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INTENTION TO ADOPT INFRASTRUCTURE AS-A SERVICE BASED E-LEARNING: DATA SCREENING AND PRELIMINARY ANALYSIS

Abubakar Magira Tom[1*], Wiwied Virgiyanti[2], Wan Rozaini[3]

[1] School of Computing, College of Arts & Sciences, Universiti Utara Malaysia, Malaysia
Email: magiratom@gmail.com
[2] School of Computing, College of Arts & Sciences, Universiti Utara Malaysia, Malaysia
Email: wiwied@uum.edu.my
[3] School of Computing, College of Arts & Sciences, Universiti Utara Malaysia, Malaysia
Email: rozai174@uum.edu.my
[*] Corresponding Author

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Abstract:

The demand for providing education in developing countries' educational institutions is growing exponentially. Hence, the need for cloud-based e-learning to provide effective and efficient e-learning content 24/7. This paper aims to provide a comprehensive step by step guide on the data cleaning procedures for evaluating the Intention to Adopt Infrastructure as-a Service-Based E-learning among the ICT top managers. Four hundred fifty-four (454) respondents were derived from universities across the Northern region of Nigeria, using a systematic random sampling technique. Likewise, the exercise was performed to suit the multivariate analysis supposition. In light of that, the pilot study, missing data analysis, as well as factor analysis via the Exploratory Factor Analysis (EFA) were performed using the Statistical Package for Social Science (SPSS v. 25). The findings revealed that the data fulfilled the condition of multivariate analysis. Therefore, these results provide intuition to perform further statistical and hypotheses assessments.

Keywords:

Cloud Computing, E-Learning, Higher Education Institutions, Developing Countries, Data Cleaning, Nigeria

Introduction

Cloud computing (CC) is a prototype which permits resources to be provisioned via the web "as-a-Service". The "as-a-Service" refers to renting the resources and service of cloud to cloud

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users on a pay-as-you-go method. The cloud is comprised of numerous deployment models which are; the "Infrastructure as a Service (IaaS), Platform as a Service (PaaS) as well as Software-as-a-Service (SaaS)" (Mell & Grance, 2011). In addition, the service models include the "private, public, hybrid, and community" cloud. The Higher Education Institutions (HEIs) could draw numerous benefits from CC such as easy and quick access to resources, improving student performance, cost savings (operational costs) and availability of learning contents anywhere and anytime without geographical restrictions.

Nonetheless, its adoption in emerging nations and precisely Nigeria is limited. Furthermore, e-learning alludes "to the environment in which student's relations with learning resources (readings, the assignment, exercise, etc.) peers, and or instructors are facilitated via innovative information technology" (Alavi & Leidner, 2001, p. 2). The CC for e-learning is comprised of a collection of resources (like hardware, software, etc.) to augment the out-dated e-learning systems. Similarly, most of the existing research on CC for e-learning concentrates on the SaaS model of the cloud, thus overlooking the PaaS as well as IaaS models. Hence, this study focuses on the IaaS service delivery model by proposing an "Infrastructure as-a Service-Based E-learning" (IaaSBEL) model. The IaaSBEL is a type of CC where the e-learning systems are accommodated on the on-premise IaaS infrastructure and thus, can be subscribed to by the Nigerian HEIs in a pay-per-use approach. The reason for proposing IaaSBEL is its cost-effectiveness, efficiency and effectiveness of delivering learning contents to users. Despite the ample benefits of the IaaSBEL infrastructure, its adoption in Nigeria is limited.

Furthermore, the importance of data screening cannot be overemphasized because it is essential in social science and IS research (Hair, Hult, Ringle, & Sarstedt, 2013). Hence, the availability of noise or outliers in the dataset heavily distorts the quality and outcome of the research findings. Nonetheless, missing data usually occurs when some questions are purposely or coincidentally skipped. The idea, besides any data cleaning, is to reduce noise or clean the data. However, overlooking the data cleaning phase would result in distorted results though Tabachnick and Fidell (2007) suggested the ideal method of dealing with missing data is to omit it from the dataset, and thus, only when the dataset is huge.

Diversely, with massive data collection, editing is arduous or even impossible (Maiyaki & Mouktar, 2011). On account of this, it is examining data via descriptive statistics utilising the SPSS. Thus, all concealed mistakes or errors can be easily uncovered (Hair, Black, Babin, & Anderson, 2010; Hair et al., 2013). This study examines concerns related to data cleaning as well as preliminary analysis to attain error-free data as endorsed by Hair et al. (2010) and Hair et al. (2013). "Data cleaning, also called data cleansing or scrubbing, deals with detecting and removing errors and inconsistencies from data in order to improve the quality of data"(Rahm, Erhard, 2000, p. 3). Therefore, a holistic analysis of data screening and preparation for evaluating the intention to adopt IaaSBEL is crucial. This study tries to answer the questions of how to perform data screening or cleaning in the area of Cloud-Based e-learning (IaaSBEL) studies. Hence, the subsequent sections provide an indebt techniques and steps of ridding research data of noise.

Literature Review

The CC provides ample benefits to teachers and students alike, where access to learning content is readily available "as-a-Service", collaboration and sharing, reliability, and affordability by HEIs in developing countries. With the recent COVID-19 pandemic, many developing

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countries are facing economic challenges and the total stoppage of education, as in the case of Nigeria. This, coupled with the recession, has compelled many developing countries to halt education. Nonetheless, there is a lack of studies on the adoption of CC for e-learning in developing countries in general and Nigeria in specific (Tom, Virgiyanti, & Rozaini, 2019). Hence, making the adoption of CC in HEIs as a viable solution towards addressing the problem as mentioned above.

Table 1: Summary of Studies on The Adoption of CC For E-Learning in Developing Countries

Authors	Independent Variables	Research Design	Theories	Findings
Odeh et al. (2017)	Barriers: Resistance to New Technology, Security, Privacy, Compatibility with In-House Lack of Management Awareness Enablers: cost effectiveness, ease to use, decentralization, management support	Qualitative research design	DOI theory	The findings suggest that academic and technical experts recommend the adoption of CC in HEI.
Shana and Abulibdeh (2017)	**IVs**: Perceived Ease of Use, Perceived Usefulness, **DVs**: Behavior Intention to Use, Actual Use	Quantitative research design	TAM theory	The findings reveal that Perceived Ease of Use, affects the Behavior Intention.
Sabi et al. (2018)	**IV**: Observability, Results Demo nstrability, Relative Advantage, Complexity, Compatibility, Trialability, ICT Infrastructure, Data Security, Risks, Upfront Cost **DVs**: CC Adoption Decision, CC Actual Usage	Quantitative research design	DOI theory	The findings indicated that CC adoption, CC usa ge, observability, result demonstrability, Socio-Cultural, and trialability are significantly supported
Almazroi et al. (2016)	**IVs**: Subjective Norm, Image, Job Relevance, Output Quality, Result Demonstrability, Self-Efficacy, Perceptions of External Control, Anxiety, Playfulness, Perceived Usefulness, Perceived Ease of Use **DV**: Behavioral Intention	Quantitative Research Design	TAM 3 theory	The result indicated that perceived usefulness and perceived ease of use are the central deterrence of the Behavioral Intention to CC

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Sabi et al. (2017)	**IVs:** Complexity, Compatibility, Relative Advantage, Trialability, Observability, Result Demonstrable Economic & Cost, Risk, Data Security Awareness, Socio-cultural, Infrastructure, Ease of Use, Usefulness, University Age, University Sie, University Location, Individual Age **DVs**: Intention to Adopt CC, Actual Usage of CC	Quantitative research design	DOI and TAM Theories	Socio-cultural factors such as result demonstrability, usefulness, and data security significantly impact their intention to adopt CC in the university
Tom et al. (2019)	**IVs:** Relative Advantage, Compatibility, Trust, Security, Top Management Commitment, Cost Savings Competitive Pressure, Service Provider Support **DV:** Intention to adopt IaaSBEL	Quantitative research design	TOE and DOI Theories	The findings indicated that Relative advantage, Cost Savings, Competitive Pressure, “Service provider Support has a significant impact on the Intention to Adopt IaaSBEL in Nigerian HEIs”.
Tom, Virgiyanti and Osman (2019)	**IVs**: “Relative Advantage, Compatibility, Trust, Security, Top Management Commitment, Cost Savings, Competitive Pressure, Service Provider Support” **DV**: Intention to Adopt IaaSBEL	Quantitative research design	TOE and DOI Theories	“The findings indicate that Relative Advantage, Cost Savings, "Service Provider Support, and Government Support are the key predictors of the Intention to Adopt IaaSBEL”.

Table 1 shows the summary of studies on the adoption of Cloud-Based E-learning in developing countries, the theories utilised, research design and the outcomes of the findings. It can be noted that studies on the adoption of Cloud-Based E-learning in developing countries and Nigeria in specific are limited.

Research Framework

Information System (IS) comprises of numerous areas such as e-government, e-learning, IaaSBEL, etc. Therefore, in this section, the theoretical foundation and conceptualization of

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the IaaSBEL infrastructure were established based on the "Diffusion of Innovation (DOI) and Technology, Organization, Environment (TOE)" theories respectively (Rogers, 1995; Tornatzky & Fleischer, 1990). For instance, the DOI, and TOE have been applied in numerous studies to establish technology adoption such as CC adoption (Tweel, 2012) RFID adoption (Wang et al., 2010) Broadband adoption (Chiu, Chen, & Chen, 2017), e-government via CC adoption (Wahsh & Dhillon, 2015), and CC in HEI adoption (Tariq et al., 2017) (Tom, Virgiyanti, & Rozaini, 2019). The TOE framework accepts the insertion of other variables (Zhu & Kraemer, 2005). On the other hand, the DOI has also been integrated with the TOE to complement the weakness of DOI (i.e. Environmental factors). Notwithstanding, both the DOI and TOE has shown good predictive power in the case of technology adoption decisions. The selected variables are derived from both DOI and TOE and some external constructs. The constructs are the "Relative Advantage, Compatibility, Trust, Security, Top Management Commitment, Cost Savings, Competitive Pressure, And Service Provider Support with Government Support" as a moderating variable, as depicted in Figure 1.

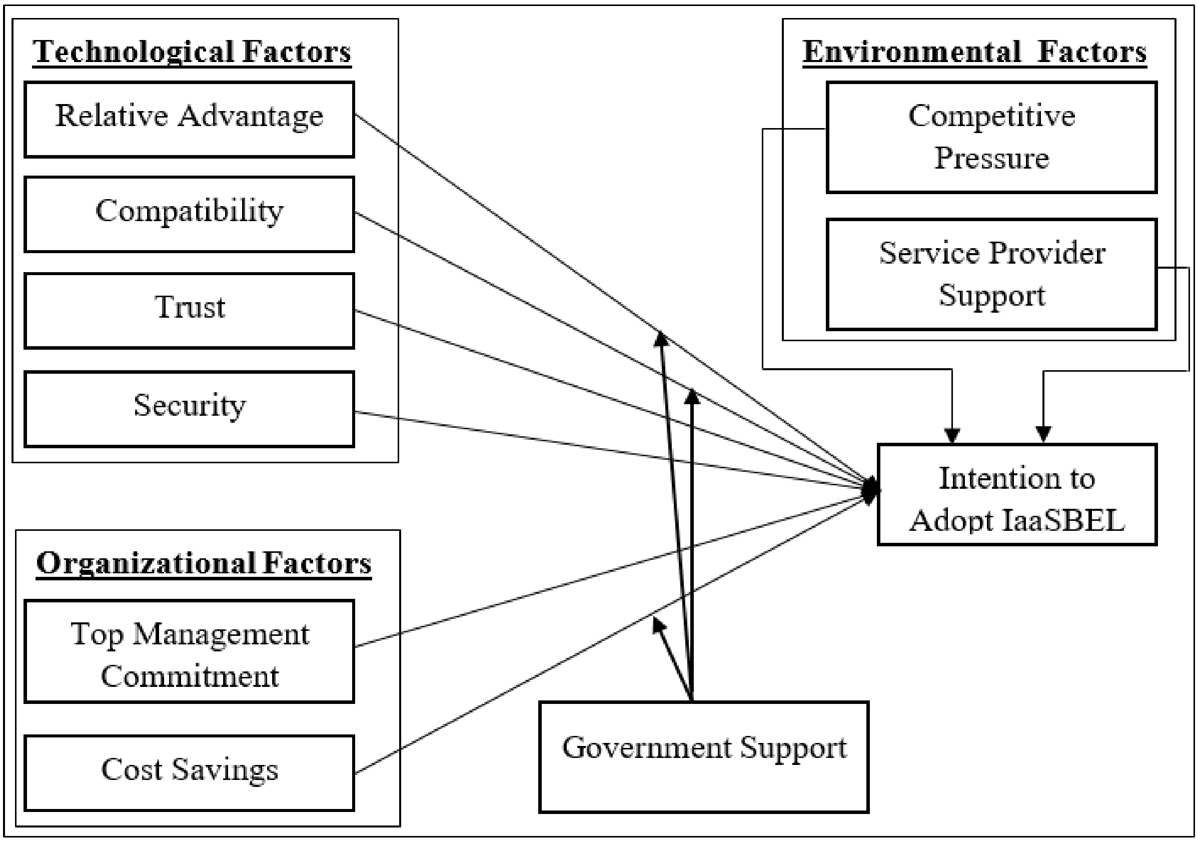

Figure 1: Research Framework

As shown in the above Figure 1, the variables were selected from the existing literature, where the variables were validated by experts from the Universiti Utara Malaysia. The TOE is the based theory and some variables of the DOI as well other external variables were used, to suit the study aim. The reason of doing the study is to understand why developing countries HEIs are still reluctant to adopting IaaSBEL, as well as providing

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Research Methodology

SPSS v. 25 was utilised for the descriptive as well as the inferential statistics. For example, "descriptive statistics, independent sample t-test, Mahalanobis distance, and correlation analysis" were utilised. The study's sample was derived from both the State and Federal universities within the Northern part of Nigeria, where the questionnaire was disseminated in a face to face manner. Disproportionate stratified random sampling and systematic random sampling were employed for the collection of data. The questionnaires were double of the sample size to lessen errors in sampling, response and nonresponse concerns (Blythe, 2005; Hair, Wolfinbarger, Ortinau, & Bush, 2009). Because, if the sample size is small, the tendency of error is high (Alreck & Settle, 1995) Hence, doubling the sample size is consistent with the studies conducted in Nigeria, to attain a minimum response of 50% of the questionnaires that were distributed (Mahmoud et al., 2018). Therefore, 227*2 = 454 questions were distributed to the respondents. The outcomes of the questionnaires have yielded 248 returned, out of the 454 questionnaires that were disseminated to the target respondents.

Measurement Scale

Numerous studies have adopted/adapted items to measure the intention to adopt innovation in an organization. A thorough review of e-learning and cloud computing was conducted to create a pool of questions, which represents ten (10) variables, as shown in Table 2. Experts from Universiti Utara Malaysia (UUM) have validated and suggested some changes to ensure the operationalization, as well as the items (questions), are consistent. Therefore, all items are confirmed to measure the variables as operationalized.

Table 2: Variables Measurement

Construct	Sources
Relative Advantage (RA)	(Ifinedo, 2011; Moore & Benbasat, 1991; Oliveira et al., 2014)
Compatibility (COM)	(Lai et al., 2014; Mohammed et al., 2018; Moore & Benbasat, 1991)
Trust (TR)	(Almazroi et al., 2016; Jarvenpaa et al., 2000; Pavlou, 2003; Wu, 2011a)
Security (SEC)	(Mohammed et al., 2018; Wu, 2011)
Top Management Commitment (TMC)	(Ifinedo, 2011; Lai et al., 2014; Oliveira et al., 2014; Premkumar & Roberts, 1999)
Cost Savings (CS)	(Gupta et al., 2013; Oliveira et al., 2014)
Competitive Pressure (CP)	(Ansong et al., 2016; Ifinedo, 2011; Oliveira et al., 2014; Premkumar & Roberts, 1999)
Service Provider Support (SPS)	(Ifinedo, 2011; Klug & Bai, 2014; Lai et al., 2014)

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Government Support (GS)	(Alhammadi et al., 2015; Chang et al., 2006; Dahnil et al., 2014; Lee et al., 2014; Tornatzky & Fleischer, 1990)
Intention to adopt IaaSBEL (INT)	(Almazroi et al., 2016; Mathieson, 1991; Nguyen et al., 2014; Teo et al., 2008; Tweel, 2012; Venkatesh et al., 2012)

Result and Discussion

This section shows the results and discussion, out of the dispersed 454 questionnaires, 248 copies were retrieved, thus, giving a 54.6% response rate. The response rate was slightly above 50%, which was consistent with the expected rate of research conducted in Nigeria. Additionally, the researcher motivates the respondents by dashing out a pen, which, to an extent, encourages and creates a mutual understanding of the participants to answer the questionnaires. During the preliminary analysis stage, 1 item was deleted due to its low Cronbach's alpha. Similarly, from the 248 questionnaires, 38 were removed because a big part was not answered by the respondents. Fourteen (14) questionnaires were further removed due to lack of experience, and 10 removed during data cleaning, and 186 questionnaires were utilised for further analysis, which accounted for 40.9% valid responses as shown in Table 3. This exceeds the minimum survey response rate of 30%, as postulated by Sekaran (2003) and Sekaran and Bougie (2010).

Table 3: Response Rate of Questionnaire

Response (s)	**Frequency/Rate**
Number of distributed questionnaires	454
Returned questionnaires	248
Returned and usable questionnaires	210
Returned and excluded questionnaires	14
Deleted questionnaire during data cleaning	10
Questionnaires not returned	206
Usable Questionnaire	186
Response rate	54.6%
Valid response rate	40.9%

Table 3 presents the frequency of the number of questionnaires distributed, returned and usable questionnaire. In addition, the response rate, as well as the valid response rate (after data cleaning) is 40.9%.

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Table 4: The Demographic Profile of Respondents

Demographic Profile	Category	Frequency (N=186)	Percentage (%)
Gender	Male	137	73.7%
	Female	49	26.3%
Education Level	Diploma	------	----
	Bachelor’s Degree	48	25.8%
	Master’s Degree	119	64.0%
	Doctorate	19	10.2%
University Position	Director	17	9.0%
	Deputy Director	17	9.0%
	Unit Head	47	24.9%
	Assistant Unit Head	83	43.9%
	Dean	25	13.2%
Institution Type	Federal University	108	57.1%
	State University	81	42.9%
Zone	North-East	45	23.8%
	North-West	86	45.5%
	North-Central	58	30.7%
University	AD (10; 5.4%); GM (5;2.7%); BC (6; 3.2%); TR (5; 2.7%); BN (6,3.2%); YB (12; 6.2%); JG (11, 5.9%); KD (13, 7.0%); KN (20, 10.8%); KT (13, 7.0%); KB (12, 6.5%); SK (11, 5.9%); ZF (6, 3.2%); AB (5, 2.7%); BN (8, 4.3%); KG (9, 4.8%); KW (12, 6.5%); NS (8, 4.3%); NG (7, 3.8%); PL (7, 3.8%)		
e-learning experience	None	----	-----
	≤ 1 Year	10	5.4%
	1-2 Years	54	29.0%
	2-3 Years	86	46.2%
	4-5 Years	32	17.2%
	> 5 Years	4	2.2%
Cloud-based e-learning Experience	Yes	189	100.0%
	No	----	----
Familiarity with Cloud-Based e-learning	Microsoft Azure	68	36.6%
	Amazon Web Service	96	51.6%
	Google GCP	22	11.8%
	Others (Specify)	----	----
	None	-----	-----
Student Population	< 5000	6	3.2%
	5,000 – 10,000	65	34.0%
	10,000 – 20,000	13	7.0%
	20,000 – 30,000	88	47.3%
	> 30,000	14	7.5%

“AD = Adamawa; GM = Gombe; BC = Bauchi; TR; Taraba; BN; Borno; YB = Yobe; JG = Jigawa; KD = Kaduna; KN = Kano; KT = Katsina; KB = Kebbi; SK = Sokoto; ZF = Zamfara; AB = Abuja; BN = Benue; KG = Kogi; KW = Kwara; NS = Nassarawa; NG = Niger; PL = Plateau”

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The descriptive analysis in Table 4 shows that 73.7% were male, and 26.3% were female. The categories of top managers show that 9.0% are directors, 9.0% are deputy directors, 24.9% are unit head, 43.9% are the assistant unit head, and 13.2% are deans respectively. Descriptive statistics show that the respondents were less than 1 year of experience at 5.4%, 1-2 years, 29%, 2-3 years, 46.2%, 4-5 years 17.2%, and above 5 years with 2.2% experience. This indicates that most of the respondents meet the experience level for this study. For the institution type, Federal universities have 57.1%, whereas State universities have 42.9%. For the familiarity with the cloud-based e-learning, 36.6% are familiar with Microsoft Azure, 51.6% are familiar with Amazon Web Service, and 11.8% are familiar with Google GCP. This shows that the respondents are conversant with cloud computing for e-learning and perfectly fit the requirement to answer the questionnaire. Similarly, the respondent's education level ranges from Bachelor's Degree with 25.8%, Master's Degree with 64.0%, and Doctorate with 10.2%. These perhaps indicate that the respondents are experienced as well as provide adequate variance regarding their background.

Test of Response Bias

Non-response bias refers to the error anticipated by researchers while estimating a sample feature due to under-representation of survey respondents to non-response (Berg, 2002).). Nonetheless, according to Malhotra, Hall, Shaw & Oppenheim (2006), the overall findings may be distorted due to respondent significant difference from the non-respondents with regards to attitude, behaviour, motivation, and demographics etc. This is also supported by the submission of Singer (2006, p. 641) "there is no minimum response rate below which a survey estimate is necessarily biased and, conversely, no response rate above which it is never biased" (Singer, 2006, p. 641). "However, no matter small the non-response, there is a possible bias which must be investigated" (Pearl & Fairley, 1985; Sheikh, 1981). Hence, the reason for testing for the non-response bias using the independent sample t-test. The assessment focuses on the demographic variables such as the gender, level of education, position in the university, institution type, institution location, experience in managing e-learning, experience using cloud computing for e-learning purposes, familiarity with type IaaSBEL, as well as a number of students in the institution respectively.

Coding

Coding was performed to ease items identification as well as ascertain that all items have a unique identification code in SPSS. The unique number will be recorded in the questionnaire.

Editing

The questionnaire that was retrieved from the respondents were checked for errors (incompleteness). The ones found to be skipped were instantly and marked and rejected. Likewise, the questionnaires with more than 25% left un-attended were removed from the dataset. However, questions with fewer missing values were used and missing value (using the mean substitution technique).

Missing Data

To lessen the percentage of missing data, precautionary measures were observed, such as giving the questionnaire to the respondents and check for any missing/skipped question. Further, the researcher swiftly checks to see if there are any missing or answered are not answered correctly, to call the attention of the respondent. This way, missing data was significantly reduced. The most conventional method to deal with missing data is case deletion

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(Tabachnick & Fidell, 2007). Deleting missing data is useful when the data is large. Nonetheless, there is no permissible threshold of missing data for making a valid statistical inference. However, Tabachnick and Fidell (2007) suggested that the missing value rate of ≤ 5% is non-significant, and thus one of the appropriate methods of missing data analysis is mean substitution. Therefore, this study adopts the mean substitution technique. Table 5 illustrates the summary of missing values in the data.

Table 5: Percentage of Missing Values

Latent Variables	No. of Missing Values
RA	8
COM	1
TR	0
SEC	0
TMS	2
CS	5
SPS	0
CP	5
INT	1
GS	3
Total	25 out of 9,261 data points
Percentage	0.26%

Assessment of Outliers

Assessment of outliers is a significant step of data cleaning, which involves extreme case count, that may likely and negatively affect the result (Maiyaki & Mouktar, 2011). Outliers are defined "in a set of data to be an observation (or subset of observations) which appears to be inconsistent with the remainder of that set of the data" (Barnett & Lewis, 1978 p. 4). Thus, in "a regression analysis, the presence of outliers in the data set can seriously hamper the estimates of the regression coefficients, which will lead to distorted results" (Verardi & Croux, 2008). This study identifies multivariate outlier's analysis using the Mahalanobis Distance method, a measure of the multivariate distance, which can be evaluated using the Chi-square (*X2*) table. The most common probability estimates for a "case being an outlier is p <0.001 for the *X2* value, is appropriate with Mahalanobis Distance" (Tabachnick & Fidell, 2007). Hence, the Chi-Square table can also be used for the Mahalanobis based on the number of items. This study comprises of 49 items with Chi-Square value of 65.17 (p = 0.05). Therefore, any Mahalanobis value greater than 65.17 is discarded from the dataset. Therefore, no deletion was made because the highest Mahalanobis distance is 43.76, which is less than 65.17 thresholds.

Normality Test

Normality test is a crucial assumption in multivariate analysis (Hair et al., 2010). Screening continuous variables for normality is an essential early step in almost every multivariate analysis, although, the normality of the variables is not always required for analysis. Thus, normality of variables is assessed by either statistical or graphical methods (Tabachnick & Fidell, 2007). The present study employs the statistical approach to assess the normality of collected data (Tabachnick & Fidell, 2007). However, since the sample of this study is less than 200, the statistical method (Skewness and Kurtosis) will be adopted.

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Table 6: Normality Test Using Statistical Methods

Variable	Skewness	Kurtosis
Relative Advantage (RA)	.295	.200
Compatibility (COM)	-1.206	3.114
Trust (TR)	-.574	-.083
Security (SEC)	-.457	-.146
Top Management Commitment (TMC)	-1.300	2.987
Cost Savings (CS)	-.726	.437
Competitive Pressure (CP)	-1.300	1.934
Service Provider Support (SPS)	-.711	.187
Intention to Adopt IaaSBEL (INT)	-.254	-.417
Government Support (GS)	-1.335	1.350

As depicted in Table 6, the values of Skewness fall between the range of -1.300 and .295, where Kurtosis fall between 3.114 and -.417, which are considered to be approximately normally distributed according to Kline (2015). In addition, Kline (2015) stated that the absolute value of Skewness greater >3 and Kurtosis > 10 indicates non-normality issues.

Multicollinearity

Multicollinearity refers to an issue that happens when the exogenous constructs are highly correlated with a value of 0.9 and above (Tabachnick & Fidell, 2007). When a number of variables are too correlated, they tend to contain redundant information and therefore, increase and inflate the size of the error, which in turn weakens the analysis. One of the easiest ways of detecting the multicollinearity problem is resolved by deleting the affected variable(s). Additionally, to identify multicollinearity, Tolerance and Variance Inflation Factor (VIF) are utilised (Chatterjee & Yilmaz, 1992; Peng & Lai, 2012). The Tolerance value of > 0.10 and VIF < 10 are the thresholds recommended by Field (2009). Hence, Multicollinearity issues are not observed in the study, as shown in Table 7.

Table 7: Multicollinearity Analysis

Exogenous Variables	Collinearity	
	Tolerance	**VIF**
Relative Advantage (RA)	.827	1.210
Compatibility (COM)	.578	1.729
Trust (TR)	.540	1.853
Security (SEC)	.600	1.667
Top Management Commitment (TMC)	.553	1.808
Cost Savings (CS)	.635	1.574
Competitive Pressure (CP)	.435	2.300
Service Provider Support (SPS)	.607	1.647
Government Support (GS)	.513	1.949

Exploratory Factor Analysis for Exogenous and Endogenous Variables

All items were subjected to Principal Components Analysis (PCA) analysis using SPSS. Performing the PCA analysis is crucial, even though the measurement were adapted from preceding research. Nonetheless, in this research, the measures were used in a different context but were a little bit altered to suit the objectives of the study. The factor analysis was conducted to scrutinize the relationships between large numbers of items which enable researchers to

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classify them into smaller groups or factors (Hooper, 2012). Hence, the Exploratory Factor Analysis (EFA) is performed during the pilot study as the basis for construct development, particularly to identify the underlying construct behind a set of measured variables (Suhr, 2006). Thus, the EFA is suitable to perform using pilot data as a foundation for the Confirmatory Factor Analysis (CFA) in the actual study data.

As an alternative, this study runs EFA based on each construct. This is principally due to the items were selected from previous studies that measured the intended constructs. Hence, this study aims to prove the structure of these items. Similarly, Hair et al. (2010) "recommended the thresholds in conducting the EFA; Bartlett Test < 0.5, Kaiser-Meyer-Olkin (KMO) > 0.8, Factor Loading ≥ 0.5, Communalities ≥ 0.3, as well as Eigenvalue ≥ 1.0" respectively. However, KMO value greater than .5 is acceptable (Field, 2013; Kaiser, 1970). Therefore, all the items meet the Hair and Kaiser's recommendations (See Table 8).

Table 8: Multicollinearity Analysis

VAR	KMO	Eigen Value	Bartlett Test	Item	Factor Loading	Communalities	Deleted Items
RA	0.691	4.055	0.000	RA1	0.823	0.762	Nil
				RA2	0.891	0.883	Nil
				RA3	0.934	0.873	Nil
				RA4	0.849	0.913	Nil
				RA5	0.951	0.904	Nil
				RA6	0.785	0.851	Nil
COM	0.624	2.502	0.000	COM1	0.771	0.611	Nil
				COM2	0.899	0.813	Nil
				COM3	0.744	0.829	Nil
				COM4	0.834	0.702	Nil
				COM5	0.520	0.719	Nil
				COM6	0.807	0.663	Nil
TR	0.692	2.115	0.000	TR1	0.832	0.692	Nil
				TR2	0.882	0.778	Nil
				TR3	0.803	0.645	Nil
SEC	0.621	2.119	0.000	SEC1	0.911	0.829	Nil
				SEC2	0.894	0.799	Nil
				SEC4	0.701	0.491	Nil
TMC	0.568	2.388	0.000	TMC1	0.926	0.867	Nil
				TMC2	0.843	0.748	Nil
				TMC3	0.850	0.750	Nil
				TMC4	0.799	0.798	Nil
				TMC5	0.729	0.799	Nil
				TMC6	0.911	0.873	Nil
CS	0.789	3.032	0.000	CS1	0.915	0.837	Nil
				CS2	0.870	0.756	Nil
				CS3	0.895	0.801	Nil
				CS4	0.798	0.638	Nil

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CP	0.741	3.974	0.000	CP1	0.731	0.665	Nil
				CP2	0.761	0.923	Nil
				CP3	0.793	0.836	Nil
				CP4	0.943	0.897	Nil
				CP5	0.921	0.857	Nil
				CP6	0.803	0.753	Nil
				CP7	0.637	0.755	Nil
SPS	0.674	3.878	0.000	SPS1	0.851	0.727	Nil
				SPS2	0.556	0.386	Nil
				SPS3	0.844	0.803	Nil
				SPS4	0.903	0.817	Nil
				SPS5	0.938	0.881	Nil
				SPS6	0.580	0.522	Nil
				SPS7	0.907	0.838	Nil
INT	0.541	1.958	0.000	INT1	0.658	0.434	Nil
				INT2	0.916	0.838	Nil
				INT3	0.828	0.686	Nil
GS	0.790	3.283	0.000	GS1	0.817	0.667	Nil
				GS2	0.907	0.823	Nil
				GS3	0.965	0.931	Nil
				GS4	0.928	0.862	Nil

Note: RA = "Relative Advantage", COM = "Compatibility", TR = "Trust", SEC = "Security", TMC = "Top Management Commitment", CS = "Cost Savings", CP = "Compatibility", SPS = "Service Provider Support", INT = "Intention", GS = "Government Support"

Discussion

The preliminary analysis is an important step that must be performed before any test can be performed in a quantitative study. The data cleaning or noise reduction involves the steps and thresholds that research data must meet before it can be used for more rigorous statistical analysis. From the above sections, it can be noted that the research data undergo numerous data cleaning or noise reduction processes which include; descriptive statistics of respondents, response bias, missing data analysis, assessment of outliers, normality of data, multicollinearity and EFA using PCA. Following the steps listed above, the data was cleaned, and outliers were eliminated. Therefore, the research data met all statistical and multivariate assumptions for further analysis using PLS-SEM.

Conclusion

This study discusses the issues related to preliminary analysis and data cleaning in IS research. The findings revealed some missing data cases (<5%), which were addressed using mean substitution as postulated by Hair et al. (2013). Similarly, the multivariate outliers and non-response bias were not an issue in this study. Data cleaning process were performed to ascertain the reliability of data. The data satisfy the primary assumption as well as the requirements for performing the multivariate analysis (Hair et al., 2010; Tabachnick & Fidell, 2007). Besides, the convergence of divergent factors into the Technology, Organization and Environmental perspective show high factor loadings, ascertaining that the variables are measuring the intended constructs as theorized. Therefore, these findings will provide an insight to further

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perform rigorous analysis as well as provide the understanding of how and why of the cloud computing studies in developing countries HEIs.

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