Big Data Analytics Adoption in Education Sector: A Study of Delhi-NCR

Vijita S Aggarwal*, Shefali** and Dinesh Rawat***

Abstract

The Teaching-Learning process is changing significantly with the introduction of Information Technology. The use of Big Data Analytics in the field of education is enabling it to strengthen and reform the system further. The paper aims to explore the understanding of the factors affecting Big Data Analytics (BDA) acceptance in the Education Sector. Quantitative research with descriptive research design is used in this study. To examine BDA acceptance, this paper uses the technology, organization, and environment (TOE) framework as a reference framework. The survey method is used where data was collected through questionnaires from different education institutes in India. Revelations from the analysis state the main factors which played the central role in the acceptance of BDA were: compatibility, complexity, IT assets, organization data environment, top management support, perceived costs, industry type, and external pressure. The proposed model would help the Education system in increasing their understanding of why some institutions successfully choose to adopt BDA.

Key Words: *Educational Sector, Analytics, Big Data, Big Data Analytics, TOE framework.*

* Professor, USMS, GGSIPU, New Delhi
** Assistant Professor, IITM, New Delhi
*** Assistant Professor, Laxman Singh Mahar, Government Post Graduate College, Pithoragarh

1. INTRODUCTION

Analytics is defined as a body of knowledge consisting of research techniques in mathematics, statistics, and operations; data collection and storage; techniques of artificial intelligence such as machine learning and deep learning algorithms; and big data technologies such as Spark, Hadoop, and Hive. In areas where a lot of data or information is stored, analytics is particularly useful. Analytics deployment is critical to businesses for providing differentiated services and developing new competitive strategies. In the present context, analytics is being used as a competitive strategy by many organizations such as Apple, Facebook, and Amazon.

Big volume of data in excess of 1 terabyte generated with wide variety and veracity at high velocity is defined as big data. Big Data over the last few years has gained much acceptance in various industries (Dagilienė & Klovienė, 2019; Côrte-Real et al., 2017; Waller & Fawcett, 2013; Gupta & George, 2016; Manyika et al., 2011). Optimization of resources, understanding consumer engagement patterns, and improving customer service are some of the major applications of big data.

In the present business scenario, there is an enormous amount of data which is generated around us from various sources. Thus, it necessary to make use of this huge data present around us. Techniques that an organization can use to analyse huge volume of complex data are defined as big data analytics (BDA) (Kwon et al., 2014; Gantz & Reinsel, 2012). The emergence of digital devices such as mobile phones, laptops, tablets, and the popularity of social media has led to a rise in the application of big data analytics (BDA) (Gandomi & Haider, 2015). Big Data technologies help organizations in becoming competitive, extending firm performance, and sustaining in the dynamic marketplace (Sivarajah et al., 2017; Goes, 2014; Dagilienė & Klovienė, 2019; Gupta & George, 2016; Kwon et al., 2014). Data discovery and visualization and advanced analytics are two solutions of big data analytics. Data discovery and visualization simplify data access and analysis for rapid decision making and reporting, whereas advanced analytics solutions help in complete optimization of resources and derive faster customer insights.

Big Data has stretched its wings in various domains of life and some of the active sectors which produce huge amount of data are technology (14%), financial services (10%), consulting (9%), healthcare (9%), education (8%) and telecommunication (7%) (Dresner Advisory Services, 2017). In recent years, big data usage in education has gained major attention. In the educational sector, huge volume of data is produced because of online courses, teaching, and learning activities (Oi, Yamada, Okubo, Shimada, & Ogata, 2017). Teachers with the help of bid data can access student's academic performance, learning patterns and provide instant feedback (Black & Wiliam, 2018). The timely and constructive feedback provided by teachers with the help of big data motivates the students and have a positive impact on their performance (Zheng & Bender, 2019). Higher Educational Institutions are relying upon the use of Big Data Analytics (BDA) for improving the teaching learning process. Patel et al. (2017) illustrated the various application of BDA in the education sector. They listed the various components of BDA in education, such as learning analytics and academic analytics, which effectively optimize the learning environment.

Given the benefits of BDA thus it is important to adopt such techniques. The bulk of technology adoption research has been performed in developed countries (Ramamurthy et al., 2008; Alshamaila et al., 2013; Low et al., 2011). Various studies have looked at factors that are considered essential for data analytics adoption by organizations (Ramamurthy et al., 2008; Labrinidis & Jagadish,2012; Kwon et al., 2014; Mehta & Pandit, 2018; Verma & Bhattacharyya, 2017; Low et al., 2011; Gandomi & Haider, 2015; Davenport & Dyche, 2013). Adopting BDA largely depends on the technological, organization, and environmental factors (Esteves & Curtos, 2013; Kwon et al., 2014; Shin, 2015; Dubey et al., 2015). Following factors influence the adoption of BDA: top management enthusiasm and compatibility, security and employee involvement, relative advantage, quality, perceived ease of use, reduction in operations and maintenance costs, perceived usefulness, real-time access to customer needs (Shin, 2015; Kwon et al., 2014; Chang et al., 2014; Dubey et al., 2015; Esteves & Curto, 2013).

As very few studies are available on implementation of big data analytics in developing countries (Saffu et al., 2007; Dubey et al., 2015) and large-scale data can play a tremendous role in managing various educational problems. Thus, implementation of big data analytics in developing countries with special focus on education sector must therefore be understood. Thus, this paper is an attempt to examine the adoption of big data analytics in the Indian context focusing on the education sector and contribute to the existing literature by testing a model integrated with the TOE framework consisting of technological, organizational, and environmental factors. The present paper comprises five sections, in which section 1 deals with the introduction of the paper, section 2 focuses on the literature review, and section 3 reflects on the objectives and research methodology used in the study. In the next section, the results are discussed. The last part of the paper closes with conclusions, implications, limitations, and future scope of research.

2. LITERATURE REVIEW

2.1 Big Data and Big Data Analytics

Big Data can be defined as a large and complex data set which requires rapid processing, and the use of standard database management and analytical tools becomes impossible on such data (Yi et al., 2014; Chen & Zhang, 2014). Big data is characterized by four V's, namely volume, variety, velocity, and veracity, where volume represents the quantity of generated and stored data; variety represents the type (text, audio, images, video) and nature of the data; velocity represent the speed with which the data is generated and analysed from various sources; and veracity refers to the degree of trustworthiness of collected and used information for taking decisions (Buhl et al., 2013 and Gandomi & Haider, 2015). The presence of such huge data has increased the demand for new analytical methods and new forms of technologies (Sandhu & Sood, 2014; Gandomi & Haider, 2015). In order to manage such data, Big Data Analytics (BDA) has evolved as a new method (Zhang et al., 2015; Ularu et al., 2012). BDA process high volumes of fast-moving data, which is diverse in nature, to derive meaning insights. BDA extracts meaningful insights from the data through two sub-processes, i.e., data management process and technologies are the first process which is used for acquiring, storing, preparing, and retrieving the data, and the second is analytics techniques which is used to acquire intelligence from big data (Labrinidis & Jagdish, 2012). For analysing structured and unstructured data in real time fundamentally, five techniques of big data analytics could be used, which are Text analytics, Audio analytics (Speech analytics), Video analytics, Social media analytics, and Predictive analytics (Gandomi & Haider, 2015).

2.2 Big Data Adoption

The acceptance and circulation of IT innovations have been considered by a wide range of research 2(Ramamurthy et al., 2008; Alshamaila et al., 2012; Zhu et al., 2006). The acceptance of innovation is a crucial factor influencing the strategic strategy of the organization (Sisaye & Birnberg, 2009). Several models for the adoption of technology advancement have been suggested, and some of the main models are: Expected Behavior Theory (TPB) (Ajzen 1991), Reasoned Action Theory (TRA) (Becker & Gibson, 1998), Technology Acceptance Model (TAM) (Davis, 1986; Davis, 1989), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003), Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer 1990) and Diffusion of Innovation (DOI) (Rogers 1995). These models help in determining the factors within an organization that can influence user adoption of innovation (Ndubisi & Jantan, 2003). Out Of these models, two models are prominent models for adopting innovation, i.e., 2Framework for DOI and TOE. At the organizational level, most of the studies on IT adoption have used these two frameworks. The TOE structure has emerged as a useful theoretical lens for understanding the adoption of technology. Oliveira & Martins (2011) indicated that the TOE framework provides a robust basis for evaluating

IT innovation adoption in various types of organizations (Pudjianto & Hangjung, 2009). The TOE framework is a useful analytical tool for distinguishing between adopting the organization's motivational capabilities, the inherent qualities of innovation, and the broader environmental context of the organization (Rui, 2007).

2.3 Technology-Organization-Environment Framework

Tornatzky & Fleisher (1990) created the technology-organization-environment (TOE) framework. TOE describes the factors that influence technology adoption decisions by influencing the firm's perception of the innovation's strategic value (Sutanonpaiboon et al., 2006). Technology, organization, and environmental context in the TOE framework present opportunities and constraints for a firm's technological innovation and influence its levels of technological innovations (Tornatzky & Fleischer, 1990). TOE is a process through which technological innovations are adopted and implemented in a firm. The technological context involve the internal and external technologies which include both equipment's as well as processes and, are essential for the firm (Rui, 2007). The organizational context represents an organization's internal factors that influence the adoption and implementation of innovations (Tornatzky & Fleischer, 1990). The environmental context includes the macroeconomic context, size, and structure of the industry, regulatory environment, and firm's competitors. Table 1 outlined the definitions for each of the constructs under the TOE framework from the detailed literature review.

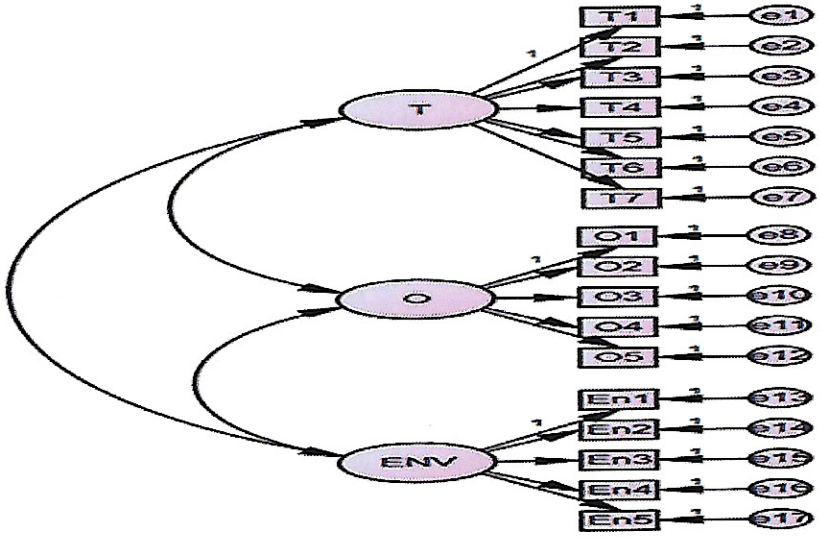
Table 1: Definitions of Constructs under TOE Framework

Construct	Sub-construct	Definition
Technological Context	Complexity	The degree to which an innovation is perceived as relatively difficult to understand and use (Rogers,1983;Verma, S. and Bhattacharyya, S.,2017)
	IT assets	The degree to which an innovation is associated with complex procedures Ramanathan. et al. 2012; Verma, S. & Bhattacharyya, S.,2017)
	Compatibility	The degree to which an innovation is perceived as consistent with the existing values, past experiences, and the needs of potential adopters (Rogers, 1983; Verma, S. & Bhattacharyya, S.,2017)
Organizational context	Top management support	Devoting time to IS program in proportion to its cost and potential, reviewing plans, following up on results and facilitating the management problems involved with integrating ICT with the management process of business (Young & Jordan,2008)
	Organizational data environment	The extent to which data resources are managed in an organization.
	Perceived cost	Expenses of implementing necessary technologies in organization and efforts devoted to organizational restructuring and process re-engineering (Verma, S. & Bhattacharyya, S.,2017)
Environmental context	External pressure	The degree of influences from the external business environment (Verma, S. & Bhattacharyya, S. ,2017)
	Industry type	The sector to which the business belonged

3. OBJECTIVES AND RESEARCH METHODOLOGY

This paper's key research objective is to review the mechanism of BDA adoption by educational institutions in India. More specifically, the research questions aim to test a conceptual model consisting of constructs affecting the adoption of big data analytics. The study involves quantitative research where a descriptive research design has been used. The survey research method has been used in this study, where data was collected through a questionnaire. The questionnaire was designed after a detailed literature review and careful selection of items for measuring various constructs. There are 17 items in the questionnaire under these three structures, i.e., Technological context, the context of the organization, and context of the environment. Each of these elements was evaluated on a scale of five points from 1 (Strongly Disagree) to 5 (Strongly Disagree) (Strongly Agree). The data was obtained from a survey of 237 teachers serving in different educational institutions' analytics departments. For the testing of the proposed model, the current research used confirmatory factor analysis (CFA) and structural equation modeling (SEM) in Figure 1, which is based on the literature review; a conceptual model of BDA adoption was suggested.

Figure 1: TOE Framework for Organization Adoption of Big Data Analytics



4. ANALYSIS AND RESULTS

This study aims to examine the factors affecting Big Data Analytics (BDA) acceptance. For answering this research objective, this study has used the technology, organization, and environment (TOE) framework as a reference framework. Before confirming the factors under TOE which influence BDA acceptance, it was required to check the importance of technology, organization, and environment construct individually. The importance of technology, organization, and environment construct has been checked by analyzing the mean score value of each construct given in Table 2.

Table 2: Mean Score Values of Technology, Organization, and Environment Construct

Factors	Mean	Mean rank
Technology	3.59	Second
Organization	3.44	Third
Environment	3.91	First

From Table 2, it can be concluded that the environmental factor was found to be the most important factor, followed by the technology factor, while the organization factor was ranked third.

4.1 Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) provides improved control for the assessment of unidimensionality compared to exploratory factor analysis (EFA) according to Ahire, Golhar & Waller (1996) and is more in line with the overall validation phase of constructs. Confirmatory factor analysis was conducted within the TOE framework for group statements/variables.

4.1.1 Reliability Analysis

A crucial phase in the development of a measurement scale is the evaluation of reliability. The reliability of the products can be evaluated by the alpha coefficient (Cronbach, 1951). The alpha of Cronbach needs to be above 0.7 (Nunnally, 1978). The Cronbach alpha values of all the constructs are shown in Table 3. In the analysis, all alpha coefficients were above 0.7, suggesting strong reliability and the reliability of the measurement system. Composite reliability (CR) is recommended as more acceptable since it considers the differential weights of the indicators (Chin, 1998; Dijkstra & Henseler, 2015). In Table 4, CR values are given.

Table 3: Cronbach Alpha Values of TOE Constructs

Constructs	Cronbach alpha
Overall Questionnaire	0.889
Technology	0.915
Organization	0.969
Environment	0.910

4.1.2 Validity Analysis

A construct's content validity can be defined as the degree to which the measure spans the domain of the theoretical description of the construct (Rungtusanatham, 1998). The questionnaire's face-to-face validity was verified by seeking feedback on the clarity of items from the 30 respondents. Content validity was tested by pre-testing by practitioners and academicians of the questionnaire. Content validity requires the evaluation of the degree to which its intended variables are correctly calculated by an operationalization (O'Leary-Kelly & Vokurka, 1998). The establishment of construct validity, according to O'Leary-Kelly & Vokurka (1998), requires the empirical evaluation of convergent and discriminatory validity.

The convergent validity of a construct is established when the following three conditions are met (Hair, Black, Babin & Anderson, 2010):

CR (Composite Reliability) > 0.7

AVE(Average Variance Extracted) > 0.5 and CR> AVE

If a test does not compare very strongly with other measures from which it is expected to vary, discriminant validity is guaranteed (O'Leary-Kelly & Vokurka, 1998). The Fornell-Larcker criterion (Fornell & Larcker, 1981), which compares the AVE (shared variance within) of the constructs to the squared correlation between the constructs (shared variance within), is a standard approach to evaluating discriminant validity.

The discriminant validity of a construct is established when the following two conditions are met (Hair, Black, Babin & Anderson, 2010).

MSV (Maximum Shared Variance) < AVE (Average Variance Explained)

ASV (Average Shared Variance) < AVE (Average Variance Explained)

In this study, convergent and discriminant validity is calculated for the first-order CFA model. Figure 2 shows the first-order CFA model. The results of composite reliability, convergent validity, and discriminant validity are given in Table 4.

Figure 2: First Order CFA Model

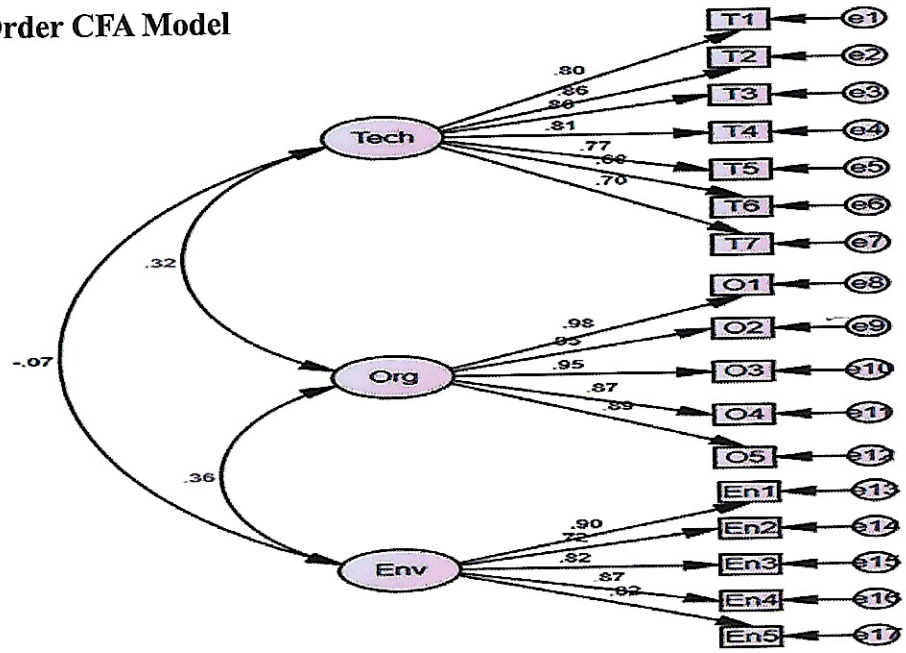


Table 4: Reliability and Validity Results of First-order CFA Model

	CR	AVE	MSV	ASV
ORG	0.969	0.862	0.132	0.117
TOE	0.918	0.616	0.102	0.053
ENV	0.915	0.683	0.132	0.068

It is clear from Table 4 that the conditions of convergent and discriminant validity are satisfied.

4.2 Testing Model fitness

The appropriate test to determine the measurement and structural models are Goodness of Fit (GOF). The Chi-square coefficient, which shows the discrepancy between the covariance matrix of the sample and the covariance matrix predicted, tests GOF. The various heuristics such as CFI, GFI, and RMSEA are more ways of testing GOF by using CB-SEM. For the first-order mode, the overall fit indices are given in Table 5.

Table 5: Model Fitness Values

Model Element	Values	Acceptable range
CMIN / DF	4.189	CMIN/DF < 3 good; < 5 sometimes permissible (Hair et al., 2010)
GFI	0.804	GFI > 0.8 is acceptable (Baumgarther & Homburg, 1996)
AGFI	0.742	AGFI > 0.8 is acceptable (Baumgarther & Homburg, 1996)
CFI	0.904	CFI > 0.95 great; 0.90 traditional; >0.80 sometimes permissible (Hair et al., 2010)

As it is clear from Table 5 values that various fit indices are in an acceptable range. This means that the said model is a good fit.

5. CONCLUSION & IMPLICATIONS

BDA has largely altered the ways organizations are doing business. In India, several businesses are introducing BDA projects to leverage customer and device data to achieve competitive benefits (Agrawal, 2013; Dubey et al., 2015). Data analytics in higher education helps the current method of teaching-learning and its administration to be transformed (Tulasi, 2013). This study has been an attempt to reveal and highlights the factors affecting the adoption of BDA in Indian educational institutions.

Implementation of Big Data Analytics in Educational Institutions has helped in improving the outcome levels of the Teaching Learning Process and has enabled the management in increasing the effectiveness of the education system by efficient mentoring, improving grades of the learners, and increasing the retention ratio. The research findings have important implications and great value to higher management for BDA adoption in their educational institutions. Since the sample of the study was only 237 so it may not be appropriate to generalize to the whole population of the educational institutes in India. For this reason, further empirical investigation with a large sample size is needed.

The applicability of the three constructs (technological, organizational, and environmental) of the TOE system in understanding the adoption of BDA was quantitatively confirmed and validated by this research. The results of this study suggest that the most important factor pursued by technology and organization was the environmental factor. In the environment construct following were the factors that affected the adoption of BDA: strategies and potential power of business partners, level of IT capability of competitors, type of industry to which an organization belongs, business processes, and computing. In the technology construct following were the factors that affected the adoption of BDA: complexity in using big data analytics, investments in IT infrastructure and related manpower, technical skills/ professional competence of employees, consistency with the existing organizational values and technological needs of the organization. Finally, in the organization construct following were the factors that affected the adoption of BDA: top management support, effective data management, financial investments, and administrative costs. With the usage of BDA, educational institutions will be in a better position to take more effective and efficient decisions for uplifting the standard of education system. This study's results are significant and have some major consequences for research into BDA adoption in the education sector.

There is low awareness and understanding amongst students and staff about the nature and extent of data analytics. Lack of computational capacities, proper infrastructure, and privacy of data are some of the challenges being faced by the educational sector (Rao & Balgodi, 2018). The adoption of Big data is the keyway to outperform the competing educational institutions. Big Data needs to uncover its full potential in the field of education since there is a heavy load of data in educational institutions which needs to be analyzed for increasing the effectiveness of learning and academic environment and developing more effective curricula, pedagogical frameworks, assessments, and learning programs. (Undavia, Patel & Patel, 2017). As per the McKinsey Global Institute (MGI) Report 2011, the education sector will revolutionize with the usage of Big Data. BDA can improve decision making, improve the teaching-learning process, higher success rates of students, and provide valuable insights for institutional growth. The use of BDA can make the education system more efficient for monitoring students' performance and institutional policies. Some of the important areas in education sector in the domain of big data are associated with assessment, individualized learning, and precision education. BDA can provide greater understanding among teachers and students about how big data technology can bring new opportunities that can be used for pedagogical practices and learning process. It is essential for professionals to understand the effectiveness of big data in education in order to minimize educational issues. BDA application can give new insight to universities to plan mixed learning programs that combine conventional learning with web-based learning.

6. REFERENCES

Agrawal, K. P. (2013). The Assimilation of Big Data Analytics (BDA) by Indian Firms: A Technology Diffusion Perspective.

Ajzen, I. (1991), The theory of planned behaviour, *Organizational Behaviour and Human Decision Processes, 50* (2), 179-211.

Ahire, S.L.; Golhar, D.Y. & Waller, M.A. (1996), Development and Validation of TQM Implementation Constructs, *Decision Sciences, 27* (1), 23-56.

Alshamaila Y., Papagiannidis S., & Li .F. (2012), Cloud computing adoption by SMEs in the north east of England, *Journal of Enterprise Information Management, 26* (3), 250-275.

Baumgarther, H., Homburg, C. (1996), Applications of Structural Equation Modeling in Marketing and Consumer Research: A Review, *International Journal of Research in Marketing, 13* (2), 139-161.

Becker, E. A., & Gibson, C. C. (1998), Fishbein and Ajzen's Theory of Reasoned Action: Accurate Prediction of Behavioral Intentions for Enrolling in Distance Education Courses, *Adult Education Quarterly , 49* (1), 43-55.

Black, P., & Wiliam, D. (2018). Classroom assessment and pedagogy. Assessment in Education: Principles, Policy & Practice, 25(6), 551–575.

Braunack-Mayer, A. J., Street, J. M., Tooher, R., Feng, X., & Scharling-Gamba, K. (2020). Student and Staff Perspectives on the Use of Big Data in the Tertiary Education Sector: A Scoping Review and Reflection on the Ethical Issues. *Review of Educational Research, 90*(6), 788-823.

Buhl H.U., Röglinger M., Moser F., & Heidemann J., (2013), Big Data - A Fashionable Topic with(out) Sustainable Relevance for Research and Practice?, *Business & Information Systems Engineering, 5* (2), 65–69.

Chang, R. M., Kauffman, R. J. & Kwon, Y. (2014), Understanding the paradigm shift to computational social science in the presence of big data, *Decision Support Systems, 63*, 67-80.

Chen C.L.P., & Zhang C.Y., (2014), Data-intensive applications, challenges, techniques and technologies: A survey on Big Data, *Information Science, 275*, 314-347.

Chin, W. W. (1998).The partial least squares approach for structural equation modeling. In G. A. Marcoulides (Ed.), Modern method for business research (pp. 295–336).

Cronbach, L. J. (1951), Coefficient alpha and the internal structure of tests, *Psychometrika, 16* (3), 297-334.

Côrte-Real, N., Oliveira, T., & Ruivo, P. (2017), Assessing business value of Big Data Analytics in European firms, *Journal of Business Research, 70*, 379-390.

Dagilienė, L. & Klovienė, L. (2019), Motivation to use big data and big data analytics in external auditing, *Managerial Auditing Journal, 34 (7), 750-782.*

Davenport, T. H., & Dyché, J. (2013), Big data in big companies, *International Institute for Analytics, 3.*

Davis, F. D. (1986), A technology acceptance model for empirically testing new end-user information systems: Theory and results, Doctoral dissertation, Sloan School of Management, Massachusetts Institute of Technology, Cambridge, MA.

Davis, F.D. (1989), Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly, 13* (3), 319-340. ,

Dijkstra, T. K., & Henseler, J. (2015), Consistent partial least squares path modelling, *MIS quarterly, 39* (2).

Dresner Advisory Services. (2017). Big data adoption: State of the market. Zoom Data. Retrieved from https://www.zoomdata. com/master-class/state-market/big-data-adoption

Dubey, R., Gunasekaran, A., Childe, S. J., Wamba, S. F., & Papadopoulos, T. (2015), The impact of big data on world-class sustainable manufacturing, *The International Journal of Advanced Manufacturing Technology,* 1-15.

Esteves, J., & Curto, J. (2013), A risk and benefits behavioral model to assess intentions to adopt big data, *Journal of Intelligence Studies in Business, 3*(1), 37–46.

Fornell, C., & Larcker, D. F. (1981), Evaluating structural equation models with unobservable variables and measurement error, *Journal of Marketing Research, 18*, 39–50.

Gandomi, A. & Haider, M. (2015), Beyond the hype: big data concepts, methods, and analytics, *International Journal of Information Management, 35* (2), 137-144.

Gantz, J., & Reinsel, D. (2012), The digital universe in 2020: Big data, bigger digital shadows, and biggest growth in the far east, *IDC iView: IDC Analyze the future*, 1-16.

Goes, P.B. (2014), Design science research in top information systems journals, *Management*

Information Systems Quarterly, 38 (1), 3-8.

Gupta, M., & George, J. F. (2016), Toward the development of a big data analytics capability, *Information & Management, 53* (8), 1049-1064.

Hair, J. F., Black, B., Babin, B., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). London: Prentice-Hall.

Kwon O., Lee N., & Shin B., (2014), Data quality management, data usage experience and acquisition intention of big data analytics, *International Journal of Information Management, 34*, 387-394.

Labrinidis, A. & Jagadish, H. V. (2012), Challenges and opportunities with big data, *Proceedings of the VLDB Endowment, 5* (12), 2032-2033.

Low C., Chen Y. & Wu M., (2011), Understanding the Determinants of Cloud Computing Adoption, *Industrial Management & Data Systems, 111* (7), 1006-1023.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. H. (2011). Big data: The next frontier for innovation, competition and productivity (Vol. 7). Technical report, McKinsey Global Institute.

Mehta, N., & Pandit, A. (2018), Concurrence of big data analytics and healthcare: A systematic review, *International journal of medical informatics, 114*, 57-65.

Ndubisi, N.O. & Jantan, M. (2003), Evaluating IS usage in Malaysian small and medium-sized firms using the technology acceptance model, *Logistics Information Management, 16* (6), 440-450.

Nunnally, J. C. (1978). *Psychometric Theory*. New York: Mc- Graw-Hill

Oi, M., Yamada, M., Okubo, F., Shimada, A., & Ogata, H. (2017). Reproducibility of findings from educational big data. In Paper presented at the proceedings of the Seventh International Learning Analytics & Knowledge Conference, (pp. 536–537).

O'Leary-Kelly, S.W. & Vokurka, R.J. (1998), The Empirical Assessment of Construct Validity, *Journal of Operations Management, 16*, 387-405.

Oliveira, T. & Martins, M. (2011), Literature review of information technology adoption models at firm level, *The Electronic Journal Information Systems Evaluation, 14*, (1), 110-121.

Patel, R & Desai , T. (2016). Big Data Analytics in Optimizing the Quality of Education: Challenges. *International Journal for Innovative Research in Science & Technology*, 3(6), 165-167.

Pudjianto, B. & Hangjung, Z. (2009), Factors affecting e-government assimilation in developing countries, Proceeding in 4th Communication Policy Research, South Conference, Negombo. Sri Lanka.

Ramamurthy, K., Sen, A., & Sinha, A. (2008), An empirical investigation of the key determinants of data warehouse adoption, *Decision Support Systems, 44*, 817-841.

Rao p n, A. & Baglodi, K. (2018). Role of Big Data in Education Sector: A Review. *International Journal of Advances in Science Engineering and Technology*, 6(1), 1-3.

Rogers, E. M. (1995). *Diffusion of innovations* (4th edition). New York. The Free Press.

Rui, G. (2007), Information Systems Innovation Adoption among Organizations a Match-Based Framework and Empirical Studies (Doctoral dissertation), National University of Singapore, Singapore.

Rungtusanatham, M. (1998), Let's not overlook content validity, *Decision Line, 29* (4), 10-13.

Saffu K., Walker J.H., & Hinson R., (2007), An Empirical study of Perceived Strategic Value and Adoption Constructs: the Ghanaian case, *Management Decision, 45* (7), 1083-1101.

Sandhu, R., & Sood, S. K. (2015), Scheduling of big data applications on distributed cloud based on QoS parameters, *Cluster Computing, 18* (2), 817-828.

Shin, D. (2014), A socio-technical framework for internet-of-things design, *Telematics and Informatics,* 31(4), 322–339

Sisaye S. & Birnberg J., (2010), Extent and scope of diffusion and adoption of process innovations in management accounting systems, *International Journal of Accounting and Information Management, 18* (2), 118-139.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017), Critical analysis of Big Data challenges and analytical methods, *Journal of Business Research, 70*, 263-286.

Sorensen, L. C. (2018). "Big data" in educational administration: An application for predicting school dropout risk. *Educational Administration Quarterly*, 45(1), 1–93.

Sutanonpaiboon, J., and Pearson, A. M. (2006), E-Commerce Adoption: Perceptions of Managers/ Owners of Small-and Medium-sized Enterprises (SMEs) in Thailand, *Journal of Internet Commerce, 5* (3), 53-82.

Tornatzky LG, Fleischer M., (1990), "The processes of technological innovation". Lexington, MA: Lexington Books.

Tornatzky, L.G. & Fleischer, M. (1990) The Processes of Technological Innovation. Lexington Books, Lexington

Ularu E.G., Puican F.C., Apostu A., Velicanu M., (2012), Perspective on Big Data and Big Data Analytics, *Database Systems Journal, 3* (4), 3-14.

Undavia, J. .N, Patel, S & Patel, A. (2017). Future Trends and scopes of Big Data Analytics in the field of Education. *International Journal of Engineering and Technology*, 9(3), 9-14.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "User acceptance of information technology: Toward a unified view", *MIS Quarterly, 27* (3), 425-478.

Verma, S. and Bhattacharyya, S. (2017), "Perceived strategic value-based adoption of Big Data Analytics in emerging economy: A qualitative approach for Indian firms", *Journal of Enterprise Information Management, 30* (3), pp. 354-382

Waller, M.A. and Fawcett, S.E. (2013), Data science, predictive analytics, and Big Data: a revolution that will transform supply chain design and management, *Journal of Business Logistics, 34* (2), 77-84.

Yi, X., Liu. F. Liu, J., & Jin, H. (2014), Building a network highway for big data: architecture and challenges, *IEEE Network, 28* (4), 5–13.

Zhang. F. Liu. M. Gui. F. Shen. W. Shami. A. & Ma. Y. (2015), A distributed frequent itemset mining algorithm using Spark for Big Data analytics, *Cluster Computing 76*(4), 1493–1501.

Zheng, M., & Bender, D. (2019). Evaluating outcomes of computer-based classroom testing: Student acceptance and impact on learning and exam performance. *Medical Teacher*, 41(1), 75–82

Zhu K., Dong S., Xu S.X., Kraemer K.L., (2006), Innovation diffusion in global contexts: determinants of post-adoption digital transformation of European companies, *European Journal of Information Systems, 15* (6), 601–616.