Information Processing and Management 56 (2019) 102095

Contents lists available at ScienceDirect

Information Processing and Management

journal homepage: www.elsevier.com/locate/infoproman

Big data adoption: State of the art and research challenges

Maria Ijaz Baig, Liyana Shuib*, Elaheh Yadegaridehkordi

Department of Information Systems, Faculty of Computer Science & Information Technology, University of Malaya, 50603 Kuala Lumpur, Malaysia

ARTICLE INFO

Keywords:
Big data adoption
Technology–Organization–Environment
Diffusion of Innovations

ABSTRACT

Big data adoption is a process through which businesses find innovative ways to enhance productivity and predict risk to satisfy customers need more efficiently. Despite the increase in demand and importance of big data adoption, there is still a lack of comprehensive review and classification of the existing studies in this area. This research aims to gain a comprehensive understanding of the current state-of-the-art by highlighting theoretical models, the influence factors, and the research challenges of big data adoption. By adopting a systematic selection process, twenty studies were identified in the domain of big data adoption and were reviewed in order to extract relevant information that answers a set of research questions. According to the findings, Technology–Organization–Environment and Diffusion of Innovations are the most popular theoretical models used for big data adoption in various domains. This research also revealed forty-two factors in technology, organization, environment, and innovation that have a significant influence on big data adoption. Finally, challenges found in the current research about big data adoption are represented, and future research directions are recommended. This study is helpful for researchers and stakeholders to take initiatives that will alleviate the challenges and facilitate big data adoption in various fields.

1. Introduction

The term ‘big data’ refers to a huge volume of data (Chamikara, Bertok, Liu, Camtepe & Khalil, 2019; John Walker, 2014). Big data is a relatively new concept, but the storage and analysis of data is a theory that has existed for several years. Before the arrival of computers and databases, data are presented in the form of paper-based registers (Tole, 2013). Due to the advent of computers, internet, and mobile technology, a large amount of data is produced on a daily basis (Abdel-Basset, Mohammed, Smarandache & Chang, 2018; Shorfuzzaman, Hossain, Nazir, Muhammad & Alamri, 2019). Nowadays, every digital action leads towards an increment of data (Tsou, 2015). Data is generated through social media, online shopping, transactions, network devices and educational records (Aguilar, 2018; Dorasamy & Pomazalová, 2016). Each day, 2.5 quintillion bytes data is produced (IBM, 2012) and its growth has been investigated to reach 50 zettabytes in 2020 (Herschel & Miori, 2017; IBM, 2018). It has become more difficult to organize, interpret, store and analyze a large amount of data (Sagiroglu & Sinanc, 2013). Therefore, as the size of data grows on a daily basis, the word ‘big’ become associated with ‘data’ (Tyagi, Priya & Rajeswari, 2015). Earlier, data storage was restricted to databases and spreadsheets, and information that seems difficult to convert into rows and columns were ignored. The big data contain different forms of structure (databases developed by using SQL server and Oracle etc.), unstructured (videos, audio, different documents, images, comment, follower, likes, Tags, tweets, clicks, and chats etc.), and semi-structured data (third party data, currency conversion weather, XML, graph or text data, and e-commerce etc.) (Elgendy & Elragal, 2014). Big data services provide advanced procedures to

* Corresponding author.
E-mail address: liyanashuib@um.edu.my (L. Shuib).

https://doi.org/10.1016/j.ipm.2019.102095
Received 27 February 2019; Received in revised form 4 July 2019; Accepted 2 August 2019
0306-4573/

analyze different kinds of data, predict the results and produce a fast-accurate response in a short time (Moat, Preis, Olivola, Liu & Chater, 2014).

Big data adoption is defined as a process that allows an innovation to alter the infrastructure of an organization (Günther, Rezazade Mehrizi, Huysman & Feldberg, 2017). Big data adoption covers advanced information processing techniques and technologies that improve the decision-making process (Raguseo, 2018). It gives new opportunities to organizations to leverage information and gain competitive advantage (Ur Rehman et al., 2019). Big data adoption enhances productivity, predict risk, and satisfy customers more effectively (Al-Qirim, Tarhini & Rouibah, 2017). Adoption is a phase in which technology is chosen by the organization or any business for their usage (Agrawal, 2015). Big data adoption provides an opportunity for organizations and industry to surpass the competitors. The adoption of big data might be laborious with a big budget, but the return advantages may develop the path of success in the long run (Al-Qirim et al., 2017). Big data are generated in almost every field (Moat et al., 2014). According to Zoom data survey report, 41% of companies are currently using big data while 46% are planning to adopt it in the future (Zoomdata, 2017). As the growth of data is increasing day-by-day, organizations are expecting more challenges (Zhao, Yu, Li, Han & Du, 2019). These challenges could be related to security, privacy, and ownership of data (Osman, 2019). The obsolete technology did not have the capability to handle the overloading of data (Sivarajah, Kamal, Irani & Weerakkody, 2017). Developed countries have adopted digital advancements more quickly but, in such countries, it is necessary to understand, accept, and adopt digital progressions (Hilbert, 2013). These technological innovations can be helpful to solve multifarious problems related to health and education (Luna, Mayan, García, Almerares & Househ, 2014; Ye, Zhao, Shang & Zhang, 2019). By adopting big data, companies can manage and analyze the large volume of data more quickly. For example, market need, and the trend can be analyzed and predicted more accurately by employing big data technologies (Janssen, Charalabidis & Zuiderwijk, 2012). Many sectors like banking, information technology (IT) companies, telecommunication, and other firms have already adopted big data (Côrte-Real, Ruivo, & Oliveira, 2019; Davenport & Dyche, 2013). Other areas, like education and healthcare sectors, are still in the initial stage of adoption (Fatt & Ramadas, 2018; Murumba & Micheni, 2017). The adoption of big data can be enhanced in other fields if the factors affecting adoption are analyzed and addressed properly by using the right theoretical framework (Surbakti, Wang, Indulska & Sadiq, 2019; Weerasinghe, Pauleen, Scahill & Taskin, 2018).

A theoretical model is the pre-existing, acceptable theories that come from scholarly literature. Technology–organization–environment (TOE) (Tornatzky et al., 1990), Technology acceptance model (TAM) (Davis, 1989), Diffusion of innovations (DOI) (Rogers, 1995), and task-technology fit (TTF) (Goodhue & Thompson, 1995) are commonly used Information systems (IS) adoption theories for explaining the adoption decisions of IT in individual or an organizational level. These theories have been already validated and tested by many researchers in different adoption contexts in e-learning, e-commerce, tourism, and healthcare (Chandra & Kumar, 2018; Fan, Liu, Zhu & Pardalos, 2018; Mittal, 2018; Yadegaridehkordi, Nilashi, Nasir & Ibrahim, 2018). They play a vital role by creating the blueprint in understanding the factors that influence any technology adoption decision (Oliveira & Martins, 2011). It is necessary to consider theoretical models to address the big data adoption and implementation related issues at the organizational or individual level.

Many factors such as IT infrastructure, usefulness and complexity are related to big data adoption. Previous researches highlighted perceived the benefits, cost, security, and risk issues associated with the adoption of big data (Ale, 2016; Clarke, 2016; Esteves & Curto, 2013; Krasnow Waterman & Bruening, 2014; Raguseo, 2018; Verma & Bhattacharyya, 2017). Some studies have also looked at the factors affecting the adoption of big data in banks (Diniz, Luvizan, Hino & Ferreira, 2018), businesses (Nguyen & Petersen, 2017), organizations (Mneney & Van Belle, 2016; Salleh & Janczewski, 2016; Sun, Cegielski, Jia & Hall, 2018), and firms (Park, Kim & Paik, 2015; Soon, Lee & Boursier, 2016) by employing different theoretical models like TAM, DOI and TOE. Many researchers have already conducted a review study on big data and highlighted its practices in various fields (Grover & Kar, 2017; Kamilaris, Kartakoullis & Prenafeta-Boldú, 2017; Kataria & Mittal, 2014; Palanisamy & Thirunavukarasu, 2017; Raut et al., 2019; Sagiroglu & Sinanc, 2013). However, despite the hype of big data adoption, none of the research conducted a comprehensive research review of big data adoption and its associated theoretical models, factors, and challenges. Hence, the objective of this study is to present a state of the art of theoretical models used by various studies for big data adoption. It also identifies the factors that influence big data adoption and its challenges. This review study will give insights into what has been done on big data adoption theoretical models. This could be helpful to identify the potential areas for further research. Therefore, this study focuses on the following research questions:

1 What are the theoretical models used for big data adoption?
2 What are the significant factors that influence big data adoption?
3 What are the challenges within current research on big data adoption?

This paper is divided further into sections as follows: Section 2 presents the research methodology. Section 3 presents existing works on big data, followed by big data adoption studies presented in Section 3.1. Next, Section 4 covers the findings (Section 4.1 Theoretical models, Section 4.2 Factors Influencing big data adoption and Section 4.3 Challenges) of this study. Finally, Section 5 discussed the conclusion and future research directions.

2. Methodology

This study presents a comprehensive review of 'big data adoption'. Big data is a broad concept. Most of the research studies had focused on 'big data' but not on its 'adoption'. Thus, only 'big data adoption' studies are included in this review paper. To achieve the objective of this study, several articles were reviewed. Articles were searched and collected by using different research engines and databases. During the initial search process, it was found that the majority of research studies were present in IEEE Xplore (408), Science Direct (96), Emerald insight (129), AIS Electronic Library (98), Taylor and Francis (46), ACM Digital Library (73) and Springer Link (57). In addition, the following keywords were used to extract relevant papers: “big data”, “big data adoption”, “big data analytics”, “big data acceptance”, and “big data plus TOE/DOI/TAM”. The following criteria were used for paper selection: (1) pertinent to the topic (big data adoption models, influencing factors and challenges) written in English language; (2) published between the years 2015 and 2018; (3) the mentioned search words should be in paper title or in the keywords list; (4) available to download as a full article.

The process of article selection has been visualized in Fig. 1. After the initial comprehensive database search, 907 research papers were found. Out of 907 papers, 589 articles were available for download. All 271 papers were downloaded and studied thoroughly while the inclusion and exclusion criteria were applied for final selection. Additionally, keywords were examined by reading the paper's title, abstract, introduction, and conclusions. 195 were excluded because most of these papers highlighted the database models for big data adoption. Papers that were not published in journals and conferences were also eliminated. Meanwhile, uncompleted and non-English studies were excluded. In total, 76 eligible articles were double-reviewed, and 62 articles were removed from the final selection because they were unrelated to the actual study area. Their actual focus was not on big data adoption and its theoretical model. Before the final selection phase (Fig. 1), the snowball technique was used to give a more comprehensive review on ‘big data adoption’ studies. The manual search method was applied on the reference list of each of ‘eligible’ paper. Through screening, 7 studies were found from Google scholar. However, it was studied and later excluded because their focus was not on big data adoption. The Google Scholar search was only used for a second search (S2) (Fig. 1) but was not applied for the initial search. Finally, the selected articles (Table 1) were from IEEE Xplore (3), Science Direct (5), Emerald Insight (3), AIS Electronic Library (2), Taylor and Francis (1), Google Scholar (6). After scrutiny finally, it was found that big data adoption related studies started from 2015 and continued till 2018. Thus, 20 highly relevant articles were included in this study that was published between the years 2015 to 2018. The number of publications related to big data adoption from the year 2015 to 2018 is shown in Fig. 2.

3. Big data

Big data is defined as a large dataset that could not be controlled or examined through conventional databases (Lin, Wang, Li & Gao, 2019; Mishra, Luo, Jiang, Papadopoulos & Dubey, 2017). From banking and finance perspective, it is “regularly expanding” information which is difficult to process through traditional data storage (Pérez-Martín, Pérez-Torregrosa & Vaca, 2018). In contrast, some scholars considered big data as a business approach, which helps organizations to analyze only a large amount of information (Malaka & Brown, 2015; Wright, Robin, Stone & Aravopoulou, 2019). Moreover, few scholars described big data as a large and complex computerized dataset (Pope, Halford, Tinati & Weal, 2014). There is no fixed standard measurement on “what size should be considered large data sets” (Hay, George, Moyes & Brownstein, 2013). Thus, there is no universal definition for distinguishing big data from all perspectives (Chen et al., 2013). However, the term ‘big data’ has expanded significantly over the past few years (Kitchin, 2014). It gained popularity in early 2000 with the arrival of electronic shopping (McAfee, Brynjolfsson, Davenport, Patil & Barton, 2012). In addition, big data are generated from multiple resources. For instance, websites, academia, graphical data, banks, and social media etc. This data can be in the form of structured, unstructured or semi-structured. The speed at which data are delivered is the most critical factor in big data adoption. Big data is further characterized as 3V's, Volume (amount of data), Velocity (speed to access data) and Veracity (types of data) (Chen et al., 2013; Ward & Barker, 2013). Demchenko, Grosso, De Laat and Membrey (2013) classified big data into 5 vs, which are Volume, Velocity, Variety, Veracity, and Value. However, Saggi and Jain (2018) characterized big data into 7V's namely Volume, Velocity, Variety, Valence, Veracity, Variability, and Value. Moreover, Volume possessed data storage challenges, Variety is related to data heterogeneity, Velocity acquires data processing provocations, Veracity procured to the accuracy of data, Valence is associated with complexity, Value is linked to revenue and Variability is allied to data inconsistency confronts. Big data has a huge level of advantages on the worldwide economic system (Johnson, Gray & Sarker, 2019). This attracts different representatives and brings rivalry among enterprises. Now, it is one of the biggest IT trends. Companies preferred employee that is armed with big data-related skills and ability (Harper, 2013). Manyika et al. (2011) summed it up that big data is beneficial for US health care and public organizations. Now, it is not only useful as data, but also helpful in solving miscellaneous problems related to banks, education, and health sector due to the advancement in technologies, etc. Earlier, banks generate a large amount of data through ordinary dealing with customers, which has been discarded in the form of books. Now, due to the advent of technology, the same data is used for customer satisfaction, banks advancement and the making of better decisions (Davenport & Dyche, 2013; Tabesh, Mousavidin & Hasani, 2019).

3.1. Big data adoption studies

Multiple studies have tested the level of adoption and usage of big data by incorporating various theoretical models. These theories have been used in firms, organizations, companies, businesses and supermarkets domains. The firm refers to the sole proprietorship that is owned by one person. However, the organization refers to a group of people working with a particular purpose. A company is a legal entity, whereas business is a process of receiving the profit through the trading of products or delivering services. In contrast, a retailer sells the product directly to consumer or wholesalers to other businesses.

Kang and Kim (2015) used the TOE framework to analyze the factors affecting innovation in firms. The study surveyed 450 industries (information, finance, wholesale, and retails). Only 58 responses were finally used for the study. The data was analyzed with the help of partial least squares (PLS) method. Another study conducted by Park et al. (2015) employed TOE model, to examine

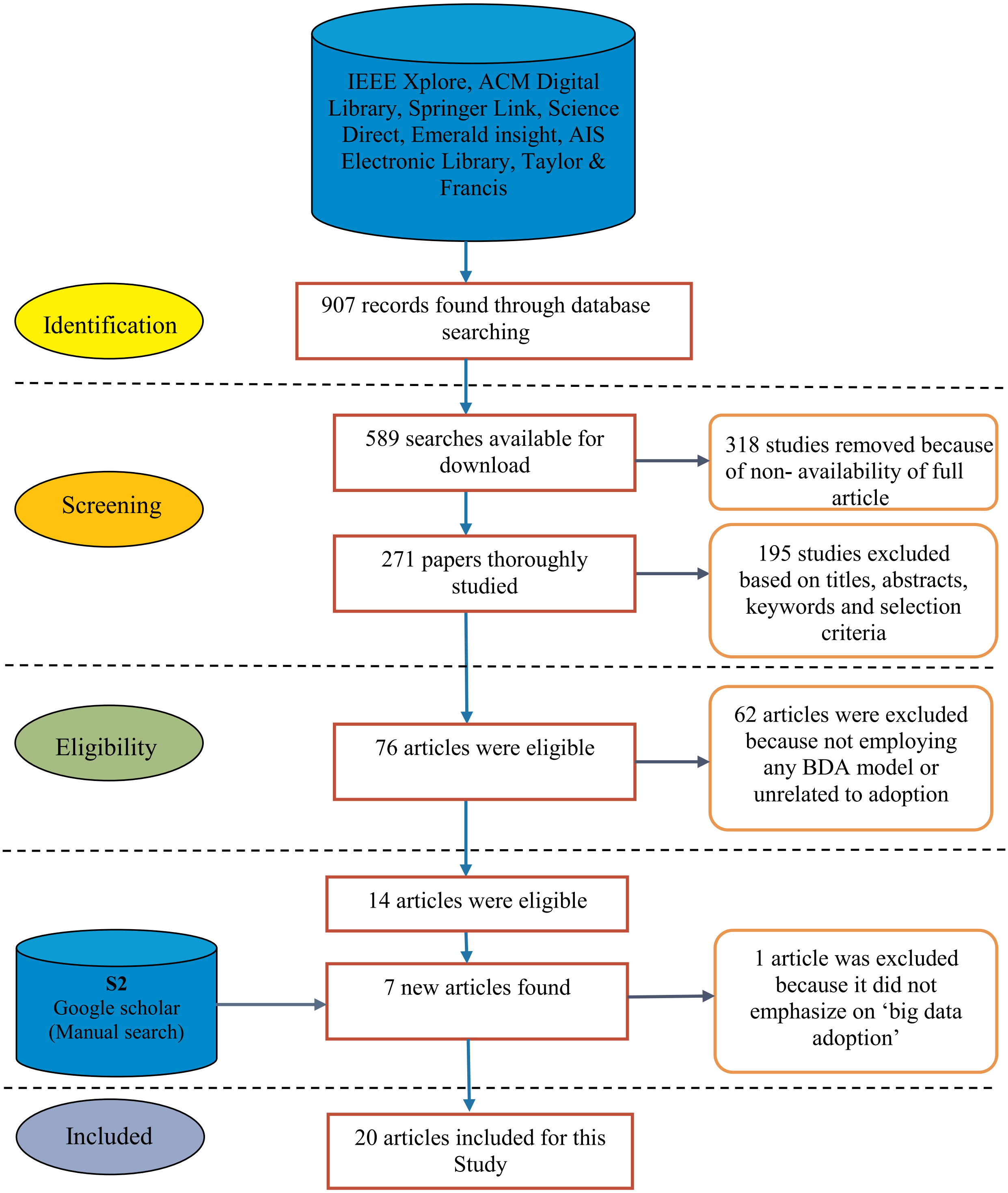

Fig. 1. Articles selection process.

the factors that influence the adoption and usage of big data in firms. Data were collected from 5 experts having 10-year research experience in IT, management, and government-funded research institutes.

Analytical hierarchical process (AHP) was used for data analyses. Similarly, Salleh et al. (2015) also employed the TOE framework in order to study the security factors that influenced big data adoption. Data were collected from New Zealand and Malaysian organization employees. Yin (2015), proposed a big data adoption framework for original equipment company employees.

Table 1
Articles selection process results.

Online database	Initial results	Relevant articles
IEEE Xplore	408	3
ScienceDirect,	96	5
Emerald insight	129	3
AIS Electronic Library	98	2
Taylor and Francis	46	1
ACM Digital Library	73	–
Springer Link	57	–
Google scholar (Second search round)	–	6
	907 (Initial searched studies found through databases)	**20** (Final selected studies)

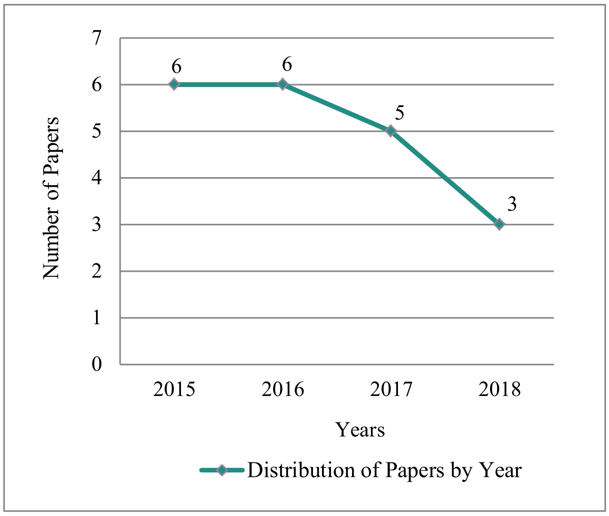

Fig. 2. Distribution of papers by year (2015–2018).

Chen, Kazman and Matthes (2015) conducted a case study and developed a big data adoption model to clarify the 'why' and 'how' questions. Ochieng (2015) used TOE and DOI models to analyze the factors that influence big data adoption in Kenya supermarkets. Almoqren and Altayar (2016) studied the factors that affect big data adoption in Saudi banks using the TOE framework. The study used an online survey approach. The survey was conducted with 54 employees' workers in data processing and IT departments in Saudi banks (Appendix). Salleh and Janczewski (2016), analyzed the big data determinants among adopters and non-adopters by incorporating TOE model. The Study used an online survey technique and received 25 responses from different organizations. Mneney and Van Belle (2016) used TOE and TTF in order to check the readiness of a retail organization in reference to big data adoption. Vendors and IT service providers to analyze the initial status of big data in the South African context conducted semi-structured interviews. The result of the study revealed that South African companies are ready to adopt big data. Soon et al. (2016) explored the factors affecting the big data adoption in Malaysia by incorporating DOI and TAM framework. Data were collected from IT executives, IT engineers, managers, and Head of departments of private Malaysian companies. The Study developed a model in order to examine the factors that affect big data adoption. Potter (2016) used a semi-structured approach and proposed a framework to analyze big data adoption in small, medium and micro-sized enterprises. Matsebula and Mnkandla (2016), highlighted the IS and innovation adoption in education and explored some TOE factors. McLeod, Bliemel and Jones (2017), explored the changes of big data analytics by examining the weblogs over four years. Wu, Li, Liu and Zheng (2017), used a two-dimensional product differentiation framework to find out the impact of big data on the health technology market. Data were gathered and analyzed through a game theoretical method. Gunasekaran et al. (2017) identified the influence of resources on top management and capability by the resource-based view (RBV), which included acceptance, routinization, and assimilation. Nguyen and Petersen (2017) identified the factors for organizational assimilation of big data by employing DOI, TOE, and TAM. Verma and Bhattacharyya (2017) highlighted the factors that affect big data adoption by employing the TOE framework. In this study, enterprises and different service provider to analyze the current situation for big data implementation conducted a face-to-face interview. The obtained results showed that the organizations were not ready to adopt technological changes. Sun et al. (2018), analyzed the organizational factors that affect big data adoption. This study utilized DOI and TOE and explored 26 factors that can affect big data adoption. Lai, Sun and Ren (2018), employed TOE to analyze the determinants of big data adoption in the organizational domain. Data were collected from 210 organizations. Verma, Bhattacharyya and Kumar (2018) proposed a research model based on an extensive literature review on TAM. The Developed model was validated through a survey. The review summary is presented in the Appendix section.

4. Findings

4.1. What are the theoretical models used for big data adoption? (RQ1)

The conducted review highlights that TOE, TAM, DOI, IT, and TTF, Two-dimensional product differentiation framework and RBV models were used by various studies in big data adoption context. The TOE framework influenced the innovation adoption-decision in three ways: technology, organization, and environmental context. The technological context comprises of internal and external technologies and all required tools, software, and processes, etc. The perceived benefits cannot be fully received through technological innovation only. It requires support from different resources of organizations. The organizational context revealed the firm environment, resources, and characteristics help in the adoption or rejection of technological innovations. The environmental context showed the external environment of an organization that carries their work. Organization external pressure and non-supportive attitude have a direct impact on the business environment and employee progress (Tornatzky et al., 1990). TAM was originally developed to predict acceptance or adoption of innovations (Davis & Venkatesh, 1996). TAM has two aspects: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU is an independent construct. It is the point at which an individual starts considering that employing a specific system would increase their job performance. PEOU is defined as "the level at which someone should start to believe that a specific system has become effortless". Individual attitude towards the use, sequentially, find out the intention to use. DOI is used to describe the innovation diffusion process. Innovation is like a novelty which takes time in the adoption or rejection by an organization, entire community, groups or individual. Adoption decision is optional at the individual level. Adoption or rejection does not only rely on all groups of members. Innovation acceptance can be seen through the individual rather than the whole community. However, when adoption is for the whole organization, then the decision is taken from the entire organization or a group of members, which is known as a collective decision. Authority decisions can adopt or reject the innovation that is accepted by a small number of technical experts. In order to understand the diffusion of innovation, comprehensive understanding of organizations' adoption behavior is necessary (Rogers, 1995). According to DOI, adoption-decision can be affected by five factors: Relative advantage, complexity, compatibility, trialability, and observation. Institutional Theory represents the institutional environments that are important in determining the organizational formation and further activities. According to this theory, organizational adoption decisions are not only influenced by organizational objectives, but also by external environmental, cultural, and social factors. The theory highlighted that organizational decisions are affected by similar types of pressures that come from the other side. The firm's decision to adopt big data is not internally driven but the pressure comes from the opponent, customers, trade associates, market and government. Due to this pressure, organizations are under pressure to reproduce the actions of leaders and industries have become homologous over time. Organizations can adopt new innovations for trading opponents to maintain their interior stability. In a favorable environment, the government can support organizations to adopt big data by providing proper facilities and relaxation in official laws. Organizations will be in less pressure if the government encourages a firm to adopt big data (Zucker, 1987). TTF is another theoretical model for examining the relationships between information systems and individual performance. TTF is significantly influenced by both task and technology characteristics; and in turn, directly related to the users' performance and utilization (Goodhue & Thompson, 1995). The RBV is a managerial model used to regulate the planned resources with the potential to deliver comparative advantage to a firm (Gunasekaran et al., 2017).

According to Table 2, the TOE model was used either as a single model or integrated with other theories in 13 out of 20 studies to analyze the big data adoption in firms, businesses, and finance sectors. Whereas, 8 out of 13 studies used TOE as a single model to observe big data adoption in firms, banks, and organizations. While, 5 out of 13 studies employed DOI, TTF, IT and TAM along with TOE to examine the big data adoption in firms and retail organizations.

Therefore, RQ1 founds that, TOE, TAM, DOI, IT, two-dimensional product differentiation, and TTF were the theoretical models used for big data adoption to understand the various aspects related to it.

It can be concluded that TOE is the most used model in big data adoption domain.

Table 2
Theories and models used in big data adoption research.

Theories and models	References	Number of studies
TOE	Kang and Kim (2015); Park et al. (2015); Salleh et al. (2015); Almoqren and Altayar (2016); Lai et al. (2018); Matsebula and Mnkandla (2016); Mneney and Van Belle (2016); Nguyen and Petersen (2017); Ochieng (2015); Salleh and Janczewski (2016); Sun et al. (2018); Verma and Bhattacharyya (2017); Yin (2015)	13
DOI	Mneney and Van Belle (2016); Nguyen and Petersen (2017); Ochieng (2015); Sun et al. (2018); Yin (2015)	5
TAM	Nguyen and Petersen (2017); Soon et al. (2016); Verma et al. (2018)	3
TTF	Mneney and Van Belle (2016)	1
IT	Sun et al. (2018)	1
Two-dimensional product differentiation framework	Wu et al. (2017)	1
RBV	Gunasekaran et al. (2017)	1

4.2. What are the significant factors that influence big data adoption? (RQ2)

This study found 42 significant factors through reviewing selected big data adoption related studies. These factors were categorized into four such as technology (11 factors) (Table 3), organization (16 factors) (Table 4), environment (8 factors) (Table 5) and innovation (7 factors) (Table 6) that influenced big data adoption. According to the findings, Perceived complexity/simplicity and Perceived compatibility factors are the most emphasized technological factors that affect the big data adoption process. Management support and Perceived financial readiness/ financial investment competence factors were the most stressed organizational factors that hampered the adoption process. It has been noticed that Competitive pressure/ Perceived industrial pressure, Security, privacy and risk factors were the most influenced environmental factors, which hindered the adoption procedure. Relative advantage factor was considered the most significant innovation related factor that affects big data adoption process. Technology, organization, environment, and innovation related factors have been explained in detail in the following sections.

Table 3
Summary of Technology related factors that affect big data adoption.

Category	Factors	References
Technology	1) Perceived benefits	Kang and Kim (2015); Park et al. (2015); Soon et al. (2016); Lai et al. (2018)
	2) Perceived complexity/Simplicity/ Ease of use	Chen et al. (2015); Park et al. (2015); Salleh et al. (2015); Salleh and Janczewski (2016); Sun et al. (2018); Mneney and Van Belle (2016); Verma and Bhattacharyya (2017); Nguyen and Petersen (2017); Lai et al. (2018); Verma et al. (2018)
	3) Perceived compatibility	Ochieng (2015); Park et al. (2015); Yin (2015); Salleh et al. (2015); Nguyen and Petersen (2017); Salleh and Janczewski (2016); Soon et al. (2016); Sun et al. (2018); Verma and Bhattacharyya (2017)
	4) Technology readiness/ technology resources	Salleh et al. (2015); Matsebula and Mnkandla (2016); Sun et al. (2018)
	5) Data quality and integration	Park et al. (2015); Lai et al. (2018); Verma et al. (2018)
	6) Wireless technology and lack of system integration	Almoqren and Altayar (2016)
	7) Knowledge about big data	Mneney and Van Belle (2016)
	8) Availability of big data tools	Mneney and Van Belle (2016)
	9) Internal versus external technologies	Mneney and Van Belle (2016)
	10) Vendor support	Mneney and Van Belle (2016)
	11) Network challenges	Mneney and Van Belle (2016)

Table 4
Summary of Organization related factors that affect big data adoption.

Category	Factors	References
Organizational	1) Perceived financial readiness/ Financial investment competence	Yin (2015); Kang and Kim (2015); Park et al. (2015); Mneney and Van Belle (2016); Potter (2016); Lai et al. (2018)
	2) IS competence/IT structure/ Weak IT infrastructure	Ochieng (2015); Kang and Kim (2015); Almoqren and Altayar (2016); Sun et al. (2018); Lai et al. (2018)
	3) Management support for big data	Ochieng (2015); Park et al. (2015); Yin (2015); Salleh et al. (2015); Mneney and Van Belle (2016); Salleh and Janczewski (2016); Verma and Bhattacharyya (2017); Nguyen and Petersen (2017); Gunasekaran et al. (2017); Lai et al. (2018); Sun et al. (2018)
	4) Organizational data environment	Verma and Bhattacharyya (2017)
	5) Perceived cost	Verma and Bhattacharyya (2017)
	6) Technological capability	Park et al. (2015); Potter (2016); Gunasekaran et al. (2017)
	7) Organizational learning culture	Ochieng (2015); Salleh et al. (2015); Mneney and Van Belle (2016); Salleh and Janczewski (2016)
	8) Human resources	Mneney and Van Belle (2016); Sun et al. (2018)
	9) Decision-making culture	Sun et al. (2018)
	10) Business strategy orientation	Sun et al. (2018)
	11) Change efficacy	Sun et al. (2018)
	12) Firm size	Nguyen and Petersen (2017); Sun et al. (2018)
	13) Appropriateness	Sun et al. (2018)
	14) Interpret unstructured data	Almoqren and Altayar (2016)
	15) Data control	Almoqren and Altayar (2016)
	16) Staffing and training	Almoqren and Altayar (2016)

Table 5
Summary of Environment related factors that affect big data adoption.

Category	Factors	References
Environment	1) Competitive pressure/ Perceived industrial pressure	Yin (2015); Kang and Kim (2015); Park et al. (2015); Almoqren and Altayar (2016); Nguyen and Petersen (2017); Verma and Bhattacharyya (2017); Sun et al. (2018)
	2) Government support, laws and policy	Ochieng (2015); Park et al. (2015); Mneney and Van Belle (2016); Sun et al. (2018)
	3) Security, privacy and Risk	Ochieng (2015); Park et al. (2015); Yin (2015); Salleh et al. (2015); Salleh and Janczewski (2016); Soon et al. (2016); Nguyen and Petersen (2017); Sun et al. (2018)
	4) Risks of outsourcing	Salleh et al. (2015); Salleh and Janczewski (2016)
	5) Trading partner readiness	Sun et al. (2018)
	6) Market turbulence	Sun et al. (2018)
	7) IS fashion	Sun et al. (2018)
	8) Marketing and inventory	Mneney and Van Belle (2016); Yin (2015)

Table 6
Summary of Innovation related factors that affect big data adoption.

Category	Factors	References
Innovation	1) Relative advantage	Chen et al. (2015); Mneney and Van Belle (2016); Nguyen and Petersen (2017); Ochieng (2015); Sun et al. (2018); Yin (2015)
	2) Cost of adoption	Sun et al. (2018)
	3) Complexity	Nguyen and Petersen (2017); Ochieng (2015); Sun et al. (2018)
	4) Observability	Ochieng (2015); Sun et al. (2018)
	5) Trialability	Ochieng (2015); Sun et al. (2018)
	6) Perceived usefulness	Soon et al. (2016); Verma et al. (2018)
	7) Predictive analytics accuracy	Soon et al. (2016)

4.2.1. Technology related factors

1 **Perceived benefit (direct/indirect):** It is the level at which an organization receives benefits from big data adoption (Davis, 1989) (Table 3). Perceived benefit basically refers to 'belief' about turnout or the outcome, which is associated with the response of the organization/individual level. The perceived benefit can be used in health, education, and organization, to analyze the behavior or perception about a specific action. It is a belief of an organization to benefit from big data. Perceived direct and indirect benefits can be significant or insignificant. For example, the perceived benefits of blood test include an individual belief about the benefits of getting a blood test (Green & Murphy, 2014). Similarly, the perceived benefits of adopting e-learning include student belief about the benefits of taking classes in e-learning mode of education (Kimiloglu, Ozturan & Kutlu, 2017).

2 **Perceived complexity/Simplicity/Ease of use:** Perceived complexity is the 'level of convolution and understandability in providing secure procedures for big data adoption' (Davis, 1989) (Table 3). With big data adoption mechanism, high cost, uncertainty, and risk are always associated with a higher level of complexity. As the level of complexity increases, the cost of adoption will also rise. The low cost is related to simplicity or ease of use. Therefore, complexity is a barrier to big data adoption.

3 **Perceived compatibility:** The 'degree to which technology perceived as being reliable and well matched with existing needs of users' (Rogers, 1995). Compatibility plays a significant role in the increase in the adoption rate. Innovative technology should be user-friendly and compatible (Table 3).

4 **Technology readiness/ Technology resources:** Companies should have experts and well-developed infrastructure before moving towards big data technologies. Technology resources play an important role in evaluating the maturity and implementation level of technology in an organization. However, the utilization of technology resources in an organization helps in analyzing the readiness level with respect to big data adoption.

5 **Data quality and integration:** Data quality is an important aspect that integrates with an objective to attain certain goals. Unauthoritative and incompleteness are also associated with low data quality, which causes hindrance in the big data adoption process (Lai et al., 2018).

6 **Wireless technology and lack of system integration:** Wireless technology is a gateway to the adoption of big data. It helps to organize data from different sources. Many devices generate big data through wireless technology. For instance, a large volume of data is produced from social media.

7 **Knowledge about big data:** It refers to awareness of the respondent about big data (velocity, variety, variety, value, and complexity) (Mneney & Van Belle, 2016). For example, what type of knowledge or understanding respondents possessed about big

data (Table 3). It is better to start with the basic level, before moving towards more technical level questions.

8 **Availability of big data Tools:** It refers to the presence of instruments or devices, which are particularly required for implementing big data (Mneney & Van Belle, 2016), an important factor that has influences on the big data adoption process. It provides support at the organizational level to execute big data technologies more quickly.
9 **Internal versus external technologies:** It refers to as the hardware and software technologies used for big data adoption (Mneney & Van Belle, 2016). Technologies revealed by retailers are internal technologies whereas those provided by vendors are called external technologies.
10 **Vendor support:** Vendors support is helpful in implementing big data technologies. Vendors can fix IT related issues more quickly and efficiently. Professional vendor support is necessary for adopting big data. Many tools and big data related technologies are open source. The vendor makes it easier to run these technologies and align tools for the big data platform.
11 **Network challenges:** Underprivileged ICT infrastructure is a hurdle in a process of big data adoption. Big data requires a high-speed consistent internet connection to ensure an uninterrupted data transfer.

Once big data setup is implemented, collection, and sorting of data is an automatic procedure.

4.2.2. Organization related factors

1 **Perceived financial readiness/Financial investment competence:** It refers to the budget or financial resources that are available for adoption of new technology, innovation or a setup (Tornatzky et al., 1990) (Table 4). Financial readiness is a significant factor that differentiates adopter from non-adopter. There will be more chances to adopt innovative technology if an organization is financially ready.
2 **IS competence/IT structure/ Weak IT infrastructure:** It is referred to as the ‘experience’ of managing and using information technology at the organizational level (Tornatzky et al., 1990). Many organizations agreed on the benefits of adopting big data. However, most of the firms overlooked the importance of infrastructure. IT infrastructure plays an important role in fulfilling the demands that are linked with big data adoption. Strong infrastructure can be helpful in analyzing the multisource data such as weblogs and social media. Weak infrastructure provides inaccurate information, which leads to the failure of big data adoption.
3 **Management support for big data:** Management support is a degree at which it perceives the significance and applicability of big data adoption (Tornatzky et al., 1990). Usually, top management does not support the ‘change’ factor. In big data, adoption process changes are required (Table 4). When top management becomes reluctant to change for improvement, then the whole organization starts following higher management decisions, which will linger the adoption process. Management support is necessary to encompass the organizational policies, rules, handling of data storage issues, technological and financial capability. Therefore, management support is a significant factor that contributes to the adoption of big data.
4 **Organizational data environment:** It refers to data resources that are controlled by an organization (Tornatzky et al., 1990) (Table 4). The organizational data environment should be secured in order to reduce the risk factor. To protect the environment from cybercrime, organizations should keep eye on people that access data. Data security-related professional can be hired to manage the proper security controls. Organizations should use legal data and decide the definition of sensitive data in the planning phase before implementing big data.
5 **Perceived cost:** It refers to the ‘cost of employing big data technologies and infrastructure in an organization’ (Tornatzky et al., 1990) (Table 4). For instance, the cost of new processors that are needed for big data implementation.
6 **Technological capability:** It refers to the recognition of individual or organization potential and abilities to handle the situation in different circumstances (Rogers, 1995). Technological capability is a collective effort of organization in adopting, improving, hiring, and implementation of big data technologies. It consists of employee's skills, knowledge, and acquaintance with technologies that are related to big data. Organizations should pay attention to the building and enhancing technological capabilities.
7 **Organizational learning culture:** It refers to the learning attributes and intention of the organization towards the adoption of big data (Tornatzky et al., 1990). Previous studies revealed that if an organization possesses strong learning characteristics, it would adopt new technology more easily. In relation to this, the organizations that showed a learning culture can take risks, identify prospects and give efficient solutions more quickly (Table 4).
8 **Human resources:** Human resources play a significant role in employing and maintaining technological innovation. Sufficient human resources are required for big data adoption. Strong programming, statistical and analytical skills help in implementing big data in retail organizations.
9 **Decision-making culture:** It refers to as a belief that the adoption of big data is a key to success in enhancing organizational productivity. At the company level, executive or managerial staffs make a decision.
10 **Business strategy orientation:** It refers to a strategy that is used to learn about business analytics and making strategic decisions for organizations in adopting big data.
11 **Change efficacy:** Employees of the organization should be capable of handling changes. For example, various types of technological and environmental changes are expected at the organizational level while implementing big data.
12 **Firm size:** Number of resources is directly related to the size of the firm. As organizational size increases, more resources, tools, technical expertise will be required to maintain the big data.

13 **Appropriateness:** Appropriateness refers to as future changes, which will provide some benefit to the organization (e.g., Big data adoption).
14 **Interpret unstructured data:** Unstructured data are generated through social media (e.g., likes and Emoji, etc.), which interrupt the adoption process. Efficient tools are needed to transfer unstructured data into a structured format. (e.g., Hadoop).
15 **Data control:** It refers to the proper storage and maintenance of data at the internal and external level. In strong data control, vendors provide tools that are modifiable by the customers. In a weak data control, the customer always requires the third-party (vendor) for amendment purpose.
16 **Staffing and training:** Company environment should promote talent-driven culture and provide an opportunity for employees to learn new skills for innovative technology. Companies can start technical or quality training for existing employees in order to enhance their skills.

4.2.3. Environment related factors

1 **Competitive pressure/ Perceived industrial pressure:** It refers to the degree at which opponents (Tornatzky et al., 1990) (Table 5) affect the organization. The organization moves towards the adoption due to the pressure of other firms who have already adopted innovative technology.
2 **Government support, laws and policy:** Companies should describe the usage of data clearly prior to the actual adoption. Most of the Government policies and laws have been developed to minimize the potential harms, associated with the 'privacy'. To get significant benefits from existing data, the government should support scientists and companies to access data without disturbing anyone privacy.
3 **Security, privacy and risk:** It is the major concern for companies that are adopting big data. Security, privacy and risk factors will not only affect the big data adoption process but will also destroy the company reputations (Table 5).
4 **Risks of outsourcing:** Outsourcing involves hiring from outside firms to implement big data adoption-related services. Privacy, security, reputation, transaction, compliance, and contractual risks are associated with outsourcing.
5 **Trading partner readiness***:* To achieve the goals more effectively requires following the partner's suggestions in adopting technology in order to balance the internal matters of the organization. In trading partnership, two or more parties agreed to trade certain products.
6 **Market turbulence:** It refers to the changes expected to occur due to the customer's preferences and demands. Big data helps in predicting customer demand by analyzing the existing trends.
7 **IS fashion:** It refers to the details of big data that are obtained from different communication mediums such as vendors, clients, management, and IT experts, etc.
8 **Marketing and inventory:** Big data play a significant role in marketing and maintaining inventory. For instance, customer preferences or trends can be analyzed through the number of clicks or sailing baskets.

4.2.4. Innovation related factors

1 **Relative advantage:** "The degree at which an innovation is perceived as better than the idea it supersedes" (Rogers, 1995). The relative advantage depends upon the field or area the innovation concept is used (Table 6).
2 **Cost of adoption:** It refers to the financial resources available in adopting new technology (Rogers, 1995).
3 **Complexity:** The attributes of big data that is not comprehensible and easy to use. Technology complexity acts as a barrier to big data adoption.
4 **Observability**: The process by which companies observe the success factor of other firms that have already adopted big data. Organizations observe other firms in order to analyze the benefits of adoption.
5 **Trialability:** Prior to actual adoption, companies can explore the innovation of big data. Basically, it is like a trial before implementing or committing big data adoption.
6 **Perceived usefulness:** The "degree at which a company believes that big data adoption would enhance company performance" (Rogers, 1995).
7 **Predictive analytics accuracy:** It is a branch of analytics that is used to make future predictions about big data (Table 6).

4.3. What are the challenges in current research about big data adoption? (RQ3)

The review studies (Appendix) highlights various confront and limitations related to big data adoption studies. These challenges are related to big data theoretical models and factors, domain, data collection, research design, population and sample size. Obviously, those challenges significantly influence the actual big data adoption in the organizations, firms, companies, businesses, commerce, IT, and education sector. The challenges faced by big data adoption can be categorized and discussed below:

4.3.1. Theoretical models and factors

TOE (Almoqren & Altayar, 2016; Kang & Kim, 2015; Lai et al., 2018; Matsebula & Mnkandla, 2016; Nguyen & Petersen, 2017;

Park et al., 2015; Salleh & Janczewski, 2016; Sun et al., 2018; Verma & Bhattacharyya, 2017), DOI (Ochieng, 2015; Soon et al., 2016; Yin, 2015), TAM (Verma et al., 2018), TTF (Mneney & Van Belle, 2016), IT, two-dimensional model (Wu et al., 2017), and RBV (Gunasekaran et al., 2017) were found to be significant theoretical models for big data adoption. Researchers believed that the reason for the limited interest in big data analytics with respect to the educational domain is due to the lack of appropriate conceptualized framework (Matsebula & Mnkandla, 2016). In big data adoption related studies, TAM was only used as an acceptance model. However, TAM is a reliable and valid model. It can be used to analyze the acceptance, adoption, or the actual user behavior of new technology. The potency of TAM is totally dependent on PU and PEOU. Both factors can affect the attitude of users and inter-reliant towards adoption (Nguyen & Petersen, 2017; Soon et al., 2016; Verma et al., 2018). Although, TOE framework has appeared to be the most common model to understand and analyze the big data adoption factor in reviewed studies. Perceived compatibility, network challenges, vendor support, and technology readiness were the interdependent constructs. These constructs were measured in terms of factors affecting big data adoption (Mneney & Van Belle, 2016; Nguyen & Petersen, 2017; Ochieng, 2015; Park et al., 2015; Salleh et al., 2015; Salleh & Janczewski, 2016; Soon et al., 2016; Sun et al., 2018; Verma & Bhattacharyya, 2017; Yin, 2015). Perceived industrial pressure, government support, laws and policy, security, privacy and risk were the co-related factors which have direct impact on adoption (Almoqren & Altayar, 2016; Kang & Kim, 2015; Mneney & Van Belle, 2016; Nguyen & Petersen, 2017; Ochieng, 2015; Park et al., 2015; Sun et al., 2018; Verma & Bhattacharyya, 2017; Yin, 2015). Similarly, perceived financial readiness, weak IT infrastructure, management support, technological capability, firm size, staffing, and training are the interdependent factors that affect adoption in firms, organizations, companies, and business. Some researchers used more than one model like TOE, TTF, DOI, IT to give a more comprehensive analysis (Mneney & Van Belle, 2016; Nguyen & Petersen, 2017; Ochieng, 2015; Sun et al., 2018; Yin, 2015). TTF helps to explain adoption decisions dynamically. The one-dimensional model provides a partial view of the situation, whereas the two-dimensional model provides real insight into reality. Due to the complexity and multi-dimensional nature of the two-dimensional model, it cannot cover the market investment opinion towards adoption (Wu et al., 2017). Resource-based view models have been used to estimate the benefits, regulate and incorporate big data in supply chain management (Gunasekaran et al., 2017). However, institutional theory helps to give deeper insight and more resilient aspects of adoption. Moreover, both DOI and TOE are helpful in minimizing the technology-related challenges. TOE framework facilitates the innovation process in modifying the structure of the organization. TOE framework includes environmental factor, whereas DOI lacks this factor. So far, the application of some well-known adoption theoretical models such as Unified Theory of Acceptance and Use of Technology (UTAUT) and Actor-Network Theory (ANT), etc. are overlooked in the big data adoption literature. More researches are required to propose, validate, and extend the existing theoretical models to fully cover the insights according to the situation. In future studies, in-depth relation of the identified factors can be analyzed in a specific condition.

4.3.2. Domain

Big data adoption studies occurs in firms (Kang & Kim, 2015; Park et al., 2015), organizations (Salleh et al., 2015; Mneney & Van Belle, 2016; Nguyen & Petersen, 2017; Potter, 2016; Salleh & Janczewski, 2016; Sun et al., 2018; Verma & Bhattacharyya, 2017), companies (Chen et al., 2015; Soon et al., 2016; Yin, 2015), finance (Almoqren & Altayar, 2016), supermarket (Ochieng, 2015), education (Matsebula & Mnkandla, 2016), IT (healthcare market), and businesses (Verma et al., 2018). However, big data adoption has not been well explored in the educational and healthcare domains. In the future, educational sector data can be used to make a considerable improvement in the obsolete learning system and curriculums. In the health care realm, big data adoption can play an effective role in uncovering the ways for the betterment of patient health. The clinical record history and medical screening data can be useful to develop a reliable and cost-effective curing system. In the future, patient's records and laboratory data can be used to form an evidence-based model.

4.3.3. Population studied and setting

Big data adoption studies that are related to firms, organizations, companies, finance, supermarket and businesses occurred in both developing (Korea, Malaysia, Kenya, South Africa, Saudi Arabia) (Almoqren & Altayar, 2016; Kang & Kim, 2015; Mneney & Van Belle, 2016; Ochieng, 2015; Park et al., 2015; Potter, 2016; Soon et al., 2016) and developed Countries (Norway, United States, New Zealand) (Chen et al., 2015; Salleh et al., 2015; Nguyen & Petersen, 2017; Salleh & Janczewski, 2016). Majority of studies from developing and developed Countries were cross-sections and lack empirical research. However, in the future, the longitudinal studies that are based on experience and observation are expected in developing and developed Countries.

Developed Countries have already adopted innovative technology (Chen et al., 2015). However, few studies were found in educational sectors especially from developed countries (McLeod et al., 2017). In future, developed Countries can enhance the adoption in the educational realm by improving the storage technologies related to big data analytics (Matsebula & Mnkandla, 2016; McLeod et al., 2017). Developing Countries still lack technological innovation at the school level. Therefore, developing Countries should consider the importance of technological advancement at the school level. In the future, studies are expected to endow cost-effective technological ways of adopting big data in schools.

4.3.4. Data collection

In most of the studies, data were collected in a single Country. Therefore, the results cannot be generalized with other countries having different economic status and adoption decisions might be affected by technological advancement and lifestyle. Few educational based studies obtained data through proprietary software's (McLeod et al., 2017). Proprietary software needs consistent developer support, high cost, and has many security concerns. In contrast, open-source software is cost effective and easy to use. In the future, open source software's can be utilized to collect data. Secondly, self- hosting is not very common at school level in developed countries. Only a few schools possessed this facility of self-hosting in America (McLeod et al., 2017). Consequently, there is a need to highlight more flexible, robust, economical, and alternate solutions of self-hosting in a future study. In some studies, data were collected from single IT manager of each company whose decisions might not reflect the firm's point of view towards novelty and technology adoption (Lai et al., 2018). Therefore, financial readiness constructs and intention towards adoption may show negative co-relation. As a single respondent is selected from each organization, thus, it may lead towards the bias condition. Majority of studies used survey for data collection (Kang & Kim, 2015; Park et al., 2015; Salleh et al., 2015; Nguyen & Petersen, 2017; Ochieng, 2015;Almoqren & Altayar, 2016; Salleh & Janczewski, 2016; Soon et al., 2016; Verma et al., 2018) while other conducted via semi-structured (Chen et al., 2015; Mneney & Van Belle, 2016; Potter, 2016) and face-to-face interviews (Verma & Bhattacharyya, 2017; Yin, 2015).

Therefore, the survey analysis found to be the most effective for big data adoption related studies. It is highly cost-effective, scalable and helpful in providing instant results. Survey technique is helpful to cover the individuality and various characteristics of a large population. In contrary, semi-structured interviews provide qualitative data through two-way communication but the quality of the semi-structured interview is highly dependent on the interviewer. Some reviewed studies used small sample sizes in the survey analyses. For instance, Verma et al. (2018) collected data from only 150 big data analytics users. Another study conducted by Soon et al. (2016) collected data from only 40 employees in private companies in Malaysia.

Small sample size in the survey leads to variability and uncoverage or voluntary response bias. The mixed method allows perceiving and incorporating the benefits of qualitative and quantitative research simultaneously. Therefore, a mix-method approach with larger sample sized is recommended in future studies, to assure the accuracy and evading sampling errors.

5. Conclusion

Big data adoption provides an opportunity for organizations, companies, industries, and businesses to surpass competitors. The adoption process might be protracted and have a high cost, but the return benefits may expand the trail to success. This study aimed to provide a comprehensive overview of big data adoption studies. Thus, three research questions were formulated to present theoretical models used for big data adoption, significant factors that influence the adoption of big data, and challenges within the current research about big data adoption. Studies were collected by performing a systematic search through IEEE Xplore, Science Direct, Emerald Insight, AIS Electronic Library, Taylor and Francis, ACM Digital Library, Springer Link and Google scholar. After a comprehensive analysis, 20 articles published between the years 2015 to 2018 were selected to extract the relevant information and to answer research questions. Through the finding of this study, it can be concluded that TOE was the most-used model in the big data adoption realm. TOE is highly viable in lessening technology related challenges. Therefore, it can be used to amend the organizational structure.

This study categorized 42 significant factors into technology (11), organization (16), environment (8) and innovation (7) related factors that influence big data adoption. Perceived benefits, Perceived Complexity/Simplicity, Perceived compatibility, Technology readiness/ Technology resources, Data quality and integration, Wireless technology and lack of system integration, Knowledge about big data, Availability of big data tools, Internal versus external technologies, and Vendor support were the factors that influence big data adoption in technology perspective. In organizational context, this review study found that Perceived financial readiness/ Financial investment competence, IS competence/IT structure/ Weak IT infrastructure, Management support for big data, Organizational data environment, Perceived cost, Technological capability, Organizational learning culture, Human resources, Decision-making culture, Business strategy orientation, Change efficacy, Firm size, Appropriateness, Interpret unstructured data, Data control, and Staffing and training were the factors that influence big data adoption. Competitive pressure/ Perceived industrial pressure, Government support, Laws and policy, Security, Privacy and risk, Risks of outsourcing, Trading partner readiness, Market turbulence, IS fashion, and Marketing and Inventory were the significant factors that influence the big data adoption in an environmental context. Relative advantage, Cost of adoption, Complexity, Observability, Trialability, Perceived usefulness, and Predictive analytics accuracy were the factors in innovation perspective that encumbered the big data adoption process. Through the findings of this study, it can be concluded that Technology (Perceived complexity/simplicity, Perceived compatibility), Organization (Management support, Perceived financial readiness/ Financial investment competence), Environment (Competitive pressure/ Perceived industrial pressure, Security Privacy, and risk), and Innovation (Relative advantage, Complexity) were the most considered factors in each category. In the future, an in-depth relation of most emphasized factors can be analyzed in a specific situation.

Finally, this study explored the various challenges of big data adoption related studies in terms of theoretical models, data collection, research design, population setting, sample size, and domain.

5.1. Research implications

This study has two folded implications for theory and practice. In terms of theoretical implications, this review is possibly the first attempt to describe the theoretical models used for big data 'adoption'. Khan, Liu, Shakil and Alam (2017), conducted a survey study and analyzed the big scholarly data in terms of data management, analytics and visualization, highlighted the related challenges, presented the big data platforms and analytical techniques. Big data platforms and analytical techniques (Hadoop based) can provide viable analytical solutions for various data management related issues. Another survey study conducted by Saggi and Jain (2018), presented big data characteristics, analytical tools, techniques, frameworks (Hadoop, HBase, Cassandra, MongoDB, NoSQL), identification of the challenges related to data type, data collection, data storage, and data processing. The identified big data analysis tools and challenges can be helpful for data handling and decision making. De Mauro, Greco, Grimaldi and Ritala (2018), categorized the big data job into four groups. This study provides substantial support for Human Resource (HR) recruiters. To solve various data analysis problems Kamilaris et al. (2017), conducted a review study and introduced different techniques and methods that can be used for big data analysis and practices. Grover and Kar (2017) carried out a review study and identified the types and usage of big data tools that can be used further with big data technologies. Palanisamy and Thirunavukarasu (2017) in their review study presented the implication of big data tools and highlighted analytical capabilities for health care domain that can open various big data analytical avenues for related realms. Oussous, Benjelloun, Ait Lahcen and Belfkih (2018), performed a survey study on big data technologies and presented its comparison with different system layers that can be used in the selection of right technology according to requirement. Ariyaluran Habeeb et al. (2019) in their study, identified big data processing and network anomalies. The research is helpful in handling the irregularities related to real-time big data processing.

However, in the context of big data adoption, there is a lack of review that investigates big data adoption, state of the art and its related research challenges. This review contributes to the closure of this research gap. Firstly, the identified adoption models contribute to the theoretical enhancement of big data adoption research. The research findings present the studies that used big data adoption theoretical model in multiple domains. In turn, this review opens innovative research opportunities to explore big data adoption theoretical models in other domains.

Secondly, unlike previous studies that addressed the issues associated with big data (Hashem et al., 2015; Tu, He, Shuai & Jiang, 2017), this review aims to list the factors that influence big data adoption that is related to technology, organization, environment, and innovation. The identified factor provides valuable insights for service providers and managers. It is important to consider the big data adoption factors in order to improve the big data adoption-related services and enhance the overall organizational performance. For instance, service providers can offer training to up-skill the managers and other employees in adjustment to the new process. This ultimately contributes to enhancing the financial performance of the organization.

Lastly, this review study is not limited on identifying the general big data challenges (Fatt & Ramadas, 2018; Sivarajah et al., 2017) that belongs to its types and data platform (Khan et al., 2017; Saggi & Jain, 2018). The identified challenges based on big data adoption comprise significant contributions to the literature. The theoretical models, factors, population setting and data collection based challenges provide profound practical implication for stakeholders to adopt big data effectively and smoothly.

6. Limitations and future research directions

This review presented numbers of useful insights into big data adoption context. However, there are some limitations inherent by this study. Firstly, the search for articles was conducted only on the following databases: IEEE Xplore, Science Direct, Emerald Insight, AIS Electronic Library, Taylor and Francis, ACM Digital Library, Springer Link and Google scholar. The search of the articles can be extended and include in other databases. This study identified the big data adoption theoretical models used in organizations, firms, businesses, companies, and supermarkets. However, the implementation of big data and its impacts on organizations, firms, businesses, companies, and supermarkets can be explored in future studies.

This study provides a foundation for researchers to imply big data adoption theoretical models in other realms. In the future, an in-depth relation of most emphasized factors can be analyzed in a specific situation. Moreover, selecting larger sample size and focusing on the mix-method approaches are recommended to assure the exactitude for future studies. Additionally, in-depth, comprehensive research is required to propose and validate the existing theoretical models.

Acknowledgments

The authors would like to thank University of Malaya for supporting and funding this research under the Grant – AFR (Frontier Science) – Grant Number: RG380-17AFR.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ipm.2019.102095.

Appendix. Summary of reviewed studies of big data adoption

Table A1.

Table A1
Summary of reviewed studies of big data adoption.

Study	Objective	Theoretical model used for big data adoption	Domain	Population studied and settings	Data collection	Limitation
(Sun et al., 2018)	Identified the main factors that affect BDA at the organizational level	DOI, TOE, IT	Organization	Content analysis	Set the criteria for including, excluding and developed coding protocol	Lack of empirical research
(Lai et al., 2018)	Identified the determinants of BDA in logistics and supply chain management	TOE	Organization	210 from IT managers at China	Survey	Respondent's viewpoint may not fully represent the organization
(Verma et al., 2018)	Proposed and validation of a model	TAM	Business	150 big data analytics users from India	Survey	Data collected from a single country, small sample size
(McLeod et al., 2017)	Explored the changes in big data and analytics are being introduced to academia	–	Education	Examined request logs of self –hosted school over four years period, at United State of America	Proprietary software vendor	Limited to a single country
(Wu et al., 2017)	Investigated the impact of big data analytics on health IT market	Two-dimensional product differentiation framework	IT (Mobile healthcare market)	Consumers of two firms in China	Survey	Investigated the fully covered market
(Gunasekaran et al., 2017)	Identified the influence of resources (top management and capability)	Resource based view (RBV)	Firms	Manufacturing companies, consulting companies, e-commerce companies, and technology in India	Survey	Mixed research approach could be better
(Nguyen & Petersen, 2017)	Identified the factors for Organizational Assimilation of BD	DOI, TOE, TAM	Organization	336 Executive-level employees in Norway companies	Survey	Limited to a single country
(Verma & Bhattacharyya, 2017)	Highlighted the factors affecting BD	TOE	Firm	22 different enterprises and service providers in India	Face-to-face semi-structured interviews	Limited to India, lack empirical study
(Almoqren & Altayar, 2016)	Examined the factors affecting the adoption of BD in banks	TOE	Finance	54 participants who work in data processing, business intelligence and IT departments in Saudi banks	Survey	Results cannot be generalized for other countries
(Salleh & Janczewski, 2016)	Analyzed the BD determinants among adopters and non-adopters	TOE	Organization	25 responses from organizations having more than 2000 employees in Auckland, New Zealand	Survey	The sample size was small
(Mneney & Van Belle, 2016)	Examined the readiness of retail organization regarding BDA	TOE, TTF	Retail organizations	Respondents were 3 retailers, 3 vendors, and 2 IT service providers in South Africa	Semi-structured interviews	Only checked the readiness situation of a single country
(Soon et al., 2016)	Studied factors affecting the adoption of Big Data	TAM, DOI	Private companies	40 employees from private companies in Malaysia	Survey	Findings are limited to a private company
(Potter, 2016)	Explored the factors that enhance BDA in SMMEs	–	Organization (SMMEs)	Senior management in South African companies	Semi-structured interviews	Sampling bias, respondent bias, research validity

(continued on next page)

Table A1 (*continued*)

Study	Objective	Theoretical model used for big data adoption	Domain	Population studied and settings	Data collection	Limitation
(Matsebula & Mnkandla, 2016)	Highlighted the IS and innovation adoption in education and stress on TOE	TOE	Education	–	–	Lack of validity
(Kang & Kim, 2015)	To test the hypotheses based on the developed model	TOE	Firms	58 top management team or IS manager in the Korean firm	Survey	Cross-sectional, single response based, lack external validity
(Park et al., 2015)	Analyzed the factors related to TOE that influence the BDA	TOE	Firms	5 experts having 10-year research experience in the Korean firm	Survey	Limited to BDA and its usage in firms only
(Salleh et al., 2015)	Examined the security factors in BDA	TOE	Organizations	Organization employees in two countries (New Zealand and Malaysia)	Survey	(research-in-progress)
(Yin, 2015)	Developed BDA process framework	TOE, DOI	Companies (OEM)	Employees of Original Equipment Manufacturer (OEM) Company	Face-to-face interviews	Limited to OEM companies
(Chen et al., 2015)	Developed Big Data Adoption model to clarify "why", and "how" questions	–	Companies	25 European enterprises of Hawaii, united states	Semi-structured interviews	Results applied to a single country
(Ochieng, 2015)	Determined the factors affecting BDA in supermarkets	TOE, DOI	Supermarkets	5 leading Supermarket chains and the 3 independent supermarkets in Kenya	Survey	Limited to a single country

Note: BDA (Big data adoption/analytics), TAM (Technology Acceptance Model), DOI (Diffusion of Innovation), TOE (Technology- Organization -Environment), IT (Institutional Theory), Task-Technology Fit (TTF), SMMEs (Small, Medium and Micro-sized Enterprises), Original Equipment Manufacturer (OEM).

References

Abdel-Basset, M., Mohammed, M., Smarandache, F., & Chang, V. (2018). Neutrosophic association rule mining algorithm for big data analysis. *Symmetry, 10*(4), 101–106. https://doi.org/10.3390/sym10040106.

Agrawal, K. P. (2015). Investigating the determinants of big data analytics (BDA) adoption in emerging economies. *Academy of management proceedings* (pp. 11210–11290). Academy of Management. https://doi.org/10.5465/AMBPP.2015.11290 10510.

Aguilar, S. J. (2018). Learning analytics: At the nexus of big data, digital innovation, and social justice in education. *TechTrends, 62*(1), 37–45. https://doi.org/10.1007/s11528-017-0226-9.

Ale, B. (2016). Risk analysis and big data. *Safety and Reliability, 36*(3), 153–165. https://doi.org/10.1080/09617353.2016.1252080.

Almoqren, N., & Altayar, M. (2016). The motivations for big data mining technologies adoption in Saudi banks. *Information technology (big data analysis), (KACSTIT), Saudi international conference* (pp. 1–8). IEEE. https://doi.org/10.1109/KACSTIT.2016.7756075.

Al-Qirim, N., Tarhini, A., & Rouibah, K. (2017). Determinants of big data adoption and success. *Proceedings of the international conference on algorithms, computing and systems* (pp. 88–92). ACM. https://doi.org/10.1145/3127942.3127961.

Ariyaluran Habeeb, R. A., Nasaruddin, F., Gani, A., Targio Hashem, I. A., Ahmed, E., & Imran, M. (2019). Real-time big data processing for anomaly detection: A survey. *International Journal of Information Management, 45*, 289–307. https://doi.org/10.1016/j.ijinfomgt.2018.08.006.

Chamikara, M. A. P., Bertok, P., Liu, D., Camtepe, S., & Khalil, I. (2019). Efficient privacy preservation of big data for accurate data mining. *Information Sciences*. https://doi.org/10.1016/j.ins.2019.05.053 In Press.

Chandra, S., & Kumar, K. N. (2018). Exploring factors influencing organizational adoption of augmented reality in e-commerce: Empirical analysis using technology-organizationenvironment model. *Journal of Electronic Commerce Research, 19*(3), 237–265. http://www.jecr.org/sites/default/files/2018vol19no3_paper3.pdf.

Chen, H.-. M., Kazman, R., & Matthes, F. (2015). Demystifying big data adoption: Beyond IT fashion and relative advantage. *Proceedings of pre-ICIS, international conference on information system* (pp. 2–15). DIGIT workshop.

Chen, J., Chen, Y., Du, X., Li, C., Lu, J., & Zhao, S. (2013). Big data challenge: A data management perspective. *Frontiers of Computer Science, 7*(2), 157–164. https://doi.org/10.1007/s11704-013-3903-7.

Clarke, R. (2016). Big data, big risks. *Information Systems Journal, 26*(1), 77–90. https://doi.org/10.1111/isj.12088.

Côrte-Real, N., Ruivo, P., & Oliveira, T. (2019). Leveraging internet of things and big data analytics initiatives in European and American firms: Is data quality a way to extract business value? *Information & Management*. https://doi.org/10.1016/j.im.2019.01.003 In Press.

Davenport, T. H., & Dyché, J. (2013). Big data in big companies. *International Institute for Analytics, 31*(2), 60–68.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008.

Davis, F. D., & Venkatesh, V. (1996). A critical assessment of potential measurement biases in the technology acceptance model: Three experiments. *International Journal of Human-Computer Studies, 45*(1), 19–45. https://doi.org/10.1006/ijhc.1996.0040.

De Mauro, A., Greco, M., Grimaldi, M., & Ritala, P. (2018). Human resources for big data professions: A systematic classification of job roles and required skill sets. *Information Processing & Management, 54*(5), 807–817. https://doi.org/10.1016/j.ipm.2017.05.004.

Demchenko, Y., Grosso, P., De Laat, C., & Membrey, P. (2013). Addressing big data issues in scientific data infrastructure. *Collaboration technologies and systems (CTS), international conference* (pp. 48–55). IEEE. https://doi.org/10.1109/CTS.2013.6567203.

Diniz, E. H., Luvizan, S. S., Hino, M. C., & Ferreira, P. C. (2018). *Unveiling the big data adoption in banks: Strategizing the implementation of a new technology. Digital technology and organizational change*. Cham: Springer149–162. https://doi.org/10.1007/978-3-319-62051-0_13.

Dorasamy, N., & Pomazalová, N. (2016). *Social impact and social media analysis relating to big data. Data science and big data computing*. Cham: Springer293–313. https://doi.org/10.1007/978-3-319-31861-5.

Elgendy, N., & Elragal, A. (2014). *Big data analytics: A literature review paper. Industrial conference on data mining*. Springer214–227. https://doi.org/10.1007/978-3-319-08976-8_16.

Esteves, J., & Curto, J. (2013). A risk and benefits behavioral model to assess intentions to adopt big data. *Proceedings of the 10th international conference on intellectual capital, knowledge management and organisational learning: ICICKM* (pp. 415–458). .

Fan, W., Liu, J., Zhu, S., & Pardalos, P. M. (2018). Investigating the impacting factors for the healthcare professionals to adopt artificial intelligence-based medical diagnosis support system (AIMDSS). *Annals of Operations Research, 74*(19), 1–26. https://doi.org/10.1007/s1047.

Fatt, Q. K., & Ramadas, A. (2018). The usefulness and challenges of big data in healthcare. *Journal of Healthcare Communications, 3*(2), 18–41. https://doi.org/10.4172/2472-1654.100131.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly, 19*(2), 213–236. https://doi.org/10.2307/249689.

Green, E. C., & Murphy, E. (2014). *Health belief model. the Wiley Blackwell encyclopedia of health, illness, behavior, and society*. American Cancer Society766–769. https://doi.org/10.1002/9781118410868.wbehibs410.

Grover, P., & Kar, A. K. (2017). Big data analytics: A review on theoretical contributions and tools used in literature. *Global Journal of Flexible, Systems Management, 18*(3), 203–229. https://doi.org/10.1007/s40171-017-0159-3.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., et al. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research, 70*(1), 308–317. https://doi.org/10.1016/j.jbusres.2016.08.004.

Günther, W. A., Rezazade Mehrizi, M. H., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *The Journal of Strategic Information Systems, 26*(3), 191–209. https://doi.org/10.1016/j.jsis.2017.07.003.

Harper, E. M. (2013). The economic value of health care data. *Nursing Administration Quarterly, 37*(2), 105–113. https://doi.org/10.1097/NAQ.0b013e318286db0d.

Hashem, I. A. T., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A., & Ullah Khan, S. (2015). The rise of "big data" on cloud computing: Review and open research issues. *Information Systems, 47*(1), 98–115. https://doi.org/10.1016/j.is.2014.07.006.

Hay, S. I., George, D. B., Moyes, C. L., & Brownstein, J. S. (2013). Big data opportunities for global infectious disease surveillance. *PLoS Medicine, 10*(4), 112–125. https://doi.org/10.1371/journal.pmed.1001413.

Herschel, R., & Miori, V. M. (2017). Ethics & big data. *Technology in Society, 49*(2), 31–36. https://doi.org/10.1016/j.techsoc.2017.03.003.

Hilbert, M. (2013). Big data for development. *From Information-to Knowledge Societies, 15*(6), 12–20.

IBM. (2012). *Big data at the speed of business.* [online] Available: http://www-01.ibm.com/soft-ware/data/bigdata/.

IBM. (2018). *IBM What is big data? – Bringing big data to the enterprise – Singapore.* (n.d.). Retrieved May 10 https://www.ibm.com/software/sg/data/bigdata/.

Janssen, M., Charalabidis, Y., & Zuiderwijk, A. (2012). Benefits, adoption barriers and myths of open data and open government. *Information Systems Management, 29*(4), 258–268. https://doi.org/10.1080/10580530.2012.716740.

John Walker, S. (2014). Big data: A revolution that will transform how we live, work, and think. *International Journal of Advertising, 33*(1), 181–183. https://doi.org/10.2501/IJA-33-1-181-183.

Johnson, S. L., Gray, P., & Sarker, S. (2019). Revisiting IS research practice in the era of big data. *Information and Organization, 29*(1), 41–56. https://doi.org/10.1016/j.infoandorg.2019.01.001.

Kamilaris, A., Kartakoullis, A., & Prenafeta-Boldú, F. X. (2017). A review on the practice of big data analysis in agriculture. *Computers and Electronics in Agriculture, 143*(3), 23–37 doi: 0.1016/j.compag.2017.09.037.

Kang, D., & Kim, S. H. (2015). Process of big data analysis adoption: Defining big data as a new IS innovation and examining factors affecting the process. *2015 48th Hawaii international conference on system sciences* (pp. 4792–4801). . https://doi.org/10.1109/HICSS.2015.569.

Kataria, M., & Mittal, M. P. (2014). Big data: A review. *International Journal of Computer Science and Mobile Computing, 3*(7), 106–110.

Khan, S., Liu, X., Shakil, K. A., & Alam, M. (2017). A survey on scholarly data: From big data perspective. *Information Processing & Management, 53*(4), 923–944. https://doi.org/10.1016/j.ipm.2017.03.006.

Kimiloglu, H., Ozturan, M., & Kutlu, B. (2017). Perceptions about and attitude toward the usage of e-learning in corporate training. *Computer Human behaviour, 72*(3),

339–349. https://doi.org/10.1016/j.chb.2017.02.062.
Kitchin, R. (2014). *The data revolution: Big data, open data, data infrastructures and their consequences*, *56*, Sage722–723. https://doi.org/10.1111/jors.12293.
Krasnow Waterman, K., & Bruening, P. J. (2014). Big data analytics: Risks and responsibilities. *International Data Privacy Law, 4*(2), 89–95. https://doi.org/10.1093/idpl/ipu002.
Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management: An empirical investigation. *The International Journal of Logistics Management, 29*(2), 676–703. https://doi.org/10.1108/IJLM-06-2017-0153.
Lin, Y., Wang, H., Li, J., & Gao, H. (2019). Data source selection for information integration in big data era. *Information Sciences, 479*, 197–213. https://doi.org/10.1016/j.ins.2018.11.029.
Luna, D. R., Mayan, J. C., García, M. J., Almerares, A. A., & Househ, M. (2014). Challenges and potential solutions for big data implementations in developing countries. *Yearbook of Medical Informatics, 9*(1), 36–52. https://doi.org/10.15265/IY-2014-0012.
Malaka, I., & Brown, I. (2015). Challenges to the organisational adoption of big data analytics: A case study in the South African telecommunications industry. *Proceedings of the 2015 annual research conference on South African institute of computer scientists and information technologists* (pp. 1–27). ACM. https://doi.org/10.1145/2815782.2815793.
Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., et al. (2011). Big data: The next frontier for innovation, competition, and productivity. *Services Computing, 112*(29), 1–6.
Matsebula, F., & Mnkandla, E. (2016). Information systems innovation adoption in higher education: Big data and analytics. *Advances in computing and communication engineering (ICACCE), 2016 international conference* (pp. 326–329). IEEE. https://doi.org/10.1109/ICACCE.2016.8073769.
McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J., & Barton, D. (2012). Big data: The management revolution. *Harvard Business Review, 90*(10), 60–68.
McLeod, A. J., Bliemel, M., & Jones, N. (2017). Examining the adoption of big data and analytics curriculum. *Business Process Management Journal, 23*(3), 506–517. https://doi.org/10.1108/BPMJ-12-2015-0174.
Mishra, D., Luo, Z., Jiang, S., Papadopoulos, T., & Dubey, R. (2017). A bibliographic study on big data: Concepts, trends and challenges. *Business Process Management Journal, 23*(3), 555–573 doi: 0.1108/BPMJ-10-2015-0149.
Mittal, S. (2018). *Understanding factors affecting university student's adoption of E-learning systems in NCR. Emerging Challenges in Business, Optimization, Technology, and industry*. Springer185–198.
Mneney, J., & Van Belle, J.-. P. (2016). Big data capabilities and readiness of south african retail organisations. *Cloud system and big data engineering (confluence), 2016 6th international conference* (pp. 279–286). IEEE. https://doi.org/10.1109/Confluence.2016.7508129.
Moat, H. S., Preis, T., Olivola, C. Y., Liu, C., & Chater, N. (2014). Using big data to predict collective behavior in the real world 1. *Behavioral and Brain Sciences, 37*(1), 92–93. https://doi.org/10.1017/S0140525X13001817.
Murumba, J., & Micheni, E. (2017). Big data analytics in higher education: A review. *International Journal of Engineering Science, 6*(6), 14–21. https://doi.org/10.9790/1813-0606021421.
Nguyen, T., & Petersen, T. E. (2017). *Technology adoption in Norway: Organizational assimilation of big data*. (Master's Thesis).
Ochieng, G. F. (2015). *The adoption of big data analytics by supermarkets in Kisumu County.* University of Nairobi.
Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. *The Electronic Journal Information Systems Evaluation, 14*(1), 110–121.
Osman, A. M. S. (2019). A novel big data analytics framework for smart cities. *Future Generation Computer Systems, 91*, 620–633. https://doi.org/10.1016/j.future.2018.06.046.
Oussous, A., Benjelloun, F.-. Z., Ait Lahcen, A., & Belfkih, S. (2018). Big data technologies: A survey. *Journal of King Saud University - Computer and Information Sciences, 30*(4), 431–448. https://doi.org/10.1016/j.jksuci.2017.06.001.
Palanisamy, V., & Thirunavukarasu, R. (2017). Implications of big data analytics in developing healthcare frameworks–A review. *Journal of King Saud University-Computer and Information Sciences*. https://doi.org/10.1016/j.jksuci.2017.12.007 In Press.
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. *Econstor, 3*(1), 121–129.
Pérez-Martín, A., Pérez-Torregrosa, A., & Vaca, M. (2018). Big data techniques to measure credit banking risk in home equity loans. *Journal of Business Research, 89*(1), 448–454. https://doi.org/10.1016/j.jbusres.2018.02.008.
Pope, C., Halford, S., Tinati, R., & Weal, M. (2014). What's the big fuss about 'big data'? *Journal of Health Services Research & Policy, 19*(2), 67–68. https://doi.org/10.1177/1355819614521181.
Potter, J. G. (2016). *Big data adoption in SMMEs.* University of Pretoria.
Raguseo, E. (2018). Big data technologies: An empirical investigation on their adoption, benefits and risks for companies. *International Journal of Information Management, 38*(1), 187–195. https://doi.org/10.1016/j.ijinfomgt.2017.07.008.
Raut, R. D., Mangla, S. K., Narwane, V. S., Gardas, B. B., Priyadarshinee, P., & Narkhede, B. E. (2019). Linking big data analytics and operational sustainability practices for sustainable business management. *Journal of Cleaner Production, 224*, 10–24. https://doi.org/10.1016/j.jclepro.2019.03.181.
Rogers, E. M. (1995). Lessons for guidelines from the diffusion of innovations. *Joint Commission Journal on Quality and Patient Safety, 21*(7), 324–328.
Saggi, M. K., & Jain, S. (2018). A survey towards an integration of big data analytics to big insights for value-creation. *Information Processing & Management, 54*(5), 758–790. https://doi.org/10.1016/j.ipm.2018.01.010.
Sagiroglu, S., & Sinanc, D. (2013). Big data: A review. *Collaboration technologies and systems (CTS), international conference* (pp. 42–47). IEEE. https://doi.org/10.1109/CTS.2013.6567202.
Salleh, K. A., & Janczewski, L. (2016). Adoption of big data Solutions: A study on its security determinants using Sec-TOE framework. *CONF-IRM* (pp. 52–66). .
Salleh, K. A., Janczewski, L., & Beltran, F. (2015). SEC-TOE framework: Exploring security determinants in big data solutions adoption. *PACIS* (pp. 190–203). .
Shorfuzzaman, M., Hossain, M. S., Nazir, A., Muhammad, G., & Alamri, A. (2019). Harnessing the power of big data analytics in the cloud to support learning analytics in mobile learning environment. *Computers in Human Behavior, 92*, 578–588. https://doi.org/10.1016/j.chb.2018.07.002.
Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of big data challenges and analytical methods. *Journal of Business Research, 70*(2), 263–286. https://doi.org/10.1016/j.jbusres.2016.08.001.
Soon, K. W. K., Lee, C. A., & Boursier, P. (2016). A study of the determinants affecting adoption of big data using integrated technology acceptance model (TAM) and diffusion of innovation (doi) in Malaysia. *International Journal of Applied Business and Economic Research, 14*(1), 17–47.
Sun, S., Cegielski, C. G., Jia, L., & Hall, D. J. (2018). Understanding the factors affecting the organizational adoption of big data. *Journal of Computer Information Systems, 58*(3), 193–203. https://doi.org/10.1080/08874417.2016.1222891.
Surbakti, F. P. S., Wang, W., Indulska, M., & Sadiq, S. (2019). Factors influencing effective use of big data: A research framework. *Information & Management*. https://doi.org/10.1016/j.im.2019.02.001 In press.
Tabesh, P., Mousavidin, E., & Hasani, S. (2019). Implementing big data strategies: A managerial perspective. *Business Horizons, 62*(3), 347–358. https://doi.org/10.1016/j.bushor.2019.02.001.
Tole, A. A. (2013). Big data challenges. *Database Systems Journal, 4*(3), 31–40.
Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *Processes of technological innovation.* Lexington Books.
Tsou, M.-. H. (2015). Research challenges and opportunities in mapping social media and big data. *Cartography and Geographic Information Science, 42*(1), 70–74.
Tu, C., He, X., Shuai, Z., & Jiang, F. (2017). Big data issues in smart grid – A review. *Renewable and Sustainable Energy Reviews, 79*(1), 999–1107. https://doi.org/10.1016/j.rser.2017.05.134.
Tyagi, A. K., Priya, R., & Rajeswari, A. (2015). Mining big data to predicting future. *International Journal of Engineering Research and Applications, 5*(3), 14–21.
Ur Rehman, M. H., Yaqoob, I., Salah, K., Imran, M., Jayaraman, P. P., & Perera, C. (2019). The role of big data analytics in industrial Internet of Things. *Future Generation Computer Systems, 99*, 247–259. https://doi.org/10.1016/j.future.2019.04.020.
Verma, S., & Bhattacharyya, S. S. (2017). Perceived strategic value-based adoption of big data analytics in emerging economy. *Journal of Enterprise Information*

Management, 30(3), 354–382. https://doi.org/10.1108/jeim-10-2015-0099.
Verma, S., Bhattacharyya, S. S., & Kumar, S. (2018). An extension of the technology acceptance model in the big data analytics system implementation environment. *Information Processing & Management, 54*(5), 791–806. https://doi.org/10.1016/j.ipm.2018.01.004.
Ward, J.S., .& Barker, A. (2013). Undefined by data: a A survey of big data definitions. *arXiv preprint arXiv:1309.5821*.
Weerasinghe, K., Pauleen, D., Scahill, S., & Taskin, N. (2018). Development of a theoretical framework to investigate alignment of big data in healthcare through a social representation lens. *Australasian Journal of Information Systems, 22*(1), 1–23. https://doi.org/10.3127/ajis.v22i0.1617.
Wright, L. T., Robin, R., Stone, M., & Aravopoulou, D. E. (2019). Adoption of big data technology for innovation in B2B marketing. *Journal of Business-to-Business Marketing,* 1–13. https://doi.org/10.1080/1051712x.2019.1611082.
Wu, J., Li, H., Liu, L., & Zheng, H. (2017). Adoption of big data and analytics in mobile healthcare market: An economic perspective. *Electronic Commerce Research and Applications, 22*(1), 24–41.
Yadegaridehkordi, E., Nilashi, M., Nasir, M. H. N. B. M., & Ibrahim, O. (2018). Predicting determinants of hotel success and development using structural equation modelling (SEM)ANFIS method. *Tourism Management, 137*(1), 199–210. https://doi.org/10.1016/j.techfore.2018.07.043.
Ye, Y., Zhao, Y., Shang, J., & Zhang, L. (2019). A hybrid IT framework for identifying high-quality physicians using big data analytics. *International Journal of Information Management, 47*, 65–75. https://doi.org/10.1016/j.ijinfomgt.2019.01.005.
Yin, Y. (2015). Developing an adoption process framework for big data analytics by OEM companies. http://resolver.tudelft.nl/uuid:b4159672-39c0-4b3d-b54a-780ed7c75ecb.
Zhao, Y., Yu, Y., Li, Y., Han, G., & Du, X. (2019). Machine learning based privacy-preserving fair data trading in big data market. *Information Sciences, 478*, 449–460. https://doi.org/10.1016/j.ins.2018.11.028.
Zoomdata. (2017). Big Data Adoption, https://www.zoomdata.com/master-class/state-market/bigdata-'adoption-part-2/.
Zucker, L. G. (1987). Institutional theories of organization. *Annual Review of Sociology, 13*(1), 443–464. https://doi.org/10.1146/annurev.so.13.080187.002303.