Journal of Business Research 108 (2020) 147–162

Contents lists available at ScienceDirect

Journal of Business Research

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

Assessing the impact of big data on firm innovation performance: Big data is not always better data

Maryam Ghasemaghaei*, Goran Calic

DeGroote School of Business, McMaster University, Hamilton, Ontario, Canada

ARTICLE INFO

Keywords:
Big data
Data velocity
Data variety
Data volume
Innovation performance
Firm performance

ABSTRACT

In this study, we explore the impacts of big data's main characteristics (i.e., volume, variety, and velocity) on innovation performance (i.e., innovation efficacy and efficiency), which eventually impacts firm performance (i.e., customer perspective, financial returns, and operational excellence). To address this objective, we collected data from 239 managers and empirically examined the relationships in the proposed model. The results reveal that, while data variety and velocity positively enhance firm innovation performance, data volume has no significant impact. The finding that data volume does not play a critical role in enhancing firm innovation performance contributes novel insights to the literature by contradicting the prevalent belief that *big data is better data*. Moreover, the findings reveal that data velocity plays a more important role in improving firm innovation performance than other big data characteristics.

1. Introduction

In today's complex business world, many firms are investing in big data to find innovative ways to differentiate themselves from their competitors (Côrte-Real, Oliveira, & Ruivo, 2017). Indeed, 87 percent of firms believe big data will change the competitive landscape, and 89 percent believe they will lose considerable market share if they do not adopt big data within the next few years (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016). The extant literature has identified big data as "the next frontier for innovation, competition, and productivity" (Manyika & Roxburgh, 2011, p. 1) and the "next big thing in innovation" (Gobble, 2013). Big data, which is characterized by data variety, velocity, and volume (Ohlhorst, 2012), is capable of changing the innovation landscape by increasing the fit between consumers' preferences and product features (Günther, Mehrizi, Huysman, & Feldberg, 2017; Johnson, Friend, & Lee, 2017). In turn, through innovation, big data may improve firm performance. However, there is still a lack of understanding about the relationships among big data, firm innovation performance, and overall firm performance. The present study investigates this "unknown."

Recent studies have called for a better understanding of the claimed positive relation between big data and innovation success (Gunasekaran et al., 2017; Johnson et al., 2017). Innovation refers to the exploitation of new information to create, accept, and implement new ideas (Calantone, Cavusgil, & Zhao, 2002). According to Alegre, Lapiedra, and Chiva (2006), innovation performance can be decomposed into innovation efficacy and innovation efficiency. Innovation efficacy refers to the extent to which innovation is beneficial to the firm, while innovation efficiency reflects the time and effort required to achieve that degree of benefit (Alegre & Chiva, 2008). Utilizing big data may allow firms to demonstrate efficient and effective firm innovation. Specifically, big data can help firms collect and process market information to better understand consumers' preferences, which can play a critical role in innovation performance. Firms that use big data in their business processes may have a better chance of enhancing their operating efficiency and revenue growth compared to their competitors (Marshall, Mueck, & Shockley, 2015). However, despite these potential benefits, many firms have failed to enhance their innovation performance through the use of big data (Johnson et al., 2017), and others are still unsure whether processing big data is positively associated with their outcomes (Ghasemaghaei, Hassanein, & Turel, 2017; Ghasemaghaei, Ebrahimi, & Hassanein, 2017; Kwon, Lee, & Shin, 2014). A recent report indicates that, in 2016, 48 percent of firms (about 3 percent higher than the previous year) invested in big data utilization. However, in the same year, the number of firms seeking to capitalize on big data utilization decreased by about 6.1 percent (Van der Meulen, 2016). Thus, our first objective is to examine the impact of each big data characteristic (i.e., velocity, volume, and variety) on firm innovation performance (i.e., innovation efficacy and innovation efficiency). In this study, we specifically focus on product innovation, as,

* Corresponding author.
E-mail addresses: ghasemm@mcmaster.ca (M. Ghasemaghaei), calicg@mcmaster.ca (G. Calic).

https://doi.org/10.1016/j.jbusres.2019.09.062
Received 30 April 2019; Received in revised form 23 September 2019; Accepted 24 September 2019
0148-2963/

for most firms, the introduction of new products is the essence of innovation. Additionally, the importance of product innovation in firm success has been supported extensively in the literature (Camisón & Villar-López, 2014).

Improving firm performance is the primary reason firms invest in big data (Akter et al., 2016; Ghasemaghaei, 2018a). Recent studies show that big data has the potential to improve firm performance by, on average, about 5.9 percent (Müller, Fay, & vom Brocke, 2018). However, big data may not lead to better performance directly; in fact, the impact of big data on firm performance could be mediated by intermediate variables (Ghasemaghaei & Calic, 2019b). Specifically, firms' innovation capability is one vital determinant in leveraging new resources, such as big data, for enhanced firm performance (Calantone et al., 2002; Covin, Prescott, & Slevin, 1990; Venkatraman, El Sawy, Pavlou, & Bharadwaj, 2014). Therefore, the second objective of this study is to investigate the mediating role of innovation performance on the relationships between big data characteristics (i.e., velocity, volume, and variety) and firm performance. As recommended by previous studies (e.g., Rai, Patnayakuni, & Seth, 2006; Wu, Straub, & Liang, 2015), organizational performance is measured using various types of performance categories (i.e., financial returns, operational excellence, and customer perspectives).

The present study's attempt to address the above objectives is novel, as most previous studies have focused on anecdotal evidence of the effect of big data on firm innovation performance. The study also has the potential to provide useful insights as there is a lack of understanding about whether big data could, indeed, improve firm performance. To address the above objectives and gaps, we utilize organizational learning theory (Huber, 1991) to develop hypotheses to answer the following research questions: (1) Do big data characteristics (i.e., velocity, volume, and variety) improve firm innovation performance (i.e., innovation efficacy and innovation efficiency)? and (2) Does innovation performance (i.e., innovation efficacy and efficiency) mediate the relationship between big data characteristics and firm performance? Although these questions have not yet been studied, the prevalent belief is that "big data is better data" (Chen, Chiang, & Storey, 2012; McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012; Wang, Kung, & Byrd, 2018). However, in this study, we leverage organizational learning theory to assert that *big data is not always better data*. To address the above questions, we collected data from 239 managers and empirically examined the links in the proposed model.

This paper makes several important contributions to the literature. The findings of this study show the necessity to conceptually and operationally differentiate among the main characteristics of big data, rather than treating big data as a holistic concept. Notably, the results indicate that whereas data velocity and variety play a vital role in enhancing firm innovation performance, data volume does not. Interestingly, the results show that data velocity plays a more important role than other big data characteristics in enhancing firm innovation performance. In addition, this study contributes to the organizational learning literature by analyzing whether big data helps firms generate new ideas successfully and efficiently which lead to enhance the overall performance of the firm. The study also has interesting results for the significance of the impact of innovation efficiency and efficacy on firm performance. Overall, the results of this study offer useful guidelines to help firms comprehend the important role of each main characteristic of big data in improving their outcomes.

In the next section, we review the relevant literature on organizational learning theory and big data. After the literature review, we present our research model and develop our hypotheses. Next, we discuss our sample and methods. In the results section, we examine our research model using structural equation modeling. Because big data, innovation, and firm performance are multivariate constructs, in the post hoc analysis, we examine the effect of each big data characteristic on three measures of firm performance, as mediated by innovation efficiency and innovation effectiveness. In the penultimate section, we discuss the theoretical and practical implications of our findings. Our study presents opportunities for future research, which we also outline in the discussion section. The paper concludes with a reiteration of our main objective and a summary of our findings.

2. Relevant literature

2.1. Organizational learning theory

Organizational learning theory (Huber, 1991) is grounded in the resource-based view (Barney, 1991), which states that a firm's learning ability cannot be easily imitated by other firms (Day, 1994). This theory grew from an interest in how organizations acquire, analyze, and use information to improve firm performance (Argote & Miron-Spektor, 2011). Organizational learning theory suggests that exploration for new information is the basis of firms' innovation capabilities (Johnson et al., 2017), as integrating new information may solve the prototypical strategic problem of finding the most profitable use for a firm's resources by reducing causal ambiguity. Thus, organizational learning theory focuses on firms' need to build a capacity to learn (Sobrero & Schrader, 1998) by integrating and processing new data to gain new insights (Seleim & Khalil, 2007). This theory has been used in various contexts, including data integration and marketing support (Hunter & Perreault, 2007) and firm innovation and customer metrics (Baker & Sinkula, 1999). Innovation is also closely related to organizational learning, because innovation involves the destruction of old knowledge and the integration of new information to generate innovative solutions (Calantone et al., 2002).

Innovation is vital for sustainable competitive advantage (Johannessen, Olsen, & Olaisen, 1999). Innovation is often undertaken in response to unexpected, unfamiliar, or non-routine problems (Anderson, Potočnik, & Zhou, 2014). Thus, innovation involves organizational intelligence and learning, as it requires changing a firm's existing cognitive paradigms (Tushman & Anderson, 1986) and resources (Damanpour & Gopalakrishnan, 2001). In executing innovations, firms must first gather data from various sources and then analyze and interpret the data (Galliers, Newell, Shanks, & Topi, 2017; Glynn, 1996). This is the process of organizational learning (Huber, 1991). In particular, learning is enhanced by gaining greater cognizance of action–outcome relationships and the influence of environmental events on these relationships (Naveh, Meilich, & Marcus, 2006), as firms often try to make rational choices in the face of causal ambiguity (Mosakowski, 1997).

Making rational choices requires a considerable investigation of various available alternatives, their consequences, and their outcomes (Choo, 1996). The sensemaking view argues that firms need to constantly attempt to understand what is happening around them to improve the quality of their decisions (Park, El Sawy, & Fiss, 2017). For instance, firms may face several alternative investment opportunities with unknown outcomes (Gavetti & Levinthal, 2000). To enhance their learning about the outcomes of different investment alternatives, firms must integrate information from internal and external sources (Cohen, 1984). Collecting large amounts of information in real time helps firms learn quickly and precisely what consumers want that other firms do not provide (Fiol & Lyles, 1985), which helps them improve their decisions before competitors corner the market, their resources run out, or consumers' interests change (Janssen, van der Voort, & Wahyudi, 2017).

In line with the above discussion, we assume that firm outcomes are stochastic: that is, they lie somewhere between deterministic and random trial and error (Mosakowski, 1997). While early research on the resource-based view has focused on the role of blind luck in determining how firms acquire and develop unique, inimitable, non-substitutable, and valuable resources (Barney, 1986; Nelson & Winter, 1982), more recent conceptualizations have focused on the innovation process as inherently stochastic (Powell, Lovallo, & Caringal, 2006).

Conceptualizations of firm outcomes as stochastic could be rooted in previous studies' claims that, as information improves, ambiguity declines (Daft & Lengel, 1986). Following from this assumption, decision-makers pursuing innovation experience ambiguity surrounding cause–effect relationships, but can, given sufficiently rich information, identify organizational attributes or develop resources that are more likely to improve firm performance. Therefore, to enhance organizational learning in the innovation process, improved use of existing information and more active assimilation and acquisition of new information become imperative (Johannessen et al., 1999).

2.2. Big data, organizational learning, and firm performance

If the exploration of new information is the basis for organizational learning, then big data presents an enormous opportunity for firms to learn and, consequently, enhance their performance (Jones, 2018). In the era of big data, previous studies have considered data to be a vital firm resource for innovation (Ghasemaghaei, 2018a, 2018b). With a large amount of available data and advanced technologies to process them, firms can quickly exploit new information to create and implement new ideas (Ghasemaghaei, 2018b, 2019a; Sivarajah, Kamal, Irani, & Weerakkody, 2017). Organizational learning through big data can be considered a constant, disruptive blend of abduction, deduction, and induction to identify patterns and link them to potential remedial actions. Big data has raised debates concerning the necessity of analyzing and interpreting raw data to benefit from the integration of large volumes of data. In fact, big data may enhance organizational learning, as it can provide interesting and surprising glimpses into areas outside what firms currently know (Calvard, 2016).

Big data has potential usefulness in various consumer areas that can enhance innovation, such as purchase behavior, problem recognition, and consumption (Wang & Hajli, 2017). In fact, big data has changed the capabilities firms need to successfully perform (Lehrer, Wieneke, vom Brocke, Jung, & Seidel, 2018). Yang, Li, and Delios (2015) argued that firms that are able to absorb new data are more likely to succeed. Particularly, firms that are capable of using big data in their business processes may have a better chance of enhancing their operating efficiency and revenue growth than their competitors (Marshall et al., 2015). Hence, big data represents a new form of capital in enhancing firm innovation performance (Satell, 2014). Still, big data is a new resource and, as such, may not yet be successfully optimized by many firms (Mithas, Lee, Earley, Murugesan, & Djavanshir, 2013). This study leverages organizational learning theory to investigate whether big data has a positive impact on firm innovation performance and, consequently, firm performance.

Whereas some studies argue for the existence of a positive relationship between big data and firm performance (Chen, Preston, & Swink, 2015; Wamba et al., 2017), other studies suggest the use of big data may not lead to improved firm performance (Ghasemaghaei, Hassanein, et al., 2017; Ghasemaghaei, Ebrahimi, et al., 2017). Therefore, some factors could exist that facilitate, or stymie, the relationship between big data and performance. One such factor is the organization's capacity to learn about and adapt to its environment. According to organizational learning theory, an organization searches for and collects information in order to learn about and adapt to its surroundings through the process of innovation in business model and internal processes. Through this process an organization's fitness, and therefore performance, is improved within a particular niche or context. Therefore, this study uses organizational learning literature to investigate the mediating role of firm innovation performance (i.e., innovation efficacy, and innovation efficiency) on the impact of big data on firm performance. The lack of clear results in previous work could be explained by a variety of performance measures. As opposed to many previous studies (e.g., Akter et al., 2016; Gunasekaran et al., 2017), this study considers various types of performance categories (i.e., financial returns, operational excellence, and customer perspectives) to measure the overall performance of the firm. Although previous work shows that there are various measures of big data, most studies have considered this variable as a holistic concept. However, in the current study, we conceptually and operationally differentiate among the main characteristics of big data, rather than treating it as a holistic concept. Table 1 presents previous studies that investigated the role of big data on firm performance.

3. Hypotheses development

The research model is shown in Fig. 1 which maps the hypothesized associations among big data characteristics (i.e., velocity, volume, and variety), innovation performance (i.e., innovation efficacy and innovation efficiency), and firm performance (i.e., financial returns, operational excellence, and customer perspectives). Table 2 presents the definitions of the model constructs.

Table 1
Summary of studies examined the impact of big data on firm performance.

Studies	Purpose
Akter et al. (2016)	This study uses resource-based theory to examine the impact of big data capability on firm performance.
Wamba et al. (2017)	This study utilizes the resource-based view and the literature on big data analytics to examine the mediating effects of process-oriented dynamic capabilities on the relationship between big data analytics capability and firm performance.
Chen et al. (2015)	This study investigates the mediating role of big data analytics on the impact of technological, environmental, and organizational factors on firm asset productivity and business growth.
Gunasekaran et al. (2017)	This study uses the resource-based view to investigate the impact of big data assimilation on supply chain and organizational performance.
Ren, Fosso Wamba, Akter, Dubey, and Childe (2017)	This study draws on the resource-based theory and the information systems success literature to examine the impact of big data system quality and information quality on big data value creation and firm performance.
Ghasemaghaei (2018a)	This study utilizes the resource-based view to examine the moderating impact of tools sophistication and employee analytical skills on the impact of big data on firm performance.
Popovič, Hackney, Tassabehji, and Castelli (2018)	This study uses the resource-based view to explore the moderating role of organizational readiness and big data capabilities on the impact of big data implementation on firm agility and its manufacturing performance.
Côrte-Real et al. (2017)	This study uses knowledge-based view and dynamic capability theories to examine the big data value in different stages of the value chain.
Müller et al. (2018)	This study examines the relationship between big data and firm productivity. It also investigates the impact of firm industry on enhancing firm productivity through big data analytics.
El-Kassar and Singh (2019)	This study examines the mediating role of green products and green process on the impact of big data utilization on firm performance and its competitive advantage.
Raguseo and Vitari (2018)	This study investigates the mediating role of customer satisfaction and market performance on the impact of big data on firm financial performance.

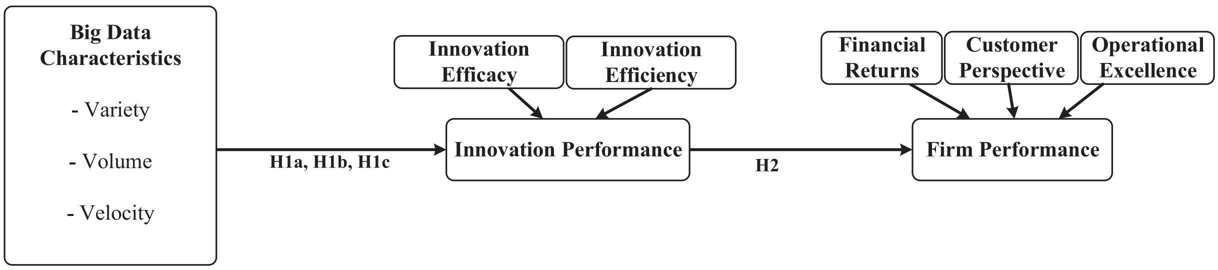

Fig. 1. Research model.

Table 2
Construct definitions.

	Construct	Definition
Big Data Characteristics	Variety	Various types of data (Ghasemaghaei, Ebrahimi, et al., 2017)
	Volume	Size of the data which is increasing dramatically (Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015).
	Velocity	The speed and the frequency of processing and integrating data (Ghasemaghaei, Ebrahimi, et al., 2017)
Innovation Performance		*Innovation Efficacy:* the extent to which an innovation is successful (Alegre & Chiva, 2008).
		Innovation Efficiency: the time and effort made to achieve the degree of success (Alegre & Chiva, 2008).
Firm Performance		*Financial Returns:* firm performance in terms of return on equity, return on assets, and return on investment (Wu et al., 2015).
		Customer Perspective: customer view of a firm's services and products, how they perceive the firm image, and their overall satisfaction level (Wu et al., 2015).
		Operational Excellence: firm's improvements in productivity and its responsiveness to customers relative to its competition (Wu et al., 2015).

3.1. Big data and innovation

Big data is capable of changing the innovation landscape by effectively and efficiently increasing the fit between consumer preferences and product features (Johnson et al., 2017). Organizational learning theory suggests that firms can build their learning capabilities (Sobrero & Schrader, 1998) by processing new data to create more accurate models of the causality between strategic choices and firm performance. In the context of this study, big data can enhance innovation performance by making it possible for firms to develop and deploy resources in an efficient and effective manner based on finely tuned data (Erevelles, Fukawa, & Swayne, 2016); these decisions are replacing laboratory-based consumer research and intuition (Erevelles et al., 2016).

Organizational learning theory suggests that firm performance will increase as firms learn about and adapt to their environments (Huber, 1991). Organizational learning begins with a search for information, which can be passive or it can be active. Active search involves the deliberate accumulation of information. Examples include firms collecting consumer data from point-of-sale terminals or running focus groups. Passive search includes everyday accumulation of tacit and explicit information by employees, such as executives reading the newspaper or employees learning about more efficient ways to get their job completed. While search is necessary for organizational learning to occur, modifications to the organization are required before the organization has learned (March, 1991). For instance, it is not enough that the executive has acquired new information from the newspaper; she must act on this information. Similarly, it is not sufficient that an employee has learned of a more effective method for performing his job, he must modify his work routines in order for organizational learning to have occurred. In all cases, learning can only occur when new information has resulted in changes or adaptations to the ways the organization does things (March & Simon, 1958). According to organizational learning theory, organizational innovations are adaptations based on new information. Thus, we expect that big data will increase innovation, and thus organizational learning, by providing managers with a high variety of voluminous data in a timely manner.

Big data is characterized by the so-called "3Vs:" variety, velocity, and volume, where variety refers to the types of data being analyzed, velocity refers to the speed and frequency of data processing and integration, and volume refers to the size of the data (Ghasemaghaei, Ebrahimi, et al., 2017). Having access to a variety of data provides firms rich information, helping them gain comprehensive views of customers that far surpass firms' traditionally siloed internal data (Erevelles et al., 2016). The main difference between traditional data and big data is the shift from structured transactional data to unstructured behavioral data (Insight, 2012). Modern firms are attempting to access unstructured data (which encompasses about 80% of existing data) about their customers to better understand consumer needs and preferences (Tan, Zhan, Ji, Ye, & Chang, 2015). Unstructured data can be captured from different sources, such as text messages, blogs, and social media, through which individuals share their behavioral and personal information with others in the online environment. With the development of new technologies, firms are attempting to integrate data from various sources (e.g., social media, pictures) to better understand consumers' preferences.

In particular, different cues (e.g., both unstructured and structured data) can be used as a proxy to examine the effectiveness of information in enhancing firm's learning in a particular context (e.g., generating new ideas) (Jiang & Benbasat, 2007). Collecting different types of data (e.g., images, texts, numbers) increases a firm's chance of discovering non-obvious and new customer insights (Dong, Liao, & Zhang, 2018), which, in turn, increase a firm's capabilities to continuously improve its product offerings (Johnson et al., 2017). Erevelles et al. (2016) argued that having access to rich customer data helps firms generate previously unknown insights, which may enable them to better understand their customers. For example, firms that extract consumers' comments about their products on social media websites and combine these with consumers' purchasing histories can better identify consumers' preferences, which may help them develop new products that match their needs. Therefore, the integration of new information enhances firms' generation of new knowledge and ideas (Calantone et al., 2002). Information variety allows firms to learn more and better. In particular, having access to different types of customer data helps firms better understand customer needs and develop novel solutions. This, in turn, enables firms to take advantage of new market opportunities and develop the resources needed to exploit those opportunities. In fact, handling both structured and unstructured data helps firms view innovation problems from different perspectives (Johnson et al., 2017), which enables them to develop new ideas better and faster to satisfy their customers' needs. Hence:

H1a: *Data variety will increase innovation performance.*

Firms once made decisions using small data sets with limited analytics platforms. However, recent changes in information technologies have enabled firms to analyze large sizes of data to make better decisions (Xu, Frankwick, & Ramirez, 2016). For example, Netflix analyzes data from millions of consumers to better understand whether adding a new show will improve the firm's performance. The insights generated from such enormous amounts of information are the main attraction of big data (Dumbill, 2012). Today, the Internet stores more data each second than it stored in its entirety 20 years ago (Hofacker, Malthouse, & Sultan, 2016): While the world created only 800,000 petabytes of data in the year 2000, it is expected to generate 35 zettabytes in the year 2020 (IBM, 2015). Together, better storage solutions (e.g., Hadoop), decreasing storage costs, and the availability of algorithms that create meaning from data allow firms to extract more benefit from large volumes of data (Johnson et al., 2017). In the past, gaining benefits from such large caches of data was difficult, as processing such data inhibited effective interpretation. However, advanced technologies and frameworks have helped firms reduce these issues. For example, Hadoop, a popular open source framework, enables parallel processing, allowing for rapid access to and analysis of huge volumes of data (Lam, 2010). As a second example, MapReduce enhances data interpretation by performing filtering and sorting using a reduce method.

Processing large amounts of data offers firms a more complete and comprehensive sense of their market, thus increasing their capacity to understand customers' needs and capitalize on unexplored opportunities (Du & Kamakura, 2012). Particularly, surging volumes of data in single data sets, combined with the aforementioned parallel processing technologies, enable firms to obtain in-depth information about their customers (e.g., where they purchase, what they like, and what they purchase) by creating coherent pictures of specific problem and, thus, generating better insights into the issue being analyzed (Tan et al., 2015). This knowledge creation process improves a firm's capacity to generate innovation by reducing ambiguity about, for instance, what consumers like and where they are likely to purchase it. Having access to large amounts of relevant data about consumers' behavior helps firms identify the products that could meet future market needs. Erevelles et al. (2016) argued that, in general, understanding customers better by processing large volumes of data about their behaviors can lead to incremental innovation. For example, to begin its own revolution in product design and innovation, Ford Motors started to collect consumer data from approximately four million of its on-the-road vehicles through built-in vehicle sensors. After analyzing the data captured from the vehicles' voice recognition systems, Ford understood that the immediate surrounding noise interfered with the software's capability to recognize driver commands, which led to the development of automatic noise reduction technology. In this example, Ford facilitated product innovation by capturing large volumes of data about its customers without waiting to obtain insights from traditional marketing research, such as surveys and focus groups (Erevelles et al., 2016). Rindfleisch, O'Hern, and Sachdev (2017) argued that processing large amounts of data in this manner allows firms to increase their innovation activities by enabling them to more effectively analyze and generate insights from data on consumer behavior.

In line with the above advantages of big data, many firms are conducting search analytics, web analytics, and search engine optimization to obtain customized and automated knowledge about their customers (Xu et al., 2016). This combined volume of customer data from various sources generates a high level of insight into customers' needs and preferences (Jaakola, 2013). For example, many firms try to obtain additional insights about their customers by extracting customers' product evaluations and recommendations to others to determine appropriate new product strategies. With the help of the recent technological advancements, firms can parse data from several sources (e.g., user-generated data, sensors) to better understand their customers and customize their offers (Hu, Wen, Chua, & Li, 2014). McAfee (2013) argued that these advances improve on prior decision-making processes, which were often based on "gut feelings" or intuition rather than evidence. Therefore, big data utilization enables firms to establish data-driven and evidence-based decision-making processes (Schermann et al., 2014), which may enhance their innovation performance by helping them better understand consumers' preferences and develop new ideas accordingly. Hence:

H1b: *Data volume will increase innovation performance.*

Data velocity focuses on the relentless rapidity of data generation, which enables firms to provide timely insights (Lycett, 2013). By integrating data in real time, firms can use the analytics that accompany streaming data to take action in a timely manner (Saboo, Kumar, & Park, 2016). Firms can make better decisions when they have access to current and insightful data based on up-to-the-minute evidence rather than historical trends (Erevelles et al., 2016). Due to the path-dependent nature of cause-and-effect relationships, historical data have limited usefulness in illuminating the current and future causal structure of choices that determine firm success, particularly for choices concerned with generating and implementing entirely new ways of doing things. For example, firms are attempting to understand consumers' transaction numbers, the products they purchase, the types of products they purchase, and their product postings on social media in a timely manner. Such rich data enable firms to make instantaneous evidence-based decisions regarding appropriate new product strategies (Erevelles et al., 2016).

To make appropriate decisions, firms must develop continuous processes for analyzing and interpreting data in real time to quickly generate new insights (Davenport, Barth, & Bean, 2012). For example, based on insights obtained from the customers' comments on social media, firms can make personalized offers in milliseconds and optimize their offers over time as they receive new data. Recently, many firms have also started to gather data from mobile devices, such as location collected from a navigation app, to create real-time personalized offers for their customers.

If firms do not make decisions in real time, new data will obviate previous data. Therefore, firms need to integrate, analyze, and act quickly (Davenport et al., 2012). Research shows that a firm's ability to innovate depends on real-time insights (Banu Goktan & Miles, 2011). To maximize their benefit, firms need to quickly utilize customer insights obtained from integrating and analyzing big data to constantly redefine their marketing activities and implement effective and efficient innovation (Erevelles et al., 2016). Real-time data can help firms quickly develop new ideas and convert them into innovative products before their competitors (Erevelles et al., 2016). Hence:

H1c: *Data velocity will increase innovation performance.*

3.2. Innovation and performance

Innovation, which refers to successfully exploiting new knowledge, has previously been linked to firm performance (Amabile, Conti, Coon, Lazenby, & Herron, 1996). Innovation is the process of manufacturing, management, commercial activities, R&D, and technical design involved in the marketing of an improved (or new) product (Alegre & Chiva, 2008). Innovation performance can be characterized by two dimensions: innovation efficiency and innovation efficacy (Alegre & Chiva, 2008). As time-based competition has become increasingly important, many firms have recognized the importance of introducing new products and services in a timely manner (Smith, 2011).

Previous studies suggest that there is a positive relationship between innovation performance and firm performance (Calantone et al., 2002; Yalcinkaya, Calantone, & Griffith, 2007). According to Geroski, Machin, and Van Reenen (1993), innovation is a critical factor for firm performance, as innovating firms are better able to benefit from spillovers and are less affected by negative macroeconomic events. According to organizational learning theory, this benefit is associated with the transformation or redeployment of a firm's internal resources as a result of adaptation to new information about the environment (Huber, 1991). For example, new product introductions increase firm performance by enhancing profit margins, increasing demand, and lowering customer acquisition and retention costs (Yalcinkaya et al., 2007). Moreover, firms that implement new ideas will be more successful in developing new capabilities and responding to customers' needs, allowing them to achieve superior profitability and firm performance (Calantone et al., 2002). Robinson (1990) stated that firms that enhance their innovation performance by improving their learning capabilities could increase their market share. In particular, firms that enhance their innovation faster than their competitors are able to increase their operational efficiency and improve their service quality by obtaining knowledge not available to competitors (Parasuraman, 2010).

According to organizational learning theory, firm capabilities (e.g., innovation performance) mediate the impact of firm resources (e.g., big data) on firm performance. As the exploration of new data is the basis for increasing a firm's learning capabilities (Jones, 2018), big data may play a critical role in providing firms enormous opportunity to learn, enhance their innovation competency, and, eventually, increase their performance. Hence:

H2: *Innovation performance will mediate the impact of big data on firm performance.*

4. Methodology

4.1. Sample

To test the research hypotheses, we employed a survey approach to collect data from top- and middle-level managers because participants needed to have adequate knowledge to answer questions about the impact of big data on firm outcomes. To control for the potential impact of culture, the nature of the position, and tasks, survey participants were limited to managers in the United States. With the help of a national market research firm, which helps researchers obtain the views of panel specialists, the survey was sent through email to 1286 individuals during two months of April and May 2018. Using market research firm to collect data has many advantages specially generalizability (Lowry, D'Arcy, Hammer, & Moody, 2016).

To ensure that participants were sufficiently knowledgeable to answer questions related to the effects of big data on firm outcomes, we asked them about the extent of their awareness with big data utilization in their firms. Those participants who were unfamiliar were excluded from the dataset. This approach has been used in many studies (e.g., Abbasi, Sarker, & Chiang, 2016; Akter et al., 2016; Ghasemaghaei & Calic, 2019a, 2019b; Sun, 2012). Moreover, we removed responses that (1) were completed in less than 10 min (since the survey was estimated to take about 20 to 25 min), (2) were incomplete, (3) were terminated at the beginning of the survey, or (4) had the same answer to all questions (e.g., all 6 s). In total, we received 239 usable responses, representing a response rate of 19 percent. Table 3 presents the demographic characteristics of the sample. We examined non-response bias by following Armstrong and Overton (1977) guideline. The results showed that the early respondents were quite similar to the later respondents in terms of key study variables and demographic characteristics; hence, for this study, non-response bias was not an issue.

Table 3
Sample characteristics.

Dimension	Category	Percentage (%)
Age	20–29 years old	17.6
	30–39 years old	39.7
	40–49 years old	20.1
	50–59 years old	13.8
	> 60	8.8
Gender	Female	51.9
	Male	48.1
Role	Executive Manager	20.1
	Vice President	10.1
	Middle Level Manager	53.1
	Business unit/department Manager	16.7
Education	High School	10.5
	College diploma	21.3
	Bachelor's degree	39.3
	Master's degree	26.4
	Ph.D. degree	2.5
Firm Size	< 100 employees	31.0
	100–1000 employees	38.9
	1001–5000 employees	19.2
	> 5000 employees	10.9
Industry Type	Manufacturing	33.4
	Services	50.2
	Utilities	13.5
	Financial	2.9
Firm Revenue	< 1 million	10.5
	1–5 million	15.9
	5–10 million	17.6
	10–20 million	11.7
	20–50 million	13.0
	50–500 million	19.7
	500-1billion	4.2
	> 1 billion	7.4

4.2. Measures

Previously validated scales (see Appendix A) were used for all the constructs, whose means and standard deviations are presented in Appendix A (see Table A1). The study considered two control variables. The first was firm size, as larger firms may have access to more resources. This variable was measured as the number of employees in each firm (Chen et al., 2014). The second was firm industry, as the utilization of big data could differ by industry.

5. Results

Structural equation modeling, specifically partial least squares (PLS) version 3.0 (Ringle, Wende, & Will, 2005) was used to examine the developed hypotheses. As explained below, we first assessed the validity and reliability of the instrument.

5.1. Test of the measurement model

To evaluate the measurement model, we examined the convergent and discriminant validity and internal consistency. Appendix B shows that all the loadings were larger than the recommended threshold of 0.70 (Gefen & Straub, 2005). As also shown in Table B1, all variables showed high reliability (Fornell & Larcker, 1981). Table 4 shows the correlations among the variables, with the diagonal values representing the square roots of the variables' average variance extracted (AVE). As

Table 4
Correlation matrix.

	Effica	Effici	P-Cu	P-Fi	P-Op	Var	Vel	Vol
Innovation Efficacy	**0.75**							
Innovation Efficiency	0.69	**0.81**						
Customer Perspective	0.55	0.51	**0.84**					
Financial Returns	0.58	0.51	0.58	**0.86**				
Operational Excellence	0.57	0.53	0.68	0.65	**0.86**			
Data Variety	0.52	0.44	0.47	0.49	0.48	**0.86**		
Data Velocity	0.55	0.53	0.51	0.55	0.58	0.64	**0.87**	
Data Volume	0.41	0.31	0.34	0.42	0.39	0.65	0.57	**0.87**

Note: Var: data variety; Vel: data velocity; Vol: data volume; P-Cu: customer perspective; P-Fi: financial returns; P-Op: operational excellence; Effica: innovation efficacy; Effici: innovation efficiency.

shown in this table, the correlations between each factor and other factors were lower than the square root of the AVE, showing discriminant validity (Barclay, Higgins, & Thompson, 1995).

To examine the measurement properties of the second-order formative constructs (i.e., innovation performance and firm performance), we used Bagozzi and Fornell (1982) guideline. First, we used weights to multiply item values. Then, we summed the item values for each first-order construct. Next, we used the weighted sum of the first-order constructs to create composite indices, which were used as the measures for innovation performance and firm performance. The variance inflation factor (VIF) values of both these second-order constructs were below the threshold of 3.3, showing that multicollinearity was not a concern for these constructs (Diamantopoulos & Siguaw, 2006).

As recommended by Gefen and Straub (2005), to further ensure the validity of the second-order variables, we evaluated the outer model loadings and their weights. The findings indicated that the outer model weights of innovation efficacy and innovation efficiency (0.124 and 0.127, respectively) significantly impacted innovation performance, indicating the importance of both efficacy and efficiency in forming innovation performance. In addition, the outer model weights of customer perspective, financial returns, and operational excellence (0.144, 0.14, and 0.153, respectively) significantly impacted firm performance, showing the importance of all these variables in determining firm performance.

The findings also suggested that the outer model loadings for both innovation efficacy and efficiency were significant (0.72 and 0.75, respectively) at the 0.05 alpha level. The results show that the loadings are higher than the threshold of 0.70, indicating that each variable is important in forming firm innovation performance (Dwivedi, Choudrie, & Brinkman, 2006). The findings also illustrated that the outer model loadings for customer perspective, financial returns, and operational excellence were significant (0.75, 0.73, 0.80, respectively) at the 0.05 alpha level, indicating the importance of each of these variables in determining firm performance.

To examine common method bias, this study conducted Harman's single-factor test (Podsakoff, 2003), which has been recommended by previous studies (e.g., Luo, Ba, & Zhang, 2012; Sun, 2012). The unrotated solution showed several factors, none of which explained more than 50 percent of the variance. Common method bias may exist if (1) one factor accounts for most of the covariance in the variables or (2) one factor emerges from the unrotated solution. The findings showed neither of these scenarios. We also conducted the marker-variable technique (Lindell & Whitney, 2001) suggested by previous studies (e.g., Malhotra, Kim, & Patil, 2006; Xu, Benbasat, & Cenfetelli, 2014). This technique recommends using a theoretically unrelated construct (a marker variable) to adjust the associations among the main constructs in the research model. We use gender, a theoretically irrelevant construct, as our marker variable. The findings show that the average correlation between the main constructs and gender was 0.03. Hence, the findings of both Harman's single-factor test and the marker-variable technique suggest minimal evidence of common method bias.

We also conducted a full collinearity test by measuring the VIF values for all the constructs in the model. The highest VIF value was that for data volume (2.47), indicating that the VIF values for all constructs in the research model were below the threshold of 3.3 (Kock & Lynn, 2012). Considering the VIF values of all constructs in the model and calculating the full collinearity test is a conservative and effective alternative for identifying common method bias (Kock, 2015). Based on the findings, neither multicollinearity nor common method bias is an issue in our study.

5.2. Test of the structural model

Fig. 2 presents the significance of the relationships in the research model. As shown in Fig. 2, the results indicate that whereas data variety and data velocity significantly impact innovation performance ($\beta = 0.283$, $p < 0.001$; $\beta = 0.417$, $p < 0.001$, respectively), providing support for H1a and H1c, interestingly, data volume does not significantly impact innovation performance ($\beta = -0.033$, $p > 0.05$), rejecting H1b. The results also show that innovation performance significantly impacts firm performance ($\beta = 0.657$; $p < 0.001$). We also assessed whether the effects of the big data characteristics on firm

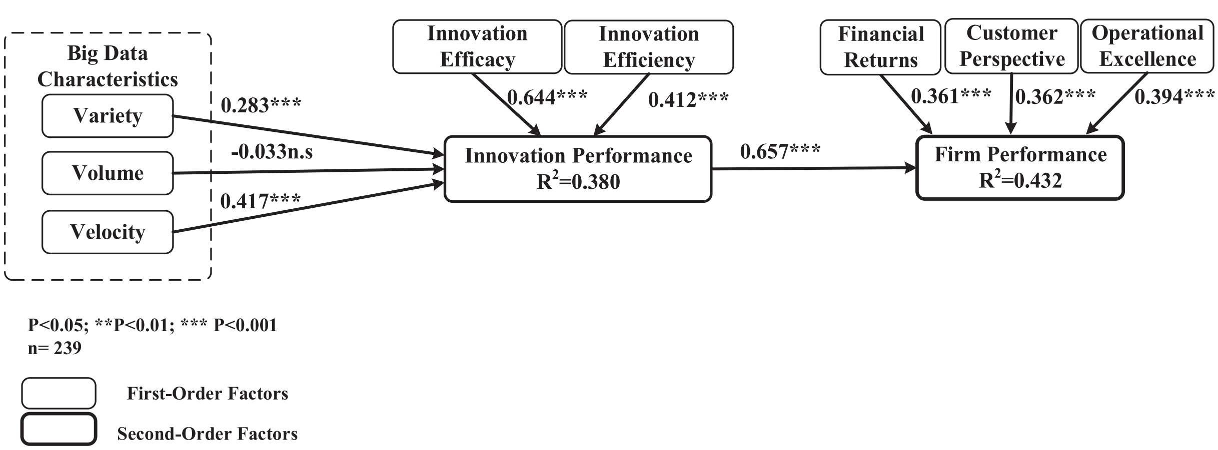

Fig. 2. Results of research model.

performance were fully or partially mediated by innovation performance. To test for mediation, we followed the procedure suggested by Baron and Kenny (1986). First, we tested the direct influence of big data characteristics on firm performance in the absence of the potential mediator. The results indicated that, while the paths from data variety and data velocity were significant ($\beta = 0.236$, $p < 0.01$ and $\beta = 0.463$, $p < 0.001$, respectively), the path from data volume was not ($\beta = 0.016$, $p > 0.05$). Then, we added innovation performance as a mediator between big data characteristics and firm performance. The results showed that, while the impact of data variety on firm performance was no longer significant, with a coefficient of 0.119 ($p > 0.05$), the impact of data velocity on firm performance was still significant, with a coefficient of 0.290 ($p < 0.01$). Moreover, the impact of data volume was still not significant ($\beta = 0.030$, $p > 0.05$). These results show that, while firm innovation fully mediates the relationship between data variety and firm performance, it only partially mediates the impact of data velocity on firm performance. Interestingly, data volume impacts neither firm innovation nor firm performance. These findings provide support for H2 regarding the mediating role of innovation competency on the impact of big data on firm performance. As Fig. 2 illustrates, big data utilization explains about 38% of the variance in innovation performance, and innovation performance explains about 43% of the variance in firm performance.

We also measured the effect size (Chin, 2010) to better understand the effect of each big data characteristic on innovation performance. The findings demonstrated that the effect size of data volume on innovation performance was zero, the effect size of data variety was small (0.058), and the effect size of data velocity was medium (0.151). This means that, compared to data variety and data volume, data velocity plays a more vital role in enhancing firm innovation performance.

We further examined the impacts of firm size and firm industry (as control variables) on firm performance, which were coded as dummy variables using the categories shown in Table 3. The findings indicated that firm industry and firm size did not significantly impact firm performance ($\beta = -0.029$, $p > 0.05$; $\beta = -0.078$, $p > 0.05$).

6. Post hoc analyses

To investigate the direct impact of big data characteristics on innovation efficacy and efficiency separately, a post hoc analysis was performed. As can be seen in Fig. 3, the findings show that, while data variety and data velocity have a significant positive impact on innovation efficacy ($\beta = 0.291$, $p < 0.001$; $\beta = 0.366$, $p < 0.001$, respectively), the impact of data volume on innovation efficacy is not significant ($\beta = 0.010$, $p > 0.05$). This means that, while utilizing different types of data in real time helps firms innovate successfully, the size of the data does not play a vital role. Likewise, the results show that, while data velocity and data variety have significant positive impacts on innovation efficiency ($\beta = 0.441$, $p < 0.001$; $\beta = 0.228$, $p < 0.01$, respectively), the impact of data volume is not significant ($\beta = -0.087$, $p > 0.05$). This means that, while utilizing different types of data in real time considerably reduces a firm's effort in attaining successful innovation, utilizing large sizes of data does not improve firm efficiency.

As shown in Fig. 3, the results also show that innovation efficacy significantly impacts a firm's customer perspective, financial returns, and operational excellence ($\beta = 0.384$, $p < 0.001$; $\beta = 0.473$, $p < 0.001$; $\beta = 0.400$, $p < 0.001$, respectively). Moreover, whereas innovation efficiency significantly impacts customer perspective and operational excellence ($\beta = 0.228$, $p < 0.05$; $\beta = 0.234$, $p < 0.05$, respectively), it does not significantly impact financial returns ($\beta = 0.162$, $p > 0.05$). This shows that successful firm innovation considerably improves firm performance; however, although decreasing the time to develop new ideas considerably improves consumers' perspectives and operational excellence, it does not increase a firm's financial returns.

We followed Ghasemaghaei, Hassanein, et al. (2017)'s procedure to further investigate the role of big data in innovation performance and firm performance. To accomplish this, we used median splits to classify firms based on their level of big data utilization in terms of variety, volume, and velocity. In total, this procedure yielded eight groups (i.e., high or low in degrees of data volume, velocity, and variety). Figs. 4–8 show the differences in means for innovation performance (innovation efficacy and innovation efficiency) and firm performance (customer perspective, financial returns, and operational excellence) when firms utilize data with different levels of volume, velocity, and variety.

As shown in these figures, the results indicate interesting findings regarding the effects of big data on firm performance and firm innovation performance. For example, Fig. 4 shows a significant reduction in the mean of financial returns for firms with low data volume, low data variety, and low data velocity. This means that, compared to other firms, firms that have not been careful to quickly integrate large amounts of various types of data cannot considerably increase their financial returns. Fig. 5 also shows novel findings. For instance, it shows a significant decrease in the mean of positive consumer perspective for firms with high data volume, but low data velocity and variety. This means that, to successfully increase consumer satisfaction, firms need to not only integrate large amounts of data, but also process different

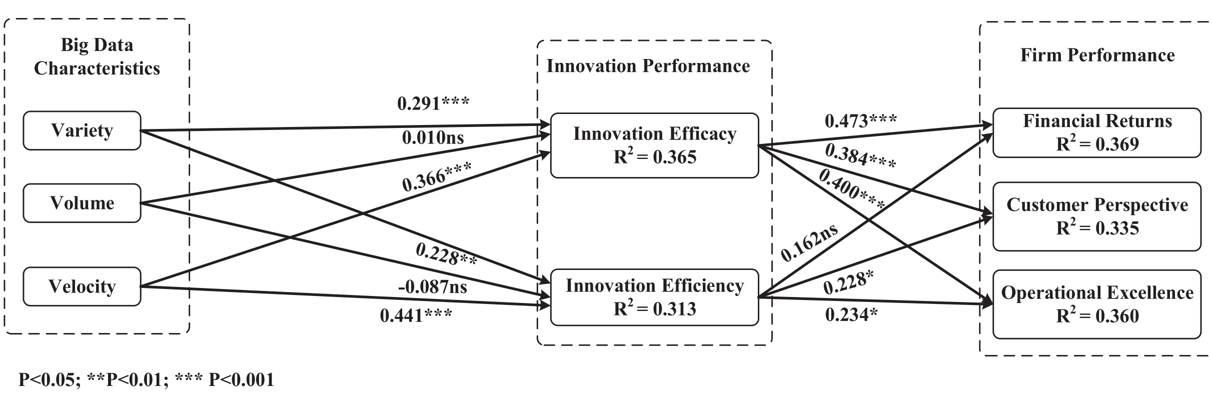

Fig. 3. Research results (considering all variables as first-order constructs).

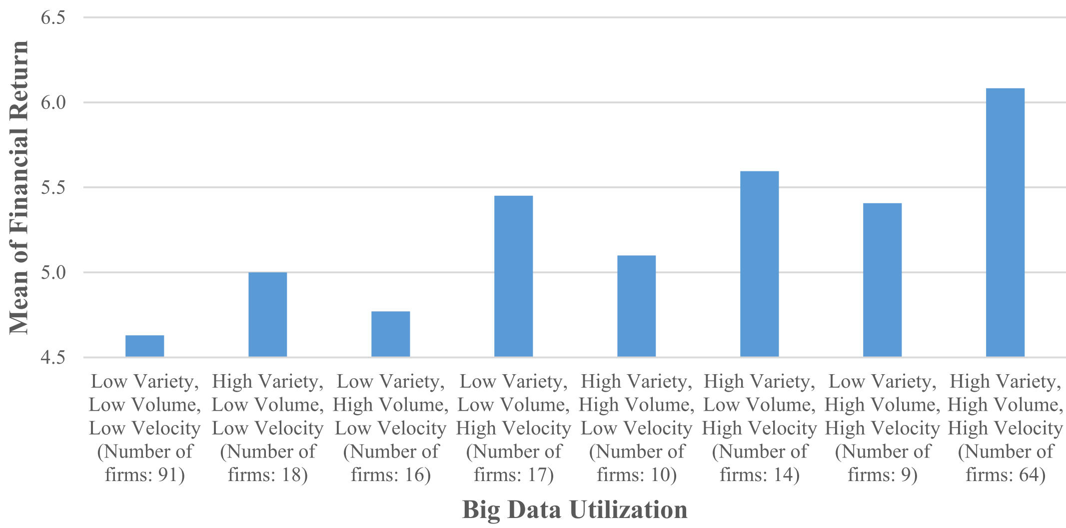

Fig. 4. Financial returns means for different levels of utilizing big data.

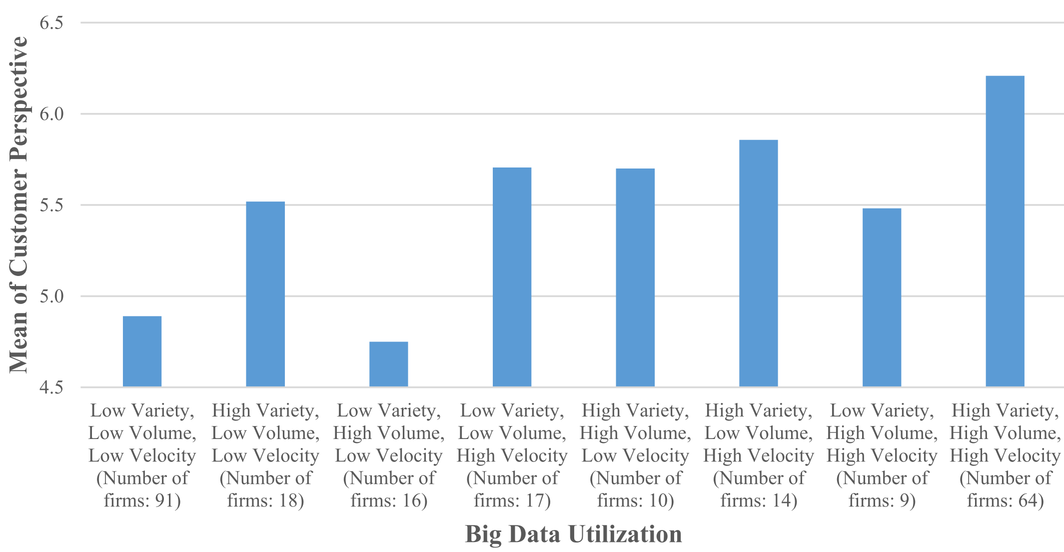

Fig. 5. Customer perspective means for different levels of utilizing big data.

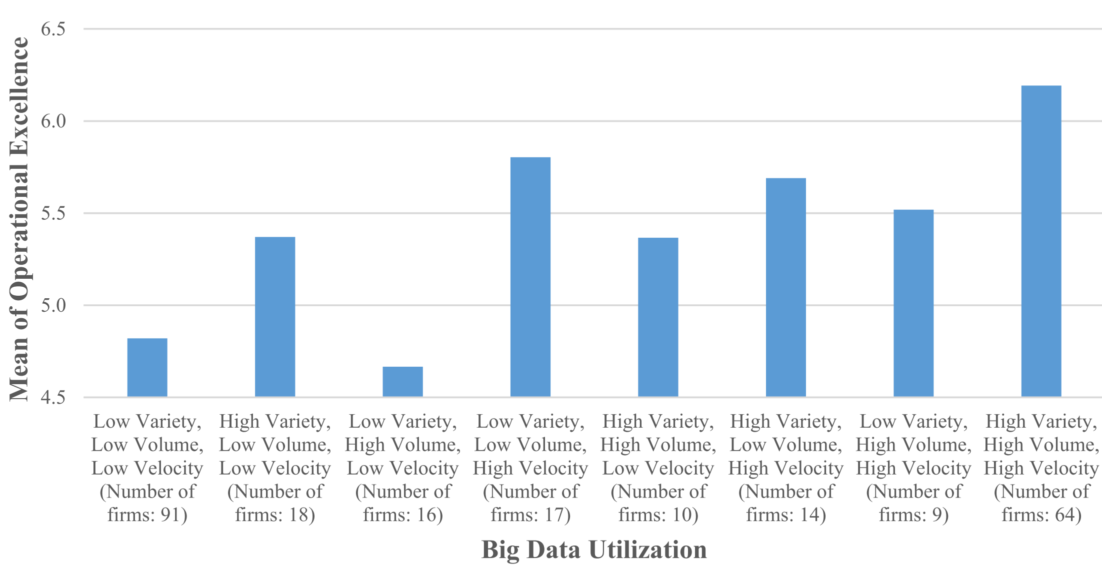

Fig. 6. Operational excellence means for different levels of utilizing big data.

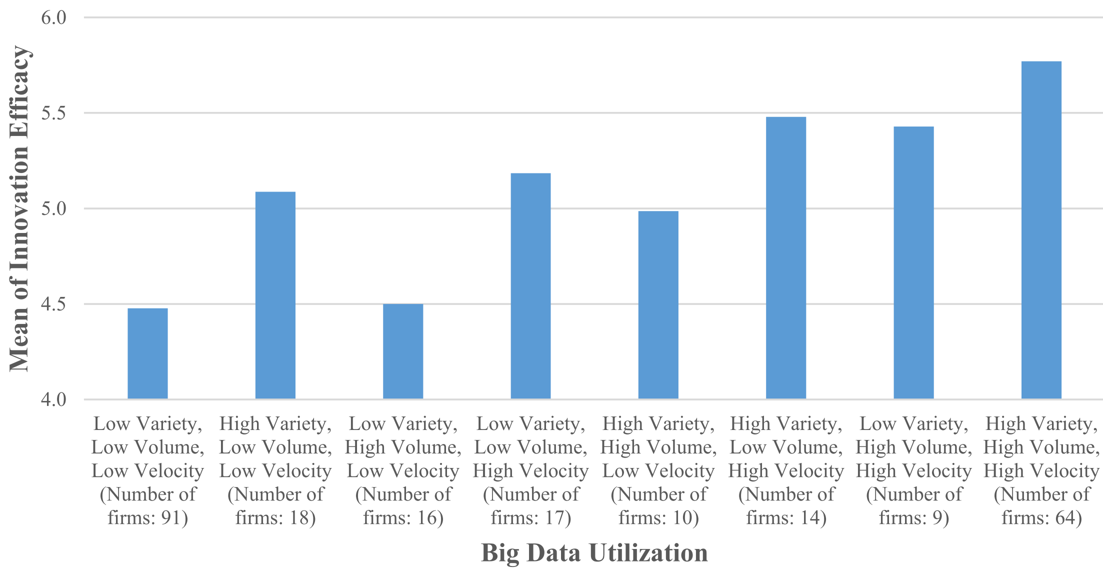

Fig. 7. Innovation efficacy means for different levels of utilizing big data.

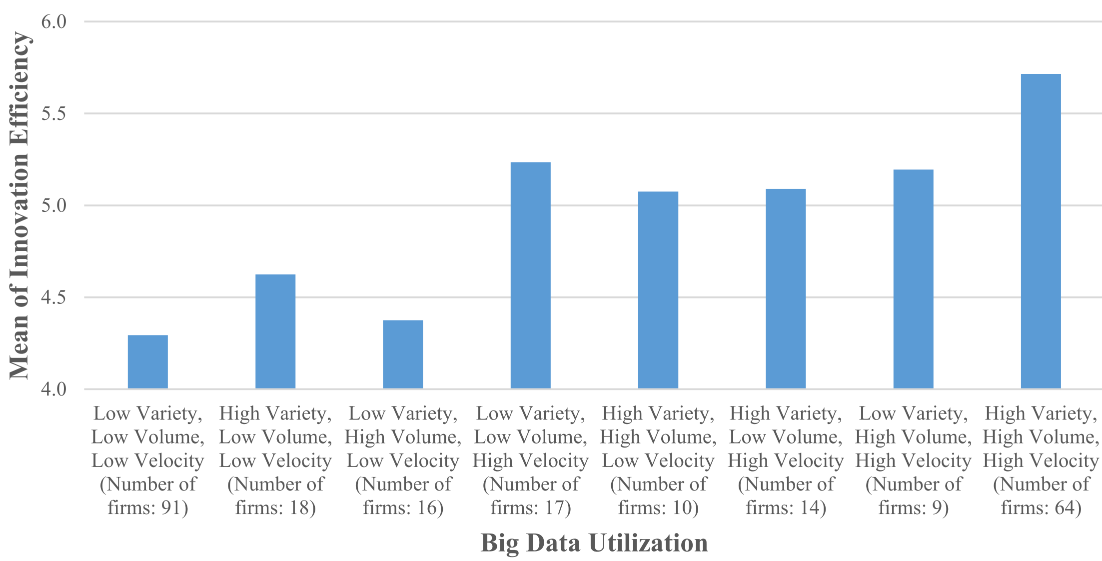

Fig. 8. Innovation efficiency means for different levels of utilizing big data.

types of data (e.g., social media, images, and pictures) in real time. Likewise, Fig. 6 shows a significant decrease in the mean of operational excellence for firms with high data volume, but low data variety and velocity. This means that, to improve productivity relative to competitors, firms need not only to focus on collecting large volumes of data, but also utilize different data formats in a timely manner. Fig. 7 also reveals interesting findings. For example, it shows a significant decrease in the mean of innovation efficacy for firms with low data volume, variety, and velocity, as well as those firms with high data volume, but low data velocity and variety. This means that, to implement new ideas successfully, firms should pay attention to the speed of processing and analyzing different types of data, rather than focusing primarily on collecting huge amounts of data. Fig. 8 also shows an interesting trend. For example, it shows that firms that collect a large amount of data, but do not pay attention to utilizing different data formats in real time, did not considerably decrease their effort in developing new ideas. One of the unique insights presented in these figures is that, when firms process data that are high in volume or variety, but low in velocity, they generally achieve outcomes inferior to those when firms process data that are high in velocity. These findings are in line with results of the effect size calculation, which showed that *data velocity* plays a more critical role than data variety and volume in enhancing firm performance. For example, the findings suggest that velocity has the most important unilateral impact on financial returns, with all categories with high velocity having strictly higher financial performance than those involving low velocity. For the other two categories of firm performance, while high velocity plays an important role in performance, the effect of velocity on performance is not as one-sided. Therefore, if firms wish to enhance their outcomes, but lack sufficient resources to process data high in all three big data characteristics, they should focus first on data velocity.

The figures also show interesting insight regarding the number of firms utilizing each big data characteristic. In particular, we found that most firms still have not started utilizing all three main characteristics of big data. In fact, 91 of the 239 firms processed data that were low in volume, variety, and velocity, while 64 firms processed high degrees of big data. As illustrated in the figures, the remainder of the firms focused on only one or two of the big data characteristics when they processed data. Our results show that firms must process data high in all three big data characteristics to considerably enhance their performance. In sum, while Fig. 3 shows the impact of each big data characteristic on firm innovation performance (and, thus, eventually firm performance), Figs. 4–8 provide interesting insights regarding the effects of big data characteristics on firm outcomes when firms utilize different levels of big data.

7. Discussion

7.1. Theoretical contributions

Many firms are integrating big data to generate new ideas and differentiate themselves from their competitors (Johnson et al., 2017). Big data are capable of changing the innovation landscape by effectively and efficiently increasing the fit between consumers' preferences and product features, which may improve firm performance. Existing research has focused mainly on anecdotal evidence; as such, there is an insufficient understanding of the effects of big data on firms' overall performance and the potential factors that facilitate this relationship. As suggested by previous studies, the effect of big data on firm performance could be mediated by intermediate variables (Ghasemaghaei, 2019b). Innovation capability is one of the important determinants in how well firms leverage new resources, such as big data, to enhance firm performance. However, there is still an incomplete understanding about the relationships among big data, firm innovation performance, and overall firm performance. This is the question we explored in this study. To address this objective, we used data collected from managers and utilized organizational learning theory to better understand the impacts of big data characteristics (i.e., velocity, volume, and variety) on innovation performance, which eventually impacts firm performance.

Our study provides new theoretical insights. As opposed to most studies that have considered big data as a holistic construct, this study shows that each big data main characteristic could have different impacts on firm outcomes, and thus there is a need to conceptually and operationally differentiate among the main characteristics of big data, rather than treating big data as a holistic concept. From an organizational learning perspective, this paper shows that a firm's capability to utilize big data is an important source of innovation. Particularly, the results show that, while data variety and velocity play a critical role in enhancing innovation performance, interestingly, data volume does not. This could be due to the fact that bigger data is *not* always better data (Fan & Bifet, 2013). Collecting large amounts of data that are noisy or not representative of what firms are looking for will not improve firm decision making and, in fact, may degrade it. Thus, although some studies have considered the size of data as the main characteristics of big data (Demchenko, Grosso, De Laat, & Membrey, 2013), one of our main contributions is to show that other big data main characteristics (i.e., variety, and velocity) play more vital roles in enhancing firm innovation performance and consequently firm overall performance. Specifically, the results reveal that, whereas data variety and velocity positively impact both innovation efficacy and efficiency, data volume does not. This is a novel and unique finding in the big data literature that will help researchers better understand the influence of big data characteristics on firm outcomes.

We also make contributions to organizational learning and innovation literature. Our results suggest that organizations do not learn from all types of data equally. When it comes to learning through innovation, a large variety of data acquired in real-time is most useful for organizations to learn. The capacity of organizations to learn from high velocity data can be explained by the value of first-mover advantages in business (Lieberman & Montgomery, 1988). High variety is also beneficial for organizational innovation. Recombination of knowledge and creativity underlie innovation and data with high variety may be especially conducive to devising new ways for organizations to compete (Perry-Smith & Mannucci, 2017). Data volume may present learning disadvantages, as boundedly rational individuals face problems dealing with high quantities of data (Simon & March, 1976). By creating tensions between multiple possible approaches, large volumes of data can result in behavioral defensiveness and cognitive anxiety, which can have deleterious effects of organizational performance (Smith & Lewis, 2011).

The findings of the effect size calculation also provide interesting insights. In particular, the findings indicate that data velocity plays a more critical role than data variety and data volume in enhancing firm innovation performance. In other words, analyzing and interpreting data in real-time to quickly generate new insights plays a more important role in innovating successfully and efficiently than does focusing on integrating large sizes of different types of data. This could be due to the fact that organizational learning is a dynamic process that requires firms to integrate new data continuously in real-time (Argote & Ren, 2012). These results are theoretically important because there is a need to understand the impact of each main characteristic of big data on firm innovation performance (Mu, 2015). Thus, this study contributes to the organizational learning literature by analyzing how a new source of information and its characteristics help firms generate new ideas successfully and efficiently.

This study uncovers interesting findings on the impacts of innovation efficacy and efficiency on firm financial returns, customer perspective, and operational excellence. In particular, both innovation efficacy and efficiency enhance the customer perspective and operational excellence. However, the results show that, while innovation efficacy increases firms' financial returns, innovation efficiency has no significant influence. This means that firms that attempt to reduce their time and effort in implementing new ideas will not improve their returns on investment, assets, or equity more than their competitors.

To further investigate the role of big data in innovation performance and firm performance, we have used median splits to classify firms based on their level of big data utilization. In total, we created eight groups, each offering interesting and novel insights regarding the impacts of utilizing different levels of data in terms of volume, velocity, and variety on innovation performance and firm performance. In particular, the findings show that considering different levels of big data (in terms of volume, variety, and velocity) could lead to different firm outcomes. We believe that this study provides useful guidelines for researchers who are interested in better understanding the impact of big data characteristics on innovation performance and overall firm performance. Future research can use the knowledge obtained from this study as a foundation to examine the influence of big data characteristics on firm outcomes.

7.2. Practical contributions

Our findings indicate that to better understand consumers' needs and preferences firms should collect both unstructured and structured data from different sources, such as previous purchases, social media, and consumer clickstream data from the web. Collecting various types of data helps firms successfully implement new ideas and products that fit consumers' preferences and reduces firms' effort and time in generating new ideas. Advanced technologies enable firms to handle both structured and unstructured data to view innovation problems from different perspectives (Johnson et al., 2017); thus, firms that utilize different varieties of data can successfully innovate by developing appropriate ideas better and faster. Based on the findings, although firms now have access to better storage solutions (e.g., Hadoop) and lower storage costs (Demirkan & Delen, 2013), there are still challenges in managing large volumes of data. Particularly, it is still difficult for existing technologies to analyze high volumes of data and produce useful information in a timely manner. Furthermore, firms may not yet have developed the internal capabilities necessary to utilize data with enormous volume. Significant time and effort are required to sort the information obtained and identify viable and relevant information (Tan et al., 2015). Therefore, firms need more advanced technologies and new capabilities to process and analyze large amounts of data in real time.

The findings also show that firms need speed in utilizing big data to improve their performance. Although Hadoop is able to store and process a massive amount of data, it is designed for batch processing and cannot process data in real time (Chen & Zhang, 2014). To quickly process and analyze large volumes of data, firms need to use real-time big data platforms, such as Storm (Gulisano, Jimenez-Peris, Patino-Martinez, Soriente, & Valduriez, 2012) and SQLstream (Chen & Zhang, 2014), to quickly digest customer needs and search for appropriate product solutions (Zhang, Wu, & Cui, 2015). This will help firms develop new ideas and convert them into innovative products in real time (Erevelles et al., 2016).

Based on the results of this study, firms need to successfully generate new ideas to improve their financial returns, customer perspective, and operational excellence. Specifically, innovation efficacy increases a firm's performance by enhancing profit margins, increasing demand, and lowering customer acquisition and retention costs (Yalcinkaya et al., 2007). In addition, firms that efficiently develop new ideas can improve their customer perspectives and operational excellence better than their competitors. However, reducing the effort and time needed to generate new ideas does not necessarily increase a firm's financial returns compared to those of its competitors.

In summary, although the extant literature has identified big data as the "next big thing in innovation" (Gobble, 2013), the existing research focuses mainly on anecdotal evidence about the effects of big data on innovation performance and, consequently, firm performance. Therefore, the findings of this study provide unique insights that will help firms understand the impact of each big data characteristic on innovation efficacy and efficiency and, thus, overall firm performance.

7.3. Limitations and future research

This study has several potential limitations. First, we investigated the main characteristics of big data on innovation efficiency and innovation efficacy. Some studies have suggested big data characteristics (e.g., data value, data veracity) other than the 3Vs (data volume, data variety, and data velocity) explored in this research (Shafer, 2018). Future studies should operationalize and validate the effects of other big data characteristics on firm outcomes. Second, the effects of big data characteristics on firm performance may be mediated by variables other than firm innovation performance. Thus, future studies should investigate the mediating roles of other constructs (e.g., firm agility, firm decision quality) on the effects of big data on firm performance. Third, participants were recruited from firms in the United States. Future studies could replicate this study using participants from other countries to investigate the effect of culture in our research model. Finally, we examined the research model using cross-sectional data. Future studies could examine the links in the model using panel data.

8. Conclusion

The main objective of this study was to address a significant gap in the literature regarding the impacts of the main characteristics of big data (i.e., variety, volume, and velocity) on innovation performance (i.e., innovation efficiency and innovation efficacy), which eventually impacts firm performance. We used organizational learning theory to explain how big data utilization can improve a firm's learning capabilities regarding the generation of new ideas, which can improve financial returns, the customer perspective, and operational excellence. Thus, one of the main contributions of this study is its examination of the mediating role of firm innovation performance on the relationships between big data characteristics and firm performance. The results reveal the importance of conceptually and operationally differentiating among the main characteristics of big data (i.e., variety, velocity, and volume) instead of treating big data as a holistic variable. In particular, while data variety and velocity positively enhance innovation efficacy and efficiency, data volume has no significant impact. Therefore, focusing exclusively on collecting large amounts of data will not help firms enhance their innovation performance. They should also integrate different types of data in a timely manner. Taken together, the findings of this study indicate that *big data is not always better data*. Notably, the findings reveal that to improve firm innovation performance *data velocity* plays a more significant role than other main characteristics of big data. In summary, the findings indicate that big data characteristics could have different impacts on firm outcomes. Understanding the effect of each big data characteristic on firm outcomes will enable firms to appropriately allocate their resources to improve their overall performance.

Acknowledgment

This work was supported by the Arts Research Board Major Seed Grant from McMaster University [grant number 20008720] and by the Social Sciences and Humanities Research Council of Canada [grant number 20006922].

Appendix A

A.1. Survey items

See Table A1.

Table A1
Descriptive statistics and construct scales.

Construct		Mean	SD	Items	Resources
Firm Performance	**Financial Returns**	5.22	1.0	Please indicate the extent to which you disagree or agree with the following statements:(7-point Likert scales ranging from "strongly disagree" to "strongly agree") ● My firm's return on investment (ROI) is better compared to other companies in the same industry. ● My firm's return on equity (ROE) is better compared to other companies in the same industry. ● My firm's return on asset (ROA) is better compared to other companies in the same industry.	Wu et al. (2015)
	Customer Perspective	5.45	1.0	● Customers perceive that my firm's quality of products and services is better compared to other firms in the same industry. ● My firm has higher customer satisfaction compared to other firms in the same industry. ● My firm has better firm image compared to other firms in the same industry.	
	Operational Excellence	5.38	1.0	● My firm has better productivity improvements compared to other firms in the same industry. ● My firm has better timeline of customer service compared to other firms in the same industry. ● My firm has better production cycle time compared to other firms in the same industry.	
Innovation Performance	**Innovation Efficacy**	5.03	0.9	Please state the performance of your firm compared to your competitors with regard to the following items:(7-point Likert scales ranging from "Much worse performance" to "Much better performance") ● Replacement of products being phased out. ● Extension of product range within main product field through new products. ● Extension of product range outside main product field. ● Development of environment-friendly products. ● Market share evolution. ● Opening of new markets abroad. ● Opening of new domestic target groups.	Alegre and Chiva (2008)
	Innovation Efficiency	4.88	1.0	Please state the performance of your firm compared to your competitors with regard to: (7-point Likert scales ranging from "Much worse performance" to "Much better performance") ● Average innovation project development time. ● Average number of working hours on innovation projects. ● Average cost per innovation project. ● Global degree of satisfaction with innovation project efficiency.	
Big Data Characteristics	**Volume**	5.44	1.1	Please indicate the extent to which you disagree or agree with the following statements: (7-point Likert scales ranging from "strongly disagree" to "strongly agree") ● In my firm, we analyze large amounts of data. ● In my firm, the quantity of data we explore is substantial. ● In my firm, we use a great deal of data. ● In my firm, we scrutinize copious volumes of data.	Ghasemaghaei and Calic (2019b)
	Velocity	5.22	1.1	● In my firm, we analyze data as soon as we receive it. ● In my firm, the time period between when we get new data and when we analyze it is short. ● In my firm, we are fast in exploring our data. ● In my firm, we analyzes data speedily.	Ghasemaghaei and Calic (2019b)
	Variety	5.51	0.9	● In my firm, we use several different sources of data to gain insights. ● In my firm, we analyzes many types of data. ● In my firm, we examine data from a multitude of sources.	Ghasemaghaei and Calic (2019b)

Appendix B

B.1. Loading of measures

See Table B1.

Table B1
Loading of measures.

	Var	Vel	Vol	P-Cu	P-Fi	P-Op	Effica	Effici
Data Variety1	**0.86**	0.59	0.59	0.40	0.44	0.40	0.46	0.43
Data Variety2	**0.84**	0.50	0.52	0.35	0.36	0.38	0.36	0.30
Data Variety3	**0.89**	0.57	0.59	0.48	0.48	0.47	0.53	0.42
Data Velocity1	0.59	**0.87**	0.53	0.43	0.49	0.49	0.49	0.47
Data Velocity2	0.56	**0.81**	0.45	0.40	0.44	0.47	0.42	0.43
Data Velocity3	0.57	**0.90**	0.53	0.50	0.47	0.53	0.53	0.51
Data Velocity4	0.52	**0.87**	0.50	0.48	0.52	0.55	0.50	0.46
Data Volume1	0.59	0.49	**0.88**	0.33	0.35	0.36	0.37	0.29
Data Volume2	0.56	0.49	**0.87**	0.27	0.37	0.30	0.33	0.28
Data Volume3	0.61	0.52	**0.87**	0.32	0.37	0.43	0.36	0.27
Data Volume4	0.56	0.53	**0.87**	0.30	0.42	0.32	0.38	0.27
Customer Perspective1	0.42	0.37	0.28	**0.79**	0.46	0.66	0.40	0.40
Customer Perspective2	0.38	0.46	0.29	**0.86**	0.46	0.63	0.49	0.44
Customer Perspective3	0.42	0.48	0.31	**0.87**	0.55	0.69	0.52	0.48
Financial Returns1	0.45	0.52	0.36	0.47	**0.85**	0.60	0.53	0.49
Financial Returns2	0.46	0.44	0.39	0.52	**0.91**	0.56	0.57	0.50
Financial Returns3	0.38	0.49	0.36	0.54	**0.82**	0.62	0.43	0.36
Operational Excellence1	0.45	0.51	0.37	0.66	0.60	**0.87**	0.54	0.50
Operational Excellence2	0.42	0.50	0.34	0.68	0.56	**0.85**	0.47	0.44
Operational Excellence3	0.38	0.52	0.34	0.67	0.61	**0.85**	0.48	0.45
Innovation Efficacy1	0.34	0.35	0.21	0.37	0.37	0.41	**0.70**	0.59
Innovation Efficacy2	0.43	0.38	0.27	0.37	0.46	0.41	**0.77**	0.65
Innovation Efficacy3	0.40	0.42	0.33	0.39	0.41	0.42	**0.73**	0.62
Innovation Efficacy4	0.34	0.40	0.25	0.43	0.43	0.43	**0.71**	0.57
Innovation Efficacy5	0.43	0.46	0.39	0.48	0.50	0.48	**0.80**	0.54
Innovation Efficacy6	0.40	0.45	0.37	0.38	0.46	0.41	**0.73**	0.49
Innovation Efficacy7	0.42	0.43	0.32	0.47	0.46	0.45	**0.74**	0.56
Innovation Efficiency1	0.38	0.45	0.28	0.40	0.47	0.45	0.60	**0.76**
Innovation Efficiency2	0.36	0.43	0.26	0.39	0.43	0.43	0.58	**0.84**
Innovation Efficiency3	0.36	0.45	0.26	0.45	0.42	0.43	0.59	**0.86**
Innovation Efficiency4	0.38	0.42	0.25	0.47	0.41	0.45	0.60	**0.79**
Cronbach's Alpha	**0.83**	**0.89**	**0.90**	**0.79**	**0.83**	**0.82**	**0.86**	**0.83**
Composite Reliability	**0.90**	**0.92**	**0.93**	**0.88**	**0.90**	**0.89**	**0.89**	**0.89**

Note: Var: data variety; Vel: data velocity; Vol: data volume; P-Cu: customer perspective; P-Fi: financial return; P-Op: performance operational excellence; Effica: innovation efficacy; Effici: innovation efficiency.
Different categories of the factors (e.g., data variety 1, data variety 2) refer to the items used to measure each factor shown in Table A1.

References

Abbasi, A., Sarker, S., & Chiang, R. H. (2016). Big data research in information systems: Toward an inclusive research agenda. *Journal of the Association for Information Systems, 17*(2), 33.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics, 182*, 113–131.

Alegre, J., & Chiva, R. (2008). Assessing the impact of organizational learning capability on product innovation performance: An empirical test. *Technovation, 28*(6), 315–326.

Alegre, J., Lapiedra, R., & Chiva, R. (2006). A measurement scale for product innovation performance. *European Journal of Innovation Management, 9*(4), 333–346.

Amabile, T. M., Conti, R., Coon, H., Lazenby, J., & Herron, M. (1996). Assessing the work environment for creativity. *Academy of Management Journal, 39*(5), 1154–1184.

Anderson, N., Potočnik, K., & Zhou, J. (2014). Innovation and creativity in organizations. A state-of-the-science review, prospective commentary, and guiding framework. *Journal of Management, 40*(5), 1297–1333.

Argote, L., & Miron-Spektor, E. (2011). Organizational learning: From experience to knowledge. *Organization Science, 22*(5), 1123–1137.

Argote, L., & Ren, Y. (2012). Transactive memory systems: A microfoundation of dynamic capabilities. *Journal of Management Studies, 49*(8), 1375–1382.

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research,* 396–402.

Bagozzi, R. P., & Fornell, C. (1982). Theoretical concepts, measurements, and meaning. *A Second Generation of Multivariate Analysis, 2*(2), 5–23.

Baker, W. E., & Sinkula, J. M. (1999). The synergistic effect of market orientation and learning orientation on organizational performance. *Journal of the Academy of Marketing Science, 27*(4), 411–427.

Banu Goktan, A., & Miles, G. (2011). Innovation speed and radicalness: Are they inversely related? *Management Decision, 49*(4), 533–547.

Barclay, D., Higgins, C., & Thompson, R. (1995). The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use as an illustration. *Technology Studies, 2*(2), 285–309.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

Barney, J. B. (1986). Strategic factor markets: Expectations, luck, and business strategy. *Management Science, 32*(10), 1231–1241.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173.

Calantone, R. J., Cavusgil, S. T., & Zhao, Y. (2002). Learning orientation, firm innovation capability, and firm performance. *Industrial Marketing Management, 31*(6), 515–524.

Calvard, T. S. (2016). Big data, organizational learning, and sensemaking: Theorizing interpretive challenges under conditions of dynamic complexity. *Management Learning, 47*(1), 65–82.

Camisón, C., & Villar-López, A. (2014). Organizational innovation as an enabler of technological innovation capabilities and firm performance. *Journal of Business Research, 67*(1), 2891–2902.

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

Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems, 32*(4), 4–39.

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly,* 1165–1188.
Chen, Y., Wang, Y., Nevo, S., Jin, J., Wang, L., & Chow, W. S. (2014). IT capability and organizational performance: The roles of business process agility and environmental factors. *European Journal of Information Systems, 23*(3), 326–342.
Chin, W. W. (2010). How to write up and report PLS analyses. In Handbook of partial least squares (pp. 655–690). Retrieved from http://link.springer.com/chapter/10.1007/978-3-540-32827-8_29.
Choo, C. W. (1996). The knowing organization: How organizations use information to construct meaning, create knowledge and make decisions. *International Journal of Information Management, 16*(5), 329–340.
Cohen, M. D. (1984). *Artificial intelligence and the dynamic performance of organizational designs.* Institute of Public Policy Studies, University of Michigan.
Côrte-Real, N., Oliveira, T., & Ruivo, P. (2017). Assessing business value of Big Data Analytics in European firms. *Journal of Business Research, 70*, 379–390.
Covin, J. G., Prescott, J. E., & Slevin, D. P. (1990). The effects of technological sophistication on strategic profiles, structure and firm performance. *Journal of Management Studies, 27*(5), 485–510.
Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science, 32*(5), 554–571.
Damanpour, F., & Gopalakrishnan, S. (2001). The dynamics of the adoption of product and process innovations in organizations. *Journal of Management Studies, 38*(1), 45–65.
Davenport, T. H., Barth, P., & Bean, R. (2012). How big data is different. *MIT Sloan Management Review, 54*(1), 43.
Day, G. S. (1994). Continuous learning about markets. *California Management Review, 36*(4), 9–31.
Demchenko, Y., Grosso, P., De Laat, C., & Membrey, P. (2013). Addressing big data issues in scientific data infrastructure. In International conference on collaboration technologies and systems (CTS), 2013 (pp. 48–55). Retrieved from http://ieeexplore.ieee.org/abstract/document/6567203/.
Demirkan, H., & Delen, D. (2013). Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud. *Decision Support Systems, 55*(1), 412–421.
Diamantopoulos, A., & Siguaw, J. A. (2006). Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. *British Journal of Management, 17*(4), 263–282.
Dong, W., Liao, S., & Zhang, Z. (2018). Leveraging financial social media data for corporate fraud detection. *Journal of Management Information Systems, 35*(2), 461–487.
Du, R. Y., & Kamakura, W. A. (2012). Quantitative trendspotting. *Journal of Marketing Research, 49*(4), 514–536.
Dumbill, E. (2012). Volume, velocity, variety: What you need to know about big data. Retrieved Jan, 19.
Dwivedi, Y. K., Choudrie, J., & Brinkman, W.-P. (2006). Development of a survey instrument to examine consumer adoption of broadband. *Industrial Management & Data Systems, 106*(5), 700–718.
El-Kassar, A.-N., & Singh, S. K. (2019). Green innovation and organizational performance: The influence of big data and the moderating role of management commitment and HR practices. *Technological Forecasting and Social Change, 144*, 483–498.
Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research, 69*(2), 897–904.
Fan, W., & Bifet, A. (2013). Mining big data: Current status, and forecast to the future. *ACM SIGKDD Explorations Newsletter, 14*(2), 1–5.
Fiol, C. M., & Lyles, M. A. (1985). Organizational learning. *Academy of Management Review, 10*(4), 803–813.
Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research,* 382–388.
Galliers, R. D., Newell, S., Shanks, G., & Topi, H. (2017). Datification and its human, organizational and societal effects. *The Journal of Strategic Information Systems, 26*(3), 185–190.
Gavetti, G., & Levinthal, D. (2000). Looking forward and looking backward: Cognitive and experiential search. *Administrative Science Quarterly, 45*(1), 113–137. https://doi.org/10.2307/2666981.
Gefen, D., & Straub, D. (2005). A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example. *Communications of the Association for Information Systems, 16*(1), 5.
Geroski, P., Machin, S., & Van Reenen, J. (1993). The profitability of innovating firms. *The RAND Journal of Economics,* 198–211.
Ghasemaghaei, M. (2018a). Improving organizational performance through the use of big data. *Journal of Computer Information Systems,* 1–14.
Ghasemaghaei, M. (2018b). The role of positive and negative valence factors on the impact of bigness of data on big data analytics usage. *International Journal of Information Management, 10*.
Ghasemaghaei, M. (2019a). Are firms ready to use big data analytics to create value? The role of structural and psychological readiness. *Enterprise Information Systems,* 1–25.
Ghasemaghaei, M. (2019b). Does data analytics use improve firm decision making quality? The role of knowledge sharing and data analytics competency. *Decision Support Systems, 120*, 14–24.
Ghasemaghaei, M., & Calic, G. (2019a). Can big data improve firm decision quality? The role of data quality and data diagnosticity. *Decision Support Systems, 120*, 38–49.
Ghasemaghaei, M., & Calic, G. (2019b). Does big data enhance firm innovation competency? The mediating role of data-driven insights. *Journal of Business Research, 104*, 69–84.
Ghasemaghaei, M., Hassanein, K., & Turel, O. (2017). Increasing firm agility through the use of data analytics: The role of fit. *Decision Support Systems, 101*, 95–105.
Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2017). Data analytics competency for improving firm decision making performance. *The Journal of Strategic Information Systems, 27*(1), 101–113.
Glynn, M. A. (1996). Innovative genius: A framework for relating individual and organizational intelligences to innovation. *Academy of Management Review, 21*(4), 1081–1111.
Gobble, M. (2013). Big data: The next big thing in innovation. *Research and Technology Management, 56*(1), 64–66.
Gulisano, V., Jimenez-Peris, R., Patino-Martinez, M., Soriente, C., & Valduriez, P. (2012). Streamcloud: An elastic and scalable data streaming system. *IEEE Transactions on Parallel and Distributed Systems, 23*(12), 2351–2365.
Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research, 70*, 308–317.
Günther, W. A., Mehrizi, M. H. R., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *The Journal of Strategic Information Systems, 26*(3), 191–209.
Hofacker, C. F., Malthouse, E. C., & Sultan, F. (2016). Big data and consumer behavior: Imminent opportunities. *Journal of Consumer Marketing, 33*(2), 89–97.
Hu, H., Wen, Y., Chua, T.-S., & Li, X. (2014). Toward scalable systems for big data analytics: A technology tutorial. *IEEE Access, 2*, 652–687.
Huber, G. P. (1991). Organizational learning: The contributing processes and the literatures. *Organization Science, 2*(1), 88–115.
Hunter, G. K., & Perreault, W. D., Jr (2007). Making sales technology effective. *Journal of Marketing, 71*(1), 16–34.
IBM (2015). IBM-Bringing Big Data to the Enterprise.
Insight, I. (2012). *Big just got bigger.* Grail Research.
Jaakola, E. (2013). Value co-creation in solution networks. *Industrial Marketing*.
Janssen, M., van der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of Business Research, 70*, 338–345.
Jiang, Z., & Benbasat, I. (2007). The effects of presentation formats and task complexity on online consumers' product understanding. *MIS Quarterly, 31*(3), 475–500.
Johannessen, J.-A., Olsen, B., & Olaisen, J. (1999). Aspects of innovation theory based on knowledge-management. *International Journal of Information Management, 19*(2), 121–139.
Johnson, J. S., Friend, S. B., & Lee, H. S. (2017). Big Data facilitation, utilization, and monetization: Exploring the 3Vs in a new product development process. *Journal of Product Innovation Management, 34*(5), 640–658.
Jones, M. (2018). What we talk about when we talk about (big) data. *The Journal of Strategic Information Systems, 28*(1), 3–16.
Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration (IJeC), 11*(4), 1–10.
Kock, N., & Lynn, G. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems, 13*(7), 546–580.
Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management, 34*(3), 387–394.
Lam, C. (2010). *Hadoop in action.* Manning Publications Co.
Lehrer, C., Wieneke, A., vom Brocke, J., Jung, R., & Seidel, S. (2018). How big data analytics enables service innovation: Materiality, affordance, and the individualization of service. *Journal of Management Information Systems, 35*(2), 424–460.
Lieberman, M. B., & Montgomery, D. B. (1988). First-mover advantages. *Strategic Management Journal, 9*(S1), 41–58.
Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology, 86*(1), 114–121.
Lowry, P. B., D'Arcy, J., Hammer, B., & Moody, G. D. (2016). "Cargo Cult" science in traditional organization and information systems survey research: A case for using nontraditional methods of data collection, including Mechanical Turk and online panels. *The Journal of Strategic Information Systems, 25*(3), 232–240.
Luo, J., Ba, S., & Zhang, H. (2012). The effectiveness of online shopping characteristics and well-designed websites on satisfaction. *Mis Quarterly,* 1131–1144.
Lycett, M. (2013). 'Datafication': Making sense of (big) data in a complex world. Retrieved from http://link.springer.com/article/10.1057/ejis.2013.10.
Malhotra, N. K., Kim, S. S., & Patil, A. (2006). Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past research. *Management Science, 52*(12), 1865–1883.
Manyika, J., & Roxburgh, C. (2011). The great transformer: The impact of the Internet on economic growth and prosperity. *McKinsey Global Institute, 1*.
March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science, 2*(1), 71–87.
March, J. G., & Simon, H. A. (1958). Organizations.
Marshall, A., Mueck, S., & Shockley, R. (2015). How leading organizations use big data and analytics to innovate. *Strategy & Leadership, 43*(5), 32–39.
McAfee, A. (2013). Big data's biggest challenge? Convincing people NOT to trust their judgment. *Harvard Business Review, 9*.
McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J., & Barton, D. (2012). Big data: The management revolution. *Harvard Business Review, 90*(10), 60–68.
Mithas, S., Lee, M. R., Earley, S., Murugesan, S., & Djavanshir, R. (2013). Leveraging Big Data and Business Analytics [Guest editors' introduction]. *IT Professional, 15*(6), 18–20.
Mosakowski, E. (1997). Strategy making under causal ambiguity: Conceptual issues and empirical evidence. *Organization Science, 8*(4), 414–442.
Mu, J. (2015). Marketing capability, organizational adaptation and new product development performance. *Industrial Marketing Management, 49*, 151–166.
Müller, O., Fay, M., & vom Brocke, J. (2018). The effect of big data and analytics on firm

performance: An econometric analysis considering industry characteristics. *Journal of Management Information Systems, 35*(2), 488–509.
Naveh, E., Meilich, O., & Marcus, A. (2006). The effects of administrative innovation implementation on performance: An organizational learning approach. *Strategic Organization, 4*(3), 275–302.
Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change.* Boston, Massachusetts: Belknap Press of Harvard University Press.
Ohlhorst, F. J. (2012). *Big data analytics: Turning big data into big money.* John Wiley & Sons.
Parasuraman, A. (2010). Service productivity, quality and innovation: Implications for service-design practice and research. *International Journal of Quality and Service Sciences, 2*(3), 277–286.
Park, Y., El Sawy, O. A., & Fiss, P. C. (2017). The role of business intelligence and communication technologies in organizational agility: A configurational approach. *Journal of the Association for Information Systems, 18*(9), 648–686.
Perry-Smith, J. E., & Mannucci, P. V. (2017). From creativity to innovation: The social network drivers of the four phases of the idea journey. *Academy of Management Review, 42*(1), 53–79.
Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 885*(879), 10–1037.
Popovič, A., Hackney, R., Tassabehji, R., & Castelli, M. (2018). The impact of big data analytics on firms' high value business performance. *Information Systems Frontiers, 20*(2), 209–222.
Powell, T. C., Lovallo, D., & Caringal, C. (2006). Causal ambiguity, management perception, and firm performance. *Academy of Management Review, 31*(1), 175–196.
Raguseo, E., & Vitari, C. (2018). Investments in big data analytics and firm performance: An empirical investigation of direct and mediating effects. *International Journal of Production Research, 56*(15), 5206–5221.
Rai, A., Patnayakuni, R., & Seth, N. (2006). Firm performance impacts of digitally enabled supply chain integration capabilities. *MIS Quarterly, 30*(2), 225–246.
Ren, S., Fosso Wamba, S., Akter, S., Dubey, R., & Childe, S. J. (2017). Modelling quality dynamics, business value and firm performance in a big data analytics environment. *International Journal of Production Research, 55*(17), 5011–5026.
Rindfleisch, A., O'Hern, M., & Sachdev, V. (2017). The digital revolution, 3D printing, and innovation as data. *Journal of Product Innovation Management, 34*(5), 681–690.
Ringle, C. M., Wende, S., & Will, A. (2005). SmartPLS (Release 2.0 M3) http://www.Smartpls.De. University of Hamburg. Hamburg: Germany.
Robinson, W. T. (1990). Product innovation and start-up business market share performance. *Management Science, 36*(10), 1279–1289.
Saboo, A. R., Kumar, V., & Park, I. (2016). Using Big Data to model time-varying effects for marketing resource (Re) allocation. *MIS Quarterly, 40*(4), 911–940.
Satell, G. (2014). 5 things managersshould know aboutthe big data economy. *Forbes*.
Schermann, M., Hemsen, H., Buchmüller, C., Bitter, T., Krcmar, H., Markl, V., & Hoeren, T. (2014). Big Data. *Business & Information Systems Engineering, 6*(5), 261–266.
Seleim, A., & Khalil, O. (2007). Knowledge management and organizational performance in the Egyptian software firms. *International Journal of Knowledge Management (IJKM), 3*(4), 37–66.
Shafer, T. (2018). The 42 V's of Big Data and Data Science. Retrieved June 4, 2018, from https://www.kdnuggets.com/2017/04/42-vs-big-data-data-science.html.
Simon, H. A., & March, J. (1976). *Administrative behavior organization.* New York: Free Press.
Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research, 70*, 263–286.
Smith, A. D. (2011). Competitive approaches to new product development: A comparison of successful organizations in an unstable economic environment. *Team Performance Management: An International Journal, 17*(3/4), 124–145.
Smith, W. K., & Lewis, M. W. (2011). Toward a theory of paradox: A dynamic equilibrium model of organizing. *Academy of Management Review, 36*(2), 381–403.
Sobrero, M., & Schrader, S. (1998). Structuring inter-firm relationships: A metaanalytic approach. *Organization Studies, 19*(4), 585–615.
Sun, H. (2012). Understanding user revisions when using information system features: Adaptive system use and triggers. *MIS Quarterly, 36*(2), 453–478.
Tan, K. H., Zhan, Y., Ji, G., Ye, F., & Chang, C. (2015). Harvesting big data to enhance supply chain innovation capabilities: An analytic infrastructure based on deduction graph. *International Journal of Production Economics, 165*, 223–233.
Tushman, M. L., & Anderson, P. (1986). Technological discontinuities and organizational environments. *Administrative Science Quarterly,* 439–465.
Van der Meulen, R. (2016). Gartner Survey Reveals Investment in Big Data Is Up but Fewer Organizations Plan to Invest. Retrieved October 2, 2017, from www.gartner.com/newsroom/id/3466117.
Venkatraman, N., El Sawy, O., Pavlou, P., & Bharadwaj, A. (2014). Theorizing digital business innovation: Platforms and capabilities in ecosystems. *Fox School of Business Research Paper,* 15–80.
Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data'can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics, 165*, 234–246.
Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356–365.
Wang, Y., & Hajli, N. (2017). Exploring the path to big data analytics success in healthcare. *Journal of Business Research, 70*, 287–299.
Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change, 126*, 3–13.
Wu, S. P.-J., Straub, D. W., & Liang, T.-P. (2015). How information technology governance mechanisms and strategic alignment influence organizational performance: Insights from a matched survey of business and it managers. *Mis Quarterly, 39*(2), 497–518.
Xu, J. D., Benbasat, I., & Cenfetelli, R. T. (2014). The nature and consequences of trade-off transparency in the context of recommendation agents. *MIS Quarterly, 38*(2), 379–406.
Xu, Z., Frankwick, G. L., & Ramirez, E. (2016). Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. *Journal of Business Research, 69*(5), 1562–1566.
Yalcinkaya, G., Calantone, R. J., & Griffith, D. A. (2007). An examination of exploration and exploitation capabilities: Implications for product innovation and market performance. *Journal of International Marketing, 15*(4), 63–93.
Yang, J. Y., Li, J., & Delios, A. (2015). Will a second mouse get the cheese? Learning from early entrants' failures in a foreign market. *Organization Science, 26*(3), 908–922.
Zhang, H., Wu, F., & Cui, A. S. (2015). Balancing market exploration and market exploitation in product innovation: A contingency perspective. *International Journal of Research in Marketing, 32*(3), 297–308.

Dr. Maryam Ghasemaghaei is an Assistant Professor of Information Systems at DeGroote School of Business at McMaster University. Her research interests relate to technology adoption, and the use of data analytics in organizations. Her research activities have resulted in over 20 peer-reviewed articles in academic journals such as MIS Quarterly, Journal of Strategic Information Systems, Journal of Business Research, Information & Management, Decision Support Systems, Computers in Human Behavior, Journal of Computer Information Systems, International Journal of Information Management, Enterprise Information Systems, Behaviour & Information Technology, and Communications of the Association for Information Systems.

Dr. Goran Calic is an Assistant Professor of Strategic Management, with associate membership in Information Systems, at McMaster University. He holds a PhD in Strategic Management from Purdue University. Goran Calic's research focuses on understanding why some individuals are more creative and some organizations are more innovative than others. His area of research is primarily concerned with early-stage entrepreneurship. His work on creativity in organizations was awarded the 2015 Max Henri Boisot Award. He has written in a variety of academic publications, such as the Journal of Management Studies, Rutgers Business Review, the Academy of Management Learning & Education, and The Oxford Handbook of Organizational Citizenship Behavior. Goran Calic worked for four years in Osnabrück, Germany at Georgsmarienhütte GmbH. During this time, he was involved in activities related to market research, sales, and organizational strategy.