog Computing adoption in the Saudi Arabian government sector. The TOE framework was used to determine the critical factors influencing the adoption of fog computing by public organizations in Saudi Arabia. Therefore, the study has been used in public organizations in general, and not specifically in particular organizations. Therefore, there is a shortage in this study because these factors differ from one organization to another.

Authors in [33] have developed an integrating framework that includes the TAM-TOE-DOI theory to assess the factors that affect the adoption of cloud computing by public universities in India to continue the operations of education when the COVID-19 pandemic occurs; thus, remote learning is becoming a popular option and may be the only way for universities to deal with this predicament. However, the results of this study cannot be generalized because they are limited to Indian public universities.

By scanning scientific papers related to the subject of this study, we found that there is still a lack of adoption and use of fog technology in public organizations. To the best of our knowledge, no study has been conducted thus far that has introduced a study on the adoption of fog computing in higher education in Yemen. It is still in the early stages of definition and exploration owing to the nature and modernity of fog technology and the lack of academic research, especially in Yemen. By investigating previous studies, we noticed that there is no framework for adopting fog computing by institutes of higher education. In particular, they have focused on proposing a framework for adopting fog computing by organizations in general. Thus, there is a need to study and analyze the possible factors provided by Fog Computing. The importance of cloud computing, the Internet of Things, and the variables that affect the adoption of fog computing have been addressed in previous studies. Despite the presentation of fog technology as a supplementary facet of cloud technology, there appears to be a deficiency in scholarly literature that comprehensively analyzes the factors that affect the adoption of fog computing in higher education institutions.

2.2. Success Stories for Fog Computing Technology

Higher education's use of fog computing has enhanced security, energy management, and lighting on smart campuses. Real-time data processing and sharing facilitates research collaboration and simplifies the analysis of large amounts of data from many sources. Fog nodes make up most of the network bandwidth and guarantee that critical applications run correctly. By managing data processing locally at nodes, decreasing student access delays, and improving the online learning experience, fog computing made remote learning possible during the COVID-19 pandemic. Fog computing improves the network capacity and educational processes.

Universities stand to benefit greatly from fog computing's higher efficiency, lower latency, and better user experience.

Berkeley, California University utilized fog computing in building control and energy management, and the University of Texas at Austin for smart lighting and environmental monitoring.

These processes collect IoT device information on the ground, enabling them to be tuned in real time and enhancing campus safety. Moreover, fog computing has been successfully deployed in Nanyang Technological University's smart-campus initiatives.

The application of fog computing to intelligent campuses has been discussed at several universities. Some of the most prominent examples are Nanyang Technological University (NTU), the University of Amsterdam, and the University of California, Berkeley. UC Berkeley used fog computing for smart energy management, which provides real-time monitoring and control of energy usage, resulting in cost savings and reduced carbon emissions. It supports existing building management systems to facilitate the smooth upgrading of existing infrastructure with minimal downtime.

NTU fog computing products are built into campus networks and IoT sensors to lower barriers to change among staff and professors. This yields quicker adoption and decreases the risk of cyberattacks. Having high security as an imperative supports faith between people and technology to a very broad degree in all areas of a campus.

The University of Amsterdam has used fog computing for smart transportation systems to improve traffic and congestion levels within the campus. Real-time infor-

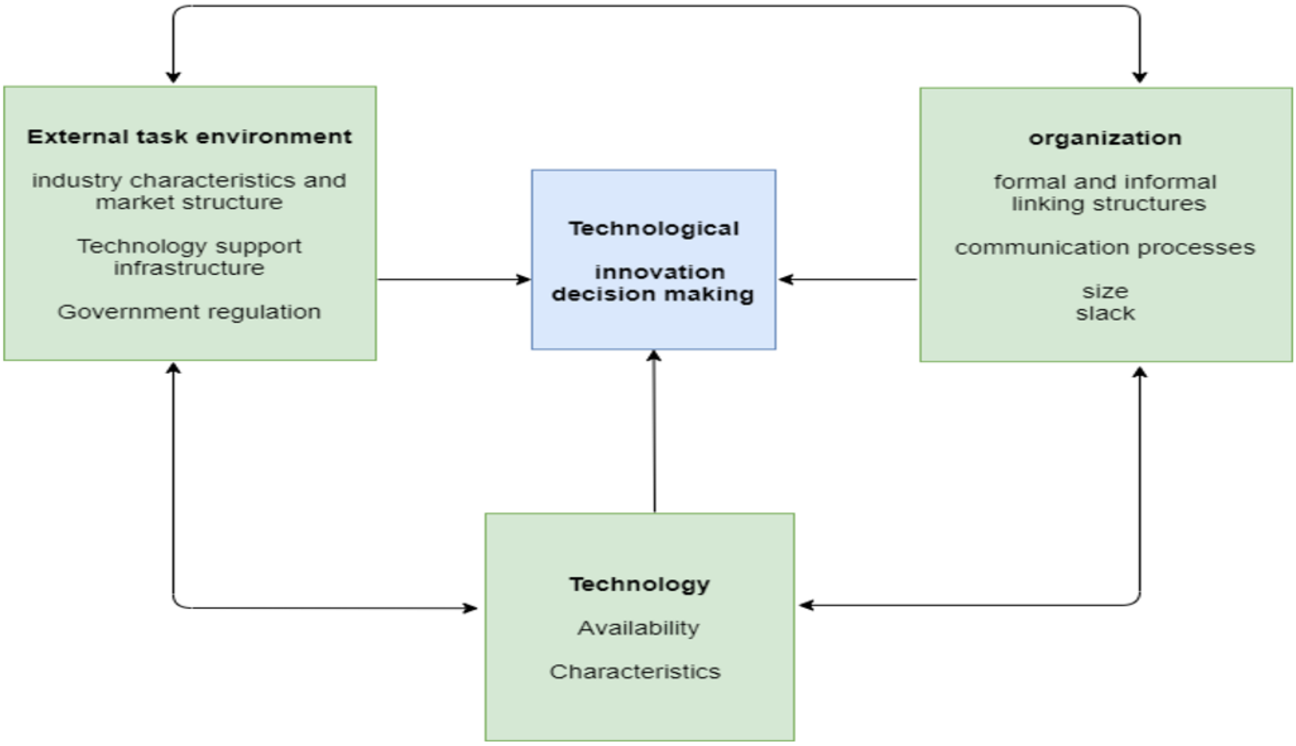

Figure 1. TOE adoption theoretical model [29]

mation and navigation assistance are facilitated through local processing, leading to an improved student experience and usability. All forms of transportation, such as shared bikes and public transport, facilitate the utilization of fog-computing platforms. Additional usage by students and employees is required to ensure backward compatibility with existing platforms [4].

Fog computing is also a part of Hong Kong Polytechnic University's intelligent building management, managing energy consumption patterns, and reducing energy costs. The model is future-proof and upgrading can be performed without replacing the entire system. Information related to building operations is protected by state-of-the-art security systems that provide confidentiality and assurance of technology safety .

In conclusion, fog computing has been proven to have significant benefits in higher education by improving efficiency, reducing costs, and driving innovation. Success stories in these institutions provide a template for other institutions. With relative advantage management, compatibility, and security, universities can realize operational efficiency, reduced costs, and a culture of innovation.

3. THE PROPOSED MODEL & HYPOTHESES

In this paper, we use the Technology, Organization, and Environment (TOE) model [34]. The TOE model is vital for providing researchers with an exhaustive understanding of and perspective on technology adoption. In addition, given the overwhelming interest in Industry 4.0, there is a need for more research in the future. Future research should focus on the adoption of Industry 4.0 technology using various adoption theories that could contribute to the development of innovative technology [34].

3.1. The Proposed Model

Consequently, the proposed model for fog computing adoption enhances the operation of HEIs. In this study, we use TOE theory to test the variables that affect the adoption of fog technology by HEIs. The TOE model was used in this study because it concentrates on examining adoption decisions at the organizational level and does not specify the individual level [35]. Through a literature review, the researchers selected nine iterative factors: security, privacy, top management support, relative advantage, compatibility, competitive pressure, technological readiness, socio-culture, and government regulation.

We investigated different models/theories, independents, and dependents that have been used in previous literature reviews since 2017. Fifty factors were the most frequent in 13 studies on factors that adopted new technology. The factors were extracted from models and theories that have been widely employed by authors and theoretical models established by researchers. By scanning previous research in the field of the adoption of new technologies, we noticed that the TOE model has been widely employed to evaluate the factors that affect the adoption of new technologies. The TOE model

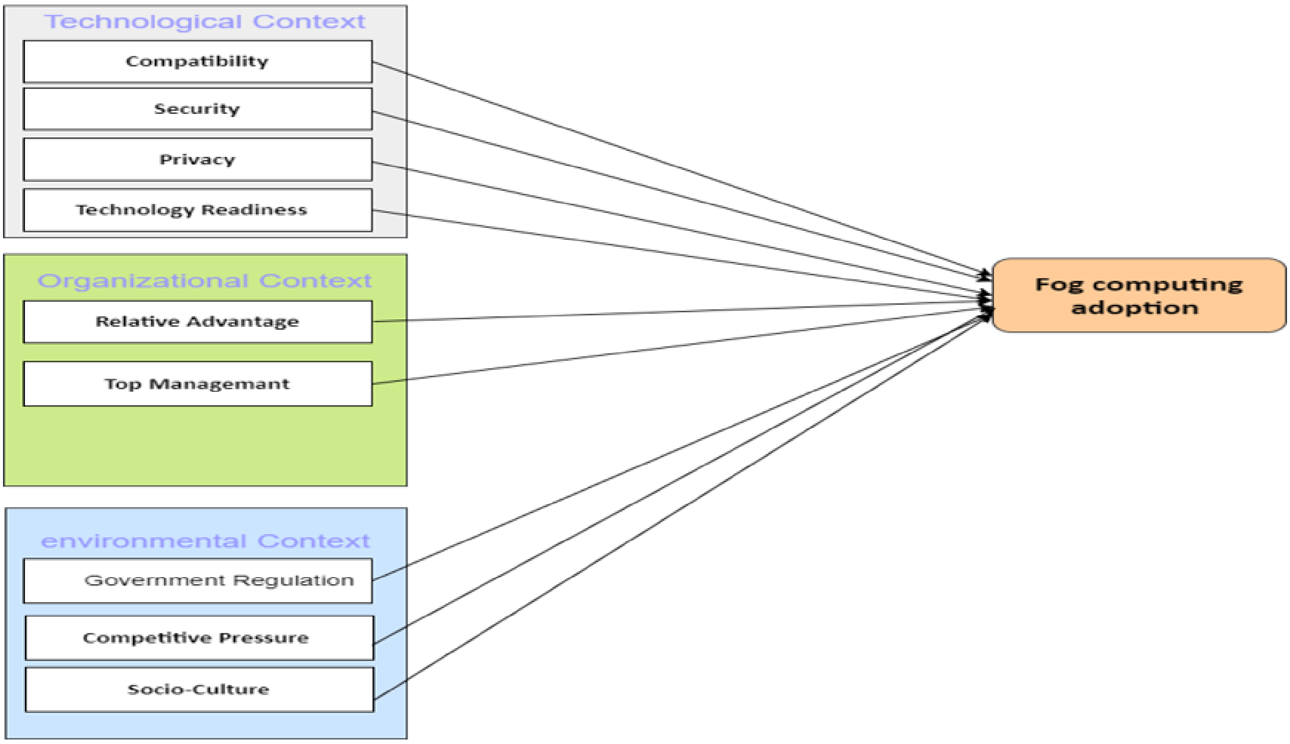

Figure 2. The Proposed Model for Fog Computing Adoption by Higher Education

was developed to examine technological innovation [25]. Therefore, the TOE model is used in this study.

3.2. Research Hypotheses

The research hypotheses and their relationships were investigated in detail, with the employment of the path coefficient. For this reason, the assumptions of this study are as follows:

- **Compatibility**
  It refers to integrating new innovative technology with existing technology or the level to which a new notion is perceived as compatible with the current system. compatibility focuses on the characteristics of a new technology invention that influence potential innovation adopters [8, 36, 37]. By scanning previous studies, this variable was used, as it is an important variable and has a positive effect on adopting new technologies [36–38]. Therefore, in this study, compatibility had a positive effect on the adoption of fog computing. Researchers measured this variable using five elements. The ranking of compatibility was four, with a relative importance score of 31%.
  Hypothesis 1. *Compatibility has a positive effect on fog computing adoption (FCA).*
- **Technology Readiness**
  Technology Readiness refers to the level of technical preparation in an organization with the related environment, IT infrastructure, staff, and ability to use IT. It is important to evaluate the technology readiness of the organization as well as the skills and IT Infrastructure [14, 39]. In this study, technology readiness positively affected the adoption of fog computing. Four items are measured. The rank of this factor was six, with a relative importance score of 31%.
  Hypothesis 2. *Technology Readiness has a positive effect on fog computing adoption (FCA).*
- **Security**
  Security issues should be considered crucial challenges that affect an organization's procedures and operations. When a firm wants to use advanced technology, security is indicated in data centers, media, and service security [2]. According to [40], the security factor has a positive influence and is significant. Thus, in this study, security had a positive effect on the adoption of fog computing. Based on the related literature in this field, fog technology is expected to benefit universities when used in educational operations. Thus, security is suitable for use in our research field. The rink of security was the third highest at 55%. for relative importance.
  Hypothesis 3. *Security has a positive effect on fog computing adoption (FCA).*
- **Privacy**
  Fog computing infrastructure is capable of performing local security surveillance, local threat identification, and local threat mitigation functions on behalf of endpoint devices [41]. Privacy is one of the leading success factors affecting the adoption of advanced technologies [2]. In this study, privacy was represented by three elements in fog computing that preserve the pri-

vacy of data better than cloud computing and reduce data access control. The privacy factor had a relative importance score of 45%, with a fifth ranking.

Hypothesis 4. *Privacy has a positive effect on fog computing adoption (FCA).*

- **Relative Advantage** Relative Advantage means that employees perceive the utility of fog computing in organizations that can improve their performance. Innovative technology will be adopted when it introduces advantages over existing technology [2]. Relative advantage has been widely employed in the context of new computing and has been found to have a positive influence on adoption in many studies; it can be observed that relative advantage is important in other contexts in the literature [42]. In this study, relative advantage (RA) was identified as the most important factor, with a relative significance of 100%. This means that the relative advantage has a significant impact on the adoption of fog technology.

Hypothesis 5. *Relative Advantage has a positive effect on fog computing adoption (FCA).*

- **TOP Management Support**
Top management support refers to the extent to which an organization's leadership advocates the incorporation of innovation within the firm, and this dimension is considered the most critical organizational factor influencing firms' decisions to embrace technology [42]. Previous studies have underscored the importance of top management support in ensuring the availability of essential resources necessary for the adoption of technology or the enhancement of its utilization; conversely, the absence of such support may result in inadequate implementation and diminished intention to adopt [43]. This variable was measured using four elements. Top management support was ranked seventh, with a relative importance score of 23%

Hypothesis 6. *TOP management support has a positive effect on fog computing adoption (FCA).*

- **Competitive Pressure**
It is represented by the intensity of competition, which can increase the possibility of adopting any technological system to achieve the competitive advantage of the firm. and defines the degree of pressure that the firm feels from rivals in the industry [34]. Numerous previous studies, such as those in [8, 30, 40, 44], have indicated that competitive pressure has a significant positive effect on the adoption of new technology. This study assumes that competitive pressure has a significant positive impact on the adoption of fog computing by higher education institutions. The results show that competitive pressure ranked sixth, with a relative importance score of 31%.

Hypothesis 7. *Competitive Pressure has a positive effect on fog computing adoption (FCA).*

- **Government Regulation**
Government regulations represent the policies and rules created in the country. Government regulations vary from country to country. A firm's intention to adopt innovative technology is influenced by government regulations and policies [34]. Many previous studies have offered a positive relationship between government regulation and the intention to adopt fog computing, as in [40]. Therefore, this study assumes that the hypothesis related to government regulation has a significant positive effect on the adoption of fog computing by higher education institutions. The ranking of GR was eighth, with a relative importance of 23 %.

Hypothesis 8. *Government Regulation has a positive effect on fog computing adoption (FCA).*

Socio-Cultural

The users of innovative technology and employees in firms have different social and cultural backgrounds toward innovative technology, which in turn have different opinions about the use and decisions to adopt technology [2]. According to current new technology adoption studies, it was found that socio-cultural influence has a significant effect on the intention to adopt new technology, as it was adopted as a major factor for intention in the study [23].

Hypothesis 9. *Socio-Culture has a positive effect on fog computing adoption (FCA).*

4. STUDY METHODOLOGY

In this study, the researchers chose a quantitative approach. The survey for the current study is designed to address the research hypotheses to develop a conceptual model. Questionnaire surveys were used, especially for data collection. A survey approach was selected for data collection [42]. This study employed a cross-sectional survey that collected raw data at a single point in time to obtain quantitative data [45]. The use of the quantitative approach helps in analyzing the survey data as well as investigating the factors that affect the adoption of modern techniques. The reason for using The survey will allow us to effectively measure the responses of a large sample from many universities in the Capital of Yemen (Sana'a) in a cost-effective and timely manner. Research methodologies can be classified into four categories: descriptive, analytical or explanatory, predictive, and exploratory. Descriptive research is defined as the examination of the relationships among variables, the verification of hypotheses, and the establishment of generalizations, principles, or theories that possess universal validity [42]. Descriptive research seeks to clarify the current situation by validating the assumptions made. It also seeks to profile individuals, events, and circumstances accurately. This study used a combination of exploratory and descriptive methods. The initial phase of exploration encompassed a review of the extant literature and prior investigations as well as the gathering of qualitative data. This exploratory phase additionally served to illuminate the research problem and facilitate the construction of the research model and hypotheses. Conversely, the subsequent phase employed a descriptive method to examine the interconnections between the various factors. Therefore, a descriptive study design seeks to obtain a precise understanding of a certain scenario and investigate the correlation between various independent variables that impact the adoption of fog technology in education institutions.

4.1. Data Collection

In this study, data analysis was conducted in two phases. Using SPSS version 27, a descriptive statistical analysis was initially employed to examine the data collected for this study. The hypotheses were then investigated using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4.0. PLS-SEM is a variance-based linear model that enables the simultaneous exploration of structural and measurement models and does not require data normality [46]. The researchers deduced that the hybrid SEM-ANN approach was the most effective strategy for the analytical examination of the data. This decision was made because it allowed for the examination of hypotheses and enhanced the identification of both linear and nonlinear relationships among the factors under investigation. The data were collected between January and March 2024. A total of 123 surveys were disseminated as integral components of the data collection procedure, which transpired between January and March 2024. The surveys were administered both in paper format and electronically through Google Forms, selected because of their prominence as a widely recognized, user-friendly mobile application equipped with numerous advantageous features. Of these, 103 responded to the questionnaire. Three completed surveys were rejected because of incomplete or illegible answers. The research factors must be measured to examine the research hypotheses. A Likert scale with five points was used to measure these factors.

4.2. Instrument Design

To ensure the highest possible response rate, the researchers prepared questionnaires in both Arabic and English. Six esteemed experts, including a professor and an associate professor from Sana'a University, along with one external expert validated the questionnaire. This step was performed to authenticate the appropriateness, accuracy, and comprehensibility of the questionnaire elements. This panel consists of two authorities in information technology, two in information systems, and two in computer science. The survey is divided into five sections as follows: the initial segment serves as a cover letter form for respondents to indicate their willingness to complete the questionnaire items, and it provides relevant information about the study itself as well as the researcher. The second part explores a comprehensive outline of fog computing technology. In the third section, the demographic data of the respondents were collected, including gender, age, education, position, and years of experience. The fourth section focuses on exploring various aspects of the study that influence the adoption of fog technology within HEIs. The remaining text centers on fog computing adoption.

4.3. Population and Sampling

The population was the research community from which the findings of the study were collected by distributing the research instruments. The target population for the current study includes lecturers and technical staff in faculties of computer science and information technology, as well as top management of universities and faculties responsible for enhancing the operations of education and presenting the strategies of institutes of higher education who are knowledgeable about fog technology and how to enhance the performance of university learning and research in Sana'a, Yemen, which consists of nine universities.

5. RESULTS STUDY AND EVALUATION

5.1. Personal/demographic information

Table 1 illustrates the demographic and personal data of the participants gathered for this study. The study found that among the 66 participants, 66.0% were male, while the remaining 34.0%, equivalent to 34 individuals, were female. The analysis of the age distribution revealed that the smallest proportion of respondents, comprising 24 individuals or 24% of the total sample, fell below the age of 25. In addition, 26–35 years and 36 or more were the same respondents (38 or 38% of the total sample for each group). The dissemination of qualifications among participants was delineated through educational frequency analysis, comprising the largest proportion of respondents; 44.0% of the participants held a bachelor's degree, totaling 44 individuals. Following this, a Master's degree was the second most prevalent educational attainment among respondents (32 individuals, 32.0% of the overall sample). Conversely, 22 individuals possessed PhDs, constituting 22.0% of all participants. The Diploma education category, encompassing 2 respondents (2.0% of the total sample), represented the least addressed group. The fourth demographic variable delineated the respondents' years of experience. They show that 46.0% of the respondents had more than 10 years of experience, 36.0% had 4 years or less, and 18.0% had 5-10 years. Of the participants, 46.0% were over

Table 1. Demographic data of the respondents

Gender	Frequency	Percent
Male	66	66.0%
Female	34	34.0%
Total	100	100.0%
Age	Frequency	Percent
25 years old or less	24	24%
26 years- 35 years	38	38%
36 or more	39	38%
Total	100	100%
Qualification	Frequency	Percent
Diploma	2	2.0%
Bachelor	44	44.0%
Master	32	32.0 %
PhD	22	22.0%
Total	100	100.0%
Experience	Frequency	Percent
4 years or less	36	36.0%
5-10 years	18	18.0%
more than 10 years	46	46.0%
Position	Frequency	Percent
Dean	3	3.0%
Department's Chief	13	13.0%
lecturer	49	49.0%
IT Manager	7	7.0%
IT staff	16	16.0%
Others	12	12.0%
Total	100	100.0%

10 years old, which is considered the largest proportion of respondents. The analysis of the position distribution revealed that the largest proportion of respondents were lecturers, totaling 49 individuals, accounting for 49.0% of all respondents. Subsequently, IT staff members constituted 16 respondents (16.0% of the total). Furthermore, there were 13 Department Chief participants, constituting 13.0% of the total respondents. Twelve respondents (12.0%) represented Others. Additionally, the IT manager group consisted of seven respondents, amounting to 7.0% of the total. Lastly, Dean was part of the final group, with three respondents representing 3.0% of all respondents.

5.2. Measurement Model Assessment

The Measurement Model frequently depicts the relationship between latent and observed variables (items) as a metric [47]. The assessment of the research model in this investigation involved the application of PLS-SEM. Within the SmartPLS program, an analysis was conducted on factors such as internal consistency (Table 2). Cronbach's alpha, ranging from reliability of indicators, convergent validity, and discriminant validity (e.g., Cross Loading Criterion, Fornell and Larcker's Criterion, and Heterotrait-Monotrait Ratio of Correlation HTMT), all aimed at estimating the dependability and accuracy of the measurement model. Research indicates that the convergent reliability is considered adequate when the AVE value reaches 0.5 or higher. An examination of Table 2 shows that the AVE values extended from 0.526 to 0.729, surpassing the suggested threshold.

- **Indicator Reliability**
  The concept of "indicator reliability is commonly used to characterize the size of external loading. The loadings for indicator reliability must exceed 0.7, 0.6, and 0.5, as indicated in [48]. As shown by the findings of the measurement model in Table 2, all factor loadings are significant, with values varying from 0.511 to 0.889. Nevertheless, the loading of P3 related to the privacy factor was 0.387. Similarly, the loading of the RA5 element associated with the relative advantage factor was 0.462 and the loading of the S2 element associated with the security variable was 0.356. Furthermore, the loading values of the AFC4 and AFC5 elements for the adoption of fog computing were 0.478 and 0.394, respectively. These values were below the predefined threshold of 0.5 Consequently, suggesting that these items could be excluded from the analysis owing to their insufficient external loading and mirroring methodologies applied in previous research studies [48].
- **Convergent Reliability**
  Convergent reliability illustrates the similarity among multiple items and quantifies the extent of such similarity. The significance of convergent validity in evaluating the validity of the measurement model was established following a previous investigation [49]. The evaluation of convergent validity involves the use of AVE values [50]. The research indicates that convergent reliability is considered adequate when the AVE value reaches 0.5 or more. An examination of Table 2 shows that the AVE values extended from 0.526 to 0.729, surpassing the suggested threshold. Consequently, it can be inferred from these results that convergent reliability was satisfactory.
- **Internal Consistency Reliability**
  that the internal consistency and reliability of these factors are sufficient for their inclusion in the analysis [42]. Internal consistency reliability was confirmed through the measures of composite reliability and Cronbach's alpha. The values of Cronbach's alpha, presented in Table 2, ranged from 0.668 to 0.876, all exceeding the minimum threshold of 0.6. Additionally, all composite reliability values, which varied between 0.804 and 0.915, exceeded the specified threshold. The research conducted in [51] demonstrated that the composite reliability and Cronbach's alpha scale are bounded between 0 and 1, with higher values indicating greater reliability. The fact that every factor is above the rate of 0.06 indicates

Table 2. Measurement Model Results

Factors	Items	Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Compatibility	CB1	0.814	0.819	0.873	0.580
	CB2	0.647			
	CB3	0.784			
	CB4	0.831			
	CB5	0.719			
Technology readiness	TR1	0.788	0.731	0.821	0.538
	TR2	0.765			
	TR3	0.764			
	TR4	0.601			
Security	S1	0.700	0.682	0.804	0.511
	S3	0.829			
	S4	0.744			
	S5	0.560			
Privacy	P1	0.688	0.842	0.808	0.587
	P2	0.708			
	P4	0.887			
Relative advantage	RA1	0.829	0.876	0.915	0.729
	RA2	0.889			
	RA3	0.872			
	RA4	0.825			
TOP management support	TMS1	0.670	0.743	0.833	0.556
	TMS2	0.771			
	TMS3	0.809			
	TMS4	0.725			
Competitive Pressure	CP1	0.766	0.769	0.850	0.586
	CP2	0.798			
	CP3	0.765			
	CP4	0.732			
Government regulation	GR1	0.866	0.842	0.893	0.679
	GR2	0.885			
	GR3	0.874			
	GR4	0.649			
Socio-Cultural	SC1	0.740	0.704	0.817	0.530
	SC2	0.584			
	SC3	0.778			
	SC4	0.792			
Adoption of Fog Computing	AFC1	0.792	0.668	0.817	0.598
	AFC2	0.804			
	AFC3	0.720			

- **Discriminant Validity**
  The extent to which a construct diverges from the empirical criteria of the other constructs is delineated as discriminant validity [52]. Discriminant validity investigates the variance in magnitude among items that exhibit overlap [42]. To measure discriminant validity, the measurement model should be evaluated using the following methods: first, the cross-loading criterion, Fornell and Larcker's criterion, and heterotrait-monotrait ratio of correlation HTMT utilizing the PLS-SEM model [50]. According to this criterion, the indicator loadings on the assigned latent variable should be larger than those on all other latent variables in the model [42]. The difference in loadings across latent variables must be greater than 0.1, according to the other conditions.

The Fornell-Larcker criterion computes the square root of the AVE values with the connections of the latent variable [47], as shown in Table 3, which demonstrates that the square root of each construct's AVE was greater than the correlation of the construct with other latent variables.

Table 3. Fornell and Larcker's Criterion

	AFC	CB	CP	GR	P	RA	S	SC	TMS	TR
AFC	**0.767**									
CB	0.495	**0.762**								
CP	0.473	0.396	**0.764**							
GR	0.517	0.341	0.594	**0.823**						
P	0.295	0.354	0.392	0.356	**0.760**					
RA	0.270	0.284	0.364	0.299	0.253	**0.762**				
S	0.561	0.596	0.458	0.390	0.397	0.356	**0.710**			
SC	0.481	0.423	0.545	0.446	0.252	0.272	0.339	**0.728**		
TMS	0.374	0.380	0.648	0.532	0.275	0.313	0.488	0.476	**0.746**	
TR	0.298	0.485		0.395	0.324	0.218	0.417	0.527	0.548	**0.733**

The heterotrait–monotrait ratio of correlation (HTMT) is the third and most reliable approach for determining discriminant validity. The Heterotrait-Monotrait ratio (HTMT) was calculated to verify discriminant validity [47]. HTMT was proposed by Henseler and his research team in 2015 [53] as a replacement method for the Fornell-Larcker criterion [54]. It has been shown that the Fornell-Larcker method is not always correct, especially when the loadings on various constructs vary slightly varied [53]. The value of HTMT should not exceed 0.9 [47, 53]. Table 4 presents the findings associated with the HTMT ratios. As illustrated, all constructs in exhibited values that remained below the established threshold of 0.85 [53].

5.3. Structural Model Assessment

Assessment of the structural model is the second phase of the analysis process that should be conducted. The structural model was subsequently evaluated using the path coefficient (beta), t-values, coefficient of determination (R Square), and effect sizes (square) through the implementation of a bootstrapping technique consisting of 5000 resamples. This procedure was conducted to empirically test the hypotheses regarding the associations between the observed and latent variables. Consequently, the entirety of the hypotheses was scrutinized utilizing the SEM (Structural Equation Modeling (SEM)). Figure 3 presents a conceptual model in which each hypothesized correlation is assessed within the scope of the analysis.

The outcomes obtained from the hypothesis testing analysis in this study are summarized in Table 5 and Figure 3. The findings indicate that the proposed model explains 0.449 of the variance in the adoption of fog technology in higher education. In addition, the current study found that fog computing adoption in higher education is significantly and positively affected by all the factors that affect the adoption of fog technology. Accordingly, all these hypotheses were supported (H1, H2, H3, H4, H5, H6, H7, H8, and H9). The coefficient of determination (R Square), which is measured as the square correlation between the specific and predictive values of a given endogenous construct, is a measure of the model's predictive capacity; the higher the R square (R2) value, the more accurate the prediction [46]. When the coefficients of determination, denoted as R2, exceed 0.67 are regarded as indicative of a strong correlation; conversely, coefficients that fall within the range of 0.67 to 0.33 are characterized as moderate, while those that lie between 0.33 and 0.19 are deemed weak. Furthermore, R2 values below 0.19 are considered unacceptable [47]. The results of this study showed that the R2 value was 0.499, which falls under moderate predictive accuracy. Table 5 presents the effect size values. According to Cohen [55], the effect size is interpreted, in which a value between 0.02 and 0.15 is considered small, 0.15 to 0.35 is medium, and above 0.35 represents a large effect size. On the other hand, values less than 0.02 indicate NO effect size.

6. ANN RESULTS

The current study includes the use of SPSS 27 software to assess a model employing the ANN multilayer perceptron network [56], and the inputs of the ANN technique are only the output predictors from PLS-SEM that confirm a significant impact in the model [57]; that is, the analysis only accounts for CB, CP, GR, P, RA, S, SC, TMS, and TR. The structure of the ANN model is shown in Fig.4, which has one output neuron (adoption fog computing) along with multiple input neurons (CB, CP, GR, P, RA, S, SC, TMS, and TR) that constitute the ANN model.

6.1. Sensitivity Analysis

The analysis of sensitivity, which separates the significance of each input through the optimal relative importance, has been employed to determine acknowledged significance in the specification of percentages to analyze the contribution of each predictor to the uptake of fog computing in higher education [32, 33, 47]. Using

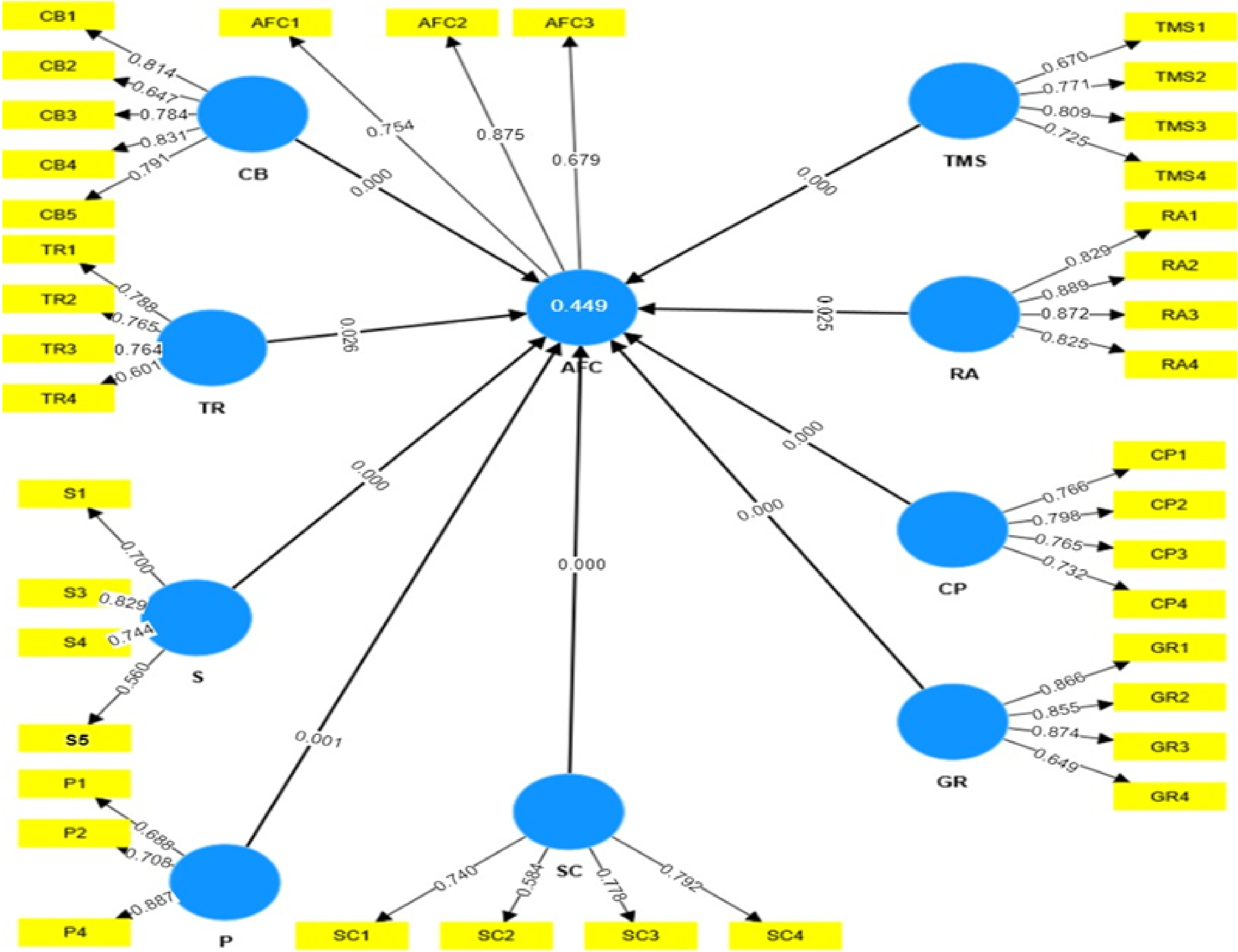

Figure 3. Proposed Model Results

Table 4. Heterotrait-Monotrait (HTMT) Ratio

Factor	AFC	CB	CP	GR	P	RA	S	SC	TMS	TR
AFC										
CB	0.632									
CP	0.547	0.476								
GR	0.570	0.412	0.708							
P	0.442	0.547	0.724	0.601						
RA	0.361	0.323	0.429	0.346	0.356					
S	0.722	0.758	0.644	0.517	0.800	0.420				
SC	0.635	0.556	0.737	0.611	0.537	0.354	0.587			
TMS	0.445	0.481	0.840	0.644	0.710	0.382	0.725	0.665		
TR	0.385	0.652	0.561	0.473	0.620	0.302	0.730	0.712	0.699	

the findings of the investigation performed on the model employing sensitivity analysis in Table 6, it is clear that relative advantage (RA) has been identified as the most significant factor that correlates with the integration of fog technology within higher education institutions, with a relative significance noted at 100%. This means that relative advantage (RA) has a significant effect on the adoption of fog computing. Socioculture (SC) is the second factor that has a high impact on the adoption of fog computing, with a relative importance score of 64.88%. The third most important factor was security, which had a relative importance score of 55%. The importance of security is followed by compatibility (CB) and privacy (P), with 49% and 44% importance, respectively. Moreover, the findings demonstrate that competitive pressure (CP) and technology readiness (TR) are in the same ranking,

Table 5. Hypothesis Testing Results

Hypothesis	Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Value	F2	Decision
H1	CB -> AFC	0.490	0.505	0.093	5.257	0.000	0.316	Supported ***
H2	TR -> AFC	0.301	0.348	0.136	2.221	0.026	0.100	Supported **
H3	S -> AFC	0.528	0.534	0.108	4.910	0.000	0.387	Supported ***
H4	P -> AFC	0.428	0.465	0.123	3.476	0.001	0.155	Supported ***
H5	TMS -> AFC	0.380	0.419	0.078	4.901	0.000	0.169	Supported ***
H6	RA -> AFC	0.317	0.367	0.142	2.242	0.025	0.101	Supported ***
H7	CP -> AFC	0.497	0.517	0.074	6.682	0.000	0.328	Supported ***
H8	GR -> AFC	0.556	0.575	0.058	9.645	0.000	0.448	Supported ***
H9	SC -> AFC	0.482	0.501	0.069	6.957	0.000	0.303	Supported ***

Note: Significant at P-Values ***= < 0.001, P-Values ** <0.05, P P-Values ** 0.10.

with a score of 31% relative importance. Finally, government regulation (GR) and top management support (TMS) have 23% and 29%, respectively.

7. GENERAL DISCUSSION

This study uses a multi-analytical approach that initially employs PLS-SEM to investigate the overall research model and test the hypotheses. Based on the outcomes of SEM, significant factors were chosen as inputs to the ANN technique for a more accurate prediction of factors. PLS-SEM handles complex models with ease and does not have suspicions about information circulation (i.e., it accepts that the information is non-regularly dispersed), and to deal efficiently with exploratory studies that involve complex models, researchers employ PLS-SEM [58].

Researchers have suggested that PLS-SEM, instead of CB-SEM, is highly accurate in identifying the full authentic model [46]. PLS-SEM evaluations focus on the inner model (structural model) and outer model [59]. The structural model examines the significant relationships between the factors, and the outer model evaluates the discriminant and convergent validity [46, 60]. The ANN technique was employed to obtain highly accurate results. It has become necessary to utilize an Artificial Neural Network (ANN) approach to identify linear and nonlinear relationships. Moreover, studies have demonstrated that methodologies utilizing artificial neural networks (ANN) yield favorable results. They offer enhanced accuracy compared to structural equation modeling (SEM) or multiple regression techniques. Therefore, using hybrid PLS-SEM-ANN analysis complements each other [60–62]. To achieve this purpose, the researchers first used PLS-SEM to measure how independent variables affected the dependent variable, while in phase two, ANN analysis was used to examine the relative importance of the significant determinants towards endogenous variables [60, 63]. Thus, the study's findings exhibit a variable of relative advantage that comes in the first rank with a high value (100%), indicating the adoption of fog computing, which effectively enhances the university's learning and research. Socioculture had the second-highest impact on the adoption of fog computing, with a relative importance score of 64.88%. The third most important factor was security, which had a relative importance score of 55%. followed by compatibility (49%), privacy (44%), competitive pressure, and technology readiness are in the same ranking, with a score of 31% relative importance. Finally, government regulations and top management support accounted for 23% and 29%, respectively. Hypothesis 1 was supported because it was statistically significant and had an Std. Beta=0.490, T-Values = 5.257, P-Values= 0.000. The results of this study confirm that compatibility has a significant positive effect on the adoption of fog computing by higher education institutions in Yemen, Therefore, decision-makers and providers of fog technology must strive to develop fog applications capable of working in all circumstances and suitable for higher education institutions' operations in Yemen. The result of Hypothesis 1 is positive, which is also supported by the literature review. The results in [2] and [40] support our approach for Hypothesis 1. However, while the impact in [2] is classified as "Positive" influence, the influence in [40] is classified as "Increase" the attention of fog

Table 6. Sensitivity analysis for the model.

Neural Networks	CB	CP	GR	P	RA	S	SC	TMS	TR
1	30.3	13.5	5.2	78.6	100	24	21.8	37.5	17.7
2	37.6	9.8	10.1	22.7	98.2	30.7	100	16.9	53.60
3	71.5	53.6	16.1	77.8	100	54.3	39.7	18.2	35.7
4	24.4	44.5	56.6	6.7	100	38.1	45.6	30	27.9
5	80.5	100	18.9	49.2	71.3	98.3	87.3	87.9	57.5
6	66.7	15.7	20.9	16.9	100	68.5	93.9	5.4	39.8
7	43.3	20.9	5.5	41.5	99.4	41.3	100	33.3	22.6
8	28.9	14.2	60.3	28.5	93.4	100	55.5	8.7	9.6
9	53.4	8.4	24.6	35.3	100	51.5	83.2	4.8	17.7
10	30.3	13.5	5.2	78.6	100	24	21.8	37.5	15.9
Mean importance	46.69	29.41	22.34	43.58	96.23	53.07	64.88	28.02	29.8
Normalize importance (%)	49%	31%	23%	45%	100%	55%	67%	29%	31%
Ranking	4	6	8	5	1	3	2	7	6

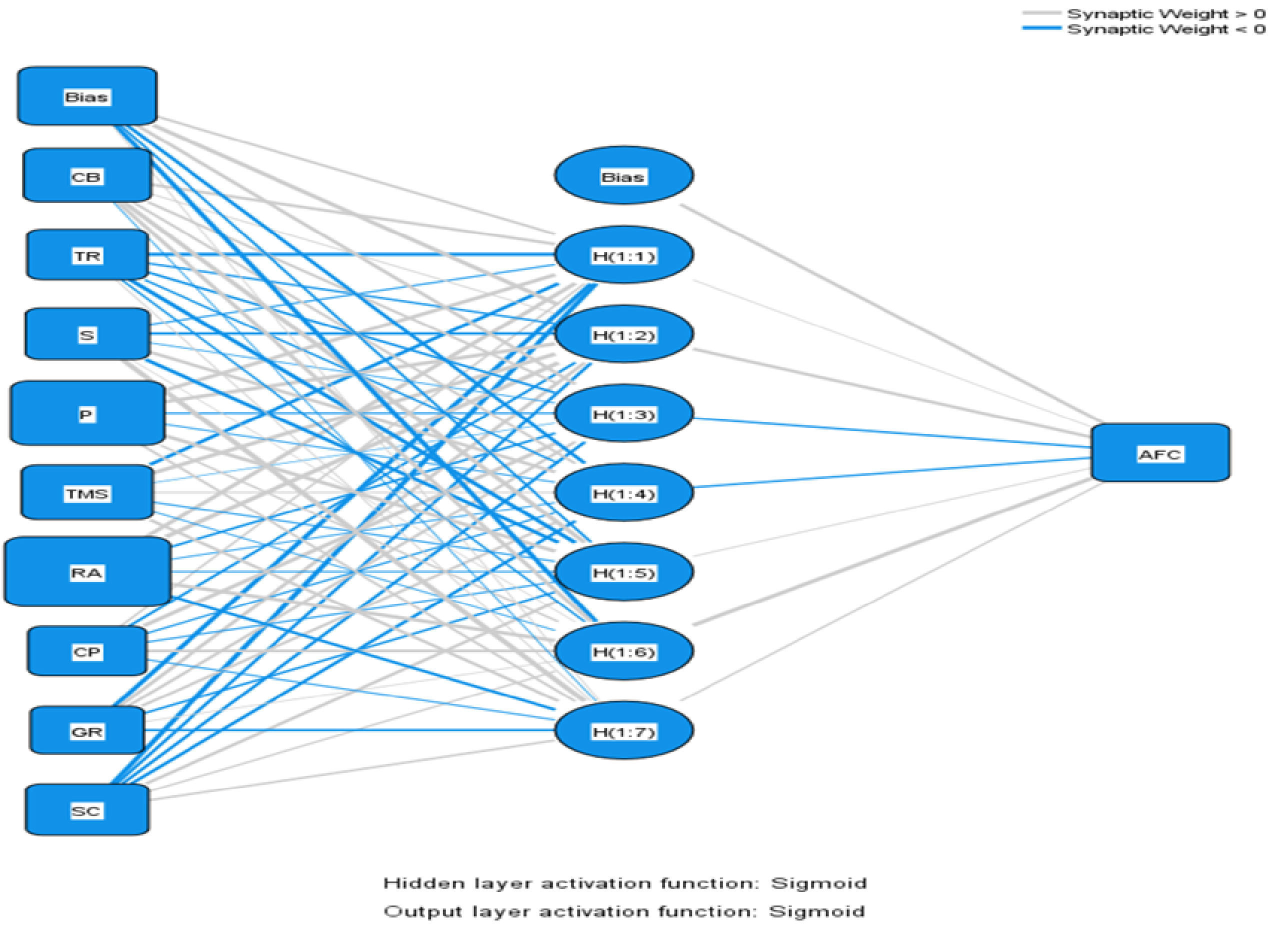

Figure 4. ANN model

technology adoption.

Hypothesis 2 was supported by the fact that Std. Beta = 0.301, T-Values = 2.221, P-Values = 0.026, which was statistically significant. This outcome confirms that Technology Readiness has a significant positive effect on the adoption of fog computing in HEIs. Decision makers at universities should prepare equipment to conform to modern education in order to move with the world to the fourth industrial revolution. The result of Hypothesis 2 is positive, which is also supported by the literature review. The results in [40] support our approach for Hypothesis 2. However, the influence in [40] is classified as “Increase” the attention of fog technology adoption.

Hypothesis 3 is supported because it is statistically significant and has a Std. Beta= 0.528, T-Values= 4.910, P-Values. This finding confirms that security has a significantly positive impact on the adoption of fog computing by higher education institutions in Yemen. The security factor is considered an obstacle for adopting cloud technology, and it is an important factor in the analysis of the factors that impact cloud adoption [2]. The greater the trust in fog technology, the greater the positive intention to use electronic education. Therefore, fog technology service providers should concentrate on security in fog services as an important factor. The security factor is important for any technology; thus, security is a critical point that should be considered. When fog technology is highly secure, the operations of higher education institutions can be sustainable for a very long time.

The result of Hypothesis 3 is positive, which is also supported by the literature review. The results in [2] and [40] support our approach for Hypothesis 3. However, while the impact in [2] is classified as “Positive” influence, the influence in [40] is classified as “Increase” the attention of fog technology adoption.

Hypothesis 4 is supported because it is statistically significant and has a Std. Beta= 0.428, T-Values = 3.476, p = 0.001. This outcome confirms that privacy has a significantly positive impact on the intention to adopt fog technology in HEIs. Given the important role of privacy, not only in motivating students to adopt fog computing, but also in the management work perception of this technology as a more productive and secure technology. The greater the privacy that saves information, the more positive the intention to adopt fog services at universities. Therefore, fog service providers consider local storage and analysis to save more privacy than cloud computing.

The result of Hypothesis 4 is positive, which is not completely supported by the literature review. While the result of influence in [40] supports the same result as our approach because the influence is classified as “Increase” the attention of fog technology adoption, the results in [2] do not support the same result as our approach for hypothesis 4 because the result of influence is “Negative.” This may be justified because this hypothesis is affected by the lack of awareness in Yemeni HEIs about the relationship between fog technology and privacy.

Hypothesis 5 was supported, because it had a Std. Beta= 0.490, T-Values= 5.257, P-Values = 0.000. Therefore, we can conclude that the relative advantage has a significant positive effect on the adoption of fog computing to enhance the operations of HEIs. Decision-makers of higher education institutions should focus on adopting and developing fog technology that is capable of improving the performance of operations in higher education institutions in Yemen. The result of Hypothesis 5 is positive, which is also supported by the literature review. The results in [2] support our approach for Hypothesis 5. The influence in [2] is classified as “Positive.”

Hypothesis 6 is supported because it is statistically significant and has a Std. Beta = 0.380, T-Values = 4.901, P-Values 0.000. The results of this study confirm that top management support has a significant positive effect on the adoption of fog computing by higher education institutions in Yemen. Top management support is still scarce, especially in some universities, when compared to foreign universities. The result of Hypothesis 6 is positive, which is also supported by the literature review. The results in [40] support the same result as our approach for hypothesis 6. However, the influence in [40] is classified as “Increase” the attention of fog technology adoption.

Hypothesis 7 is supported because it is statistically significant and has a Std. Beta= 0.556, T-Values = 9.645, P-Values = 0.000. The P-value was less than the 5% significance threshold. This finding confirms that Regulatory Policy has a significant positive impact on the adoption of fog computing by education institutions in Yemen. Therefore, government regulations should be strategic policies and should activate all regulations to protect users from violations and encourage fog service providers to present their services in Yemen.

The result of Hypothesis 7 is positive, which is also supported by the literature review. The results in [40] support the same result as our approach for Hypothesis 7. However, the influence in [40] is classified as “Increase” the attention of fog technology adoption.

Hypothesis 8 is supported because of the presence of Std. Beta = 0.497, T-Values = 6.682, p = 0.000 was statistically significant. In other words, the null hypothesis was rejected. Thus, Competitive Pressure has a significantly positive effect on the adoption of fog computing.

The result of Hypothesis 8 is positive, which is also supported by the literature review. The results in [40] support the same result as our approach for hypothesis 8. However, the influence in [40] is classified as “Increase” the attention of fog technology adoption.

Hypothesis 9 is supported because Std. Beta = 0.482, T-values = 6.957, P-Values =0.000, and was statistically significant. These results indicate that sociocultural influence has a significant impact on the adoption of fog technology by HEIs. This indicates that Yemeni academics intend to adopt and use fog computing services, and there is interest in the recommendations and attitudes of the surrounding social environment, for example, students, professors, colleagues, and managers of information technology at universities. The surrounding social environment positively affects the intention to adopt such techniques.

The result for Hypothesis 9 is positive, which is not supported by the literature review. Results in [2] do not support the same result as our approach for hypothesis 9 because the result of influence is “Negative.” This may be justified because this hypothesis is affected by the lack of awareness in Yemeni HEIs about the impact of fog technology on social culture.

8. CONCLUSION

This study examined the factors influencing the adoption of fog computing among higher education institutions. This case study was conducted at Yemeni University. The findings of the current study will be of significant importance to top management and principal decision makers at higher education institutions. It presents a proactive perception of the crucial factors affecting fog computing adoption, thereby facilitating more efficient adoption of fog computing systems. Furthermore, the results of this study provide valuable insights into the appropriateness of fog computing within the higher education sector. The researcher proposes a model for adopting fog computing in higher education institutions. The proposed model is based on TOE theory, which is the most widely used model. This study investigates nine factors (Compatibility, Technology readiness, Security, Privacy, Relative advantage, TOP management support, Competitive Pressure, Government regulation, and sociocultural) using a quantitative method through questionnaires to collect information. The findings showed that there was a significant effect on all factors.

Research Contributions:

The current study contributes to the body of knowledge by providing a complete understanding of the factors that impact the adoption of fog technology by higher education institutions. This study employs a hybrid approach to develop a conceptual model to examine the factors that may affect the adoption of fog computing, as well as the intention of institutions to adopt fog technology. Despite extensive studies conducted in recent years on fog technology, no study has examined the factors influencing intention to adopt fog technology for educational purposes. Thus, the findings of this study offer new insights into the factors that encourage the adoption of fog computing by higher education institutions for learning activities. The current findings are useful for decision makers and researchers interested in fog technology.

Recommendations:

Based on the outcomes of this study, there are some recommendations for governments regarding the adoption of fog computing. The recommendations are as follows:

- Governments should develop strategies to adopt fog technology services in higher edu-cation institutions.
- Governments should develop strategies to activate and increase government regulations and laws of modern technology to enhance users' confidence in the use of this technol-ogy.
- Develop a strategy to increase awareness of modern technology for lecturers, staff, and students to increase their knowledge and gain more experience through training cours-es, workshops, conferences, and books.
- In collaboration with the Ministry of Educa-tion and Scientific Research, the Ministry of Communications and Information Technol-ogy extends the range of the intranet with active fourth- and fifth-generation services across all borders of countries.

Future work:

- The main objective of this study is to identi-fy and analyze the variables that affect the adoption of fog technology within HEIs. This provides an opportunity for additional researchers to conduct the study in different sectors and compare the findings with those of their own.
- For this study, a total of 100 participants completed the questionnaire. Larger samples from a greater variety of universities could be used in future studies.
- In the future, a comparative study can be conducted between a university that uses fog technology and another that does not to understand the value of fog computing in reality.
- While the current study employed question-naire methods to collect data and used a hy-brid SEM-ANN method to analyze the data, future researchers could conduct experi-ments with different approaches.

Moderating factors such as gender, education level, and level of experience were not examined to identify whether the independent factors impacted the adoption of fog technology in higher education. Future studies on moderating factors may yield more compelling results since there is a lack of knowledge about their influence.

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