Managing Big Data: A Research on Adoption Issues

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Abstract

The adoption of big data presents significant challenges for managers and organizations, which has precipitated increased research on the effective utilization of big data. In order to successfully adopt big data, the organization must ensure its managers are on board with the changes because the support of the managerial staff of the organization can be associated with the adoption of new technology. The purpose of this quantitative study, thus, was to investigate factors related to the use of big data by managers and decision-makers whose organizations have adopted, or are considering adopting, big data. The results of this study showed that the three constructs of perceived ease of use, perceived usefulness, and attitude toward use had a strong correlation to actual use and the behavioural intention to use big data.

Keywords: Big data, TAM, Behavioural intention, Quantitative research.

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Introduction

The introduction of new technology into an organization presents implementation and usage challenges (Subashini & Kavitha, 2011). The computational analysis of big data, which consists of exceptionally large sets of data, provides that function by revealing patterns, trends, and associations valuable in making informed decisions. The processes used to analyze big data, however, are relatively new, and there is still much about big data and its use that remains unknown (Esteves & Curto, 2013). In addition, assessing factors that assist organizational decision-makers involved in the use or management of information technology (IT) with making informed decisions that influence the organizational acceptance and effective utilization of IT has become a critical direction for research (Venkatesh & Bala, 2008). Managers and decision-makers anticipate organizational business needs and provide a range of services to the organization that comply with the enterprise architecture. Executive officers in the organization look to the managers and other decision-makers to recommend the use of new technology, but its adoption into daily use involves cooperative effort (Miller, 2014).

By adopting systems that allow for the use of big data, organizations can realize cost reductions and improvements in the time required to offer a new service or product. The ability to use big data effectively also provides financial benefits and supports internal business decisions and objectives. Despite the benefits of adopting big data, there is a lack of support for the adoption and use of big data by organizational management and decision-makers. In 2011, the International Data Corporation (IDC) found that 47% of the 502 companies surveyed believed they did not need big data. Twenty-five percent of the companies surveyed did not see the value of big data. Esteves and Curto (2013) found that 33% of big data projects did not meet the organization's expectations in terms of cost and performance. According to a 2011 survey conducted by MIT Sloan Management Review and IBM, barriers to the successful adoption of the use of big data faced by organizations are predominately managerial (LaValle et al., 2011). Thirty-three percent of respondents to the survey stated lack of management support as an obstacle to the adoption of the use of big data (LaValle et al., 2011). The problem addressed by this study was the lack of support for use of big data by organizational management and decision-makers.

The adoption of big data presents significant challenges for managers and organizations, which has precipitated increased research on the effective utilization of big data (Venkatesh & Bala, 2008). One area of specific research interest has been management acceptance of the changes in technology necessary to handle big data. Negative attitudes or behaviors from managers with responsibilities in the daily use of technology who resist adopting big data negatively affect productivity and innovation within the organization (de Araújo, Burcharth, Knudsen, & Sondergarrd, 2014) In order to successfully adopt big data, the organization must ensure its managers are on board with the changes because the support of the managerial staff of the organization can be associated with the adoption of new technology (Stace, Courtney, & Holthan, 2012). Decision-makers and IT managers are strategic partners crucial for development and execution of marketing strategies in organizations. Without the cooperation of managers with responsibility for IT decisions or use, the likelihood of an organization to effectively adopt big data technology drops significantly (McAfee & Brynjolfsson, 2012).

The problem addressed by this study was the lack of information about factors related to organizational managers and decision-makers' decision to adopt the use of big data. The IDC (Villars, Olofson, & Eastwood, 2011) found that 47% of the respondents of 502 companies surveyed believe they do not need big data, and 25% of those surveyed did not see the value of big data. Esteves and Curto (2013) found that 33% of big data projects did not meet the organization's expectations in terms of cost and performance.

Barriers to the successful adoption of the use of big data faced are predominately managerial (LaValle et al., 2011); thus, a study of factors relating to managers' incorporation of technology was important. Understanding acceptance factors of big data will help organizations be better prepared for adoption of the use of the technology.

As the review of the extant published literature indicates, senior executives realize the need to make data-driven decisions, and they want data that provides guidance on the best courses of action (LaValle et al., 2011). Collecting, managing, and using big data means organizations' IT departments must embrace new technology (McAfee & Brynjolfsson, 2012). The review indicated a lack of research into factors related to manager and decision-maker acceptance and intention to use big data. The purpose of this quantitative study, thus, was to investigate factors related to the use of big data by managers and decision-makers whose organizations have adopted, or are considering adopting, big data, and was based on the factors of (a) perceived usefulness, (b) perceived ease of use, (c) attitude toward use, (d) behavioral intention to use, and (e) actual use of big data technology.

Literature Review and Theoretical Framework

The emerging capacity of big data, which moved from the theoretical to the actual only since the late 1990s, has yet to become commonplace (Press, 2013). McKinsey (2011) found that the adoption of big data presented significant challenges managers needed to address, such as (a) hiring specialized analytical and managerial talent, (b) investing in technology capable of storing and utilizing big data, and (c) providing organizational and data security. Although big data may be popular in the abstract, these challenges still presented significant impediments to the wide-spread adoption of big data technologies. In their work on cloud computing, Subashini and Kavitha (2011) found that the introduction of new technology of any sort impacts managers. McKinsey (2011) documented specific managerial challenges and concerns associated with the use of big data. Despite difficulties associated with its adoption, big data has been recognized as an increasingly important source of insight for cost-effective decision-making in an array of public and private endeavors (Adler-Milstein & Jha, 2013; Esteves & Curto, 2013).

Big data technologies allow organizations to react in new ways to market changes (Esteves & Curto, 2013). Furthermore, LaValle et al. (2011) noted the essential role of managers in guiding and supporting organizational assimilation of big data technology. Manager attitudes toward big data technology may be important factors in their decision to adopt such technologies. Consequently, critical directions for research involved identifying (a) ways to build managers' understanding and support of big data, and (b) factors that assist managers to make informed decisions regarding its effective utilization (Venkatesh & Bala, 2008). Because leadership and support by the managerial staff of an organization tend to have a direct effect on the successful adoption of new technology (Stace et al., 2012), managers' attitudes about big data and feeling of self-efficacy related to big data have been widely studied.

The influx of big data has historically transformed the daily operations of many organizations (Changqing, Yu, Wenming, Uchechukwu, & Keqiu, 2012; H. Chen, Chiang, & Storey, 2012; P. Chen, Qi, Li, & Su, 2013). Due to worldwide yearly increases in data in the range of 35% to 50%, organizations have been compelled to adopt strategies that incorporated the use of big data (Beath, Becerra-Fernandez, Ross, & Short, 2012). Beath et al. (2012) found that organizations operationally work with about 60 terabytes (1012) of data on an annual basis, and that this represents about a 1000-fold increase in the amount of operational data since 2002. Beath et al. (2012) found, however, that the need to extract value from this increase in data volume was, instead, frequently eclipsed by organizational concern with how to access, process, and store the vast amounts of data. Leaders within organizations recognized the potential benefits of incorporating the use of big data into their strategies, but staff were frequently unprepared for its practical implementation.

Organizations' managers have strong incentives to transform big data into something of monetary value (Cheng, Hu, Li, Lin, & Zuo, 2013). In the healthcare field, for instance, big data has been used to analyze cost and quality issues with the result of finding cost-effective solutions for the industry (Adler-Milstein & Jha, 2013). In healthcare, quality issues regarding big data have been particularly critical because most data were entered manually, and manual entry allowed for systematic errors to be quickly introduced into the data stream, which caused some of the entered data to be fragmented. These errors can be errors of omission, data entry errors, and physician documentation styles (Adler-Milstein & Jha, 2013).

According to McAfee & Brynjolfsson (2012), managers often found it hard to break out of their comfort zone, are not sure how big data could benefit their organization, and feel that converting to big data is overly complicated and time consuming. The financial performance of the organizations, therefore, was about 20% lower than organizations that extracted value from big data. One organizational area where this monetary transformation was active was in the supply-chain management (Najjar & Kettinger, 2013). Information from big data can be shared with all organizational partners in the supply chain, and a stronger financial performance could be achieved up and down the supply chain (Najjar & Kettinger, 2013). For managers, a successful cooperative effort of this sort demonstrates practical advantages of big data.

Initial barriers to the use of big data have slowly been removed. Researchers, for instance, discovered that bandwidth capacity is maximized by the transfer of big data between and among various data centers and clouds (Gorcitz, Jarma, Spathis, Dias de Amorim, & Wakikawa, 2012). There are still issues with distributed data centers that need to process big data in a cost effective manner (Gu, Zeng, Li, & Guo, 2014), but these centers have also become more energy aware and efficient in the processing of big data (Kaushik & Nahrstedt, 2012). As storage for big data became cheaper, organizations were able to store more data. Many organizations were professionally advised that their data should be analyzed to provide more value; therefore, all data is being saved. While the availability of more data supports big data technology use, it also poses challenges as researchers develop methods for analyzing big data and producing effective results. In some fields, regulations and court cases require organizations to keep all data in perpetuity (Tallon, 2013). Tallon (2013) presented a case study on the difficulty of the process the Intel Corporation went through to create governance policies for its big data. Intel had amassed data in the 65 petabyte (1015) range by 2013, an amount of data that was found to be 150 times that held by the US Library of Congress. The researchers also found that Intel's vast amount of data needed a companywide governance policy. This policy needed to secure Intel's big data, but at the same time allow employees to access the data and provide Intel with its valuable competitive information (Tallon, 2013). Despite Intel being a large corporation at the forefront of technological advances, assimilating the challenges of big data has required managerial resources in terms of attention and creative problem-solving.

The technology barriers that previously prevented widespread acceptance of big data are decreasing, allowing increased access to big data technologies; however, it is clear that the adoption of big data technologies presents a challenge to managers and leaders (McKinsey, 2011). In developing an understanding of the factors that affect whether or not managers will adopt big data technologies, several theories may provide useful frameworks. It is important to consider the framework provided by social cognitive theory (Bandura, 1982) and manager levels of self-efficacy, as well as the framework of contingent decision behavior theory (Beach & Mitchell, 1978) and the cost-benefit analyses that managers perform as they decide whether or not to accept big data technologies. Manager attitudes and subjective norms may also be important predictors of manager acceptance of big data (Ajzen & Fishbein, 2011). The TAM (Davis, 1989) provided a model for understanding manager acceptance of such technologies, or behavioral intention, through mapping manager perceptions of usefulness and ease of use (Davis, 1989; Venkatesh et al., 2003).

Current literature on big data focuses primarily on the value created for the organization by the use of big data and the use of analytics to manage big data. While researchers discuss the reluctance of organization leaders to promote or consistently promote its use (Esteves & Curto, 2013), and especially to do so with the urgency indicated by certain oft-cited studies (McGuire et al., 2012), there was a gap in the literature regarding issues related to decisions managers and decision-makers make to adopt the use of big data. A study about manager and decision-maker acceptance or adoption of big data was important because organizations incurred significant costs integrating big data into their existing IT framework. Implementation fears played against the incorporation of big data into IT because of the high level of sophistication required for its use (Esteves & Curto, 2013). Understanding acceptance issues of big data will help organizations become better prepared for adoption of the technology and the costs incurred.

Research Method

The variance in rates of assimilation of new technology among managers and decision makers regarding IT is a cause of concern in organizations that rely heavily on information technology. Factors that affect that assimilation are, therefore, of great interest. The use of big data is similar to other IT applications with regard to who bears responsibility within an organization for its adoption and use, but the challenges are both dissimilar and significant in terms of data storage and security, monetary investment, specialized talent needed for analytics and data management (McKinsey, 2011). The research findings, therefore, of factors associated with the assimilation of technology by organizational managers and decision makers cannot be directly applied to the use of big data. Research that specifically addressed the assimilation of big data technology was needed to yield a greater understanding of these factors.

Davis's (1989) instrument, the TAM, has been used in both specific and general contexts with good success (Adams et al., 1992; Davis & Venkatesh, 1996; Hendrickson, Massey, & Cronan, 1993). An adaptation of the TAM (Davis, 1989) was used in the current research, which was a quantitative study to assess the influencing factors of the use and intention to use big data by decision makers and managers whose organizations used or were considering using big data in daily operations.

The objective of this study was to quantify and measure the determinants of use and the intention to use big data. A non-experimental, quantitative, exploratory, correlational design was used. The purpose of a non-experimental design is to explore for the presence of, and to describe associations between variables of interest that cannot be manipulated, such as achievement, attitudes, or relationships (Johnson, 2001). The focus of this study, thus, was to explore for, and determine the relationships among, (a) perceived usefulness, (b) perceived ease of use, (c) attitudes toward use, (d) behavioral intention to use, and (e) use behavior in the use and intention to adopt the use of big data by organizational managers and decision-makers. The statistical models used for this study were correlation analysis and regression analysis. Correlation analysis and regression analysis are both standard statistical tests used with data resulting from the TAM (Park, Nam, & Cha, 2011; Turner, Kitchenham, Brereton, Charters, & Budgen, 2010). When the relationships between intention and attitude are measured through correlation and regression analysis, the TAM can predict the behavior of use for technology (Davis, 1989, Park et al., 2011). The behavior studied in this research was the use and intention to adopt the use of big data. A graphic representation of the research design derived from Davis, Bagozzi, & Warshaw (1989) is shown in Figure 1.

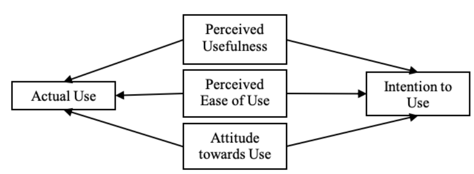

Figure 1. Research model.

Two specific research questions were posed for this study. Each question was framed to support measurement of IT decision-makers' perceptions of big data corresponding to the factors (a) perceived usefulness, (b) perceived ease of use, and (c) attitude toward use. The research questions and the hypotheses considered in this research are as follows:

RQ1: To what extent does perceived usefulness, perceived ease of use, and attitude toward use relate to the use of big data by managers and decision- makers in organizations?

RQ2: To what extent does perceived usefulness, perceived ease of use, and attitude toward use relate to the behavioral intention to adopt the use of big data by managers and decision-makers in organizations?

The three independent variables related to the adoption of big data were (a) perceived usefulness, (b) perceived ease of use, and

(c) attitude toward use. There was extensive literature on the relationship of these variables to the adoption and use of technology (Turner et al., 2010), but a gap in the literature regarding factors influencing managers and decision-makers to adopt big data.

The specific dependent variable of intention to use big data has been supported by researchers who use the TAM to study the use of technology. The variable, intention to use big data, contributes to the intention to use a particular technology (S. Chen et al., 2011). The dependent variables (a) use of technology, and (b) behavioral intent to use were used by Aquino (2014) to study the intent to use medical laboratory information system (LIS)-EHR interface technology by medical doctors. The construct, behavioral intent to use, was also used by Shin (2014) in a study of the use of cloud services by public employees. For the purpose of this study, operational definitions of the dependent variables referred to (a) the behavioral intention to use big data, and (b) the actual use of big data by managers and decision-makers. The use of big data was measured on the summary score of the modified TAM on questions one and two of the use subscale for which a Likert-type scale was used to measure frequency of use. The intention to use big data was measured on the summary score of questions one through four of the intention to use subscale of the modified TAM, for which a Likert-type scale was used to measure frequency of use.

In order to recruit an appropriate sample, the researcher conducted systematic, purposive, random sampling to survey the target frame of organization managers and decision-makers who were knowledgeable about big data and worked in organizations that used or were considering using big data in daily operations. For this research, the sample was composed of (a) mid- and upper-level managers in industries; (a) who were at least 18 years of age; (c) had a minimum education of a high school degree; (d) were knowledgeable about big data; and (e) worked for an organization that was using, or was considering the use, of big data. These criteria were chosen to assure a representative sample of managers whose work involved leadership or managerial roles in organizations where big data was or would be used in their daily operations. 120 managers and decision-makers attended the survey. Of these, 111 completed the questionnaire, which included one each of CIOs, CEOs, and COOs; two vice presidents of technology; 11 IT directors, 29 IT managers, 12 program managers, 11 IT supervisors, and 43 other managers, department managers, and project managers. Participants under 18 years-of-age were excluded. Demographic information collected included age, gender, years of experience, education, organization type, and position.

The researcher completed a priori test to ensure the change in wording and addition of demographic questions would not adversely affect internal validity. Four senior IT professionals agreed to participate in the priori test to ensure (a) the format and content of the questionnaire were appropriate for the intended participants, (b) the survey items were clear and comprehensive, (c) the instructions were clear, and (d) the survey items were non-intrusive or sensitive in nature. Each expert received an email requesting they provide a review of the survey instrument. The email included an attached copy of the survey instrument with the questions grouped into sections according to each variable.

Each expert provided feedback to assist the researcher in improving the overall quality and content of the survey. The four experts agreed that the survey instructions were clear in directing the participants on how to complete the survey. Two experts recommended adding age and length of employment to the demographics section of the questionnaire. One expert recommended moving the demographic questions to the end of the questionnaire. Collectively, the four experts agreed the survey addressed the research questions and hypotheses. They found the questionnaire to be appropriate and the survey items to be clear and comprehensive, and the four experts agreed the questions were not intrusive or sensitive. Each of the expert's recommendations were reviewed and implemented.

Findings

Organizational access and use of big data has become increasingly important as a cost-effective source of insight toward informed decision-making in areas such as marketing, customer care, data reduction, and diagnostics. Previous research has established, however, that there are significant and unique challenges involved in using big data (Subashini & Kavitha, 2011). Researchers have also established that organizations' managers and decision makers play a critical role in guiding and supporting a change to this relatively new technology (LaValle et al., 2011), which can transform daily operations (Changqing et al., 2012; H. Chen et al., 2012; P. Chen et al., 2013).

Table 1 shows the results of the various job titles of the decision-makers and managers who participated in the study. Respondents chose the category that best fit their job responsibilities from a list of eight possible job titles.

Table 1. Respondents by title.

	Frequency	Valid Percent
Chief Information Officer (CIO)	1	.9
Chief Executive Officer (CEO)	1	.9
Chief Operating Officer (COO)	1	.9
VP of Information Technology	2	1.8
Information Technology (IT) Director	11	9.9
Information Technology (IT) Manager	29	26.1
Program Manager	12	10.8
IT Supervisor	11	9.9
Other Managers	43	38.7
Total	111	100.0

A Cronbach's alpha reliability analysis was conducted to determine if the TAM survey attributes were reliable. The analysis suggested a strong reliability measurement for each of the four variables: (a) perceived ease of use, (b) perceived use, (c) attitude toward use, and (d) behavioral intention to use. Each variable had an alpha coefficient greater than 0.70, which is considered good, with the least strong being perceived ease of use at 0.774. Table 2 shows the values of Cronbach's alpha testing for the variables.

Table 2. Reliability Test - Cronbach's Alpha Method.

Variable	Cronbach's Alpha	Number of Items
Perceived Ease of Use	.774	10
Perceived Use	.962	10
Attitude Toward Use	.841	4
Behavioral Intention to Use	.952	4

Spearman's rank-order correlation was run to assess the correlation between variables. The results indicated that independent variables noted in table 3 are dependent on the listed dependent variables.

Table 3. Correlation analysis of variables.

Independent Variable	Dependent Variable	Spearman's rho Sig (2-tailed)	Result
Perceived Usefulness	Actual Use	0,506 (,000)**	Strong positive correlation
Perceived Ease of Use	Actual Use	0,219 (,021)*	Strong positive correlation
Attitude Toward Use	Actual Use	0,279 (,003)**	Strong positive correlation
Perceived Usefulness	Behavioural Intention to Use	0,684 (,000)**	Strong positive correlation
Perceived Ease of Use	Behavioural Intention to Use	0,224 (,018)*	Strong positive correlation
Attitude Toward Use	Behavioural Intention to Use	0,771 (,000)**	Strong positive correlation

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

A correlation quantitative methodology is used to explore the relationship between perceived ease of use, perceived usefulness, and attitude toward use with (a) actual use and (b) behavioral intent to use big data. The analysis revealed perceived ease of use, perceived usefulness, and attitude toward use are significantly correlated with the actual use of and the behavioral intention to use big data by manager and decision-makers of IT in organizations. Parametric and nonparametric data analysis confirmed the significant differences and rejection of the null hypotheses.

To further explore the hypotheses tests, the t-test was used to determine group statistics of big data users and big data non-users by comparing the mean, standard deviation, and standard of error of mean. No significance was found. Big data users and non-users had approximately equal means. The independent samples test for big data use indicated some differences in the significance of the associations between the perceived ease of use subscales. Perceived ease of use was not statistically significant among big data users.

RQ1. To what extent does perceived usefulness, perceived ease of use, and attitude toward use relate to the use of big data by managers and decision- makers in organizations?

Results of the statistical analysis established that there was a statistically significant relationship among perceived usefulness, perceived ease of use, and attitude toward the use of big data with the actual use of big data by managers and decision-makers in organizations. The level of significance for the combined effect of the three constructs was $p < 0.05$, indicating a strong predictive relationship. The survey results indicated there was an independent significant relationship between each of the three constructs with the use of big data by managers and decision-makers in organizations. Two of these, perceived usefulness and attitude toward use, had a level of significance of $p < 0.01$, whereas perceived ease of use was significant at the somewhat weaker p - value of $p < 0.05$.

Similar results were found with the second research question:

RQ2. To what extent does perceived usefulness, perceived ease of use, and attitude toward use relate to the behavioral intention to adopt the use of big data by managers and decision-makers in organizations?

Results indicated there was a statistically significant relationship among the three constructs perceived usefulness, perceived ease of use, and attitude toward use with the behavioral intention to use big data by managers and decision-makers in organizations. The level of significance for the combined effect of the three constructs was $p < 0.02$, indicating homogeneity of variance and a strong predictive relationship. The null hypothesis, therefore, was rejected. As with the first research question, results indicated there was a significant relationship between each construct, perceived usefulness, perceived ease of use, and the behavioral intention to use big data that had an independent significant relationship with the behavioral intention to use big data by managers and decision-makers in organizations. As with actual use of big data, two of these, perceived usefulness and attitude toward use, had a level of significance of $p < 0.01$, whereas perceived ease of use was significant at the weaker p-value of $p < 0.05$.

Conclusion and Discussions

Researchers have indicated that the challenges of adopting the use of big data into the daily operations of an organization are significant, but are facilitated by a positive attitude toward its use by managers and decision-makers who recognize its value in achieving organizational goals (Esteves & Curto, 2013; McAfee & Brynjolfsson, 2012; Miller, 2014). Researchers using the TAM instrument found a positive correlation between perceived ease of use, perceived usefulness, and attitude towards use of technology, and the intention to use and actual use of that technology (S. Chen et al., 2011; Nair & Das, 2011). The purpose of this quantitative study was to assess how the predictor, or independent variables, of (a) perceived usefulness, (b) perceived ease of use, and (c) attitude toward the adoption of using big data, related to the outcome, or dependent variables, of (a) behavioral intent to use and (b) actual use of big data by organizational managers and decision-makers.

The market is at the beginning stages of adopting technology associated with big data, where the main challenge of using and adopting the use of big data is transforming the culture, processes, and people in the organizations (Esteves & Curto, 2013). The results of this study add to overall understanding of how decisions are made concerning adoption of emerging technologies associated with the use of big data. If leadership is considering adding technology to use and manage big data, organizational strategies may benefit by including manager and decision-maker perceptions regarding the use of big data. The perceptions of those who are in positions of power for decision-making with regard to big data will not only affect organizational policies, but may have a significant impact on an organization's overall performance and competitive advantage.

This study was proposed to increase understanding of the factors that determine the use and intention to use big data by managers and decision makers. The factors examined included the determinants of actual use and behavioral intention to use as proposed by Davis (1989) in the TAM. The results of this study showed that the three constructs of perceived ease of use, perceived usefulness, and attitude toward use had a strong correlation to actual use and the behavioral intention to use big data. The implication is that the strong correlation may have something to do with manager and decision maker behavioral intentions and actual use of big data. However, there may be other factors that contributed to these results that were not considered in this study, but other factors can serve as basis for further investigation.

The strongest correlation was between perceived usefulness and a manager or decision makers' actual use or intention to use big data. Questions regarding usefulness addressed quality, productivity, performance, and effectiveness. This strong correlation implies that the value and benefit to the business and the job being performed is considered when adopting a new technology. Managers and decision-makers look for evidence that the investment in big data will improve business performance

(McAfee & Brynjolfsson, 2012). If management finds value in big data, they may be more likely to use it. A strong correlation was also found between attitude toward use and actual use and behavioral intention to use. The implication here was that attitude can determine whether big data is successfully used in an organization. Questions regarding attitude included the benefits and pleasantness associated with the use of big data. Attitude toward use does not address value and benefit as well as usefulness. Although managers may recognize that big data provides factual information and knowledge about trends useful in making decisions, they may still be unwilling to support its use (Esteves & Curto, 2013). As Payne noted (1982), the implementation of every decision carries both benefits and costs. Other factors may contribute to the attitude of managers and decision makers that were not a focus of this study.

While still significant, the construct perceived ease of use showed the lowest correlation between use and intention to use. Survey questions regarding ease of use focused on interaction, frustration, mental effort, clarity, and understandability. While still a factor, managers do not consider ease of use of a technology as highly as usefulness of a technology. In independent t-tests, perceived ease of use was not statistically significant for big data use, gender-based big data use, and IT responsibility. The implications of the results are that perceived ease of use has very little impact on actual use or intention to use big data.

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