Technology acceptance model (TAM) for analysing cloud computing acceptance in higher education institution (HEI)

M T Amron* and N H M Noh

Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA (UiTM), 21080 Kuala Terengganu, Terengganu, Malaysia

*Corresponding author: talmizie@uitm.edu.my

Abstract. Cloud computing is a fast-growing and up-and-coming technology. Cloud computing allows educational users a more flexible, accessible, and wide range of education resources. In this study, the technology acceptance model (TAM) was used as the foundation to explore the effects of perceived usefulness, perceived ease of use with two proposed additional variable: security and learning environment towards using cloud computing. The questionnaire was distributed using convenient sampling and a total of 664 higher education institution members consisting of lecturers, students and staffs participated in this research. The response was analysed using the Partial Least Squares Structural Equation modeling (PLS-SEM), which provides evidence of the reliability and validity of the Technology Acceptance Model (TAM) in this study. The result shows that perceived ease of use and perceived usefulness positively and significantly influence the intention to use cloud computing. It is also seen that security and learning environment also have a positive and significant impact on the intention to use cloud computing.

1. Introduction

The evolution of computing today has given consumers more options to be more frugal and use more user-friendly technological facilities. Cloud computing offers users more convenience when they no longer need to install software on their device [1][2]. Even more economical, they do not have to bear the cost of purchasing or expensive software licenses. Cloud computing is a platform where data is stored in a network-connected via the internet, and applications and software are shared across servers [3]. Various cloud computing service providers are available such as Google Cloud, Amazon Web Server, IBM Cloud, Alibaba Cloud and Microsoft Azure.

As a result of the COVID-19 pandemic, many sectors were severely affected and even faced problems and challenges in surviving operations. The education sector was also affected when schools and universities had to be closed, and online learning had to be done from home. Therefore, reliance on online resources becomes very important to continue learning sessions from home. The use of online applications such as Google Classroom, OpenLearning.com, Teachable and other learning management systems (LMS) is beneficial [4]. Almost all these applications use the cloud computing platform where information resources, applications, and others are shared. For example, Google Cloud provides Google Classroom, Google Drive, Google Form, Google Docs, Google Sheets, and many other applications that help with the teaching and learning process.

A study by [5] revealed that only 29% of the study respondents said they use cloud-based applications, while 90% of respondents used it. This situation shows that many users are unaware that they have been exposed to and using cloud-based applications. They are probably using cloud
application already yet do not know it. Many studies have been conducted in higher education to evaluate cloud computing technology adoption in organisations, especially to measure organisational readiness, ICT infrastructure compatibility, service quality, cost, security, and risk. However, very few studies evaluate individuals such as students, lecturers, and administrative staff who use this technology, especially in developing countries.

This study will understand the determinants and the underlying relationship of cloud computing acceptance. A practical acceptance of cloud computing can be facilitated in the education field, particularly in the new norm of teaching and learning environment. Therefore, this study investigates the factors and attempts to develop and test the proposed modified TAM model that makes the model more relevant to cloud computing in HEI. Furthermore, this study attempts to fill a research gap by addressing the effects on security and learning environment with intentions towards the use of cloud computing.

2. Theoretical background
There have been many previous studies that have adapted various theories of acceptance of new technologies, such as the theory of planned behaviour (TPB), the theory of reason action (TRA), the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT). These theories are widely used for individual units of analysis. For this study, the author uses TAM theory to accept cloud computing technology among higher education institution students, lecturers, and staff in Malaysia.

2.1. Technology acceptance model
TAM is a theory developed by [6] that models how users accept and use technology. In general, TAM focuses on individual acceptance of technology by emphasising two main factors: perceived usefulness (PU) and perceived ease of use (PEOU). PU is defined as the degree to which a person believes that using technology would enhance their job performance. While PEOU refers to the degree to which a person believes that using a particular system would be free from effort.

Literature has demonstrated TAM's capacity to clarify the factors that affect the decision to implement new technology. As proposed by [7–9], it is suitable for analysing new technology acceptance. However, the finding of past studies also concluded that adopting new technology is limited to TAM's original factors. This study uses TAM because this theory is one of the earliest fundamental theories of acceptance that allows external variables to be tested together with the two factors of the theory [10]. Besides, TAM is also suitable for predicting factors that influence the acceptance of technology [11].

2.2. Security and Learning Environment, and acceptance of technology
Security aspects are critical in ensuring data protection and information stored in cloud computing [12]. Therefore, a standard security mechanism needs to be applied and implemented in the cloud environment platform. The security aspect is also a question and doubts for many users to start accepting cloud computing technology. Many users are unclear about the security and privacy of information in the cloud, causing them to avoid using cloud-based applications. Therefore, this study will directly assess the security factors to the influence of intentional use.

The environment greatly influences the acceptance of technology. In this study, the learning environment either helped or became a barrier to individuals’ acceptance of cloud computing. According to [13], elements such as self-determination, learning content, support system and knowledge sharing in the learning environment will influence technology acceptance in education. Therefore, the learning environment is seen as a vital factor to be tested in this study, especially in online and distance learning that requires the use of technologies such as cloud computing.

External security factors and learning environment are associated with the use intention to test the relationship between them. Past studies also did the same method of the direct relationship of external factors to the use intention, and it showed mixed results on the studies [14–16]. Figure 1 shows the study model based on the theory of TAM.
Figure 1. Research model.

2.3. Hypothesis development

The research model consists of five factors: perceived usefulness (PU), perceived ease of use (PEOU), security (SEC), learning environment (LE), and use intention (UI). PU means whether someone perceives that the technology to be useful for what they want to do. A study by [17] proved that PU influenced university students in Britain to accept new technologies. Hence, the study proposes that:

H1: PU is positively related to the intention to use cloud computing among HEIs.

The PEOU refers to the individuals feeling that technology is easy to use and is less difficult. This sense of fun accelerates one’s use of new technology. A study by [14] concludes that PEOU is a key factor that allows many students to accept the use of e-Book in learning. Hence, the study proposes:

H2: PEOU is positively related to the intention to use cloud computing among HEIs.
H3: PEOU is positively related to the PU to use cloud computing among HEIs.

The SEC is a factor that is difficult to separate from new technologies, especially when it involves data and information. In cloud computing technology, the SEC is often the subject of controversy, especially in security and trust matters [18]. Many past studies have concluded that this factor greatly influences the adoption of new technologies such as cloud computing [19][20]. Hence, the study proposes:

H4: SEC is positively related to the intention to use cloud computing among HEIs.

LE refers to the current state of the learning and teaching (T&L) process that drives a person to adopt cloud computing technology. The current situation opens space for the T&L process to be more dynamic and no longer revolve around conventional methods. According to [21], the environment greatly influences individuals to adopt new technologies. A study by [22] agrees that in implementing e-Learning, the learning environment is very important in encouraging students to accept new technologies. Hence, the study proposes that:

H5: LE is positively related to the intention to use cloud computing among HEIs.

3. Research Method

An individual is the unit of analysis in this study. Students, lecturers, and staff at HEI in Malaysia are the respondents in this research. The instrument was developed based on five variables of the research model. All the items were adopted from the previous study. There were five items of Perceived Usefulness adopted from [6] and [23]; while five items of Perceived Ease of Use adopted from [23]; four items of Use Intention adopted from [24] and [23]. The seven items of security adopted from [25] and five Learning Environment items are self-developed due to no previous studies on these variables.

For data collection, a convenience sampling method was used as supported by [26] and [27] stated that convenience sampling allows researchers to get responses cost-effectively. The G*Power software has been used to determine the sample size of the respondents. The minimum number of respondents needed is 85. An online survey questionnaire was distributed to the sample of this study via email and WhatsApp group application. A total of 664 completed responses were received, which is above the scholar’s recommendation [28].
4. Results and Discussion

4.1. Data

The survey questions are divided into two major sections: the respondent profile and the technology acceptance model's application. The items and measurements used in this questionnaire were mainly adapted from previous TAM related studies published by renowned scholars. Some questions were changed to match the context of the research. Respondents were asked about adopting cloud computing in HEI using a five-point Likert scale ranging from Strongly Disagree to Strongly Agree for each statement.

To investigate the research model, partial least squares (PLS) analysis was conducted using the SmartPLS Software [29]. The measurement model (validity and reliability of the measures) was tested followed by an examination of the structural model (testing the hypothesised relationship) [30–32] by following the recommended two-stage analytical procedures developed by [33]. A resample of 3000 was used to find out the significance of the path coefficients and the loadings.

When data is collected through self-reported questionnaires, common method variance needs to be examined, particularly when both the predictor and criterion variables are obtained from the same individual [34]. To test response bias, Harman's single factor test was assimilated [35]. The maximum co-variance explained by a single factor was only 42.565% which is less than 50%, indicating that common method bias is not a likely issue in this study [36][37].

Data normality was assessed via multivariate skewness and kurtosis analysis as recommended by [30] and [38] at https://webpower.psychstat.org/models/kurtosis/results.php?url=dcd49fd96ae7dca77016c3031fe29dad. The Mardia’s multivariate skewness (β = 1.1858, p<0.01) is above the cut of +1 and Mardia’s multivariate kurtosis (β= 47.86, p<0.01) above the cut of +20 computed showed that the data collected is not multivariate normal. Thus, the use of PLS-SEM in this analysis is justified.

4.2. Measurement model

The construct validity for each latent variable in the model was first checked prior to proceeding to the hypothesis testing. Five latent constructs comprise the measurement model used in this research. Before proceeding to hypothesis testing, the construct validity for each latent variable in the model was first verified. In this analysis, the measurement model used consists of five latent constructs: Use Intention, Perceived Ease of Use, Perceived Usefulness, Learning Environment and Security. Table 1 presents the output assessment of reliability and validity in the data of the study. Composite reliability (CR) of more than 0.7 values suggest that these constructs have a reasonable degree of internal consistency [39]. The average variance extracted (AVE) values above the minimum threshold value of 0.5 indicate good convergent validity [40]. As shown in table 1, no items were dropped since all the loadings are more than 0.7. The convergent validity is then verified and now can assess the data's discriminant validity.

Table 1. Convergent validity.

| Items | Outer Loadings | CR | AVE |
|-------|----------------|----|-----|
| U1    | 0.7463         | 0.908 | 0.714 |
| U2    | 0.8573         |      |     |
| U3    | 0.8797         |      |     |
| U4    | 0.8883         |      |     |
| PE1   | 0.8657         | 0.938 | 0.753 |
| PE2   | 0.8515         |      |     |
| PE3   | 0.8974         |      |     |
| PE4   | 0.8874         |      |     |
| PE5   | 0.8351         |      |     |
| PU1   | 0.7948         | 0.927 | 0.717 |
| PU2   | 0.8585         |      |     |
| PU3   | 0.8623         |      |     |

| PU4 | 0.8697 |
| PU5 | 0.8457 |
| LE1 | 0.7595 |
| LE2 | 0.7579 |
| LE3 | 0.6756 |
| LE4 | 0.7360 |
| LE5 | 0.7181 |
| SEC1| 0.7828 |
| SEC2| 0.8404 |
| SEC3| 0.8415 |
| SEC4| 0.8367 |
| SEC5| 0.7655 |
| SEC6| 0.8621 |
| SEC7| 0.7908 |
The discriminant validity of all latent variables in the model was determined by using heterotrait-monotrait (HTMT) ratio of correlations criterion [41]. Since the correlation values corresponding to the respective constructs did not exceed the threshold of the HTMT 0.90 criterion as shown in table 2, it is safe to say that the discriminant validity is established in the measurement model. Consequently, structural measurement research is now sufficient to proceed.

### Table 2. Discriminant validity.

|     | UI   | PEOU  | PU    | LE    | SEC   |
|-----|------|-------|-------|-------|-------|
| UI  | 0.724| 0.666 | 0.542 | 0.408 |       |
| PEOU| 0.629| 0.623 | 0.457 |       |       |
| PU  | 0.559| 0.457 |       |       |       |
| LE  | 0.422| 0.439 | 0.408 |       |       |
| SEC | 0.422| 0.439 | 0.408 |       |       |

4.3. Structural model

The bootstrapping procedure is used to test the hypotheses to produce results for each path relationship in the model, as shown in table 3. To allow the procedure to estimate the model for each sub-sample, bootstrap sub-samples with 3000 cases were computed. All path relationships are found to be significant at 99 and 95% confidence level (PU -> UI, $\beta = 0.2182$, $p < 0.01$; PEOU -> UI, $\beta = 0.4771$, $p < 0.01$; PEOU -> PU, $\beta = 0.6658$, $p < 0.01$; SEC -> UI, $\beta = 0.0653$, $p < 0.05$; LE -> UI, $\beta = 0.1169$, $p < 0.01$). Thus, all five hypotheses in this study are supported. Using the suggested threshold value of 3.3 [42] for the criteria of variance inflation factor (VIF), the multicollinearity index among the variables computed in the model did not cause concern.

### Table 3. Path coefficient and hypothesis testing.

| H  | Beta | SE  | T values | P values | LL  | UL  | VIF | Decision   |
|----|------|-----|----------|----------|-----|-----|-----|------------|
| 1  | 0.2182 | 0.0493 | 4.4275 | 0.0000 | 0.1383 | 0.3003 | 1.9763 | Supported  |
| 2  | 0.4771 | 0.0397 | 12.0143 | 0.0000 | 0.4028 | 0.5425 | 2.2135 | Supported  |
| 3  | 0.6558 | 0.027 | 24.6392 | 0.0000 | 0.6189 | 0.7093 | 1.0000 | Supported  |
| 4  | 0.0653 | 0.0316 | 2.0648 | 0.0195 | 0.0133 | 0.1182 | 1.3472 | Supported  |
| 5  | 0.1169 | 0.0384 | 3.0433 | 0.0012 | 0.0531 | 0.1819 | 1.7547 | Supported  |

SmartPLS 3 software can also generate quality outputs for the coefficient of determination ($R^2$) and the effect size ($f^2$) of all independent variables on the dependent variable, as shown in table 4. The values for $R^2$ of 0.5757 suggests that the independent variables in this study explain 57.57% of variances in UI, while $R^2$ of 0.4425 indicate 44.25% variance in PU can be attributed to UI, respectively.

Additionally, the $F^2$ effect size values exhibit the importance of each independent variables to the dependent variable. A scholar [43] defined values near 0.02 as small, near 0.15 as a medium, and above 0.35 as large. It is shown that the effect size of PEOU on UI ($F^2 = 0.2431$) is medium to large followed by PU ($F^2 = 0.0565$), LE ($F^2 = 0.0184$) and SEC ($F^2 = 0.0074$) which has small effective size respectively. It is observed that PEOU has the largest effect size on PU ($F^2 = 0.7963$).
Table 4. Effect size and prediction summary.

| Constructs | $R^2$ | $F^2$  | $Q^2$ |
|------------|-------|--------|-------|
| UI         | 0.5757| 0.5433 |       |
| PEOU       | 0.2431| 0.7963 |       |
| PU         | 0.4425| 0.0565 | 0.4404|
| LE         | 0.0184|        |       |
| SEC        | 0.0074|        |       |

To test for predictive efficiency, PLS Predict analysis was carried out. Predictive validity implies that a given set of measures can predict a given outcome variable for a specific construct [44][45]. The corresponding $Q^2$ from the PLS-Predict analysis was UI (0.5433) and PU (0.4404), which are all greater than 0, suggesting sufficient predictive relevance.

5. Conclusion

The study revealed that the positive perception of ease of use of cloud computing is a stronger predictor of intention than perceived usefulness. Perceived ease of use is defined as the degree to which the user thinks that using cloud computing will be effortless, and perceived usefulness is defined as the degree to which the user thinks that using cloud computing will be useful in completing tasks. The result implies that the intention to use cloud computing is largely influenced by the perception that cloud computing is effortless and easy to use more than its benefit. At the same time, perceived ease of use is a strong contributor to perceived usefulness, suggesting that if the user thinks it's easy to use and operate cloud computing, they'll think it's going to beneficial to make the job done.

This study also offers evidence that both the learning environment and security are possible factors influencing cloud computing use intention among part of the lecturers, students, and staff among HEIs. The learning environment had slowly shifted from face-to-face to blended learning, embracing several innovations. Some of these involve the use of technology through blended learning. Given the covid-19 pandemic situation, students and lecturers are forced to implement distance learning. Following these conditions, students, lecturers and staffs must use online tools, and one of them is the cloud computing application.

On the other hand, security refers to how much the users feel safe to use Cloud Computing application. It is quite clear that if users feel safe and secure upon using Cloud Computing, they will be generally open to using it and learning it to perform their tasks. This study reveals that both the learning environment and security are a positive predictor that contributes to the use intention of cloud computing among part of lecturers, students, and staff among HEIs. This indicates that the requirement of a learning environment nowadays had a positive impact on their intention to use cloud computing and feel safe and secure using it.

The development in cloud computing has produced innovative functions towards helping the education and learning endeavours of teachers and students. Numerous educational frameworks and functions, particularly cloud computing, have been introduced in recent years. Thus, understanding academicians' intention, students and HEIs staff towards using cloud computing applications are crucial. This study validated the proposed theoretical model for predicting the intention to use cloud computing among HEIs in Malaysian. The convenience sampling technique reduces the reliability of the findings to HEIs in Malaysia, so the findings should be interpreted with caution.

References

[1] Maresova P and Kacetl J 2015 Cloud Computing in the Public Sector–Case Study in Educational Institution Procedia - Soc. Behav. Sci. 182 341-348.
[2] Mokwena S, Hlebela C 2018 Factors affecting the adoption of Software as a Service in South African Small Medium Enterprises Open Innov Conf. 1–6.
[3] Amron M T, Ibrahim R, Abu Bakar N A, Chuprat S 2019 Acceptance of cloud computing in the Malaysian public sector: a proposed model Int. J. Eng. Bus. Manag. 11.
[4] Dhawan S 2020 Online Learning: A Panacea in the Time of COVID-19 Crisis *J. Educ. Technol. Syst.* **49**(1) 5–22.

[5] Dixon C 2014 New research shows cloud storage awareness, usage high [internet] nScreenMedia [cited 2020 Dec 11] Available from: https://nscreenmedia.com/new-research-shows-cloud-storage-awareness-usage-high/

[6] Davis F D 1989 Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology *MIS Q.* **13**(3) 319–40.

[7] Ashjari S Eydgahi A Student perceptions of cloud applications effectiveness in higher education. *J. Comput. Sci.* **49**(1) 5–22.

[8] Aharony N 2015 An exploratory study on factors affecting the adoption of cloud computing by information professionals *Electron. Libr.* **33**(2) 308–23.

[9] Taib S M, De Coster R, Nyamu J 2016 Innovation diffusion of wearable mobile computing: Pervasive computing perspective *Int. Conf. on Information Society (Dublin, Ireland)* p 97–101.

[10] Hong S H and Yu J H 2018 Identification of external variables for the Technology Acceptance Model(TAM) in the assessment of BIM application for mobile devices *IOP Conf. Series: Materials Science and Engineering*.

[11] Sharma S K, Al-Badi A H, Govindaluri S M and Al-Kharusi M H 2016 Predicting motivators of cloud computing adoption: A developing country perspective *Comput. Human. Behav.* 62 p 61-69.

[12] Amron M T, Ibrahim R, Bakar N A A 2020 Cloud computing acceptance among public sector employees *Telkomnika (Telecommunication Comput. Electron. Control)* **19**(1) 124–33.

[13] Hsu T S and Kadir S L S A 2016 Predicting instructional effectiveness of cloud-based virtual learning environment *Ind. Mana.g Data Syst.* **116**(8) 1557–84.

[14] Ahmed M M, Houssein E H, Hassanien E A, Taha A and Hassanien E 2018 Adoption of E-Book for University Students *Int. Conf. on Advanced Intelligent Systems and Informatics (Cairo, Egypt)* p 481–94.

[15] Gangwar H, Date H and Ramaswamy R 2015 Understanding determinants of cloud computing adoption using an integrated TAM-TOE model *J. Enterp. Inf. Manag.* **28**(1) 107–30.

[16] Farooq M S, Salam M, Jaafar N, Fayolle A, Ayupp K, Radovic-Markovic M, et al 2017 Acceptance and use of lecture capture system (LCS) in executive business studies: Extending UTAUT2 *Interact. Technol. Smart. Educ.* **14**(4) 329–48.

[17] Hajli N, Wang Y, Tajvidi M and Hajli M S 2017 People, Technologies, and Organisations Interactions in a Social Commerce Era *IEEE Trans. Eng. Manag.* **64**(4) 594–604.

[18] Amron M T M, Ibrahim R and Chuprat S 2017 A review on cloud computing acceptance factors. *Proc. Computer Science* p 639–46.

[19] Rahi S and Abd. Ghani M 2018 The role of UTAUT, DOI, perceived technology security and game elements in internet banking adoption *World J. Sci. Technol. Sustain. Dev.* **15**(4).

[20] Zhang H, Tang Z and Jayakar K 2018 A socio-technical analysis of China’s cybersecurity policy: Towards delivering trusted e-government services *Telecomm. Policy* **42**(5) 409–20.

[21] Mahesh D D, Vijayapala S and Dasanayaka S W S B B 2018 Factors affecting the intention to adopt big data technology : A study based on financial services industry of Sri Lanka *4th Int. Multidisciplinary Moratuwa Engineering Research Conf. (Sri Lanka)* p 420–5.

[22] Nyeko S and Moya M 2017 Determinants of eLearning adoption among instructors in Ugandan public universities *IST-Africa Week Conf.* 1–10.

[23] Ibrahim R, Leng N S, Yusoff R C M, Samy G N, Masrom S and Rizman Z I 2017 E-Learning Acceptance Based on Technology Acceptance Mode (TAM) *J. Fundam. Appl. Psychol. Mark.* [Internet] **9**(4S) 871–89.

[24] Lin C-H, Shih H-Y and Sher P J 2007 Integrating technology readiness into technology acceptance: The TRAM model *Psychol. Mark.* [Internet] **24**(7) 641–57.

[25] Amron M T, Ibrahim R, Bakar N A, Chuprat S, Abu Bakar N A and Chuprat S 2019 Development and Validation of a Questionnaire to Measure the Acceptance of Cloud Computing in Public Sectors. *Open Int. J. Informatics.* **7**(2) 85–95.

[26] Hair J F, Matthews L M, Matthews R L and Sarstedt M 2017 PLS-SEM or CB-SEM: updated
guidelines on which method to use Int. J. Multivar. Data Anal. 1(2) 107.

[27] Ngah A H, Ramayah T, Ali M H and Khan M I 2019 Halal transportation adoption among pharmaceuticals and comestics manufacturers J. Islam Mark.

[28] Baruch Y 1999 Response Rate in Academic Studies Human Relations. 52 p 421–38.

[29] Ringle, Christian M, Wende S and Becker J-M 2015 SmartPLS 3 [Internet]. Bönningstedt Available from: http://www.smartpls.com

[30] Hair J F, Hult G T M, Ringle C M and Sarstedt M A 2017 Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). 2nd ed. SAGE Publication.

[31] Ramayah T, Yeap J A L and Ignatius J 2013 An Empirical Inquiry on Knowledge Sharing Among Academicians in Higher Learning Institutions Minerva 51(2) 131–54.

[32] Ramayah T and Lee J W C 2011 JBC Network collaboration and performance in the tourism sector. Serv Bus. 5(4) 411–28.

[33] Anderson J C and Gerbing D W 1988 Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach Psychol Bull. 103(3) 411–23.

[34] Podsakoff P M, MacKenzie S B, Lee J Y and Podsakoff N P 2003 Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies J. Appl. Psychol. 88(5) 879–903.

[35] Podsakoff P M, MacKenzie S B and Podsakoff N P 2012 Sources of Method Bias in Social Science Research and Recommendations on How to Control It Annu. Rev. Psychol. 63(1) 539–69.

[36] Eichhorn B R 2014 Common Method Variance Techniques Midwest SAS Users Gr Conf. (Chicago) 1–11

[37] Dupuis M, Khadeer S and Huang J 2017 I Got the Job: An exploratory study examining the psychological factors related to status updates on facebook. Comput. Human Behav. 73 132–40.

[38] Cain M K, Zhang Z and Yuan K H 2017 Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation Behav. Res. Methods. 49(5) 1716–35.

[39] Gefen D, Straub D and Boudreau M-C 2000 Structural Equation Modeling and Regression: Guidelines for Research Practice Commun. Assoc. Inf. Syst. 4(October).

[40] Bagozzi R P and Yi Y 1988 On the evaluation of structural equation models. J. Acad. Mark. Sci. 16(1) 74–94.

[41] Henseler J, Ringle C M and Sarstedt M 2015 A new criterion for assessing discriminant validity in variance-based structural equation modeling J. Acad. Mark. Sci. 43(1) 115–35.

[42] Hair J F, Black W C, Babin B J and Anderson R E 2014 Multivariate data analysis. 7th ed. Vol. 16 Statistica Neerlandica. England: Pearson Education Limited.

[43] Cohen J 1988 Statistical Power Analysis for the Behavioral Sciences. 2nd ed. Lawrence Erlbaum Associates 567 p.

[44] Shmueli G, Ray S, Velasquez Estrada J M and Chatla S B 2016 The elephant in the room: Predictive performance of PLS models. J. Bus. Res. 69(10) 4552–64.

[45] Felipe C M, Roldán J L and Leal-Rodriguez A L 2017 Impact of organisational culture values on organisational agility Sustain. 9(12).