Accounting 8 (2022) 403–408

Contents lists available at GrowingScience

Accounting

homepage: www.GrowingScience.com/ac/ac.html

Technological, organizational and environmental factors influencing on user intention towards big data technology adoption in Malaysian educational organization

Noor Baizura Harun[a*], Habibah Ab Jalil[b] and Maslina Zolkepli[c]

[a]*Institute of Aminuddin Baki Genting Highlands, Malaysia*
[b]*Associate Professor, Universiti Putra Malaysia, Malaysia*
[c]*Universiti Putra Malaysia, Malayisa*

C H R O N I C L E

Article history:
Received March 25, 2022
Received in revised format June 10 2022
Accepted June 30 2022
Available online
June 30 2022

Keywords:
Organizational
Environmental
User intention
Big data technology
Technology adoption
Educational organization

A B S T R A C T

Studying the factors in influencing the users' intentions to adopt Big Data technology in Malaysia is crucial. This study adopted three grand theories which consisted of Dissemination of Innovation (DOI) theory, Technology Acceptance Model (TAM), and Technology-Organization Environment (TOE) framework. The model specifies technological, organizational, and environmental factors as determinants of the users' intentions to adopt big data technology. This study aims to review the technology, organizational and environmental factors that can determine the intentions towards big data technology adoption. A total of 224 questionnaires were obtained and screened. Data was analyzed using the Partial Least Square Modelling of Structural Equations due to one of the best software for verifying structured data on structural equations modelling (SEM) Smart PLS 3.0 as analytical tools. This study finds that the predictor variables of compatibility, security are significant and critically direct to the users' intentions to adopt big data technology. The results indicate that the model is suited for studying users' intentions to adopt Big Data technology in educational organizations. This study can help the Malaysian ministry of education to emphasize the important factors in further developing the use of Big Data technology in organizations. The findings provide important recommendations and implications for BDA technology practitioners and application developers, which could coincide with successful BDA technology deployment. This study provides practitioners with practical recommendations for guidance in incorporating and endorsing BDA activities in their organizations in order to maximize the benefits of revolutionary technology, particularly in government agencies.

1. Introduction

Big Data Analytics (BDA) (Arun, 2014; Baker & Yacef, 2009) is increasingly becoming a trending practice that many organizations are adopting to construct valuable information from Big Data (Utayasankar, Muhammad, Zahir & Vishant, 2017). It can be used to better data management and improve the decision-making process in an organization (Fazidah, 2016; Aliah, 2014). The use of Big Data technology shall accelerate in the field of education to serve as a shield in dealing with threats such as the covid-19 pandemic. The Malaysian Government has allocated a total of 160 million Ringgit Malaysia to achieve the government's ambition in the implementation of Malaysia's education plan in the field of educational technology. Furthermore, Big Data in education is one of the most important areas of the Big Data scenario as supported by Utayasankar, Muhammad, Zahir & Vishant, (2017). Ironically, the adoption and use of Big Data technology (BDT) in Malaysia are still un-actualized (Sin & Muthu, 2015; PADU Malaysian Education Blueprint Annual Report, 2018), particularly in the public sector. Big Data technology is still underused as the data cannot be simply obtained due to various

* Corresponding author.
E-mail address: noorbaizura@iab.edu.my (N. B. Harun)

doi: 10.5267/j.ac.2022.6.002

factors, for example, privacy, security, and so forth (PADU Malaysian Education Blueprint Annual Report, 2018). In reality, Big Data is still an emerging phenomenon but in the recent past years its significance in different industries and countries (Uthayasankar et al., 2017). Additionally, not all organizations and government agencies are financially capable of taking on the challenge (Charde, Yadaw, Kumar, Sood, Singh, & Sahu 2018). Therefore, this research has been conducted to determine the factors that influence the adoption of Big Data technology in the Ministry of Education.

2. Factors influencing Big Data Adoption: Technological, Organizational and Environmental

This study integrates the Diffusion of Innovation (DOI), Technology Acceptance Model (TAM), and Technology-Organization-Environment (TOE) Model as the grand theories (Davis, 1986, 1989, 1993; Davis et al., 1989). Considerations including perceived usefulness, perceived ease of use, compatibility, and security are explored in the context of technology (Gangwar, 2015). The use of Big Data technology in the educational organisation is then explored in the context of the organisation, including the role of organisational size, top management support, IT skills, and organisational resources. Then, in the context of the environment, it is examined how issues like government assistance, government regulations, competitive pressure, outside support, and privacy may affect the adoption of big data technologies in educational institutions. Therefore, as a result, all the predictive factors are mentioned in the theory on Fig. 1.

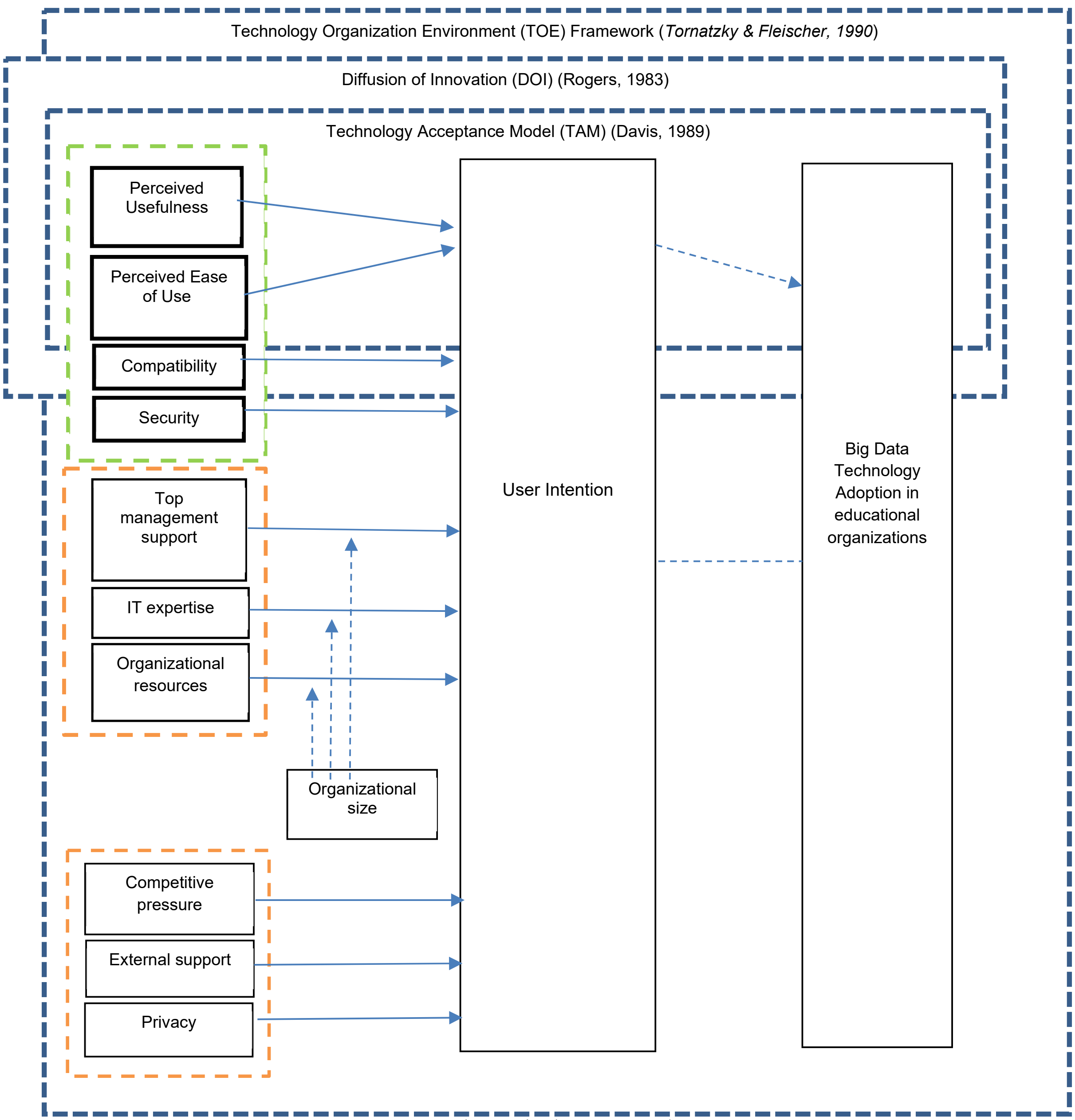

Fig. 1. Theoretical Framework

3. Research methodology

The researcher used a deductive methodology. This study used a quantitative research approach combined with a survey design. IT officers were analysed as a unit of analysis. A total of 227 questionnaires in total were obtained and evaluated.

4. Research Findings

Results of this study are portrayed in Table 1 below. The composite reliability (CR) and AVE for their assessment of convergent validity have fulfilled the recommended threshold. The measurement model analysis and structural analysis have been presented.

4.1 Measurement Model

In General, composite reliability values are interpreted in the same way as Cronbach's Alpha. The value of the composite reliability acceptable in research is 0.60 to 0. 70. While in more advanced studies, values between 0.70 and 0.90 can be considered satisfactory. The values which are above 0.90 (and > 0.95) are not desirable because they show that all the variable indicators measure the same phenomenon and therefore may not be a valid measurement of constructs (Hair et al., 2014a). In an empirical study, the discriminant validity constructs are the extent to which the constructs are different by empirical standards. The discriminant validity of the construct suggests that the characteristics of the constructs are unique compared with other constructs in the model. The cross-loading result for each indicator used in assessing the discriminant validity and the value of the external loading at particular constructs should be higher than all other constructs (Hair et al., 2014). This model consists namely the internal consistency reliability (composite reliability and Cronbach's alpha), convergent validity (indicator reliability or outer loading and average variance extracted (AVE)) and discriminant validity (cross-factor loading and Fornell Larcker's criterion).

4.1.1 Internal Consistency Reliability

Reliability is an assessment of the degree of consistency between multiple measurements of a variable (Hair et al., 2017). As a measure of internal consistency, the composite reliability fulfills the same task as Cronbach's alpha. Composite reliability is preferred compared to Cronbach's alpha as it is not influenced by existent items number in each scale and uses item loadings extracted from the causal model analyzed (Barroso, Carrion & Roldan, 2010). As can be seen in Table 1, all the composite reliability values ranging from 0.827 to 1.000 exceed the cut off value of 0.6 (Bagozzi & Yi, 1988). As such, based on the composite reliability, we can conclude that the measurement is reliable.

Table 1
Internal Consistency Reliability

Constructs	Cronb	Composite
Compatibility	0.923	0.923
Competitive	0.846	0.846
External	0.828	0.828
IT Expertise	0.827	0.827
Organizational	0.874	0.874
Perceived Ease of	0.914	0.914
Perceived	0.945	0.945
Privacy	0.944	0.944
Security	0.911	0.911
Top Management	0.883	0.883

Table 2
Discriminant Validity based on Fornell-Larcker Criterion

	CO	CP	EX	IE	IU	OR	PE	PU	PV	SC	TM
C	0.8										
C	0.1	0.7									
E	0.4	0.3	0.7								
IE	0.2	0.5	0.4	0.8							
IU	0.4	0.0	0.4	0.2	0.8						
O	0.2	0.1	0.1	0.2	0.5	0.8					
P	0.4	0.3	0.3	0.4	0.2	0.2	0.7				
P	0.3	0.2	0.3	0.4	0.2	0.1	0.3	0.8			
P	0.3	0.3	0.5	0.6	0.4	0.3	0.2	0.4	0.8		
S	0.4	0.0	0.3	0.1	0.4	0.2	0.4	0.3	0.1	0.7	
T	0.5	0.0	0.5	0.3	0.5	0.3	0.1	0.3	0.5	0.2	0.8

4.1.2 Discriminant Validity

The Fornell-Larcker criterion is a method for assessing discriminant validity. It compares the square root of the AVE values with the latent variable correlations. Specifically, the square root of each construct's AVE should be greater than its highest correlation with any other construct. An alternative approach to evaluating the results of the Fornell-Larcker criterion is to determine whether the AVE is larger than the squared correlation with any other construct. The logic of the Fornell-Larcker method is based on the idea that a construct shares more variance with its associated indicators than with any other construct (Hair et.al, 2017). Therefore, in this study, the result of the Fornell-Larcker test is presented in Table 2 and reveals that the measurement model exceeds the threshold criteria. As can be seen from the table, the AVE square roots of each construct are greater than the off-diagonal cross of all other constructs. Thus, it can be concluded that the measurement model of this study has distinct discriminant validity.

4.2 Structural Model

This paper has been analysed and assessing the Structural Model using PLS-SEM (Hair, Hult, Ringle & Sarstedt, 2017) on assessment of Structural Model for Collinearity Issues (VIF) and assessment of the significance and relevance of the structural model relationships.

Bootstrap samples are derived by estimating repeatedly the coefficients with a minimum of 500 bootstrap samples, each of which comprises N cases randomly sampled with replacement from the original samples (N=224). Additionally, the bootstrap result approximates the normality of data. The reason for this is that the character of PLS-SEM is distribution-free. Table 3 represents the level of acceptance of structural models in this study.

Table 3
Level of Acceptance of Structural Model Assessment

	Original Sample (O)	2.5%	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
CO → UI	0.380	0.179	0.371	0.090	4.245	**0.000**
CP → UI	0.122	-0.172	0.088	0.118	1.038	0.300
EX → UI	-0.066	-0.239	-0.086	0.078	0.848	0.397
IE → UI	-0.130	-0.248	-0.104	0.080	1.616	0.107
OR → UI	0.282	0.152	0.280	0.064	4.386	**0.000**
PE → UI	0.081	-0.035	0.098	0.072	1.133	0.258
PU → UI	-0.026	-0.128	-0.028	0.054	0.477	0.633
PV → UI	-0.048	-0.195	-0.044	0.074	0.641	0.522
SC → UI	-0.214	-0.331	-0.210	0.064	3.324	**0.001**
TM → UI	0.481	0.308	0.481	0.084	5.725	**0.000**

To the significant effect for hypotheses, the size of the path coefficients was examined via PLS-SEM Algorithm, and the significance of the relationship was examined via PLS-SEM bootstrapping procedure in the Smart PLS 3.0. Fig. 2 below represents the overall PLS-SEM algorithm for this study. The round shape refers to all constructs. All cross-loadings are shown above. Table 4 exhibits the path coefficients, t-statistics(value), P-value, VIF, R, Q and size effect (f).

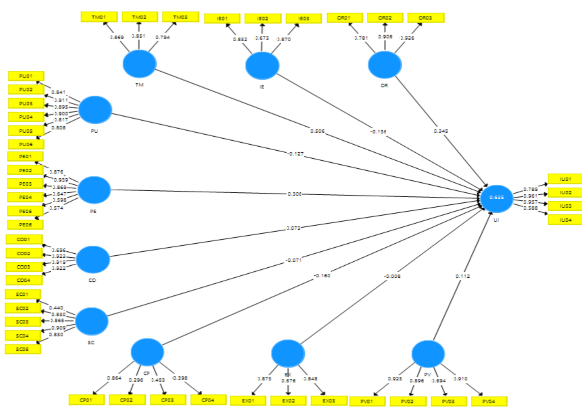

Fig. 2. Std. Beta values based on PLS-SEM algorithm

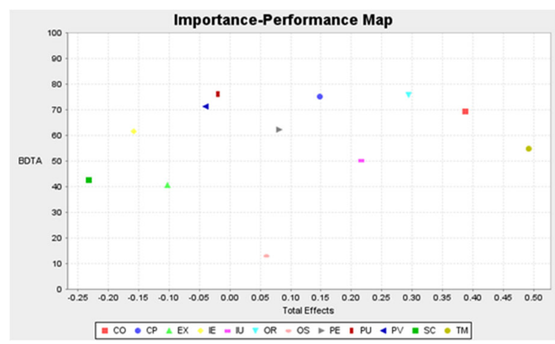

Fig. 3. IPMA Reporting Result

Table 4
Results of Findings

	Hypotheses	Results
H_1	Perceived usefulness has a significant relationship with user intention towards Big Data technology adoption	Not Supported
H_2	Perceived ease of use has a significant relationship with user intention towards Big Data technology adoption	Not Supported
H_3	Perceived compatibility has a significant relationship with user intention towards Big Data technology adoption	Supported
H_4	Security has a significant relationship with user intention towards Big Data technology adoption	Supported
H_5	Top management support has a significant relationship with user intention towards Big Data technology adoption	Supported
H_6	IT expertise has a significant relationship with user intention towards Big Data technology adoption	Not Supported
H_7	Organizational resources have a significant relationship with user intention towards Big Data technology adoption	Supported
H_8	Competitive pressure has a significant relationship with user intention towards the adoption of Big Data technology	Not Supported
H_9	External support has a significant relationship with user intention towards the adoption of Big Data technology	Not Supported
H_{10}	Privacy has a significant relationship with user intention towards the adoption of Big Data technology of Big Data technology	Not Supported
H_{11}	Organizational size significantly moderates the relationship between top management support and users' intention to adopt big data technology in educational organizations	Supported
H_{12}	Organizational size significantly moderates the relationship between IT Expertise and users' intention to adopt big data technology in educational organizations	Not Supported
H_{13}	Organizational size significantly moderates the relationship between organizational resources and users' intention to adopt big data technology in educational organizations	Supported

4.3 IPMA (Importance Performance Matrix Analysis) Report

Importance Performance Matrix Analysis (IPMA) is useful in extending the findings of the basic PLS-SEM outcomes using the latent variable scores (Hair et. al, 2017). In this study, it is vital to identify the important constructs in the models. As a point of departure, all the requirements for carrying out IPMA were checked and refilled. Subsequently, the IPMA test was performed. Fig.3 presents the results from IPMA Analysis, where axis "y" represents the performance of the target and all the factors that influence user intentions towards big data technology adoption.

The above results provide important understandings pertaining to the structural model assessment by recognizing the important constructs in each dimension of the model. Therefore, the factors which are Top Management Support, Organizational Resources, compatibility and security are important to obtain big data technology adoption.

5. Discussions

Through analysis, there was no evidence of a correlation between perceived usefulness and adoption of big data technology. These results indicate that, despite the construct's prevalence in adoption studies, perceived usefulness may not be as important as one would expect in the context of big data. Crucially, Nam et al. (2015) and Agrawal (2015) found no evidence for perceived usefulness when studying big data adoption, suggesting that perceived usefulness shows that most adopters found that Big data is important and not related to the intention of adopting this technology (Rahman, 2016; Rahman & Aldhaban, 2015).

Besides, two possible hypotheses are compatible with Nam et al. (2015) for why perceived usefulness is negligible. Adopters are yet to feel the full potential of the technology. Despite this, there was evidence of a negative correlation between perceived usefulness and Big data adoption (Park et al., 2015). A negative relationship between perceived ease of use and adoption of Big data technology was discovered. This finding shows that educationa organizations either with or without the intention to use or for the adoption of big data technology, the big data technology is seen as difficult to handle or use.

Regarding the security factor, this study refers to Rahman (2016) who has provided empirically where security factors and privacy factors are very important. However, as discussed in chapter four, this security factor has a positive relationship between security and the use of big data technology in a direct relationship rather than with the presence of a moderator.

When predicting the technology adoption in a general context, perceived usefulness, perceived ease of use, compatibility, and security, show various patterns where security and compatibility have a significant direct relationship to user intention adoption. The results from the survey questions indicate that organizations believe security capabilities and integrated security policies do not require an intention to use but directly lead to adoption.

Through this research, the additional interpretation of these findings indicates that a lack of IT knowledge is a barrier to the adoption of big data technologies, but not to the intention to use it. The findings of this research show that there is no link between competitive pressure and the adoption of Big Data technology. Because this study was conducted in the public sector, competitive pressure does not enable the adoption of Big data technology, contrary to results in comparable adoption studies. There was no evidence in this research that there is a link between external support and Big Data technology adoption. There are some credible explanations for the study's lack of importance. Thong (1999), Premkumar and Roberts (1999) and Al-Isma'ili (2016) examined previous literature.

6. Conclusion

In conclusion, all the findings of the study are important in providing feedback to the mandate providers, especially to the Ministry of education of Malaysia in empowering the adoption of big data technology at the organizational level. All parties need to play a role in its success, especially top management in an educational organization in the Ministry of Education in Malaysia to take it seriously in motivating and give the best platform such as training and resources to implement and then adopt this technology.

References

Agrawal, K. P. (2015). Investigating the Determinants of Big Data analytics (BDA) Adoption in Asian Emerging Economies, Patna: Chandragupt Institute of Management.

Aliah, M. Z. (2014). Rangka Kerja Big Data Sektor Awam, Seminar Big Data & Open Data Sektor Awam, MITC Melaka.

Al-Isma'ili, S., Li, M., Shen, J. & He, Q. (2016). Cloud computing adoption determinants: An analysis of Australian SMES. PACIS 2016 proceedings, pp. 1-17.

Arun, C. (2014). Using Big Data Analytics to Improve Government Performance, Gartner, Inc.

Baker, R., & Yacef, K. (2009). The State of Educational Data Mining in 2009: A Review and Future Visions. *Journal of Educational Data Mining, 1*(1), 3-16.

Bagozzi, R. & Yi, Y. (1991). Multitrait–multimethod matrices in consumer research. *Journal of Consumer Research, 17*(4), 426-439.

Charde, R.Y., Yadaw, T., Kumar, A., Sood, A., Singh, S., & Sahu, R. (2018). A Scenario on Big Data.

Davis, F. D. (1986). A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results, New England: Massachusetts Institute of Technology.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*(3), 319-3440.

Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. *International Journal of Man-Machine Studies, 38*(3), 475-487.

Davis, F. D., Bagozzi, R. P. & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science, 35*(8), 982-1003.

Fazidah A. B. (2016). Masa Depan Analitis Data Raya, Konvesyen Pengurusan Rekod: Pengurusan Rekod Dalam Era Digital Dewan Seri Siantan, Perbadanan Putrajaya 16 – 17 Ogos 2016

Hair, J. J. F., Black, W. C., Babin, B. J. & Anderson, R. E. (2010). *Multivariate Data Analysis*. 7th ed. United States: Pearson.

Hair, J.F., Hult, G.T.M., Ringle, C.M., & Sarstedt, M. (2017) A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). 2nd ed., Sage Publications Inc., Thousand Oaks, CA.

Gangwar, H. & Date, H. & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management, 28*, 107-130. 10.1108/JEIM-08-2013-0065.

MAMPU. (2016). Analitis Data Raya Sektor Awam (DRSA). Available at: http://www.mampu.gov.my/ms/data raya-sektorawam-drsa

Nam, D., Kang, D. & Kim, S. (2015). Process of big data analysis adoption: Defining big data as a new IS innovation and examining factors affecting the process. Hawaii, Hawaii International Conference on Systems Sciences.

PADU. (2018). Malaysian Education Blueprint Annual Report. Malaysia Education Blueprint 2013-2025.

Park, J.-H., Kim, M.-K., & Paik, J.-H. (2015). The Factors of Technology, Organization and Environment Influencing the Adoption and Usage of Big Data in Korean Firms. Madrid, Spain, Electronics and Telecommunications Research Institute.

Premkumar, G., & Roberts, M. (1999). Adoption of new information technologies in rural small businesses. *Omega: The International Journal of Management Science, 27*(1), 467-484.

Rahman, N., & Aldhaban, F. (2015). Assessing the Effectiveness of Big Data Initiatives. *Proceedings of the IEEE Portland International Center for Management of Engineering and Technology (PICMET 2015) Conference, Portland, Oregon, USA*. August 2 - 6, 2015, pp. 478-484.

Rahman, N., (2016). Factors Affecting Big Data Technology Adoption. Portland, Student Research Symposium.

Schwab, K. (2016) The Fourth Industrial Revolution. World Economic Forum.

Sin, K., & Muthu, L. (2015). Application of Big Data in Education Data Mining and Learning Analytics – A Literature Review. *Ictact Journal on Soft Computing, 5*, 1035-1049. 10.21917/ijsc.2015.0145.

Thong, J. Y. (1999). An Integrated Model of Information Systems Adoption in Small Businesses. *Journal of Management Information Systems, 15*(4), 187-214.

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *Processes of technological innovation*. Lexington books.

Uthayasankar, S., Muhammad M. K., Zahir I., & Vishanth W. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research, 70*, 263-286.