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DISCOVERING CONSUMER INTENTIONS TOWARD THE ADOPTION OF CLOUD COMPUTING IN HIGHER EDUCATION INSTITUTIONS IN KUWAIT

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ABSTRACT: *Cloud computing has grown immensely over the past few years in the Information Technology field. Optimism for supplier of cloud service and the possible risks associated with privacy and security of users is essential factors for implementation of successful and suitable cloud. Therefore, the main challenge of cloud computing is it's perceptual and approaches. This research focuses on Technology Acceptance Model (TAM), which mixes Anxiety, Optimism and Risk, to study student's attitude and behavior toward the implementation of cloud service. The planned model was studied using the Structure Equation Model (SEM) to examine data collected by a survey of both IT experts and users. The analysis showed that three variables of Optimism, Innovativeness and perceived risk can be positively combined within the Technology Acceptance Model (TAM). Innovativeness were suggested to have significant positive influence on the Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). On the other hand, Optimism has positive impact on the PEOU, but had no influence on PU. Moreover, Behavioral Intention is predictable by Optimism, attitude and PU. Students behavior and intentions is explainable through PR, Optimism, and Innovativeness in the projected model in Kuwait.*

KEYWORDS: Optimism, *Innovativeness*, Cloud Computing Service, Technology Acceptance, Risk, Student's Behavior, Kuwait.

INTRODUCTION

According to Marinescu (2013), cloud-computing service is a developing technology and has dominated the digital setting, and cloud service provides the huge amount of storage and processing cycles required by many applications. Cloud storage is file services that lets users to sync files and advanced approach them from a web browser or self phone device. The cloud computing storage services are like Apple iCloud and Amazon Cloud Drive are used and have become common in today life style (Moryson & Moeser, 2015). The growth of technology has been so rapid in last few years, which lead to increases in capital investment in this field. In addition, the cloud hype which recently merged a top in terms of its opportunities generally explains the consumer's perception of cloud computing (Buyya et al., 2009b). On the other hand, migration from internal data focuses on clouds includes clear tradeoffs (Khajeh Hosseini et al., 2010). The migration provides many chances to manage salaries and productivity while advancing management, satisfaction, and organizational growth (Khajeh-Hosseini et al., 2010). Equally it shows a hazard to the quality of users care and support as well as potentials to the reducing of IT departments.

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According to Khajeh-Hosseini et al., (2010) cloud service includes outsourcing serious processes and migrating serious data for third-party organizations. Optimism for cloud computing service suppliers and potential risks, such as security and privacy matters are essential for the success of implementation of cloud service. Many researches have suggested that the biggest challenge of cloud computing service is its perceptual or behavior aspects not necessary the technological aspects. As a result, this study objective is to examine consumer's behavior and intention toward cloud service computing atmospheres, with focusing on the perceived risks, Optimism and anxiety, to expand the factors impacting the acceptance of cloud services in Kuwait. In addition, these factors will be analyzed by implementing a planned conceptual model that is based on the Technology Acceptance Model (TAM) while the three factors of Optimism, Innovativeness and perceived risk will be merged. The objective of this research is to cover the attitude and behavior towards cloud computing such as Optimism and the investigation will involve the observations of IT experts and customer users.

The objective of this study is to acknowledge the implementation behavior of cloud service computing more specifically the consumer's intention toward cloud technology and its services. This research will focus on the role of perceived risks, Optimism and Innovativeness in the implementation of cloud service. In addition, it will shows whether the TAM is a strong model based on the way in which consumers attitude and behavior can be showed in the framework of cloud computing. The paper is organized as follows: in section 2, we will discuss academic background in order to present the way in which cloud computing and the TAM appeared and have advanced. Section 3 will shows the research development hypothesis and section 4 shows the empirical study by identifying the research approaches, result analysis. Section 5 will show discussions, which wills shows the result limitation and recommendation for future research and section 6 will show the conclusions.

LITERATURE REVIEW

Cloud Computing Service

Cloud computing provides a new model that assist the pay-for-use and IT services over Internet. According to K. Hwang *et al*., (2010), the Internet cloud machineries are a service workshop that made around virtualized data insides. Cloud computing services are vigorously made through virtualization with running hardware, software, networks, and datasets (K. Hwang *et al*., 2009). According to Marston *et al* (2011), the cloud computing reveals the convergent growth of two developing and crucial business tendencies: IT effectiveness and business quickness. The earlier refers to the operation of computing resources in a well-organized and accessible manner, while the recent signifies the use of IT as a competitive advantage to respond rapidly to market modifications in order to ensure fast growth and initiative flexibility.

Cloud computing is an IT service that provides hardware and software services to IT users in a demanding form, per-usage portraying volume which quickly grew, customizable and

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global in its routine (Fox et al., 2009). Youseff *et al.,* (2008) states cloud suppliers can categorize cloud-computing service into three categories the infrastructure as service, the platform as a service, and the software as a service. The infrastructure as a service (IaaS) provides a self-service virtualization of IT resources, such as storing, communicating, and computing (Sotomayor *et al*., 2009). The Platform as a Service (PaaS) offers an accessible cloud-based software improvement and deployment atmosphere. Lastly the Software as a Service (SaaS) offers online software such as application on desktop that is delivered as a service on the web ((Mohana and Thangaraj, 2013). This shows that Saas loads all protection utilities at all layers, and IaaS loads protection mostly at the networking, reliable computing and storage levels. While Paas represents the IaaS care in addition protection at the supply management level.

Sotomayor et al., (2009) states the cloud organization models are characterized as public or private clouds. Previously the cloud service meant to offer for public in pay-per-usage manners, but the recent cloud service data focuses on within services a specific organization and as such is not accessible to the community. Cloud computing provides many opportunities and benefits for business such as reduction in cost, saving time and energy, advancing the speed to catch up with market, service scalability and many technical advantages. In short, Buyya et al (2009b) believes that cloud computing delivers large volume of computing power and space for fairly small resources and at lower energy utilization. Moreover, to consume energy and minimizing costs cloud computing also provides organizations to gain the advantages of the use of IT without the requirement for open deal. The cloud computing service model costs are shown as strangely operative expenses therefore, assisting to minimize the open costs and improving the time to market are key factors in cloud computing service. In addition, managers can provide their business models by climbing services up or down in the track with business requirement variations, because computing funds are completely coped with insignificant user communication (Buyya *et al*., 2009b). Cloud computing capably handles points in request by the virtualization of computer capitals (Aymerich *et al*., 2008). Moreover, the cloud computing can offer immediate and frequent access to deposited data, anytime anywhere, through the use of self phone devices. In short, cloud computing provides many technical and economical profit.

The cloud-computing model is still facing many challenges despite the characters and prospective in the business market. According to Fox et al., (2009), it is difficult for the cloud computing to provide protected services for IT atmosphere that are equal to those found in-house-data midpoints. In addition, the sides of cloud computing worsen the privacy issues more, due to the huge participation of third-party structures and presenting services. Moreover, the implementation of cloud computing brings legal and authoritarian issues affecting the physical place of introduced data as well as the purpose of data management rules which need to be affected to data gap circumstances (Dillon et al., 2010). Also, cloud computing needs transportability mechanisms that ensures the consumers to drift from one supplier to another. Finally, the quality associated with cloud services desires to be fixed in advance through the usage of Service Level Agreements (SLA) in order to

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assurance consistency, obtainability and routine at the anticipated levels.

Recently, according to Marston *et al.*, (2011), the implementation of cloud computing has become space of improving importance for IT research and exercise. For instance, a study used different technology implementation models to know the user's adaption behavior. For instance, a research by Taylor and Hunsinger (2011), showed the behavior and intention of university students to use Google Docs, is predicted by students' attitude toward cloud (ATC) technology and other concepts resulting from the Theory of Planned Behavior (TPB). Another study, focused on the switching behavior to a cloud setting and the cloud influence to improve organizational productivity. In addition, another research by Obeidat and Turgay (2012) prolonged the evaluation of cloud computing adjustment, beyond the possibility of technology acceptance behavior, to cover multiple viewpoints consuming the Triple-T Model; they found that the benefits of cloud services outweighed its weaknesses. Therefore, this research showed experimental evidence that cloud computing application is fulfilling to organizations as it pays to advance overall innovativeness routine.

Technology Acceptance Model(TAM)

The Technology Acceptance Model (TAM) is measured to be the most recognized theories of technology adjustment and it has been confirmed to be extremely projecting of the adaption of numerous IT systems (Lee et al., 2003). The aim of TAM was to predict consumer's acceptance of IT, which can be showed by two perceptual principles: Percieved Usefulness (PU) and Perceived Ease of Use (PEOU). PU represents the extents to which the user believe that IT can donate to the development of their job implementation (Davis, 1989). PEOU, on the other hand, is focused with the basic of applying a new technology which can be explained as the degree to which the consumer believe that their use of the new IT would be uncomplicated. The main elements of the TAM are PU and PEOU, which is includes attitude toward practice and behavioral purpose toward applying new IT.

Barua et al. (1995) stated that when the consumers approve the use of a specific technology, the usefulness of the stated technology is affected by two variables: cost and productivity. The cost focuses negatively to user attitude toward technology, on the other hand, the productivity pays positively. As a result, it can be mentioned that PU has a significant positive effect on both the attitude toward new technologies and behavioral intention to practice that technology.
PU is positively related with the attitude toward usage and behavioral intentions to practice the fresh technology. In addition, according to Davis (1989), the PEOU is significantly positively related with attitudes toward the new and fresh technology. Also according to Barua et al, (1995), as lower the difficulty of new technology relatively makes lower costs and higher values. Moreover, PEOU has a significantly positive effect on PU in numerous field researches, such as E-mails, online banking systems and shopping online. As a result, it can be mentioned that PEOU has significantly positive effect on PU and attitude toward using the new and fresh technology. Also, attitude toward usage have been significantly

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positively affect the behavioral intentions to use the new technology ((Fishbein and Ajzen, 2011). Lastly, it was also discovered that intentions toward the use of new technology also positively influence the usage of that technology (Pavlou and Chai, 2002; Venkatesh and Davis, 1996). The TAM model showed in the figure below where the influence of external variables was conceived to be antiseptic by PU and PEOU (Venkatesh and Bala, 2008).

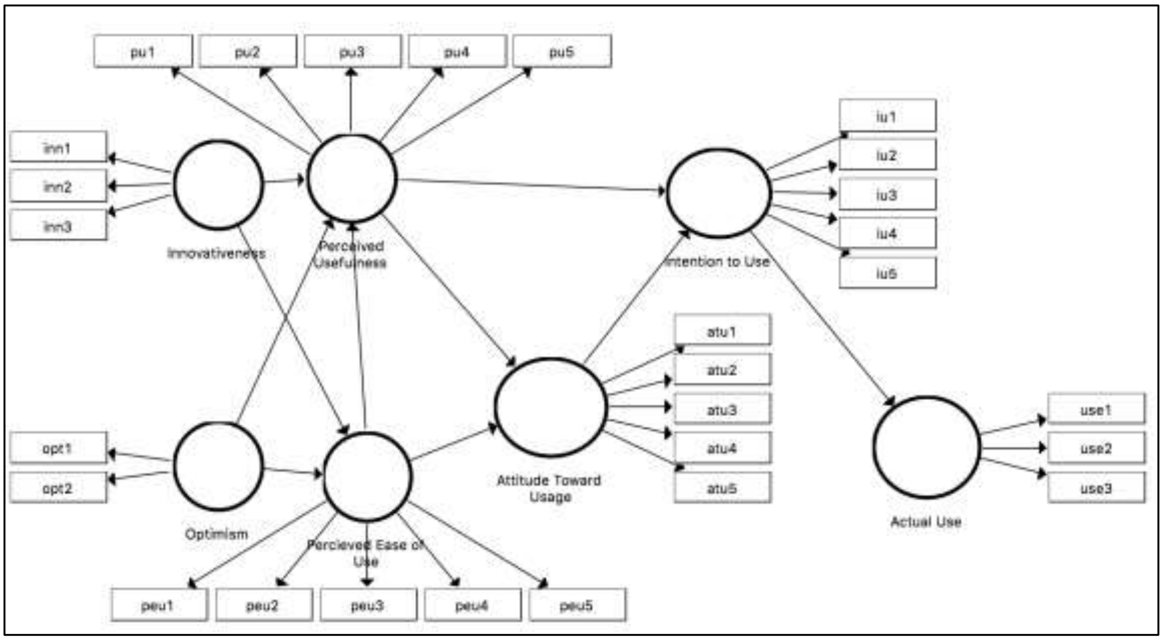

Figure 1:The Technology Acceptance Model (TAM)

Hypothesis

In the current study, TAM was applied to fit the content of cloud computing, in specific, the adjustment of the TAM involves joining fresh external factors that have been proved to have a possible effect on cloud computing implementation. Moreover, according to the planned model suggests a limit impact that the factors influencing PEOU will have Venkatesh and Bala, (2008), same effect on PU. Overall, in order to evaluate the recognition of cloud computing, an investigation and sympathetic of the implementation behavior of cloud computing should happen. In the content of TAM, many variables were planned to expect the acceptance of cloud computing, these external factors were imagine to be refereed by PU and PEOU. In specific, Optimism and *Innovativeness* were variables that could potentially influence cloud-computing acceptance (Nyoni and Piderit, 2012; Wu, 2013; Wu *et al*., 2013). As a result, it can be mentioned that Optimism is related positively with PEOU and PU of cloud computing

People who are optimistic and innovative with reference to technology in general are thought to hold positive attitudes toward new technology and technology use. As a result, it is very essential to join optimistic as cause of PEOU as fastening belief that is disconnected from both perceived risk and Optimism. It can be stated that computer Innovativeness is positivly related with both PEOU and PU, in the content of cloud

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computing

- Hypothesis (*H1): * Optimism is positively related to perceived usefulness (PU).
- Hypothesis (*H2): * Optimism is positively related to perceived ease of use (PEOU).

PR shows a mix of uncertainty and adverse results that usually impact the user's decision to implement a definite technology. Researchers in the E-business market stressed that element and filling business involves less risk, in compare to online business (Drennan *et al*., 2006; Samadi and Nejadi, 2009). Having cloud-computing service showed as an Internet based service-providing atmosphere, which provides security and safety. As a result, it can be mentioned the decision to implement cloud-computing service shows uncertain and risky environment. Therefore, we hypothesized that optimism and innovativeness are enablers that have positive effects on how people perceive and relate to new technology (Parasuraman & Colby, 2001; Tsikriktsis, 2004).

- Hypothesis (*H3): Innovativeness of the cloud computing service positively effects perceived usefulness (*PU) *of the cloud computing service.*
- *Hypothesis (H4): Innovativeness of the cloud positively effects perceived ease of use (*PEOU) *using the cloud computing service.*

In addition, according to TAM, it is assumed that PEOU have a relatively positive effect on PU. Also, PEOU and PU were assumed to be predictors of attitudes toward the fresh technology. Based on the TAM model, the following three hypotheses were formed specifically for this study.

- *Hypothesis (H5): Perceived usefulness of the cloud significantly positively impacts attitudes toward the cloud computing service.*
- *Hypothesis (H6): Perceived ease of use significantly positively impacts perceived usefulness of the cloud computing service.*
- *Hypothesis (H7): Perceived ease of use significantly positively impacts attitudes toward the cloud computing service.*

Optimism and attitude have been showed to be mainly originators of BI to use the cloud service. For instance, Udoh (2012), stated on the elements influencing the implementation of cloud technology applying an adapted TAM, showed that attitude and Optimism were described as 27% and 21% of the variance in BI.

- *Hypothesis (H8): Optimism significantly positively effects behavioral intention to use the cloud computing service.*
- *Hypothesis (H9): Attitudes toward the cloud significantly positively have effect on behavioral intention to use the cloud computing service.*

Moreover, according to Alharbi (2012), BI to use for cloud service is significantly positively related wit PU. Therefore, the hypothesis that was implemented from the study of original TAM model (Alharbi, 2012)

- Hypothesis (*H10): Perceived usefulness of the cloud service have a positive effect on behavioral intention to use the cloud computing service.*

This research study mixed the two extra elements of Optimism and *Innovativeness* into the TAM model to show consumer acceptance in the content of cloud computing. The objective of the TAM were to fit into the content of cloud computing. The external factors were combined into the model. Also, this research shows participants' demographic data by four elements such as gender, age, education and background.

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METHODOLOGY

This study follows a quantitative data format by distributing survey questionnaire to examine the proposed hypothesis and the theoretical TAM model. Data was collected from the cloud computing service content, which includes information from consumers and potential implementers of the cloud service. Same studies such as Opitz *et al*., and Alharbi, (2012), argued that cloud computing researches must focus on IT experts. However, the main objective of this study has been extended to mark an audience of IT expertise and consumers.

Questionnaire and sample design

An empirical study was designed to investigate the influences of the proposed antecedents on adoption of cloud computing services in Kuwait. A questionnaire was developed in order to obtaining responses from participants in Kuwait with regard to their perception of cloud computing. The questionnaire consisted of seven factors, as shown in Table (3). In order to be able to select the appropriate method of analysis, the level of measurement must be understood. For each type of measurement, there is an appropriate method that can be applied rather than others. In this research, ordinal scales are used. Ordinal scale is a ranking or a rating data that normally uses integers in ascending or descending order. In addition, a Likert scale (1-5) was utilized for all items in the questionnaire, with anchors ranging from strongly disagree to strongly agree. A number of other instruments were validated by the current literature; these have been utilized to suggest the items for each construct. In particular, the TAM scales were drawn from previous studies (Davis et al., 1989; Venkatesh and Davis, 2000) and tailored to fit the context at hand (cloud computing). To separate Innovativenessfrom both Optimism and perceived risk, Innovativenessscales were also adapted (Venkatesh, 2000).

In addition, PR in cloud technological risks was focused on privacy and reliability, which is important challenges that cloud computing, is facing. Optimism of the cloud service supplier can be evaluated in the content based on the perception of supplier's honesty, so Optimism was formed to show the beliefs of provider in this study.

Data Collection

The study was organized as an online survey, and data were collected during a period of 15 days in the beginning of August 2016. The sample was gathered from Kuwait University students. We received around 579 surveys using random approach in sampling method; the valid surveys were about 452 (78%) respondents. The majority of questionnaire survey was distributed through online E-mails and participants answered questionnaire through email. The email context showed a majority of various work atmospheres. The email showed a brief explanation to the meaning of cloud computing for participants to make sure that they are familiar with the idea.

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Data Analysis and Reporting Procedures

In this section, various analytical techniques and methods are recruited for data analysis. In the first step, demographic and technographic moderator variables are numerically and visually presented. Next, the relevancy of the explanatory constructs in the model are validated and overviewed. Lastly, the Structural Equation Modeling (SEM) is critically examined for the overall testing of the empirical model.

Demographic and Technographic Analysis and Reporting

Statistical analysis of the Demographic and technographic questions is conducted by Descriptive Statistics and Nonparametric Statistical Tests. Descriptive Statistics is designed to arrange, summarize, and present a set of data in a specific way to produce useful information by graphical techniques and numerical measures (Keller, 2007). In addition, Microsoft Excel 2010 is used for calculating and presentation of the survey results. Nonparametric Statistical Tests which include binomial and chi-squared are suitable for nominal or ordinal data (Zhao et al, 2012). They compare the propositions associated with various categories on different variables. The tests are specifically powerful tools where distributional assumptions with parametric procedures cannot be met (Green & Salkind, 2003).

Structural Equation Modeling Analysis of Theoretical Model

Structural Equation Modeling (SEM) is used to study relationships among multiple outcomes involving latent variables (Jöreskog, Sörbom, & Magidson, 1979). Component-based SEM approach is adopted through SmartPLS for path modeling with latent variables (LVP).

Structural Equation Modeling (SEM) is a multivariate technique combining aspects of multiple regression (examining dependence relationships) and factor analysis (representing unmeasured concepts -factors- with multiple variables) to estimate a series of interrelated dependence relationships simultaneously (Hair et al., 1998). Partial Least Squares (PLS) regression analysis, developed in the late seventies (Wold, 1975, Wold et al., 1984), is a statistical tool that has been specifically designed to deal with multiple regression problems where the number of observations is limited, missing data are numerous and the correlations between the predictor variables are high. These characteristics of PLS regression have been demonstrated both with real data and in simulations (Garthwaite, 1994; Tenenhaus, 1998). In this study, SmartPLS path analysis technique was used to identify the direct and indirect relationships among secondary school students' environmental behaviours, environmental knowledge, and environmental attitudes. With PLS-SEM, all the previous data analysing approaches was done in one go using SmartPLS.

Evaluation of Measurement Model Reliability and Validity

Based on the global criteria, several tests have been used to ensure the validity, reliability and accuracy of measurement in the model. Table 15 illustrates these techniques and explains their application in this study.

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Table 1: Evaluation of Measurement Model Reliability and Validity

Purpose of Evaluation	Test Criteria	Heuristics Applied	Explanation
Item Reliability	Item Loadings on Target Construct	- Item Loadings of 0.70or higher are recommended; - 0.60 for exploratory models or new measurement scales is acceptable (Chin, 1998; Nunnally, 1978).	- Item Loadings on their target construct s represent the strength of substantive association between items and their constructs
Convergent Validity	Communality Index or Average Variance Extracted (AVE) for a Construct	- Value should be greater than 0.50 (Chin, 1998b, Fornell &Lacrcker, 1981)	- Communality Index or AVE represents a measure of the proportion of variance captured by a construct from its indicators. - AVE of 0.50 or higher implies that a latent construct can account for at least 50 % of the variance in the item.
	Composite Reliability	- Value should be greater than0.60 (Bagozzi &Yi, 1988); or 0.70 according to some researchers (Fornell &Lacrcker, 1981)	- It is a measure of internal consistency reliability of a construct as compared with other constructs in the model.
	Cronbach's alph	- Value should exceed 0.70 (Cronbach, 1951; Nunnally, 1978; Chin, 1998b, Gefen et al., 2000b)	- It also measures the internal consistency reliability of a construct on a single basis, i.e. it is not a relative index like composite reliability.
Discriminant Validity	Inter-Correlation among constructs cross-tabulated with square roots of AVE	- The square root of the AVE should exceed the inter-correlations of a construct with other constructs in the model (Fornell &Lacrcker, 1981; Chin, 1998b, Gefen et al., 2000b).	- A construct should have discernable as a valid individual component within the overall model.
	Item Cross-Loadings	- Item Correlations with Target Construct should be higher compared to its correlations with other constructs in the model (Chin, 1998b).	- Indicators that are meant to measure their target construct should me more strongly associated with them as compared to other constructs in the model.

Evaluation of the Structural Model

In order to assess the significance of relationships in the structural model, a round of bootstrapping is conducted. Using the re-sampling technique with 200 replications provides a more conservative testing of the parameters (Fornell & Barclay, 1983; Chin, 2001). Table 16 shows the different evaluation techniques applied to the assessment.

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Table 2: Evaluation of Measurement Model Reliability and Validity

Purpose of Evaluation	Test Criteria	Heuristics Applied	Explanation
Nomological Validity (Construct Level)	- Model Fit/ Predictability: Variance Explained (R^2) for all constructs in the model. - Average Predictability of entire model (R^2)	- No specific heuristics available. Value needs to be interpreted in comparison to similar studies or norm in the discipline (Gefen et al., 2000b). - Falk et al. (1992) recommended minimum value of 0.10 for a construct to be considered viable within the nomological network.	- R^2 value for endogenous variable represents the proportion of its variance that can be explained by the predictors in the model. - Average R^2 allows comparison across competing models.
	- Path Validity Coefficients; Significance (p-values)	- Inner model paths should be significant at <0.05 level to provide support for proposition in the theoretical model.	- A significant path represents the an association between two latent variables was not a chance happening.
	-Predictability Effect Size: Effect Size (f^2) for criterion variables based on the exclusion of a predictor variable from the model	- Predictor variable should ideally have a large or medium effect. - The following scheme can be used to determine effect sizes: Small Effect: 0.02; Medium Effect: 0.15; Large Effect: 0.35 (Chin, 1998b).	- f^2 value between a predictor an a criterion variable represents the effect of the predictor on the criterion variable. Higher values imply that greater importance
Goodness of Fit	- Global Criterion of goodness-of fit (GoF)	- The following baseline values can be used to evaluate the overall model fit: Low fit: 0.1; Medium fit: 0.25; High fit; 0.36 (Tenenhaus et al., 2005; Wetzels et al., 2009).	- GoF values allow a scalar based assessment (summative index) of the model as whole. - GoF values allow comparisons across competing models.

RESULTS

Cronbach alpha coefficients were calculated for the following scales: Trus, Inno, Opt, PU, PEOU, Attitude, Intention, and Use. Cronbach's alpha coefficients were evaluated using the guidelines suggested by George and Mallery (2016) where > .9 excellent, > .8 good, > .7 acceptable, > .6 questionable, > .5 poor, and ≤ .5 unacceptable. The items for Inno had a Cronbach's alpha coefficient of 0.89, indicating good reliability. The items for Opt had a Cronbach's alpha coefficient of 0.84, indicating good reliability. The items for PU had a Cronbach's alpha coefficient of 0.91, indicating excellent reliability. The items for PEOU had a Cronbach's alpha coefficient of 0.83, indicating good reliability. The items for Attitude had a Cronbach's alpha coefficient of 0.93, indicating excellent reliability. The items for Intention had a Cronbach's alpha coefficient of 0.95, indicating excellent reliability. The items for Use had a Cronbach's alpha coefficient of 0.90, indicating excellent reliability. Table 3 presents the results of the reliability analysis.

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Table 3: *Reliability Table for Trus, Inno, Opt, PU, PEOU, Attitude, Intention, and Use*

Scale	No. of Items	α
Inno	3	0.89
Opt	2	0.84
PU	5	0.91
PEOU	5	0.83
Attitude	5	0.93
Intention	5	0.95
Use	3	0.90

Frequencies and Percentages for Nominal Variables

The most frequently observed category of gender was female (*n* = 360, 80%). The most frequently observed category of Nationality was Kuwaiti (*n* = 324, 72%). The most frequently observed category of Age was 20-30 years (*n* = 168, 37%). The most frequently observed category of Experience was over 10 years (*n* = 191, 42%). The most frequently observed category of income was below 1000 KD (*n* = 194, 43%).

Table 4: *Frequency Table for Nominal Variables*

Variable	*n*	%
gender		
female	360	80
male	88	20
Missing	2	0
Nationality		
Kuwaiti	324	72
Non-Kuwaiti	123	27
Missing	3	1
Age		
20-30 years	168	37
30-40 years	105	23
below 20 years	117	26
over 40 years	60	13
Missing	0	0
Experience		
2-6 years	94	21
6-10 years	142	32
below 2 years	19	4
over 10 years	191	42
Missing	4	1
income		
1001-2000 KD	138	31
2001-3000 KD	74	16
above 3001 KD	34	8
below 1000 KD	194	43
Missing	10	2

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Summary Statistics for Numeric Variables

The observations for Innovativeness ranged from 1.00 to 6.00, with an average of 3.25 (*SD* = 1.35). The observations for Optimism ranged from 1.00 to 6.00, with an average of 3.29 (*SD* = 1.40). The observations for Perceived Usefulness ranged from 1.00 to 6.00, with an average of 3.62 (*SD* = 1.17). The observations for Perceived Ease of Use ranged from 1.00 to 6.00, with an average of 4.01 (*SD* = 0.92). The observations for Attitude Toward Usage ranged from 1.00 to 6.00, with an average of 4.08 (*SD* = 1.07). The observations for Intention to Use ranged from 1.00 to 6.00, with an average of 3.76 (*SD* = 1.21). The observations for Actual Use ranged from 1.00 to 4.00, with an average of 2.42 (*SD* = 0.75). Skewness and kurtosis were also calculated in Table 3. When the skewness is greater than or equal to 2 or less than or equal to -2, then the variable is considered to be asymmetrical about its mean. When the kurtosis is greater than or equal to 3, then the variable's distribution is markedly different than a normal distribution in its tendency to produce outliers (Westfall & Henning, 2013).

Table 5: *Summary Statistics Table for Numeric Variables*

Variable	*M*	*SD*	*n*	Min.	Max.	Skewness	Kurtosis
Innovativeness	3.25	1.35	441	1.00	6.00	0.54	-0.24
Optimism	3.29	1.40	448	1.00	6.00	0.37	-0.46
Perceived Usefulness	3.62	1.17	445	1.00	6.00	0.47	-0.09
Perceived Ease of Use	4.01	0.92	442	1.00	6.00	0.56	0.76
Attitude Toward Usage	4.08	1.07	447	1.00	6.00	-0.15	0.01
Intention to Use	3.76	1.21	436	1.00	6.00	0.10	-0.37
Actual Use	2.42	0.75	440	1.00	4.00	0.57	0.10

Pearson Correlation Analysis

A correlation expresses the strength of linkage or co-occurrence between two variables in a single value between -1 and +1. This value that measures the strength of linkage is called correlation coefficient, which is represented typically as the letter r. The correlation coefficient between two continuous-level variables is also called Pearson's r or Pearson product-moment correlation coefficient. A positive r value expresses a positive relationship between the two variables (the larger A becomes, the larger B becomes) while a negative r value indicates a negative relationship (the larger A becomes, the smaller B becomes). A correlation coefficient of zero indicates no relationship between the variables. However, correlations are limited to linear relationships between variables. Even if the correlation coefficient is zero, a non-linear relationship might exist. Gives the probability of obtaining the observed results if the null hypothesis (the frequency of observations is equal across groups) is true; in most social science research, a result is considered statistically significant if this value is ≤ .05.

A Pearson correlation analysis was conducted among Optimism, Innovativeness, Optimism, Perceived Usefulness, Perceived Ease of Use, Attitude Toward Usage, Intention to Use, and Actual Use. Cohen's standard was used to evaluate the strength of the

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relationships, where coefficients between .10 and .29 represent a small association, coefficients between .30 and .49 represent a moderate association, and coefficients above .50 indicate a large association. A Pearson correlation requires that the relationship between each pair of variables is monotonic (does not change direction). This assumption is violated if the points on the scatterplot between any pair of variables appear to shift from a positive to negative or negative to positive relationship.

The correlation coefficient between Innovativeness and Optimism was 0.88 indicating a large relationship. This indicates that as Innovativeness increases, Optimism tends to increase. There was a significant positive correlation between Innovativeness and Perceived Usefulness (r = 0.74, $p < .001$). The correlation coefficient between Innovativeness and Perceived Usefulness was 0.74 indicating a large relationship. This indicates that as Innovativeness increases, Perceived Usefulness tends to increase. There was a significant positive correlation between Innovativeness and Perceived Ease of Use (r = 0.74, $p < .001$). The correlation coefficient between Innovativeness and Perceived Ease of Use was 0.74 indicating a large relationship. This indicates that as Innovativeness increases, Perceived Ease of Use tends to increase. There was a significant positive correlation between Innovativeness and Attitude Toward Usage (r = 0.69, $p < .001$). The correlation coefficient between Innovativeness and Attitude Toward Usage was 0.69 indicating a large relationship. This indicates that as Innovativeness increases, Attitude Toward Usage tends to increase. There was a significant positive correlation between Innovativeness and Intention to Use (r = 0.74, $p < .001$). The correlation coefficient between Innovativeness and Intention to Use was 0.74 indicating a large relationship. This indicates that as Innovativeness increases, Intention to Use tends to increase. There was a significant positive correlation between Innovativeness and Actual Use (r = 0.66, $p < .001$). The correlation coefficient between Innovativeness and Actual Use was 0.66 indicating a large relationship. This indicates that as Innovativeness increases, Actual Use tends to increase. There was a significant positive correlation between Optimism and Perceived Usefulness (r = 0.74, $p < .001$). The correlation coefficient between Optimism and Perceived Usefulness was 0.74 indicating a large relationship. This indicates that as Optimism increases, Perceived Usefulness tends to increase. There was a significant positive correlation between Optimism and Perceived Ease of Use (r = 0.73, $p < .001$). The correlation coefficient between Optimism and Perceived Ease of Use was 0.73 indicating a large relationship. This indicates that as Optimism increases, Perceived Ease of Use tends to increase. There was a significant positive correlation between Optimism and Attitude Toward Usage (r = 0.70, $p < .001$). The correlation coefficient between Optimism and Attitude Toward Usage was 0.70 indicating a large relationship. This indicates that as Optimism increases, Attitude Toward Usage tends to increase. There was a significant positive correlation between Optimism and Intention to Use (r = 0.76, $p < .001$). The correlation coefficient between Optimism and Intention to Use was 0.76 indicating a large relationship. This indicates that as Optimism increases, Intention to Use tends to increase. There was a significant positive correlation between Optimism and Actual Use (r = 0.68, $p < .001$). The correlation coefficient between Optimism and Actual Use was 0.68 indicating a large relationship. This indicates that as Optimism increases, Actual Use tends to increase. There was a significant positive correlation between Perceived Usefulness and Perceived Ease of Use (r = 0.84, $p < .001$). The correlation coefficient between Perceived Usefulness and Perceived Ease of Use was 0.84 indicating a large relationship. This indicates that as Perceived Usefulness increases, Perceived Ease of Use tends to increase. There was a significant positive correlation between Perceived Usefulness and Attitude Toward Usage (r = 0.75, $p < .001$). The correlation coefficient between Perceived Usefulness and Attitude Toward Usage was 0.75 indicating a large relationship. This indicates that as Perceived Usefulness increases, Attitude Toward Usage tends to increase. There was a significant positive correlation between Perceived Usefulness and Intention to Use (r = 0.73, $p < .001$). The correlation coefficient between Perceived Usefulness and Intention to Use was 0.73 indicating a large relationship. This indicates that as Perceived Usefulness increases, Intention to Use tends to increase. There was a significant positive correlation between Perceived Usefulness and Actual Use (r = 0.69, $p < .001$). The correlation coefficient between Perceived Usefulness and Actual Use was 0.69 indicating a large relationship. This indicates that as Perceived Usefulness increases, Actual Use tends to increase. There was a significant positive correlation between Perceived Ease of Use and Attitude Toward Usage (r = 0.83, $p < .001$). The correlation coefficient between Perceived Ease of Use and Attitude Toward Usage was 0.83 indicating a large relationship. This indicates that as Perceived Ease of Use increases, Attitude Toward Usage tends to increase. There was a significant positive correlation between Perceived Ease of Use and Intention to Use (r = 0.76, $p < .001$). The correlation coefficient between Perceived Ease of Use and Intention to Use was 0.76 indicating a large relationship. This indicates that as Perceived Ease of Use increases, Intention to Use tends to increase. There was a significant positive correlation between Perceived Ease of Use and Actual Use (r = 0.76, $p < .001$). The correlation coefficient between Perceived Ease of Use and Actual Use was 0.76 indicating a large relationship. This indicates that as Perceived Ease of Use increases, Actual Use tends to increase. There was a significant positive correlation between Attitude Toward Usage and Intention to Use (r = 0.81, $p < .001$). The correlation coefficient between Attitude Toward Usage and Intention to Use was 0.81 indicating a large relationship. This indicates that as Attitude Toward Usage increases, Intention to Use tends to increase. There was a significant positive correlation between Attitude Toward Usage and Actual Use (r = 0.75, $p < .001$). The correlation coefficient between Attitude Toward Usage and Actual Use was 0.75 indicating a large relationship. This indicates that as Attitude Toward Usage increases, Actual Use tends to increase. There was a significant positive correlation between Intention to Use and Actual Use (r = 0.69, $p < .001$). The correlation coefficient between Intention to Use and Actual Use was 0.69 indicating a large relationship. This indicates that as Intention to Use increases, Actual Use tends to increase. Table 6 presents the results of the correlations.

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Table 6: *Pearson Correlation Matrix among Innovativeness, Optimism, Perceived Usefulness, Perceived Ease of Use, Attitude Toward Usage, Intention to Use, and Actual Use*

Variable	1	2	3	4	5	6	7
1. Innovativeness	-						
2. Optimism	0.88	-					
3. Perceived Usefulness	0.74	0.74	-				
4. Perceived Ease of Use	0.74	0.73	0.84	-			
5. Attitude Toward Usage	0.69	0.70	0.75	0.83	-		
6. Intention to Use	0.74	0.76	0.73	0.76	0.81	-	
7. Actual Use	0.66	0.68	0.69	0.76	0.75	0.69	-

Note. The critical values are 0.10, 0.13, and 0.16 for significance levels .05, .01, and .001 respectively.

SEM Model Using Smart-PLS

This part about testing our proposed conceptual model using Smart-PLS, the following results showing model stability and validity:

Model Validity and Reliability

Validity refers to how accurately the construct reflects what it intends to measure, and reliability refers to the consistency of the results obtained. As suggested by Hair et al. (2010), this study used factor loadings, composite reliability, and the average variance extracted to assess convergent validity. As recommended by Hair et al. (2010), the loadings for all items exceeded the value of 0.5. In addition, the composite reliability values, as shown in Table 3, describe the degree to which the construct indicators indicate the latent construct and they ranged from 0.80 to 0.95. These indicators exceeded the recommended value of 0.7 (Hair et al., 2010). Moreover, the average variance extracted (AVE), which reflects the overall amount of variance in the indicators accounted for by the latent construct, ranged between 0.600 and 0.85. These indicators exceeded the recommended value of 0.5 (Hair et al., 2010). This suggests that all measures in this study sufficiently meet the validity. Discriminant validity was also established as the indicator variables loaded better on their associated constructs than other constructs as indicated in the next section.

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Table 7: Result of the measurement model

Item	Loading	CA	CR	AVE
atu1 <- Attitude Toward Usage	0.864	0.934	0.95	0.792
atu2 <- Attitude Toward Usage	0.899			
atu3 <- Attitude Toward Usage	0.903			
atu4 <- Attitude Toward Usage	0.873			
atu5 <- Attitude Toward Usage	0.91			
inn1 <- Innovativeness	0.871	0.892	0.933	0.823
inn2 <- Innovativeness	0.931			
inn3 <- Innovativeness	0.918			
iu1 <- Intention to Use	0.85	0.945	0.958	0.821
iu2 <- Intention to Use	0.9			
iu3 <- Intention to Use	0.931			
iu4 <- Intention to Use	0.921			
iu5 <- Intention to Use	0.926			
opt1 <- Optimism	0.925	0.842	0.927	0.863
opt2 <- Optimism	0.934			
peu1 <- Percieved Ease of Use	0.779	0.845	0.936	0.746
peu2 <- Percieved Ease of Use	0.649			
peu3 <- Percieved Ease of Use	0.82			
peu4 <- Percieved Ease of Use	0.858			
peu5 <- Percieved Ease of Use	0.822			
pu1 <- Perceived Usefulness	0.899	0.912	0.891	0.622
pu2 <- Perceived Usefulness	0.886			
pu3 <- Perceived Usefulness	0.706			
pu4 <- Perceived Usefulness	0.907			
pu5 <- Perceived Usefulness	0.904			

Item	Loading	CA	CR	AVE
use1 <- Actual Use	0.898	0.902	0.939	0.837
use2 <- Actual Use	0.939			
use3 <- Actual Use	0.907			

Note: CA: Cronbach's Alpha; CI: Composite Reliability; AVE: Average Variance Extracted

Table 8: Discriminant Validity of Latent Variables

	Actual Use	Attitude Toward Usage	Innovativeness	Intention to Use	Optimism	Perceived Usefulness	Percieved Ease of Use
Actual Use	**0.915**						
Attitude Toward Usage	0.739	**0.89**					
Innovativeness	0.638	0.66	**0.907**				
Intention to Use	0.671	0.771	0.726	**0.906**			
Optimism	0.658	0.673	0.865	0.735	**0.929**		
Perceived Usefulness	0.687	0.734	0.718	0.713	0.723	**0.864**	
Percieved Ease of Use	0.749	0.821	0.703	0.746	0.693	0.815	**0.789**

Discriminant validity is the degree to which a construct is truly different from other constructs both in terms of how much it correlates with other constructs and how its particularly measured variables represent only this single construct (Hair et al., 2010). Measures of discriminant validity are supported when the square root of the average variance extracted for each construct is the highest for its assigned construct (Fornell and Lacker, 1981). As shown in Table 4, the correlations for each construct are less than the square root of the average variance extracted by the indicators suggesting adequate discriminant validity. In total, the measurement model demonstrated adequate convergent validity and discriminant validity.

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Table 9: SRMR Composite Model

Original Sample (O)	Sample Mean (M)	Standard Error (STERR)	T Statistics (|O/STERR|)	P Values
0.052	0.057	0.004	11.878	0.000

For non-normal continuous data when N>250, the SB based CFI cut-off value is 0.95 and SRMR at 0.07 (acceptable Type I and Type II error). When N>500, the TLIML and CFIML at the suggested values were acceptable within normal data. In line with general recommendations, our model's SRMR of 0.07 is below the threshold of 0.10 and thus indicates a good model fit (Jo ̈rg Henseler, 2014).

Structural Model test of hypothesis

Subsequently, this study assessed the structural model for the hypotheses testing. In this test, the statistical significance was assessed by t-tests based on a bootstrap procedure with 1,000 bootstrapping samples. To evaluate the results, the explained variances, R^2, and path coefficients can be interpreted similar to those in the simple regression (Hair et al., 2010). Using SmartPLS, we calculated a PLS path model to analyze the behavioral structure of participants. We report results in two steps. First, we investigate the relationship between items and corresponding latent variables in a measurement model. Second, we investigate the relationship between latent variables as part of a structural model. This study begins the interpretation with the hypothesized factors. As shown in Table 5,

Table 10: Path coefficients and hypotheses testing

Hypothesis	Beta	Sample Mean (M)	Standard Error (STERR)	T Statistics (|O/STERR|)	P Values
Attitude Toward Usage -> Intention to Use	0.538	0.540	0.049	11.088	0.000
Innovativeness -> Perceived Usefulness	0.130	0.134	0.062	2.094	0.037
Innovativeness -> Perceived Ease of Use	0.414	0.415	0.062	6.712	0.000
Intention to Use -> Actual Use	0.671	0.670	0.033	20.216	0.000
Optimism -> Perceived Usefulness	0.210	0.205	0.063	3.340	0.001
Optimism -> Perceived Ease of Use	0.334	0.335	0.058	5.744	0.000
Perceived Usefulness -> Attitude Toward Usage	0.193	0.197	0.045	4.318	0.000
Perceived Usefulness -> Intention to Use	0.318	0.315	0.048	6.633	0.000
Perceived Ease of Use -> Attitude Toward Usage	0.664	0.661	0.041	16.346	0.000
Perceived Ease of Use -> Perceived Usefulness	0.579	0.579	0.034	16.980	0.000

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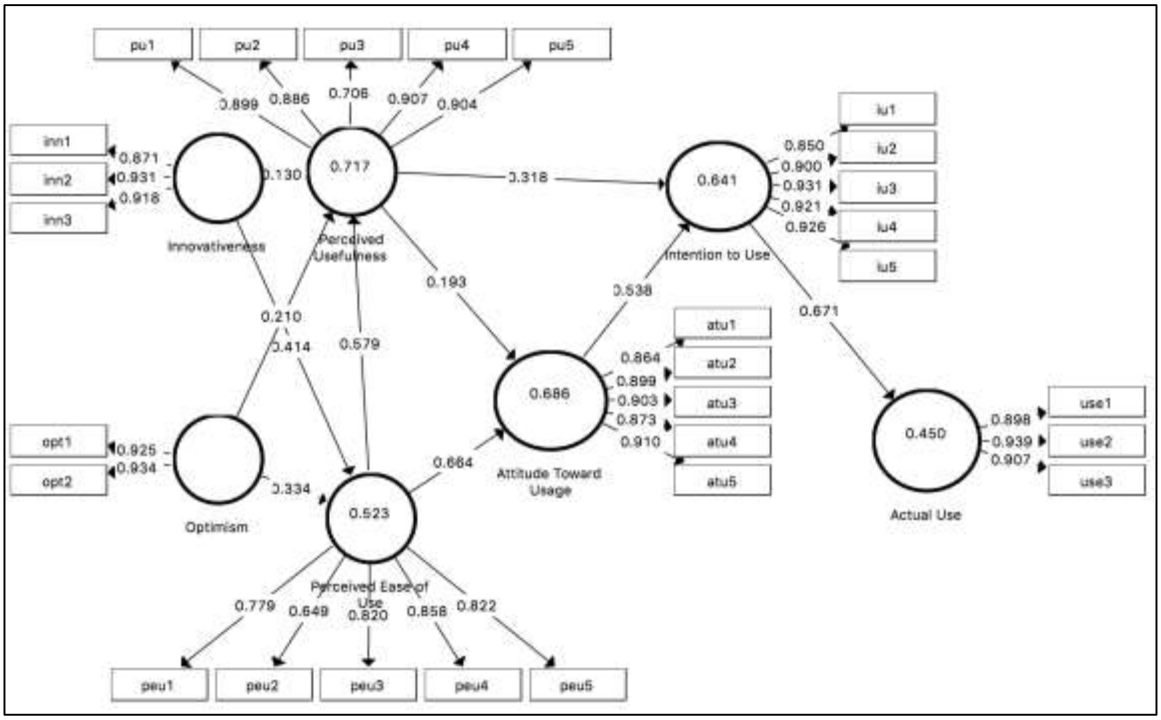

Figure (2): Research Proposed Theoretical Model

The proposed theoretical research model explains the relationship between perceived usefulness, perceived ease of use, attitude toward usage, intention to buy and actual usage. The PU can be predicted by three factors of optimism, Innovation and PEU, and the path coefficient for PEU and Optimism were 0.579 both optimism had beta of 0.210 and PEU Beta 0.579 and have significant positive effect on the PU since the p value were <0.001. In addition, the Beta value for innovation were 0.103 and the p value of less than p<0.037. Secondly, the PEU can be predicted by two factors of Optimism and Innovation, both beta of 0.334 and 0.414 with P value =0. Both variables have significantly positive effect on perceived ease of usage. Thirdly, the ATU can be predicted by two factors of Perceived ease of usage and Perceived usefulness, both had beta of 0.664 and 0.193 with p value of 0. Both variables have significantly positive effect on Attitude toward usage. Fourthly, the Intentions to use can be predicted by two factors of ATU and PU, both beta of 0.538 and 0.318 with p value=0. Both variables have significantly positive effect on the intention to use. Finally, actual usage can be predicted by the intention to use, and beta of 0.671 and p value =0. The intention to use has significantly positive effect on the actual usage.

DISCUSSION

The TAM model has been proved to be a strong model for analyzing consumers' perception toward cloud computing in Kuwait. The table (10) above showed that the hypothesis that was implemented from the TAM model have been accepted and approved in the content of cloud computing service. In addition, the two innovations and optimism variables were successfully merged within the TAM. And both variables showed to have a significant positive impact on the PEU and PU. As a result, the hypothesis related to these variables has been approved. It appeared that ATU and PU have significantly positive effect on the intention to use for users, so the hypotheses related to these factors have been accepted. Lastly the intention to use also had positive effect on the actual use, and the hypothesis related to this variable also has been accepted in the TAM model in figure (2) above.

CONCLUSION

The major aim of business organization now days is to find the factors that benefits the implementation of cloud computing. This research study evaluated numerous models through literature review to understand the main reason effecting cloud-computing implementation more specifically in Kuwait. It projected stretched TAM model personalized to suit the content of cloud computing, by merging two variables of optimism and innovativeness. Based on the Pearson correlation it appeared to be valid for actual user of cloud computing, and SEM model formed around 14 hypothesis which appeared to be confirmed and positively effective on the actual user of cloud computing.

FUTURES AND LIMITATION OF THE STUDY

This research had some limitation due to the fact that respondents were in Kuwait specifically the E-mail response made the distribution also limited to those who were aware of the online E-mail. Further studies needs to be done to evaluate user of cloud computing more specifically due to the sample size, which represent very small portion of the population. In addition, mostly the participants were those who worked in IT department of organization since the topic of cloud computing was more familiar with IT respondents. Finally, it was clear to understand that mostly Kuwait population rely on Google or Amazon which happened to be internationally known because people still lack privacy and concern about the safety and security of cloud computing. Therefore, mostly Kuwait populations rely heavily on local supplier of cloud computing service.

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