Exploring the Factors Influencing Big Data Technology Acceptance

Nayem Rahman, Tugrul Daim, and Nuri Basoglu

***Abstract*—Big Data has received great attention in academic literature and industry papers. Most of the experiments and studies focused on publishing results of big data technologies development, machine learning algorithms, and data analytics. To the best of our knowledge, there is not yet any comprehensive empirical study in the academic literature on big data technology acceptance. The statistical results of this model provide a compelling explanation of the relationships among the antecedent variables and the dependent variables. The analysis of the structural model reveals that the hypothesis tests are significant for 8 out of 12 path relationships.**

***Index Terms*—Artificial intelligence, business, business data processing, computational and artificial intelligence, data systems engineering management, decision support systems, decision making, expert systems, intelligent systems, knowledge based systems, management, technology management.**

I. Introduction

THE purpose of this article is to conduct empirical research to advance knowledge in the field of technology acceptance. We investigate the factors that influence the acceptance of big data technology by companies. First, this article collects most of the variables from existing IT theory [35], [106], [132], utility theory of economics [64], [113], adoption factors taxonomy based on prior research, industry technical papers, and other documentation. Through this method, 32 factors have been identified. Later, these factors were presented to industry experts who have hands-on experience in both big data technologies (e.g., Hadoop) and traditional data management software, including Teradata, Oracle, and MS SQL Server [98], [99]. The qualitative studies consisting of the brainstorming sessions, expert panel, focus groups, and interviews were used to get the input in selecting the most important variables of big data technology adoption. Out of 32 factors, the top 12 factors (by voting) are selected to be part of this article. Thus, this research model consists of 12 factors that are used to understand big data technology adoption. More than 60 construct items are developed using these variables and are finally used in the survey instrument. Hypotheses have been developed based on 12 factors identified by the qualitative study results. The survey instrument is developed based on the questionnaire used in the existing literature and on new questions added based on big data specific factors. The survey instrument is tested and validated. A web-based survey was developed and sent to big data user groups in the United States. Out of 14 big data user groups (available on the Internet) consisting of 33 thousand subscribers, two Hadoop user groups were sent survey questions. A cluster sampling technique is used by randomly selecting these two user groups. Collected data are analyzed using the statistical software, AMOS. Conclusions are drawn relating to theoretical contribution and practical implications.

Manuscript received November 17, 2020; accepted March 7, 2021. Review of this manuscript was arranged by Department Editor E. Kongar. *(Corresponding author: Tugrul Daim.)*

Nayem Rahman and Tugrul Daim are with Portland State University, Portland, OR 97201 USA (e-mail: nayem.rahman@yahoo.com; tugrul.u.daim@pdx.edu).

Nuri Basoglu is with the Izmir Institute of Technology, Izmir 35430, Turkey (e-mail: nuribasoglu@iyte.edu.tr).

Digital Object Identifier 10.1109/TEM.2021.3066153

II. Literature Review

Davis [34] introduces the technology acceptance model (TAM) which is rooted in TRA [38]. Later, Venkatesh and Davis [130] developed a revised version called TAM2. Legris *et al*. [74] report that overall the two (TAM and TAM2) can explain about 40% of the system's use. The TAM consists of two constructs, "perceived usefulness" (PU) and "perceived ease of use" (PEOU), which are influenced by independent variables that in turn determine the latent variable "behavioral intention to use (BI)." The "intention to use" in TAM overlaps with TRA and TPB. The PU and PEOU replace "attitudes" and "subjective norms" used in TRA. On the other hand, those two TAM factors (PU and PEOU) replace the effect of attitude, subjective norm, and perceived behavioral control under TPB [9]. Davis *et al*. [36] and Venkatesh *et al*. [132] studies proved that TAM outperforms TRA and TPB in terms of explaining variances. However, in their article on TAM titled, "re-examining PEOU and usefulness," Segars and Grover [110] comment that "no absolute measures for these constructs exist across varying technological and organizational contexts." The authors observe that task and user characteristics change the nature and importance of perceptions that explain technology use. We assert that besides task and user characteristics, it is important to independently evaluate technology in terms of its usefulness and core capabilities.

The TAM is considered the most influential and widely used model, especially in the information systems (IS) field [131]. Bagozzi [9] identifies parsimony as the main strength of TAM. Several TAM studies in IS research are listed in Table I.

Venkatesh *et al*. [132] propose a modified and enhanced model called the unified theory of acceptance and use of technology (UTAUT). This model consolidates other models including that of TAM. The authors claim this model to be a parsimonious model. The UTAUT is an impressive-sounding name but makes

TABLE I
SUMMARY OF TAM STUDIES (1989–2019)

Authors	Constructs	Applications	Methodology
Davis (1989)	Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Usage (U)	XEDIT	Survey
Davis et al. (1989)	PU, PEOU, Attitude (A), Behavioral Intention (BI), U	Write One	Experiment
Basoglu et al. (2007)	PU, PEOU, U	ERP	Survey
Mathieson (1991)	PU, PEOU, A, BI, U	Spreadsheet	Experiment
Adams et al. (1992)	PU, PEOU, U	E-mail, WordPerfect	Survey
Straub et al. (1995)	PU, PEOU, U	V-mail	Survey
Igbaria et al. (1995)	PU, PEOU, U	Micro-Computer	Survey
Szajna (1996)	PU, PEOU, BI, U	E-mail	Experiment
Hendrickson & Collins (1996)	PU, PEOU, U	1-2-3, WordPerfect	Experiment
Morris & Dillon (1997)	PU, PEOU, A, BI, U	Netscape	Survey
Gefen & Straub (1997)	PU, PEOU, U	E-mail	Survey
Lederer et al. (2000)	PU, PEOU, A, BI, U	World wide web	Survey
Qin et al. (2011)	PU, PEOU, BI	Online Social Networks	Survey
Choi and Ji (2015)	PU, PEOU, BI	Autonomous Vehicle	Survey
Rajan & Baral (2015)	PU, PEOU, BI, U	ERP	Survey
Wang et al. (2012)	PU, PEOU, U	Instant Messaging	Survey
Hood-Clark (2016)	PU, PEOU, A, BI, U	Big Data	Survey

TABLE II
TAXONOMY OF FACTORS BASED ON LITERATURE REVIEW

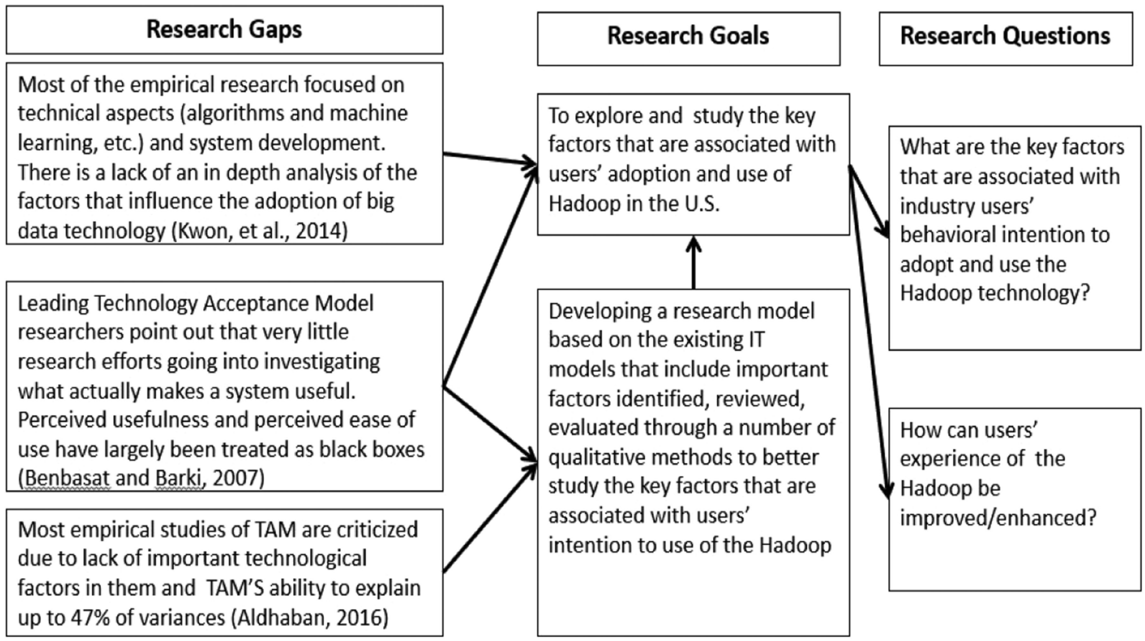
Adoption of Big Data Technology					
Environmental	**Individual**	**Organizational**	**Technological**	**Economic**	**Legal**
Facilitating Conditions	Image	Organizational commitment	**Performance Expectancy**	**Cost effectiveness**	**Security and Privacy**
Subjective Norm/Social Influence	Self-Efficacy	Top Management Support	Relative advantage	Total Cost of Ownership	
Competitive/Industry Pressure	Voluntariness	Job Relevance	**Scalability**		
		Organizational size	Compatibility		
		Training and required skills	Complexity		
		Facilitating Conditions	Observability		
			Flexibility		
			Fault tolerance capability		
			Reliability		
			Data Storage & Processing Capability		
			Output Quality		
			Results Demonstrability		
			Functionality		
			Effort Expectancy		
			Data Analytics Capability		
			Enjoyment		
			Absorptive capacity		
			Trialability		

no mistake, the pundits of technology acceptance research consider this "parsimonious claim" deceptive [114]. For example, performance expectancy (PE) is defined as one of the five UTAUT constructs. The authors list as many as five underlying constructs, including PU, extrinsic motivation, job-fit, relative advantage, and outcome expectations. Nonetheless, several empirical studies have tested the effectiveness of this model [50], [60], [133], [135]. The UTAUT proposes five predictors, "PE," "effort expectancy," "social influence," "facilitating conditions (FC)." Since the introduction of this model in 2003, this model has been used extensively mainly in IS research [134].

A literature review on data management software has provided 32 factors that are categorized in a taxonomy into six dimensions (see Table II). These dimensions include environmental, individual, organizational, technological, economic, and legal. Under those six dimensions consisting of 32 factors, 12

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

TABLE III
RESEARCH GAPS AND RESEARCH GOALS



factors have been selected by an expert panel of big data to use in the proposed research model.

Some of the factors, classified as adoption taxonomy, have reference to different technology adoption theory factors and some from industry papers. The TAM has reference to PU and PEOU. The TAM framework allows for applying external factors identified under six dimensions (see Table II). Past research applied several of these factors using TAM [15], [73]. These factors are task performance, efficiency, innovativeness, management commitment, results from demonstrability, quality, relative advantage, compatibility, complexity, observability, subjective norms, visibility, FC, and prior experience. Many of these variables belong to factors classified under environmental, organizational, and technological classifications in Table IV. Resource-based view theory has reference to environmental and economic dimensions that include business value, rareness, imitability, and substitutability to achieve competitiveness by a firm [40], [62], [124], [139]. Big data capability has implications for important resources such as technological, strategic, and economic. Several factors in Table IV have reference to other TAMs (Fishbain and Ajzen, [43], [68], [132]): TRA (subjective norms), TPB (perceived behavioral control), TOE (technological, organizational, and environmental) and UTAUT (performance, FC) [133].

As big data is a new discipline, there are a few studies conducted on big data technology adoption [26], [41], [69], [83], [136].

Existing literature provides the state of big data technology development [108] and results of case studies, machine learning techniques, predictive modeling, surveys, and experiments [3], [24], [63], [65], [71]. But this literature did not provide much insight into the overall usage of big data tools and technologies. Technology acceptance is considered to be the determinant of the success of a product or technology. Studying acceptance from the users' perspective gives new insight about likes and dislikes of different features, the product itself, and the user's attitude toward the product. A systematic study of the review of big data is needed to understand the overall picture of the big data technology acceptance rate.

The TAM has been developed by Davis [33] as part of his doctoral research at MIT Sloan School of Management to empirically test new end-user IS. Since then, TAM has been applied frequently for research into the acceptance of new information technology.

This model has gained popularity among practitioners and researchers over the last two decades. The model has been tested and applied in many fields. These include switching cost on accounting software use [49], enterprise resource planning (ERP), software system implementation [4], [13], [103], software evaluation and choice [118], world wide web [72], ease of use and usage of information technology [1], [34], and user acceptance of computer technology [35], [36], to name a few. In [131], Venkatesh *et al.* put it in the title as to whether TAM is "dead or alive." And later, in Section VI, they pronounced the verdict that the research on technology adoption is not dead! However, they suggest continuing research on TAM by focusing on interesting questions that solve business problems.

To our knowledge, there are a few empirical studies on big data technology (e.g., Hadoop) that used TAM [57]. This makes sense since big data, core big data technologies, and big data ecosystems have emerged during the middle of the last decade. This could be considered a research gap. This article conducts formal research on the user acceptance of big data technology, namely, the Hadoop distributed file system (HDFS). The research gaps are provided in Table III.

TABLE IV
SUMMARY OF STEPS TO DEVELOP THE QUALITATIVE STUDY

Research Steps	Description	Target Participants
Literature Review	An extensive literature search related to technology acceptance in general and big data technology acceptance in particular has been conducted.	
Brainstorming	An extensive interactive session to be conducted with nine industry experts via a one-hour session.	Experienced user of big data technology has been invited. They have more than three years of experience.
Focus Group	A one-hour session was conducted with another group of big data users consisting of 10 participants.	The criteria for selecting participants were based on experience as developers, systems analysts, user community.
Interviews	This was a one on one interview with a total of 21 persons. Interviews took 15 to 20 minutes for each participant.	The persons interviewed had hands-on experience with the big data tools and technologies development and use.

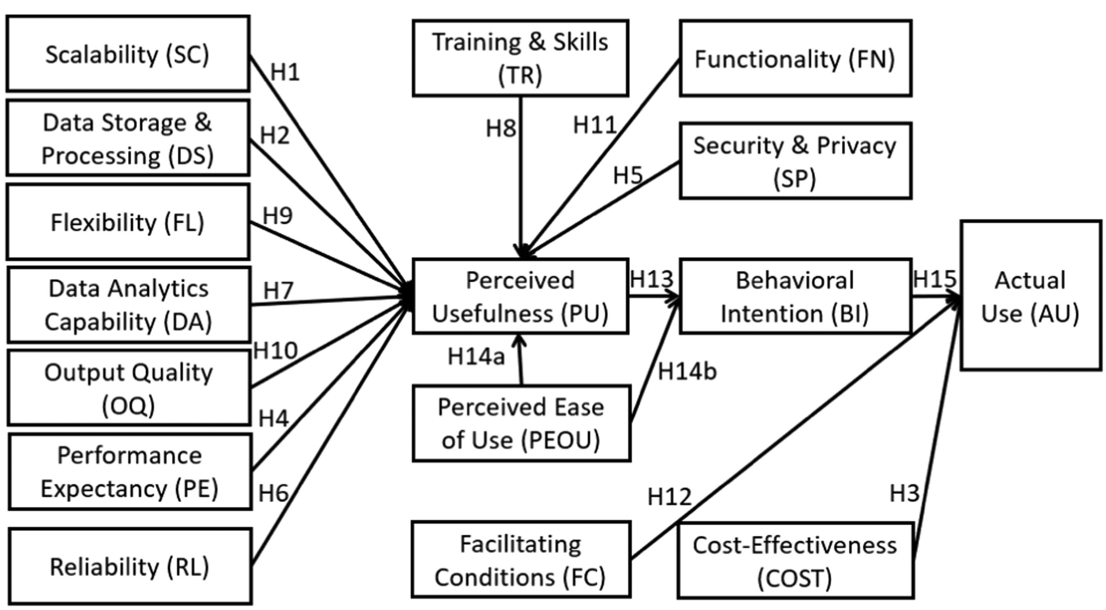


Fig. 1. Proposed research model.

III. RESEARCH MODEL AND HYPOTHESES

This article consists of distinct studies: qualitative study and quantitative study. Table IV lists the research steps of the qualitative study.

Based on the qualitative studies, we have come up with 12 factors for further study. We also have core constructs of the TAM, PU, PEOU, BI, and AU, by default in our research model (see Fig. 1).

Among these factors, a few of them were tested in past empirical research: output quality (OQ) [130], [141], FC [69], [104], [123], and PE [128]. The article has incorporated nine new factors, including scalability (SC), data storage and processing

(DS), flexibility (FL), data analytics capability (DA), reliability (RL), security and privacy (SP), training and skills (TR), functionality (FN), and cost effectiveness (COST). Successful testing of the influence of these factors on TAM is expected to contribute to the body of knowledge. These factors are related to the five characteristics of big data. For example, volume and velocity (DS), variety (FL), veracity (OQ), and value (COST). Big data technology and ecosystem tools have been built based on their five characteristics.

Since this model is built based on 12 factors that are selected out of 32 factors, this research would like to validate these factors through survey data. This research uses the structural equal model (SEM) that allows for factor analysis and performance of other statistical analysis to understand which factor and items under each factor will be influential [10]. This statistical analysis can be used to identify the desired factors. Hence, we develop hypotheses in the next section.

To evaluate the research model, the outcome of the hypotheses tests must be informative. The results of hypothesis tests need to draw correct conclusions about the population. “If the model is truly a good model in terms of its level of fit in the population, we wish to avoid concluding that the model is a bad one. Alternatively, if the model is truly a bad one, we wish to avoid concluding that it is a good one” [81]. Based on the proposed research model, we have developed the following hypotheses against each construct. The measures from previous studies are incorporated to reflect the big data context in this article.

Most of the traditional relational databases lack SC in dealing with hundreds of terabytes of data. In big data, new NoSQL technologies emerged to provide performance and SC [76]. Research findings revealed that one of the technological challenges to the adoption of big data analytics is performance and SC [83]. Big data technologies are scalable in terms of storage, data processing, and building a robust machine learning model. Big data pioneer companies such as Facebook choose Hadoop and HBase for availability, tolerance, and SC reasons [17]. Hence

Hypothesis H1: *SC in terms of Hadoop scale-out-storage system has a positive effect on PU.*

Hadoop is considered highly scalable in terms of storage and data processing. “By distributing storage and computation across many servers, the resource can grow with demand while remaining economical at every size” [111, p. 1]. Traditional databases are not capable of handling hundreds of terabytes of data and are also not scalable. It is worth checking if Hadoop’s storage capacity and data processing capability are related to big data acceptance. Hence

Hypothesis H2: *DS has a positive effect on PU.*

Several case studies’ results show that big data applications have made organizations avoid the cost. Balac *et al.* [12] developed a predictive analytics model for real-time energy management using the time series approach. Their model is destined to realize tangible improvements in energy efficiency and cost reductions [12]. Bologa *et al.* [16] report that big data has made it possible to detect insurance fraud within a reasonable time. They point out that in the past, in many cases, insurance fraud detection was not considered efficient because the cost and duration of the investigation were very high. The author provides analysis methods for detecting fraud in health insurance [16]. Villars *et al.* [137] state that the timeliness of the response using big data helped in eliminating the legal and financial costs associated with fund recovery. One of the big data characteristics is that its tools and technology can hold a large volume of data with minimal cost. This allows for analyzing almost all data rather than a small subset or sample [20]. Srinivasan and Arunasalam [112] reported that their big data application was able to detect claim anomalies to identify hidden cost overruns of health insurers. Russom [107] and Hartmann *et al.* [53] also report cost containment and cost advantage by using big data technologies.

Roger [105] asserts that the less expensive the technology, the greater the possibility that it will be adopted. The cost of technology is associated with the benefit achieved. For small companies, the cost might be a major barrier to procure innovation [95]. Firms that perceive the cost of big data Hadoop to be high might not adopt it. On the other hand, medium and large companies might not perceive the cost as a barrier. Hence

Hypothesis H3: *COST is positively related to the actual use (AU) of Hadoop.*

The performance of the technology is a pivotal factor for technology acceptance. Successful innovations cannot take place without reasonable PE. If technology has the necessary performance capability, it would be perceived as useful. Hence

Hypothesis H4: *PE is positively related to the PU of Hadoop.*

Big data is mostly unstructured and come from many places including health care. SP concerns are getting attention these days [61], [125]. Data breach gets news headlines quite often. User’s private information gets into the hands of hackers. Companies are subject to spending millions of dollars to compensate for such data breaches. Hence

Hypothesis H5: *SP are positively related to PU of Hadoop.*

RL is the degree to which the new technology is perceived to be dependable by the users. Organizations adopt new technology to overcome the unreliability, deficiencies, or to embark on new generation tools and technologies to achieve RL and efficiency. Before accepting any tools or technology, users want to be sure that it is reliable and able to show proof that spending money on it is worth it. Hence

Hypothesis H6: *RL is positively related to the PU of Hadoop.*

One key aspect of the Hadoop-based model is data that are stored in the HDFS with no data movement needed to relational database systems. All analytical, data mining, and reporting tools will run against HDFS. With Hadoop distributed files system, there is a great prospect of running robust data mining against a complete set of data stored in HDFS. Kranjc *et al.* [66] developed a capability of mining real-time streams by transforming batch data processing into a real-time stream mining platform. Tsumoto and Hirano [127] applied clustering data mining rules to a large dataset consisting of ten years of historical data stored in the hospital IS to discover knowledge from massive healthcare claims data. Wu *et al*. [142] published a paper titled "Data mining with big data" in which they propose a big data processing model from the data mining capabilities standpoint. Chen *et al*. [27] listed areas of emerging research in (big) data analytics, especially using machine learning and data mining. DA is the driver of today's business operations. Zhang *et al*. [143] and Tsai *et al*. [125], [126] provide a detailed framework for big data analytics. This is worth studying. Hence

Hypothesis H7: *DA is positively related to the PU of Hadoop.*

Training and skillset let company developers and knowledge workers use technology effectively and efficiently. This ensures productivity. Hence, we hypothesize

Hypothesis H8: *Training and required skills are positively related to the PU of Hadoop.*

Big data tools and technologies providing greater FL bring data from different sources and store it in a single place (i.e., Hadoop HDFS). These sources include traditional data such as transactional data from ERP, new data such as social media, sensor data, and email messages. Hadoop can be used for a wide variety of purposes, such as real-time streaming and processing, log processing, developing recommendation systems, building a data warehousing environment, market campaign analysis, and fraud detection [91]. Consolidated data into a single platform provide improved data mining and business intelligence capabilities [100]. Hence

Hypothesis H9: *Hadoop's FL to consolidate data from various sources to a single place (HDFS) will have a positive effect on the PU of Hadoop.*

Data integrity and quality fall under veracity, which is one of the five characteristics of big data. New tools are emerging to map out data lineage [101]. This effort is still at the beginning stage. The empirical study by Kwon *et al.* [69] suggests that "a firm's intention for big data analytics can be positively affected by its competence in maintaining the quality of corporate data." Lu *et al.* [77] assert that if big data cannot provide quality decisions due to data veracity, newly mined knowledge will not be convincing to the analytical community. However, big data is also considered to have the capability of improving quality monitoring clinical trials and decreasing spending from patients to the government level [90]. Hence

Hypothesis H10: *OQ is positively related to the PU of Hadoop.*

FN is the aspects of what technology, a product, or a system can do for users. FN includes the features of the product or technology. FN is the ability of technology to interact as expected by the users. Hadoop is expected to perform certain functions such as access and process data from many sources, tools, and devices. Hadoop provides a distributed file system. Hadoop replicates datasets on commodity servers making the process run in parallel. These functionalities beg validation. Hence

Hypothesis H11: *FN is positively related to the PU of Hadoop.*

"The degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" [132, p. 453]. FC are considered as one of the key factors in data warehouse architecture selection [6]. Even though Hadoop is an open-source system, there are vendors such as Cloudera, Horton Works, and MapR that have come up with customized versions of the system with features that might help companies in using it easily [137]. These vendors take care of the newer versions of the software as well as customization [22]. Some companies might not want to invest resources to customize and make enhancements to this system. In such cases, those companies might be willing to use the technology. Some companies might have internal platform infrastructure teams to maintain it and provides support in initiating projects. We need to see if big data technology acceptance is influenced by FC. Hence

Hypothesis H12: *FC have a positive effect on the AU of Hadoop.*

PU is the core construct of TAM. It has been tested and validated by prior empirical research. Therefore, the following hypothesis has been developed:

Hypothesis H13: *PU has a positive effect on BI in using Hadoop.*

PEOU is the core construct of TAM. Two other core constructs, PU, and BI have a dependence on this construct. It has been tested and validated by prior empirical research. Therefore, the following two hypotheses have been developed.

Hypothesis H14a: *PEOU has a positive effect on perceive usefulness (PU) in using Hadoop.*

Hypothesis H14b: *PEOU has a positive effect on BI to using Hadoop.*

BI is the core construct of TAM. The extant literature reveals that BI is the strongest influencer of the AU of a system [35], [37]. It has been tested and validated by prior empirical research. This is one of the two constructs that directly influence the AU of Hadoop. Therefore, the following hypothesis has been developed:

Hypothesis H15: *BI has a positive effect on the AU of Hadoop.*

IV. Research Design and Results

A survey instrument is used to "gather information about the characteristics, actions, or opinions of a large group of people, referred to as a population" [122]. The study attempts to find relationships between variables that might give insight into users' adoption of big data. As part of the survey, questions are designed to get answers to the questions asked in relation to each hypothesis. Survey research questions are developed based on previous empirical studies [34], [69], [132] as well as the incorporation of new questions relevant to the topic of research. Some of these questions are borrowed from existing theories (Davis, 198; [128]) and some others are derived from empirical studies (in big data case: [69]). In this article, survey questions are inherited from several theories and empirical studies [34], [132]. Survey questions are classified into two broad categories: open-ended and closed-ended. Since this article uses a quantitative method of studies, the questions being asked are closed-ended. As part of closed-ended questions, Likert's five-point scale is used [75].

Likert-scale questions consist of "strongly disagree," "disagree," "neutral," "agree," and "strongly disagree."

We have studied two prominent publications on construct item development, measurement, and validation. Morgado *et al.* [87] classify "item generations" into two categories: deductive and inductive. The extant literature suggests 35.2% of studies used deductive methods, 7.6% used inductive methods, and 56.2% used both deductive and inductive approaches to develop construct items [87]. Exclusive use of the deductive method is reported as a limitation of qualitative research [87]. Compared to that, this research used both deductive and inductive approaches to generate construct items. One of the limitations in scale development is that items with ambiguity or difficulty in answering are reported to be the main weakness [87]. The goal of construct-items generation is to develop a set of items that sufficiently captures the essential aspects of a construct [82], [93]. There are five steps required to frame sampling strategies, which include determining the target population, defining a sampling frame, outlining a sampling method, determining the sampling size, and drawing actual sampling [5].

This research takes advantage of cluster sampling since Hadoop users are already organized in different Hadoop user groups. Hence, the clusters of Hadoop user groups are readily available. There are 21 Hadoop user groups found online, out of which 14 user groups are found active. And out of 14 user groups, 2 user groups or clusters are randomly selected. This allows sending survey instruments to 10 500 users under two user groups. That means the sample consists of every member of these two Hadoop user groups. Thus, clusters are supposed to reflect the whole population.

The most recent survey suggests that "Big data adoption reached 53% in 2017 for all companies interviewed, up from 17% in 2015, with telecom and financial services leading early adopters" [31]. Since there is no publicly available list of big data user companies, this research will use big data user groups available on the Internet to conduct the survey. Using the user groups as intended users is consistent with the literature that suggests that information technology needs to be accepted by intended users as opposed to "procurers" [37]. There are 14 active Hadoop user groups in the United States found in the Apache Org Wiki site [51]. There are close to 33 000 users belonging to these 14 Hadoop user groups. Selecting all these 33 000 users will be a large number and a poor response might cause a big nonresponse bias issue. The research will work on two user groups called "bay area hadoop user group" and "New York group." These groups consist of 10 500 users.

There are 21 Hadoop user groups found in the Hadoop Wiki site maintained by the Apache organization [51].

The sample determination needs to make sure it has adequate power to conduct planned hypothesis tests about model fit. The sample size *N* needs to have adequate power to detect when hypotheses are false [81]. A sample that is large enough tends to impact time, money, and other resources. A researcher needs to make the tradeoff in specifying a sample size. If the sample is too few that might cause the risk of sampling error and, hence, not tolerable. On the other hand, if the sample size is too large that could increase the cost of research which might not be affordable but is helpful in reducing the sampling error [78].

The data collection for this research is based on two Hadoop user groups including 1) "Hadoop New York user group" with 4060 members, on the East coast, and 2) "Bay area Hadoop user group" with 6440 members, on the West coast. The data were collected using a survey instrument via the Qualtrics web-based tool. The survey period spans over a period of three months: July 25, 2019 to September 30, 2019. There are 402 respondents who participated in this survey. After data screening, 53 responses were found to be incomplete. Hence, we rejected those 53 responses. That means 349 responses are identified as valid.

The confirmatory factor analysis (CFA) is conducted to "examine whether or not existing data are consistent with a highly constrained *a priori* structure that meets conditions of model identification" [84].

As part of a single measurement model test, all independent and dependent variables looked good from statistical estimation and model fit indicators perspectives. Then, we have drawn covariance of DS_3 and DS_4, SP_2 and SP_4, COST_1 and COST_2, COST_1 and COST_3, PU_3 and PU_4, PEOU_1_PEOU_2, and PEOU_1 and PEOU_4. This has helped in improving the fit indices shown under the third column. All fit indices are above the acceptable threshold numbers. The comparative results between the initial run and final run show that the initial model is weaker than the final model. Therefore, fit statistics justify the deletion of two items from two constructs (FN and AU). In the final CFA model, chi-square value is reduced by 386.37 (df 126, $p < 0.001$). The other fit indices also show improved values. This final model suggests a reasonable congruity between data and the CFA model (see Table V).

Given we had to drop a few constructs and items, we have regenerated the CFA. Based on CFA with 12 constructs and 40 items, the fit statistics under individual measurement models are provided in Table VI.

It is clear from Table VII that the fit statistics justified the deletion of some specific constructs from the model and some items from different construct measures which resulted in the better model fit in terms of that fit indices presented.

Here is the final research model, drawn based on the path analysis results (see Fig. 2).

Fig. 3 shows the R-squared values for PU, BI, and AU are 80, 67, and 85, respectively.

The path diagram (SEM) of the final research model in Fig. 3 shows the following standard regression weights (see Tables VIII and IX).

V. Hypotheses Testing and Discussion

The outputs of the model show R-squared values of 0.80, 0.67, and 0.85 for PU, BI, and AU respectively. Here we discuss the hypothesized path results of the final model. The following terms are used to identify the independent and dependent variables of this model.

SC = Scalability (IV).
DS = Data storage and processing (IV).
FL = Flexibility (IV).

TABLE V
REGRESSION WEIGHTS—PATH MODEL: RESULTS OF FIVE ITERATIONS

Regression Path (Influence of IV on DV)	Iteration-1 p-value	Iteration-2 p-value	Iteration-3 p-value	Iteration-4 p-value	Iteration-5 (FINAL) p-value
SC → PU	.330	.083	.070	.032	.004
DS → PU	.592	.401	.397	.397	.027
FL → PU	.430	.552	.550	.013	.005
RL → PU	.696	.082	.076	.068	.013
PE → PU	.846	***	***	***	***
OQ → PU	.507	***	***	***	.002
TR → PU	.776	.023	.024	.022	.038
SP → PU	.560	.783	Dropped	Dropped	Dropped
DA → PU	.354	.536	.484	Dropped	Dropped
FN → PU	.397	.363	.339	.352	Dropped
PEOU → PU	.350	.017	.016	.020	.010
PU → BI	***	***	***	***	***
PEOU → BI	.003	.002	.002	.002	.002
FC → AU	***	***	***	***	***
COST → AU	.731	Dropped	Dropped	Dropped	Dropped
BI → AU	***	***	***	***	***

TABLE VI
CFA CONSTRUCT RELIABILITY

Construct	Std. Reg. Wt. 1	Std. Reg. Wt. 2	Std. Reg. Wt. 3	Std. Reg. Wt. 4	AVE	CR
Scalability	0.693	0.839	0.643		0.532	0.77
Data Storage & Processing		0.771	0.831	0.600	0.548	0.78
Performance Expectancy	0.740	0.834	0.866	0.743	0.636	0.87
Reliability	0.789	0.678	0.685	0.789	0.544	0.83
Flexibility	0.805	0.807	0.782	0.768	0.625	0.87
Facilitating Conditions	0.708	0.822	0.844	0.714	0.600	0.86
Output Quality	0.778	0.834	0.811	0.837	0.665	0.89
Training and Required Skills	0.788		0.747	0.800	0.606	0.82
Perceive Usefulness	0.863	0.888	0.770	0.778	0.683	0.89
Perceived Ease of Us	0.764	0.844	0.857	0.858	0.692	0.90
Behavioral Intention	0.766	0.726	0.804		0.586	0.81
Actual Use		0.774	0.831		0.645	0.78

OQ = Output quality (IV).
PE = Performance expectancy (IV).
RL = Reliability (IV).
TR = Training and skills (IV).
FC = Facilitating conditions (IV).
PEOU = Perceived ease of use (IV).
PU = Perceived usefulness (DV).
BI = Behavioral intention to use (DV).
AU = Actual use (DV).

The values in Table X reflect the output of regression weights: (Group number 1—Default model) under the Estimates tab.

A. *Scalability and Perceived Usefulness*

There is a strong positive correlation between SC and PU. The experts in the qualitative study of this research have correctly identified it as a significant variable of Hadoop adoption. Industry papers also suggest SC as an important factor of Hadoop adoption. The term SC has been widely used in industry when it comes to buying or using technology. Due to a lack of SC, we experienced a SC crisis in large-scale websites, eBay, and healthcare.gov [21]. SC and performance have received special attention in the software performance review journals as well [67]. In the data management field, we experience that some database systems cannot expand beyond a certain data size limit. This makes companies switch to another database system. Ariyachandra and Watson [6] propose that database architecture selection should be based on SC. Most of the conventional database systems are not built on top of a scalable system except the Teradata database system [83], [99]. In big data space, due to a large volume of data, SC plays an important role [44], [76], [86]. Hadoop is considered a highly scalable storage platform

TABLE VII
SUMMARY OF OVERALL CFA: FIT INDICES

Fit Indices	Overall Measurement Model	
	CFA (16 Variables: 60 items)	CFA (12 Variables: 40 items)
χ^2 (df)	2710.611 (1583)	1536.635 (894)
CMIN	1.712	1.719
IFI	.925	.939
TLI	.915	.932
CFI	.924	.938
RMSEA	.045	.045

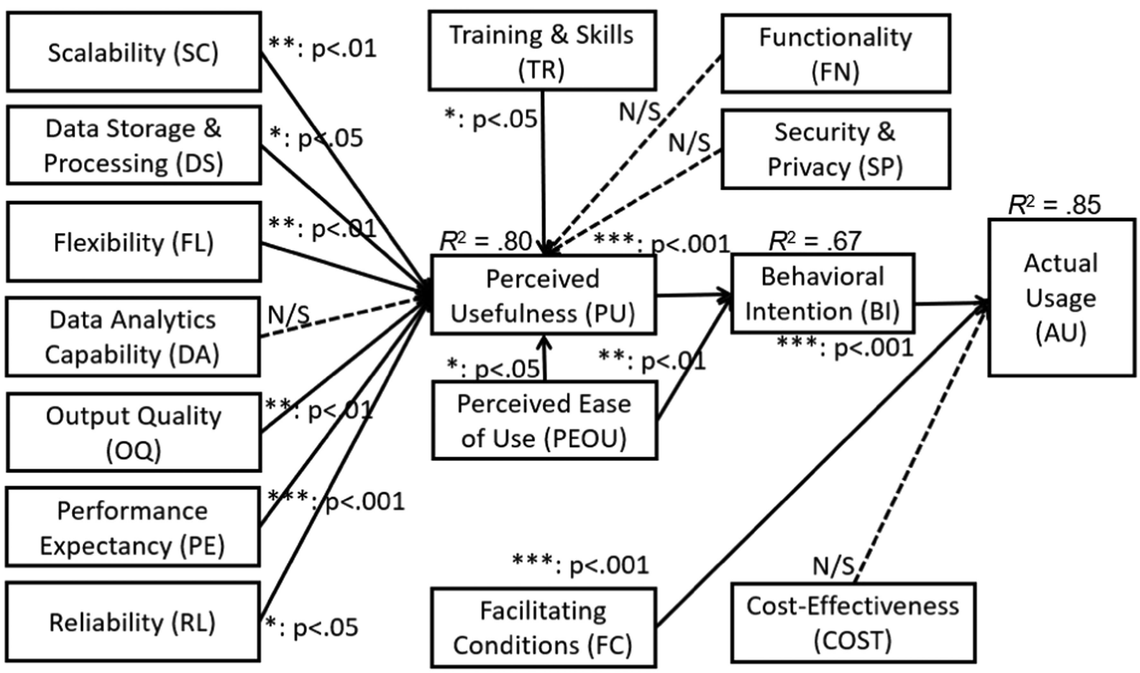


Fig. 2 Final research model—big data technology acceptance.

TABLE VIII
SUMMARY OF OVERALL PATH MODEL

Fit Indices	Overall Path Model
	SEM (12 Variables: 40 items)
χ^2 (df)	1228.474 (689)
CMIN	1.783
IFI	.941
TLI	.932
CFI	.940
RMSEA	.047

[91]. Big data technology and database systems' experts of the qualitative study of this research selected SC as the number one factor for further study as part of this research. A total of 35 of the 40 (88%) participants who participated in the qualitative study voted for this factor for study. The performance and SC challenges are apparent in a platform as a service cloud applications and network topology [67], to name a few. Malaka and Brown [83] report that SC is one of the technological challenges that is faced in the data analytics domain. Chen *et al*. [26] propose measures of SC relating to frame theory. Industry papers on big data technologies highlight SC as one of the important elements of the Hadoop framework [7], [17], [76], [91].

B. Data Storage and Processing and Perceived Usefulness

There is a strong positive correlation between DS and PU. The path model shows that this newly introduced construct has a 17% influence (estimates) on PU. The exponential data growth necessitates robust DS of those data efficiently. To address this challenge, emerging big data technologies are thought to play a critical role [7], [25], [101]. The HDFS is considered a scalable mass storage system along with MapReduce, its processing engine [39], [111].

C. Flexibility and Perceived Usefulness

There is a strong positive correlation between FL and PU. This construct has a 24% influence (std. reg. estimate) on the PU.

TABLE IX
PATH MODEL STANDARD REGRESSION WEIGHTS

Constructs	Path	Standardized Regression Estimates
Perceived Ease of Use (PEOU)	PEOU → PU	.141
Reliability (RL)	RL → PU	.191
Performance Expectance (PE)	PE → PU	.360
Data Storage & Processing (DS)	DS → PU	.168
Training & Skills (TR)	TR → PU	.149
Scalability (SC)	SC → PU	.208
Output Quality (OQ)	OQ → PU	.261
Flexibility (FL)	FL → PU	.243
Perceived Usefulness (PU)	PU → BI	.667
Perceived Ease of Use (PEOU)	PEOU → BI	.206
Behavioral Intention (BI)	BI → AU	.721
Facilitating Conditions (FC)	FC → AU	.292

TABLE X
PATH MODEL ESTIMATES

Hypotheses	Paths	SEM Output: Proposed Model				Results*
		Estimate (β)	S.E.	C.R. (t)	p-value	
H1: Scalability in terms of Hadoop scale-out-storage system will have a positive effect on perceived usefulness.	SC → PU	.241	.083	2.907	.004	Supported
H2: Data storage and processing have a positive effect on perceived usefulness.	DS → PU	.198	.089	2.219	.027	Supported
H9: Hadoop's flexibility to consolidate data from various sources to single place (HDFS) have a positive effect on perceived usefulness of Hadoop.	FL → PU	.257	.091	2.827	.005	Supported
H7: Data analytics capability is positively related to perceived usefulness of Hadoop.	DA → PU	.239	.342	.700	.484	Not Supported
H10: Output Quality are positively related to the perceived usefulness of Hadoop.	OQ → PU	.286	.090	3.168	.002	Supported
H4: Performance Expectancy/Usability is positively related to perceived usefulness of Hadoop.	PE → PU	.433	.103	4.185	***	Supported
H6: Reliability is positively related to perceived usefulness of Hadoop.	RL → PU	.249	.100	2.490	.013	Supported
H5: Security and Privacy is positively related to perceived usefulness of Hadoop.	SP → PU	.027	.099	.276	.783	Not Supported
H8: Training and required skills are positively related to perceived usefulness of Hadoop.	TR → PU	.180	.087	2.079	.038	Supported
H11: Functionality is positively related to perceived usefulness of Hadoop.	FN → PU	-.274	.295	-.930	.352	Not Supported
H14a: Perceived Ease of Use (PEOU) have positive effect on Perceived Usefulness (PU).	PEOU → PU	.116	.045	2.561	.010	Supported
H14b: Perceived Ease of Use (PEOU) have positive effect on Behavioral Intention to use Hadoop (BI).	PEOU → BI	.163	.052	3.154	.002	Supported
H13: Perceived Usefulness (PU) have positive effect on Behavioral Intention to use Hadoop (BI).	PU → BI	.645	.070	9.156	***	Supported
H12: Facilitating Conditions have positive effect on attitude toward using Hadoop.	FC → AU	.366	.083	4.411	***	Supported
H3: Cost effectiveness is positively related to adoption of Hadoop.	COST → AU	-.019	.055	-.344	.731	Not Supported
H15: Behavioral Intention (BI) is positively related to Actual Use (AU) of Hadoop.	BI → AU	.748	.080	9.394	***	Supported

*Results supported as significance level: $p <= 0.001$, $p <= 0.01$, and $p <= 0.05$.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

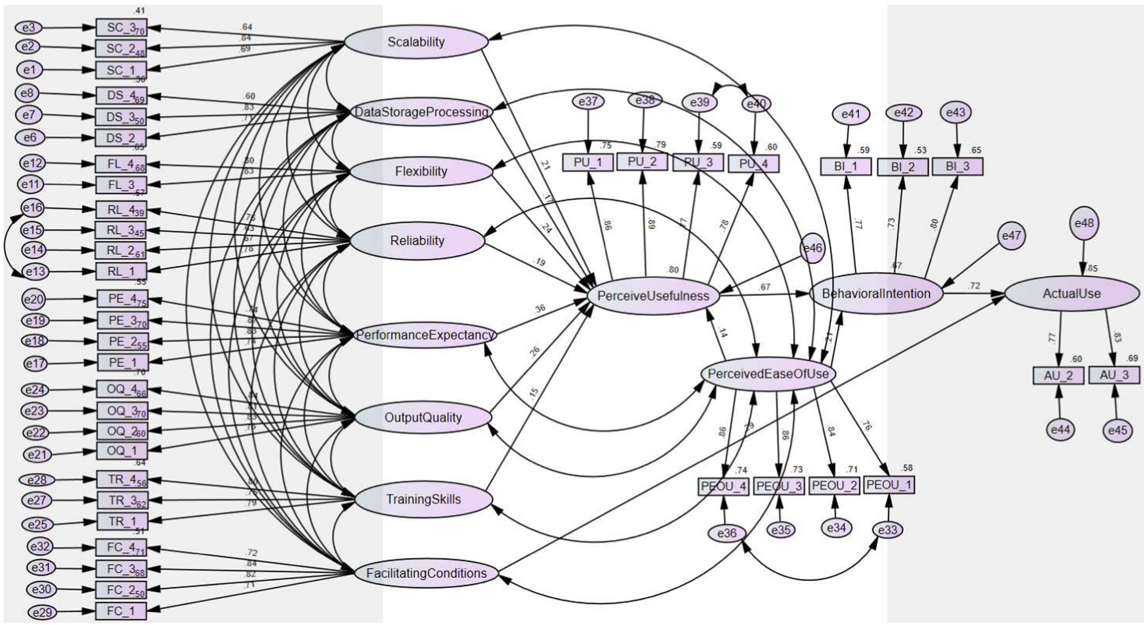


Fig. 3 Path diagram (SEM) of the final research model.

Fichman and Kemerer [42] report that innovation attributes play an important role in adoptions by an organization. The extant literature shows the importance of software FL. Scherrer-Rathje and Boyle [109] have identified five dimensions of enterprise systems FL, including system connectivity, process integration, hierarchical integration, user-customizability, and consistency. Gebauer and Lee [47] emphasize the importance of software FL in terms of operational efficiency and the long-term effectiveness of an enterprise system.

D. Output Quality and Perceived Usefulness

There is a strong positive correlation between OQ and PU. OQ remains to be a significant determinant of PU. Subsequently, this factor along with the TAM2 model was validated by many other researchers [29], [129]. Chismar and Wiley-Patton [29] successfully validate the TAM2 along with OQ to understand the physicians' intention to use the Internet-based health applications.

E. Performance Expectancy and Perceived Usefulness

There is a strong positive correlation between PE and PU. The PE construct has a 36% (std. reg. estimate) influence on PU. This construct was examined and retained by previous research as well. The findings of this study results are consistent with theoretical underpinnings as well as findings of several past studies [132].

F. Reliability and Perceived Usefulness

There is a strong positive correlation between RL and PU. Based on the extant literature [52], [73], [144], this construct has not been tested by IS theories or models in general and TAMs in particular. In the data management field, ensuring the availability of data or no data loss in any circumstance is critical for an organization's sensitive data. RL is also critical from a data consistency standpoint.

G. Training and Skills and Perceived Usefulness

There is a strong positive correlation between TR and PU. Recent research on big data highlighted the firm value of big data investments relating to training [121]. There are many tools and technologies related to big data and these are a new set of tools that were not used in the processing and analysis of conventional structured data. Big data technical skill is needed in many areas, including data extraction, data processing, machine learning, statistical analysis, learning MapReduce, or Spark programing. Hence, training is important.

H. Perceived Ease of Use and Perceived Usefulness

There is a strong positive correlation between PEOU and PU. This construct was developed by Davis [35] as part of his original TAM model. This construct is supported by numerous research findings [55].

I. Perceived Usefulness and Behavioral Intention to Use

There is a strong positive correlation between PU and BI. PU as a significant predictor of BI technology was supported in studies by Davis [34], [35], Adams *et al.* [1], Igbaria *et al.* [59], Hendrickson *et al.* [54], Hess *et al.* [55], Brown *et al.* [18], and many other researchers (see meta-analysis in [55], [74], [80]).

J. Perceived Ease of Use and Behavioral Intention to Use

There is a strong positive correlation between PEOU and BI. The findings of this study results are consistent with theoretical underpinnings as well as findings of several past studies [34].

K. Facilitating Conditions and Actual Use

There is a strong positive correlation between FC and AU. Moddy *et al*. [88] found this construct to be insignificant in their "unified model of information security policy compliance" model. They commented that it failed the test in their information security model context, but speculated that this factor might pass the test for a more technically challenging action. This research found this construct significant for a complex and challenging technology such as Hadoop.

L. Behavioral Intention to Use and Actual Use

There is a strong positive correlation between BI and AU. The findings of this study results are consistent with theoretical underpinnings as well as findings of several past studies [34].

The hypotheses results show that 8 of the 12 independent variables passed the test. These include SC, DS, FL, OQ, PE, RL, TR, and FC. Four independent variables could not pass the hypothesis test: DA, SP, FN, and COST. Among four original TAM variables (that Davis identified), PEOU was used as an independent variable in this research and it passed the hypothesis test. Three-other TAM factors include PU, BI, and AU, all of which passed the hypothesis test. The path model results show that AU can explain 85% of the variances. Prior studies validated PU and PEOU by showing that the TAM measures can explain 48.7% of the variance in self-reported system use [37]. Extant literature also reports that the BI construct in TAM was able to explain 34%–52% of the variance [130] and 52% of the variance [123], respectively. Straub *et al*. [115] report a result of their empirical study of perceived systems use with 49% explained variance. Later, the UTAUT model by Venkatesh *et al*. [132] showed that it explained 72% variance. Compared to past research results, our model is able to explain a much higher percentage of variance in usage intention (67%) and 85% in AU.

VI. Conclusion, Limitations, and Future Research

This article contributes to the literature in several ways. No other TAM-based research has tested these variables [73]. The TAM has been mostly applied to understand users' intentions [56] from an individual's usage context (e.g., smartphone). This research provides an outcome from industrial/organizational level users' acceptance context (big data). The research contributes to the literature on SC by identifying a few important measures. This has a great implication for data management platforms. It contributes to the SC theory [26] and systems theory [92]. Our research is based on data collected from actual Hadoop users who have industry job experience in the big data field. We developed and validated our model based on industry context [28]. Thus, we evaluate the boundaries of existing IS theory and contribute to enhancing the existing TAM model with new external factors.

Prior research suggests that many firms are at the early stage of big data adoption due to a lack of understanding and empirical evidence of the impact of big data technology on organizations [14], [45]. This empirical study provides IT practitioners with insights into whether big data is capable of increasing the data-driven decision performance of organizations. Previous research on TAM and UTAUT found that factors, such as PE, OQ, and FC [35], [132], are needed to provide seamless access to quality information in an enterprise data management platform. This research introduces new dimensions (e.g., technological) to such data management platforms that are required to handle today's new data (e.g., unstructured data) in an enterprise data management platform. Existing developers and knowledge workers who work in traditional data management technologies might not have the skills to use Hadoop. They might need the training to brush up on their programming language skills. These developers need to be proficient at least in one of the programming languages Java, Python, Scala, R, etc. [32]. The managers might expect that the developers and knowledge workers will show low productivity and initially decreases in quality. Some of them who are not confident enough to use this technology might be moved to other job roles. In many cases, new and complex enterprise systems implementation causes major changes in terms of job characteristics and interpersonal relationships in employees' work-life [11]. By using Hadoop, organizations might be able to put together internal data (e.g., transactional or dimension data) and external data (e.g., social media and other sources) in HDFS [97]. That might help business organizations to get a 360° view of data and, thus, improve organizations' decision performance. Given big data is able to consolidate all kinds of data (structured and unstructured) from both internal and external sources, the RL and OQ of those data need to be understood. This is important as data-driven decision-making has a dependence on data quality [8]. In his seminal paper in Harvard Business Review, Garvin [46] pointed out eight dimensions of quality as part of strategic quality management. This research has validated the OQ construct, and hence, it speaks for the importance of big data storage systems. The results of this article might be helpful and encouraging for new companies in adopting big data. The new findings of this article are expected to be valuable to big data vendors as well as other stakeholders (e.g., semiconductor manufacturers who supply special server processors for big data processing).

Prior research on big data focused on technical algorithms or system development [69]. Since the emergence of big data terminology over the past decade, a lot of research was undertaken to develop big data technologies, tools, and techniques [70]. There are also numerous experiments and use-cases conducted to prove the capability and efficiency of those individual tools and techniques. That indeed made significant research contributions to this new discipline. However, there is very limited research conducted toward understanding the acceptance of big data by business organizations. In this area, one study was conducted by Kwon *et al.* [69]. That research only investigated the acceptance of big data from a data quality and data usage standpoint (internal versus external data usage). This research provides other aspects of big data that are important in understanding the adoption of big data. They include technological variables (e.g., SC, FL, RL, data storage, and processing capability), organizational variables (e.g., TR), and environmental variables (e.g., FC). With these new variables having been identified by survey results as significantly influential variables, this research is able to contribute to big data adoption research.

The findings of this article rely on respondents' self-reported data. Some researchers suggest that self-reported usage does not always reflect actual usage [19], [119]. The concern is that self-reported usage might distort and inflate causal relations between independent and dependent variables [73], [94] and thus cause validity problems. This concern is the strongest when both exploratory variable and dependent variable data are collected from the same person [94]. Self-reported data are cited as one of the commonly reported limitations [73]. Self-reported data are also considered as one of the reasons for the common method bias problem. To address this concern, we have conducted the Harman one-factor analysis to check whether variance in the data largely extrapolates to a single factor [23]. Our study finds no such issue. Nonetheless, future researchers might test this model by collecting data for predictor and criterion variables separately [23].

We collected data at a single point of time. The IS scholars call out to be careful about the generalization problem of such a single point of time study or collecting data from a homogenous group of subjects [73]. The extant literature reveals that in technology acceptance research, there is a dominance of cross-sectional study. To avoid the risk of homogenous data collection, we used Hadoop user groups, the members of which belong to all major industries with responses from a variety of stakeholders. Further, to address the issue of a cross-sectional study, future research might consider a longitudinal study of these variables. Given the user's perception and intention to change over a period of time, it is worth collecting data at several points of time to perform longitudinal comparisons [73].

The survey responses were collected from many stakeholders data scientists, data analysts, CTO, application developers, engineers; - the professionals who actually used the tool. This is consistent with the observation that technical persons and consultants are the best people to get input in making the decision to buy a new technology [140]. Therefore, the study cannot be generalized as the responses are of the managers and other company executives.

This article has found four new factors nonsignificant (FN, SP, DA, and COST) even though the expert panel of the qualitative study voted for them and the CFA successfully validated them. These factors failed the SEM validation as part of the path model analysis. We conducted a survey consisting of 62 questions (IV and DV) for which 351 responses were received. The response rate per construct item was 5.63 (349/62). Still, future researchers might run this model with many responses. Some researchers suggest ten responses per construct item [116]. Hence, ten responses per construct item, that is, $62 * 10 = 610$ could be used to see if those four factors get valid. We aspire that this could be the source of new topics for future research.

Big data is here to stay! Given the footprint of data everywhere, we do not foresee a paradigm shift in the near future when it comes to big data. Big data technology might change for a good user experience. Research on big data and its technologies is expected to continue from both data-driven and theory-driven research standpoint [79].

References

[1] D. Adams, R. Nelson, and P. Todd, "Perceived usefulness, ease of use and usage of information technology: A replication," *MIS Quart.,* vol. 16, no. 2, pp. 227–247, 1992.

[2] F. Aldhaban, "Exploratory study of the adoption and use of the smartphone technology in emerging regions: Case of saudi arabia," Ph.D. dissertation, Dept. Eng. Technol. Manage., Portland State Univ., Portland, OR, USA, 2016.

[3] O. Y. Al-Jarrah, P. D. Yoo, S. Muhaidat, G. K. Karagiannidis, and K. Taha, "Efficient machine learning for big data: A review," *Big Data Res.,* vol. 2, pp. 87–93, 2015.

[4] K. Amoako-Gyampah and A. F. Salam, "An extension of the technology acceptance model in an ERP implementation environment," *Inf. Manage.,* vol. 41, pp. 731–745, 2004.

[5] T. R. Anderson, "Research methods for technology management and other fields," Portland State Univ., Portland, OR, USA, 2012.

[6] T. Ariyachandra and H. Watson, "Key organizational factors in data warehouse architecture selection," *Decis. Support Syst.,* vol. 49, no. 2010, pp. 200–212, 2010.

[7] K. N. Aye and T. Thein, "A platform for big data analytics on distributed scale-out storage system," *Int. J. Big Data Intell.,* vol. 2, no. 2, pp. 127–141, 2015.

[8] B. Baesens, R. Bapna, J. R. Marsden, J. Vanthienen, and J. L. Zhao, "Transformational issues of big data and analytics in networked business," *MIS Quart.,* vol. 40, no. 4, pp. 807–818, 2016.

[9] R. P. Bagozzi, "The legacy of the technology acceptance model and a proposal for a paradigm shift," *J. Assoc. Inf. Syst.,* vol. 8, no. 4, pp. 244–254, 2007.

[10] R. P. Bagozzi and Y. Yi, "On the evaluation of structural equation models," *J. Acad. Market. Sci.,* vol. 16, no. 1, pp. 74–94, 1988.

[11] H. K. Bala, "Nothing endures but change: Understanding employees' responses to enterprise systems implementation and business process change," Ph.D. dissertation, Univ. Arkansas, Fayetteville, AR, USA, 2008.

[12] N. Balac, T. Sipes, N. Wolter, K. Nunes, B. Sinkovits, and H. Karimabadi, "Large scale predictive analytics for real-time energy management," in *Proc. IEEE Int. Conf. Big Data*, Santa Clara, CA, USA, Oct. 6–9, 2013, pp. 657–664.

[13] N. Basoglu, T. Daim, and O. Kerimoglu, "Organizational adoption of enterprise resource planning systems: A conceptual framework," *J. High Technol. Manage. Res.*, vol. 18, pp. 73–97, 2007.

[14] R. Bean, "Firms must overcome human barriers to enable data-driven transformation," 2020. [Online]. Available: https://www.forbes.com/sites/ciocentral/2020/01/02/firms-must-overcome-human-barriers-to-enable-data-driven-transformation/#5d8267f42a56

[15] I. Benbasat and H. Barki, "Quo vadis, TAM?," *J. Assoc. Inf. Syst.,* vol. 8, no. 4, pp. 211–218, 2007.

[16] A. Bologa, R. Bologa, and A. Florea, "Big data and specific analysis methods for insurance fraud detection," *Database Syst. J.,* vol. 1, no. 1, pp. 30–39, 2010.

[17] D. Borthakur, "The hadoop distributed file system: Architecture and design," Apache Softw. Found., Forest Hill, MD, USA, White Paper, pp. 1–14, 2007.

[18] S. A. Brown, V. Venkatesh, and S. Goyal, "Expectation confirmation in information systems research: A test of six competing models," *MIS Quart.,* vol. 38, no. 3, pp. 729–756, 2014.

[19] A. Burton-Jones, "Minimizing method bias through programmatic research," *MIS Quart.,* vol. 33, no. 3, pp. 445–471, 2009.

[20] M. Cao, R. Chychyla, and T. Stewart, "Big data analytics in financial statement audits," *Accounting Horiz.,* vol. 29, no. 2, pp. 423–429, 2015.

[21] D. F. Carr, "How we'd fix healthcare.gov: Scalability experts speak," 2013. [Online]. Available: https://www.informationweek.com/healthcare/policy-and-regulation/how-wed-fix-healthcaregov-scalability-experts-speak/d/d-id/1112867

[22] F. Ceci, A. Masini, and A. Prencipe, "Impact of IT offerings strategies and IT integration capability on IT vendor value creation," *Eur. J. Inf. Syst.,* vol. 28, no. 6, pp. 591–611, 2019.

[23] S.-J. Chang, A. van Witteloostuijn, and L. Eden, "From the Eds.: Common method variance in international business research," *J. Int. Bus. Stud.,* vol. 41, pp. 178–184, 2010.
[24] T. Chardonnens, P. Cudre-Mauroux, and M. Grund, "Big data analytics on high velocity streams: A case study," in *Proc. IEEE Int. Conf. Big Data*, Santa Clara, CA, USA, Oct. 1–6, 2013, pp. 784–787.
[25] H. Chauhan and J. Murphy, "Harnessing hadoop: Understanding the big data processing options for optimizing analytical workloads," Cognizant 20-20 Insights, pp. 1–8, 2013. [Online]. Available: https://www.cognizant.com/InsightsWhitepapers/Harnessing-Hadoop-Understanding-the-Big-Data-Processing-Options-for-Optimizing-Analytical-Workloads.pdf
[26] D. Q. Chen, D. S. Preston, and M. Swink, "How the use of big data analytics affects value creation in supply chain management," *J. Manage. Inf. Syst.,* vol. 32, no. 4, pp. 4–39, 2015.
[27] H. Chen, R. H. L. Chiang, and V. C. Storey, "Business intelligence and analytics: From big data to big impact," *MIS Quart.,* vol. 36, no. 4, pp. 1165–1188, 2012.
[28] M. W. Chiasson and E. Davidson, "Taking industry seriously in information systems research," *MIS Quart.,* vol. 29, no. 4, pp. 591–605, 2005.
[29] W. G. Chismar and S. Wiley-Patton, "Does the extended technology acceptance model apply to physicians," in *Proc. 36th Hawaii Int. Conf. System Sci.*, HI, USA, 2003, pp. 1–8.
[30] J. K. Choi and Y. G. Ji, "Investigating the importance of trust on adopting an autonomous vehicle," *Int. J. Hum.-Comput. Interact.,* vol. 31, pp. 692–702, 2015.
[31] L. Columbus, "53% of companies are adopting big data analytics," 2017. [Online]. Available: https://www.forbes.com/sites/louiscolumbus/2017/12/24/53-of-companies-are-adopting-big-data-analytics/#62fbcefc39a1
[32] T. H. Davenport, and D. J. Patil, "Data scientist: The sexiest job of the 21st Century," *Harvard Bus. Rev.*, vol. 90, no. 10, pp. 70–76, Oct. 2012.
[33] F. D. Davis, "A technology acceptance model for empirically testing new end-user information systems: Theory and results," Ph.D. dissertation, Sloan School Manage., Massachusetts Inst. Technol., Cambridge, MA, USA, 1986.
[34] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quart.,* vol. 13, no. 3, pp. 319–340, 1989.
[35] F. D. Davis, "User acceptance of computer technology: System characteristics, user perceptions," *Int. J. Man-Mach. Stud.,* vol. 38, no. 3, pp. 475–487, 1993.
[36] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User acceptance of computer technology: A comparison of two theoretical models," *Manage. Sci.,* vol. 35, no. 8, pp. 982–1003, 1989.
[37] A. Dillon, and M. G. Morris, "User acceptance of new information technology: Theories and models," *Annu. Rev. Inf. Sci. Technol.,* vol. 31, pp. 3–32, 1996.
[38] M. T. Dishaw, "The construction of theory in MIS research," *Int. J. Inf. Manage.,* vol. 7, no. 1, pp. 39–52, 1998.
[39] S. Dolev, P. Florissi, E. Gudes, S. Sharma, and I. Singer, "A survey on geographically distributed big-data processing using mapreduce," *IEEE Trans. Big Data,* vol. 5, no. 1, pp. 60–80, Mar. 2019.
[40] K. M. Eisenhardt and C. B. Schoonhoven, "Resource-based view of strategic alliance formation: Strategic and social effects in entrepreneurial firms," *Org. Sci.,* vol. 7, no. 2, pp. 136–150, 1996.
[41] J. Esteves and J. Curto, "A risk and benefits behavioral model to assess intentions to adopt big data," *J. Intell. Stud. Bus.,* vol. 3, no. 2013, pp. 37–46, 2013.
[42] R. G. Fichman and C. E. Kemerer, "Adoption of software engineering process innovations: The case of object orientation," *Sloan Manage. Rev.*, vol. 34, no. 2, pp. 7–22, 1993.
[43] M. Fishbein and I. Ajzen, *Beliefs, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Reading, MA, USA: Addison-Wesley, 1975.
[44] D. García-Gil, S. Ramírez-Gallego, S. García, and F. Herrera, "A comparison on scalability for batch big data processing on apache spark and apache flink," *Big Data Analytics*, vol. 2, no. 1, pp. 1–11, 2017.
[45] Gartner, Inc., *Gartner Survey Highlights Challenges to Hadoop adoption*. Stamford, CT, USA: Gartner, 2015. [Online]. Available: https://www.gartner.com/en/newsroom/press-releases/2015-05-13-gartner-survey-highlights-challenges-to-hadoop-adoption
[46] D. A. Garvin, "Competing on the eight dimensions of quality," *Harvard Bus. Rev.*, vol. 65, no. 6, pp. 100–109, 1987.
[47] J. Gebauer and F. Lee, "Enterprise system flexibility and implementation strategies: Aligning theory with evidence from a case study," *Inf. Syst. Manage.,* vol. 25, no. 1, pp. 71–82, 2008.
[48] D. Gefen and D. W. Straub, "Gender differences in the perception and use of e-mail: An extension to the technology acceptance model," *MIS Quart.*, vol. 21, no. 4, pp. 389–400, 1997.
[49] C. G. Gogus and G. Ozer, "The roles of technology acceptance model antecedents and switching cost on accounting software use," *Acad. Inf. Manage. Sci. J.,* vol. 17, no. 1, pp. 1–24, 2014.
[50] B. Gupta, S. Dasgupta, and A. Gupta, "Adoption of ICT in a government organization in a developing country: An empirical study," *J. Strategic Inf. Syst.*, vol. 17, pp. 140–154, 2008.
[51] HadoopUserGroups, 2019. [Online]. Available: https://cwiki.apache.org/confluence/display/HADOOP2/HadoopUserGroups
[52] M. A. Hameed, S. Counsell, and S. Swift, "A conceptual model for the process of IT innovation adoption in organizations," *J. Eng. Technol. Manage.*, vol. 29, pp. 358–390, 2012.
[53] P. M. Hartmann, M. Zaki, N. Feldmann, and A. Neely, "Big data for big business? A taxonomy of data-driven business models used by start-up firms," Univ. of Cambridge, London, U.K., pp. 1–29, 2014.
[54] A. R. Hendrickson, P. D. Massey, and T. P. Cronan, "On the test-retest reliability of perceived usefulness and perceived ease of use scales," *MIS Quart.*, vol. 17, no. 2, pp. 227–230, 1993.
[55] T. J. Hess, A. L. McNab, and K. A. Basoglu, "Reliability generalization of perceived ease of use, perceived usefulness, and behavioral intentions," *MIS Quart.,* vol. 38, no. 1, pp. 1–28, 2014.
[56] R. J. Holden and B.-T. Karsh, "The technology acceptance model: Its past and its future in health care," *J. Biomed. Inform.*, vol. 43, pp. 159–172, 2010.
[57] S. F. Hood-Clark, "Influences on the use and behavioral intention to use big data," Ph.D. dissertation, School Bus. Technol., Capella Univ., Minneapolis, MN, USA, 2016.
[58] L. Hu, and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," *Struct. Equ. Model.,* vol. 6, pp. 1–55, 1999.
[59] M. Igbaria, J. Iivari, and H. Maragahh, "Why do individuals use computer technology? A finsih case study," *Inf. Manage.,* vol. 29, pp. 227–238, 1995.
[60] I. Im, S. Hong, and M. S. Kang, "An international comparison of technology of technology adoption: Testing the UTAUT model," *Inf. Manage.,* vol. 48, no. 1, pp. 1–8, 2011.
[61] P. Jain, M. Gyanchandani, and N. Khare, "Big data privacy: A technological perspective and review," *J. Big Data,* vol. 3, no. 25, pp. 1–25, 2016.
[62] M. Jelinek and P. Bergey, "Innovation as the strategic driver of sustainability: Big data knowledge for profit and survival," *IEEE Eng. Manage. Rev.,* vol. 41, no. 2, pp. 14–22, Apr./Jun. 2013.
[63] K. Kambatla, G. Kollias, V. Kumar, and A. Grama, "Trends in big data analytics," *J. Parallel Distrib. Comput.,* vol. 74, pp. 2561–2573, 2014.
[64] A. Kapteyn, "Utility and economics," *De Economist*, vol. 133, no. 1, pp. 1–20, 1985.
[65] D. Kiron, R. B. Ferguson, and P. K. Prentice, "From value to vision: Reimagining the possible with data analytics," MIT Sloan Manage., Cambridge, MA, USA, pp. 1–19, 2013. [Online]. Available: https://sloanreview.mit.edu/wp-content/uploads/2013/03/13a218d008.pdf
[66] J. Kranjc, V. Podpecan, and N. Lavrac, "Real-time data analysis in clowdflows," in *Proc. IEEE Int. Conf. Big Data*, Santa Clara, CA, USA, Oct. 6–9, 2013, pp. 15–22.
[67] D. Krishnamurthy and A. Koziolek. "Special issue on challenges in software performance," *Perform. Eval. Rev.,* vol. 43, no. 4, pp. 1–2, 2016.
[68] K. K. Y. Kuan and P. Y. K. Chau., "A perception-based model for EDI adoption in small businesses using a technology-organization-environment framework," *Inf. Manage.,* vol. 38, pp. 507–521, 2001.
[69] O. Kwon, N. Lee, and B. Shin, "Data quality management, data usage experience and acquisition intention of big data analytics," *Int. J. Inf. Manage.,* vol. 34, no. 2014, pp. 387–394, 2014.
[70] S. Landset, T. M. Khoshgoftaar, A. N. Richter, and T. Hasanin, "A survey of open source tools for machine learning with big data in the hadoop ecosystem," *J. Big Data,* vol. 2, no. 24, pp. 1–36, 2015.
[71] S. LaValle, E. Lesser, R. Shockley, M. S. Hopkins, and N. Kruschwitz, "Big data, analytics and the path from insights to value," *MIT Sloan Manage. Rev.,* vol. 52, no. 2, pp. 20–32, 2011.

[72] A. L. Lederer, D. J. Maupin, and M. P. Sena, and Y. Zhuang, "The technology acceptance model and the world wide web," *Decis. Support Syst.,* vol. 29, no. 3, pp. 269–282, 2000.

[73] Y. Lee, K. A. Kizar, and K. R. T. Larsen, "The technology acceptance model: Past, present, and future," *Commun. Assoc. Inf. Syst.,* vol. 12, pp. 752–780, 2003.

[74] P. Legris, J. Ingham, and P. Collerette, "Why do people use information technology? A critical review of the technology acceptance model," *Inf. Manage.,* vol. 40, pp. 191–204, 2003.

[75] R. Likert, "A technique for the measurement of attitudes," *Arch. Psychol.*, vol. 22, pp. 5–55, 1932.

[76] J. R. Lourenco, B. Cabral, P. Carreiro, M. Vieira, and J. Bernardino, "Choosing the right NoSQL database for the job: A quality attribute evaluation," *J. Big Data,* vol. 2, no. 18, pp. 1–26, 2015.

[77] R. Lu, H. Zhu, X. Liu, J. K. Liu, and J. Shao, "Toward efficient and privacy-preserving computing in big data era," *IEEE Netw.*, vol. 28, no. 4, pp. 46–50, Jul./Aug. 2014.

[78] D. J. Luck and R. S. Rubin, *Marketing Research*, 7th ed. Englewood Cliffs, NJ, USA: Prentice-Hall, 1987.

[79] W. Maass, J. Parsons, S. Purao, V. C. Storey, and C. Woo, "Data-driven meets theory-driven research in the era of big data: Opportunities and challenges for information systems research," *J. Assoc. Inf. Syst.,* vol. 19, no. 12, 2018, Art. no. 1

[80] Q. Ma, and L. Liu, "The technology acceptance model: A meta-analysis of empirical findings," *J. Org. End User Comput.,* vol. 16, no. 1, pp. 59–72, 2004.

[81] R. C. MacCallum, M. W. Browne, and H. M. Sugawara, "Power analysis and determination of sample size for covariance structure modeling," *Psychol. Methods*, vol. 1, pp. 130–149, 1996.

[82] S. B. MacKenzie, P. M. Podsakoff, and N. P. Podsakoff, "Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques," *MIS Quart.*, vol. 35, no. 2, pp. 293–334, 2011.

[83] I. Malaka and I. Brown, "Challenges to the organisational adoption of big data analytics: A case study in the south african telecommunications industry," in *Proc. ACM Annu. Conf. South Afr. Inst. Comput. Scientists Inf. Technol.*, Stellenbosch, South Africa, Sep. 28–30, 2015, pp. 1–9.

[84] G. M. Maruyama, *Basics of Structural Equation Modeling*. Thousand Oaks, CA, USA: SAGE, 1998.

[85] K. Mathieson, "Predicting user intention: Comparing the technology acceptance model with the theory of planned behavior," *Inf. Syst. Res.,* vol. 2, no. 3, pp. 173–191, 1991.

[86] S. Menon and S. Sarkar, "Privacy and big data: Scalable approaches to sanitize large transactional databases for sharing," *MIS Quart.,* vol. 40, no. 4, pp. 963–981, 2016.

[87] F. F. R. Morgado, J. F. F. Meireles, C. M. Neves, A. C. S. Amaral, and M. E. C. Ferreira, "Scale development: Ten main limitations and recommendations to improve future research practices," *Psicologia, Reflexão e Crítica,* vol. 30, no. 3, pp. 1–20, 2017.

[88] G. D. Moody, M. Siponen, and S. Pahnila, "Toward a unified model of information security policy compliance," *MIS Quart.,* vol. 42, no. 1, pp. 285–311, 2018.

[89] M. G. Morris and A. Dillon, "How user perceptions influence software use," *IEEE Softw.,* vol. 14, no. 4, pp. 58–65, Jul./Aug. 1997.

[90] R. Nambiar, A. Sethi, R. Bhardwaj, and R. Vargheese, "A look at challenges and opportunities of big data analytics in healthcare," in *Proc. IEEE Int. Conf. Big Data*, Santa Clara, CA, USA, Oct. 6–9, 2013, pp. 17–22.

[91] M. Nemschoff, "Big data: 5 major advantages of hadoop," *ITProPortal*, 2013. [Online]. Available: http://www.itproportal.com/2013/12/20/big-data-5-major-advantages-of-hadoop/#ixzz3tEAqQMHL

[92] K. Paetow, M. Schmitt, and T. Malsch, "Scalability, scaling processes, and the management of complexity. A system theoretical approach," in *Socionics. Lecture Notes in Computer Science*, K. Fischer, M. Florian, T. Malsch, Eds. Berlin, Germany: Springer, 2005, pp. 132–154.

[93] S. Petter, D. Straub, and A. Rai, "Specifying formative constructs in information systems research," *MIS Quart.,* vol. 31, no. 4, pp. 623–656, 2007.

[94] P. M. Podsakoff, S. B. MacKenzie, J.-Y. Y. Lee, and N. P. Podsakoff, "Common method biases in behavioral research: A critical review of the literature and recommended remedies," *J. Appl. Psychol.,* vol. 88, no. 5, pp. 879–903, 2003.

[95] G. Premkumar, and M. Potter, "Adoption of computer aided software engineering (CASE) technology: An innovation adoption perspective," *ACM SIGMIS Database Adv. Inf. Syst.*, vol. 26, no. 2/3, pp. 105–124, 1995.

[96] L. Qin, Y. Kim, J. Hsu, and X. Tan, "The effects of social influence on user acceptance of online social networks," *Int. J. Hum.-Comput. Interaction,* vol. 27, no. 9, pp. 885–889, 2011.

[97] N. Rahman, "Data warehousing and business intelligence with big data," in *Proc. Int. Annu. Conf. Amer. Soc. Eng. Manage.*, Oct. 17–20, 2018, pp. 1–6.

[98] N. Rahman, "SQL scorecard for improved stability and performance of data warehouses," *Int. J. Softw. Innov.,* vol. 4, no. 3, pp. 22–37, 2016.

[99] N. Rahman, "SQL optimization in a parallel processing database system," in *Proc. IEEE 26th Can. Conf. Elect. Comput. Eng.*, Regina, SK, Canada, May 5–8, 2013, pp. 1–5.

[100] N. Rahman and S. Iverson, "Big data business intelligence in bank risk analysis," *Int. J. Bus. Intell. Res.,* vol. 6, no. 2, pp. 55–77, 2015.

[101] N. Rahman, D. Rutz, S. Akhter, and F. Aldhaban, "Emerging technologies in business intelligence and advanced analytics," *ULAB J. Sci. Eng.,* vol. 5, no. 1, pp. 7–17, 2014.

[102] N. Rahman and L. Sutton, "Optimizing SQL performance in a parallel processing DBMS architecture," *ULAB J. Sci. Eng.,* vol. 7, no. 1, pp. 33–44, 2016.

[103] C. A. Rajan and R. Baral, "Adoption of ERP system: An empirical study of factors influencing the usage of ERP and its impact on end user," *IIMB Manage. Rev.,* vol. 27, pp. 105–117, 2015.

[104] K. Ramamurthy, A. Sen, and A. P. Sinha, "An empirical investigation of the key determinants of data warehouse adoption," *Decis. Support Syst.,* vol. 44, pp. 817–841, 2008.

[105] E. M. Rogers, *Diffusion of Innovations*, 3rd ed. New York, NY, USA: Free Press, 1983.

[106] E. M. Rogers, *Diffusion of Innovations*, 5th ed. New York, NY, USA: Free Press, 2003.

[107] P. Russom, "Managing big data," TDWI Best Practices Rep., TDWI Res., pp. 1–40, 2013. http://epictechpage.com/sms/sas/wp-content/uploads/2014/07/managing-big-data.pdf

[108] T. Saheb and T. Saheb, "Understanding the development trends of big data technologies: An analysis of patents and the cited scholarly works," *J. Big Data,* vol. 7, no. 12, pp. 1–26, 2020.

[109] M. Scherrer-Rathje and T. A. Boyle, "An end-user taxonomy of enterprise systems flexibility: Evidence from a leading european apparel manufacturer," *Inf. Syst. Manage.,* vol. 29, no. 2, pp. 86–99, 2012.

[110] A. H. Segars and V. Grover, "Re-examining perceived ease of use and usefulness: A confirmatory factor analysis," *MIS Quart.,* vol. 17, no. 4, pp. 517–525, 1993.

[111] K. Shvachko, H. Kuang, S. Radia, and R. Chansler, "The hadoop distributed file system," in *Proc. IEEE 26th Symp. Mass Storage Syst. Technol.*, WA, DC, USA, 2010, pp. 1–10.

[112] U. Srinivasan and B. Arunasalam, "Leveraging big data analytics to reduce healthcare costs," *IT Prof.*, vol. 15, pp. 21–28, 2013.

[113] G. J. Stigler, "The development of utility theory," *J. Polit. Econ.,* vol. 58, no. 4, pp. 307–327, 1950.

[114] D. Straub and A. Burton-Jones, "Veni, vidi, vici: Breaking the TAM logjam," *J. Assoc. Inf. Syst.,* vol. 8, no. 4, pp. 223–229, 2007.

[115] D. Straub, M. Limayem, and K. Karahanna-Evaristo, "Measuring system usage: Implications for IS theory testing," *Manage. Sci.*, vol. 41, no. 8, pp. 1328–1342, 1995.

[116] D. Suhr, "The basics of structural equation modeling," 2006. [Online]. Available: http://www.lexjansen.com/wuss/2006/tutorials/TUT-Suhr.pdf

[117] F. P. S. Surbakti, W. Wang, M. Marta Indulska, and S. Sadiq, "Factors influencing effective use of big data: A research framework," *Inf. Manage.,* vol. 57, no. 1, 2020, Art. No. 103146.

[118] B. Szajna, "Software evaluation and choice: Predictive evaluation of the technology acceptance instrument," *MIS Quart.,* vol. 18, no. 3, pp. 319–324, 1994.

[119] B. Szajna, "Empirical evaluation of the revised technology acceptance model," *Manage. Sci.,* vol. 42, no. 1, pp. 85–92, 1996.

[120] B. G. Tabachnick and L. S. Fidell, *Using Multivariate Statistics*, 6th ed. New York, NY, USA: Pearson, 2012.

[121] P. Tambe, "Big data investment, skills, and firm value," *Manage. Sci.,* vol. 60, no. 6, pp. 1452–1469, 2014.

[122] J. M. Tanur, “Advances in methods for large-scale surveys and experiments,” in *Behavioral and Social Science Research: A National Resource, II,* R. Mcadams, N. J. Smelser, and D. J. Treiman, Eds. Washington, DC, USA: Nat. Acad. Press, 1982.

[123] S. Taylor and P. A. Todd, “Understanding information technology usage: A test of competing models,” *Inf. Syst. Res.,* vol. 6, no. 2, pp. 144–176, 1995.

[124] D. J. Teece, G. Pisano, and A. Shuen, “Dynamic capabilities and strategic management,” *Strategic Manage. J.,* vol. 18, no. 7, pp. 509–533, 1997.

[125] C.-W. Tsai, C.-F. Lai, H.-C. Chao, and A. V. Vasilakos, “Big data analytics: A survey,” *J. Big Data,* vol. 2, no. 21, pp. 1–32, 2015.

[126] C.-W. Tsai, Y.-L. Yang, M.-C. Chiang, and C.-S. Yang, “Intelligent big data analysis: A review,” *Int. J. Big Data Intell.,* vol. 1, no. 4, 2014.

[127] S. Tsumoto and S. Hirano, “Granularity-based temporal data mining in hospital information system,” in *Proc. IEEE Int. Conf. Big Data*, Santa Clara, CA, USA, Oct. 6-9, 2013, pp. 32–40.

[128] V. Venkatesh, “Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model,” *Inf. Syst. Res.,* vol. 11, no. 4, pp. 342–365, 2000.

[129] V. Venkatesh and H. Bala, “Technology acceptance model 3 and a research agenda on interventions,” *Decis. Sci.*, vol. 39, no. 2, pp. 273–315, 2008.

[130] V. Venkatesh and F. D. Davis, “A theoretical extension of the technology acceptance model: Four longitudinal field studies,” *Manage. Sci.,* vol. 46, no. 2, pp. 186–204, 2000.

[131] V. Venkatesh, F. Davis, and M. G. Morris, “Dead or alive? The development, trajectory and future of technology adoption research,” *J. Assoc. Inf. Syst.,* vol. 8, no. 4, pp. 267–286, 2007.

[132] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, “User acceptance of information technology: Toward a unified view,” *MIS Quart.,* vol. 27, no. 3, pp. 425–478, 2003.

[133] V. Venkatesh, J. Y. L. Thong, and X. Xu., “Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology,” *MIS Quart.,* vol. 36, no. 1, pp. 157–178, 2012.

[134] V. Venkatesh, J. Y. L. Thong, and X. Xu, “Unified theory of acceptance and use of technology: A synthesis and the road ahead,” *J. Assoc. Inf. Syst.,* vol. 17, no. 5, pp. 328–376, 2016.

[135] V. Venkatesh and X. Zhang, “Unified theory of acceptance and use of technology: U.S. vs. China,” *J. Glob. Inf. Technol. Manage.*, vol. 13, no. 1, pp. 5–27, 2010.

[136] S. Verma, S. S. Bhattacharyya, and S. Kumar, “An extension of the technology acceptance model in the big data analytics system implementation environment,” *Inf. Process. Manage.*, vol. 54, pp. 791–806, 2018.

[137] R. L. Villars, C. W. Olofson, and M. Eastwood, “Big data: What it is and why you should care,” IDC White Paper, 2011, Art. no. 228827.

[138] W. Wang, J. J. P.-A. Hsieh, and B. Song, “Understanding user satisfaction with instant messaging: An empirical survey study,” *Int. J. Hum.-Comput. Interaction*, vol. 28, pp. 153–162, 2012.

[139] B. Wernerfelt, “A resource-based view of the firm,” *Strategic Manage. J.*, vol. 5, pp. 171–180, 1984.

[140] M. D. Wheelock, “Factors influencing the adoption of cloud storage by information technology decision makers,” Ph.D. dissertation, School Bus. Technol., Capella Univ., Minneapolis, MN, USA, 2013.

[141] B. H. Wixom, and H. J. Watson, “An empirical investigation of the factors affecting data warehousing success,” *MIS Quart.,* vol. 25, no. 1, pp. 17–32, 2001.

[142] X. Wu, X. Zhu, G. - Q. Wu, and W. Ding, “Data mining with big data,” *IEEE Trans. Knowl. Data Eng.,* vol. 26, no. 1, pp. 97–107, Jan. 2014.

[143] D. Zhang, S. L. Pan, J. Yu, and W. Liu, “Orchestrating big data analytics capability for sustainability: A study of air pollution management in china,” *Inf. Manage.*, vol. 9, 2019, Art. no. 103231. [Online]. Available: https://doi.org/10.1016/j.im.2019.103231.

[144] X. Zhang and H. Pham, “An analysis of factors affecting software reliability,” *J. Syst. Softw.*, vol. 50, pp. 43–56, 2000.

Nayem Rahman received the M.S. degree in systems science (modeling and simulation) from Portland State University, Portland, OR, USA, in 2013, the MBA degree in management information systems, project management, and marketing from Wright State University, Dayton, OH, USA, in 1999, and the Ph.D. degree in technology management (big data tech adoption from Portland State University, Portland, in 2020.

He is currently an Information Technology Professional. He has implemented several large projects using data warehousing and big data technologies in enterprise DSS platforms. He has presented his research in both the industry (Teradata Partners, 2005 and 2008; Intel’s Supply Chain Tech Leadership Forum, 2015) and academic (AMCIS, 2008; IEEE Canada, 2013; PICMET, 2013 and 2015, ASEM, 2018) conferences. He has authored or coauthored more than 40 articles published in various conference proceedings and academic journals. His principal research areas are changed data capture and management in temporal data warehouses, self-service BI in HANA in-memory databases, performance optimization in database systems, big data analytics, machine learning, technology adoption, and sustainability of information technology.

Tugrul Daim received the B.S. degree in mechanical engineering from Bogazici University, Istanbul, Turkey, in 1989, the M.S. degree in engineering management from Portland State University, Portland, OR, USA, in 1994, the M.S. degree in mechanical engineering in 1991 from Lehigh University, Bethlehem, PA, USA, and the Ph.D. degree in systems science and engineering management from Portland State University, in 1998.

He leads a research group on technology evaluations and research applications. His group has had 23 Ph.D. graduates. He has authored or coauthored more than 200 refereed journal papers, more than 20 special issues, and more than 20 books. He made more than 200 conference presentations. He is the fifth Editor-in-Chief for the IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT. Prior to that, he had led the *International Journal of Innovation and Technology Management* for a decade and made it a well-known journal in the field. In addition, he had served as an Associate Editor for other journals including *Technological Forecasting and Social Change*, *Technology in Society*, and *Engineering Management Journal*.

Nuri Basoglu received the B.S. degree in industrial engineering from Bogazici University, Istanbul, Turkey, in 1982, and the M.S. and Ph.D. degrees in business administration from Istanbul University, Istanbul, 1984 and 1990, respectively.

He is a currently Professor in Industrial Design and Technology Design and Innovation Management, Izmir Institute of Technology, Izmir, Turkey. His research interests include sociotechnical aspects of technology projects, customer-focused product development, information technology adoption, mobile service design, adaptive human–computer interfaces, and Intelligent electronic health care applications. He has authored or coauthored articles in journals such as the *Journal of Product Innovation Management*, *Technology Forecasting and Social Change*, *Foresight*, *Journal of High Technology Management Research*, *Technology in Society*, *Computers in Human Behavior*, *Technology Analysis and Strategic Management*, *International Journal of Information Technology and Decision Making*, *International Journal of Information Systems in the Service Sector*, *International Journal of Services Sciences*, *Journal of Enterprise Information Management*, *Health Policy and Technology*, and *Journal of Medical Systems*.