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Improving Agility Using Big Data Analytics: The Role of Democratization Culture

Youyung Hyun[1,*], Taro Kamioka[2], Ryuichi Hosoya[3]

[1]Hitotsubashi University, Japan, bd181012@g.hit-u.ac.jp
[2]Hitotsubashi University, Japan, t.kami@r.hit-u.ac.jp
[3]3KI-Star Real Estate Co., Ltd., Japan, hosoyaryuichi@gmail.com

Abstract

Background: *Big data analytics (BDA) is considered an enabler of organizational agility because it helps firms to sense market-based changes and improve decision making in a more informed and timely manner. However, in reality, only a handful of firms have achieved improvement in their outcomes by using BDA. To address this inconsistency, our study explores the conditions under which BDA use translates into agility. We particularly focus on organizational culture because in the pursuit of agility, culture is emphasized as a source of stability that allows firms to successfully adapt to the changing environment. Therefore, by assuming organizational culture as a contextual factor, this study examines the moderating effect of organizational culture on the link between BDA use and agility.*

Method: *We employ a concept from data democratization called "democratization culture," which values the willingness to share information and the acceptance of diversity. We also adopt collectivistic culture for comparison with democratization culture. Further, BDA use is decomposed into advanced and basic use based on the functions and BDA types. A model is proposed and empirically validated through survey data collected from 304 senior-level managers.*

Results: *Our findings suggest that the moderating effects of democratization culture on agility are different depending on whether it is combined with advanced or basic BDA use.*

Conclusions: *This study provides initial empirical evidence that contributes to the scarce research on the role of organizational culture in the link between BDA use and agility.*

Keywords: Big data analytics (BDA), organizational agility, organizational culture, democratization culture, collectivistic culture

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Introduction

Organizational agility—a firm's critical ability to sense and respond to market changes to seize opportunities and effectively handle threats—is a core aspect of surviving and thriving in a turbulent business environment (Overby et al., 2006; Sambamurthy et al., 2003; Tallon, 2008). When firms are better able to sense changes in their market spaces and marshal the necessary knowledge and assets for competitive action, they are more likely to experience higher profits, reduced costs, and improved market shares (Sambamurthy et al., 2003; Tallon & Pinsonneault, 2011).

To enhance agility, firms have recently begun relying on big data analytics (BDA) as an increasing amount of data is flowing in real time from multiple sources (Ghasemaghaei et al., 2017; Kamioka et al., 2016; McAfee et al., 2012; Wamba et al., 2015). By effectively processing and analyzing big data, BDA plays a key role in helping organizations make more informed and timely decisions, i.e., be more agile (Chatfield & Reddick, 2018; Ghasemaghaei et al., 2017; Mandal, 2018).

However, in reality, a number of companies that have incorporated BDA into their business processes have struggled to show any significant improvement in their outcomes (Chen et al., 2012, 2015; Ghasemaghaei et al., 2017). Hence, it is worthwhile asking what factors make BDA use more fruitful. To answer this question, this paper elucidates the underlying mechanism by which BDA use translates into agility, with a particular focus on organizational culture.

Recent studies have shown that the major barrier organizations face for effective use of data analytics is cultural rather than data and technical skills (Díaz et al., 2018; Kiron et al., 2012; LaValle et al., 2011). For example, industry reports (e.g., McKinsey Quarterly and MIT Sloan Management Review) have highlighted the importance of data-driven culture for effective decision making based on data analytics (Chin et al., 2017; Davenport, 2006; Kiron et al., 2012). They state that without an organizational culture that values use of data analytics and evidence-based decision making, it is difficult to embed data analytics into core business processes and induce organization-wide impacts.

The impact of organizational culture has also been emphasized in agility studies. It is argued that in the pursuit of agility, a firm must build a backbone of stability that strengthens the reliability of organizations and allows them to effectively manage environmental changes (Aghina et al., 2015; Ahlbäck et al., 2017; Gregory et al., 2015). A stable foundation holds firms accountable and provides room for handling new opportunities and unexpected threats. In this respect, organizational culture has recently been considered a source of stability, allowing firms to adapt their governance, structures, and processes in accordance with the changing environment (Aghina et al., 2015; Nold & Michel, 2016).

As such, despite increasing attention being given to organizational culture, there has been a relative dearth of research on how organizational culture relates to the impact of BDA use on agility. Thus, elucidating the role of organizational culture in shaping the relationship between BDA use and agility is expected to address the significant gap in information systems (IS) literature and provide actionable insights to practitioners.

Specifically, we assume organizational culture as a contextual factor (i.e., moderator) and then introduce "democratization culture" by employing a concept from data democratization which has recently come into discussion in multiple industry reports (e.g., McKinsey Quarterly and MIT Sloan Management Review). These reports suggest that data should be democratized across enterprises to encourage the effective use of data analytics and drive positive organizational outcomes (Díaz et al., 2018; Kiron et al., 2012, 2014). With democratization of data, employees could readily draw on information to do their jobs effectively and make more

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informed decisions through data analytics by capturing, combining, and using necessary information (Kiron et al., 2012). For this approach to work, we propose that it is necessary to create democratization culture that values the willingness to share information and the acceptance of diversity.

In addition, we compare collectivistic culture with democratization culture. Since collectivistic culture was proven to be conducive to cooperation (Wagner III, 1995), its impact has been examined in relation to agility and flexibility (Lin et al., 2015; Liu et al., 2015). While collectivistic culture shares similarities with democratization culture in that both are closely related to the interaction among members which potentially leads to knowledge sharing, there seems to be a significant difference in terms of the acceptance of diversity (Arpaci & Baloğlu, 2016; Triandis et al., 1988). To be specific, employees in collectivistic culture value the interaction to receive social support, resources, and security from their group (Hofstede & Bond, 1984; Triandis et al., 1988). Because they receive such support in exchange for loyalty, they tend to behave in a communal way and emphasize conformity within group rather than pursuing diversity of opinions (Triandis & Gelfand 1998). On the other hand, in democratization culture, people value interaction among members to draw on diversity of knowledge, e.g., diverse information, viewpoints, or opinions from different angles (Baogang, 1992; Janssen et al., 2012; Powell, 2012). People in such cultural context are more tolerant for opinions different from their own and willing to accept various viewpoints. Hence, we hypothesize that the two types of culture may have different moderating effects on the link between BDA use and agility. Such a comparison is expected to further clarify the features and role of democratization culture.

Furthermore, we classify BDA use into advanced and basic use based on the functions and types of BDA being used. To the best of our knowledge, previous research has broadly defined BDA use as a single factor and examined its impact on agility (Chatfield & Reddick, 2018; Ghasemaghaei et al., 2017). However, because different types of BDA are built for different purposes (Sivarajah et al., 2017), the impact of BDA use on agility may differ by the type of BDA and its functions. Thus, we believe that this classification of BDA use may provide enhanced understanding of how BDA use influences agility. Our research is driven by the following research questions, which guides our investigation:

(1) Does democratization culture have a moderating effect on the link between BDA use and organizational agility?

(2) If it does, is there any difference between the moderating effect of democratization culture and that of collectivistic culture?

(3) Does advanced or basic BDA use positively affect organizational agility? If so, is there any difference in the impact of each BDA use type on organizational agility?

The research questions were empirically examined via quantitative research using data collected from 304 managers and executives in Japanese firms. The remainder of this paper is organized into the following sections in sequence: Literature Review, Hypotheses Development, Research Methodology, Results, Discussion, and Conclusions.

Literature Review

Figure 1 illustrates the proposed conceptual model for examining the moderating role of organizational culture in the link between BDA use and agility. Based on the conceptual model, we adopted two types of BDA use (advanced and basic use) and two types of culture (democratization culture and collectivistic culture). In this section, we first describe the resource-based view (RBV) that provides theoretical framework for our research model. Next, the study elaborates each element of our model, giving special emphasis on democratization culture which is newly introduced in this study.

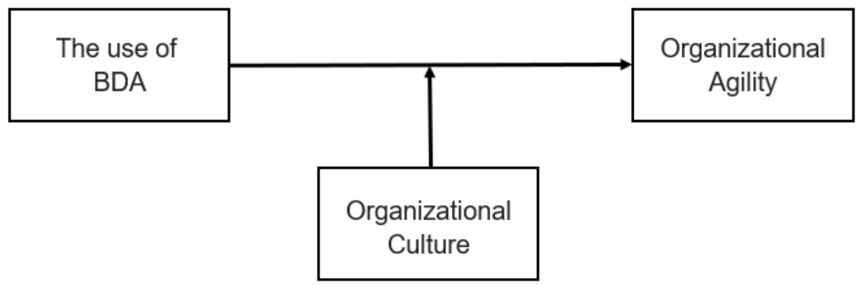

Figure 1 - Proposed Conceptual Model

Resource Based View

This study explores the role of organizational culture in the link between BDA use and organizational agility (Figure 1). To address this, we draw on RBV as a theoretical foundation. The RBV is a valuable theoretical base for understanding the way in which several and dissimilar resources are combined to generate strategic value to organizations (Palmatier et al., 2007; Wade & Hulland, 2004). This is important, given the context of our research, because BDA use and organizational culture are considered resources that can be combined to provide competitive advantages to the firm (Bharadwaj, 2000; Sanchez et al., 1996; Wade & Hulland, 2004; Wang et al., 2019). In this sense, we attempt to demonstrate BDA use that is appropriately combined with organizational culture plays a key role in attaining organizational agility (i.e., competitive advantage).

In the RBV, resources can be identified into three categories in terms of tangible, intangible, and human skills (Grant, 2010). Tangible resources include the financial and physical resources. Intangible resources include dimensions such as organizational culture and learning while human skills encompass employees' knowledge and skills. From the RBV perspective, resources serving as the basic units of analyses do not provide competitive advantage unless they are valuable, rare, inimitable, and non-substitutable or are integrated with other resources that work together to create competitive advantages (Barney, 1991; Bharadwaj, 2000; Grant, 1991).

Consistent with the view of RBV, BDA use alone is less likely to be a source of competitive advantages, because BDA can fairly easily be acquired and used by any organizations (Bharadwaj, 2000; Gupta & George, 2016; Wade & Hulland, 2004; Wang et al., 2019). However, having BDA use intertwined with complementary resources such as organizational culture, firms can create a set of routines in relation to BDA use, which is not easily imitated by rival firms (Barney, 1991; Wade & Hulland, 2004; Wang et al., 2019). Because organizational culture is a key determinant of employees' behavior (Schein, 1990), a culture that supports BDA use will encourage employees to appropriately utilize BDA and help imbue its use within an organization. When BDA use is deeply embedded in the organization, it could

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be naturally leveraged into employees' day-to-day business activities and thus effectively support management decision making (Barney, 1991; Wang et al., 2019). In this sense, BDA use combined with organizational culture that appropriately supports it can create competitive advantages (e.g., organizational agility) that are socially embedded in the business process and bounded to the organization (Barney, 1991; Wang et al., 2019). This confers competitive advantages to the firm by making it difficult to imitate by competitors who simply purchase BDA systems (Bharadwaj, 2000; Wang et al., 2019).

Organizational Agility

Organizational agility is defined as a firm's ability to sense and respond to environmental changes to seize market opportunities and effectively handle threats in a timely manner (Overby et al., 2006; Roberts & Grover, 2012; Sambamurthy et al., 2003). As environmental conditions become increasingly turbulent across industries, organizational agility has become imperative for success (Overby et al., 2006; Tallon & Pinsonneault, 2011). When firms can effectively respond to market-related changes (e.g., demand for new products and services, increasing pace of innovation, or expansion of a new market), they are more likely to experience higher profits, reduced costs, and improved market shares (Sambamurthy et al., 2003).

To achieve organizational agility, companies must implement both high-speed and high-quality decision making (Ghasemaghaei et al., 2018; Hyun et al., 2020; Westerman, 2009). For example, to achieve greater alignment with trends and shifts in product and service markets, firms should be able to make more informed decisions in a timely manner based on accurate information (Lu & Ramamurthy, 2011; Sambamurthy et al., 2003). In addition, to efficiently manage business processes at lower costs relative to their competitors, firms should respond to environmental changes in an efficient and rapid manner (Ghasemaghaei et al., 2017; Lu & Ramamurthy, 2011). Hence, achieving agility requires firms to deal with timing, cost, and information accuracy for speed and quality of decision making (Park et al., 2017; Sambamurthy et al., 2003; Westerman, 2009).

Big Data Analytics Use

BDA involves big data, analytical tools, and techniques to derive actionable insights from the big data (i.e., high-volume, high-velocity, and high-variety information assets) (Gandomi & Haider, 2015; Kamioka et al., 2017; Wamba et al., 2017). The extant literature has identified and classified BDA in a number of ways, including text analytics, audio analytics, video analytics, social media analytics, and predictive analytics (Bose, 2009; Gandomi & Haider, 2015). Among them, BDA is most commonly categorized into three types: descriptive analytics, predictive analytics, and prescriptive analytics (Joseph & Johnson, 2013; Sivarajah et al., 2017). As it moves from descriptive to prescriptive analytics, BDA supposedly spans the past, present, and future to give us more concrete information and valuable insights (Banerjee et al., 2013).

As such, there are different types of BDA, and they are built for different purposes and functions. Thus, the impact of BDA use on agility is likely to differ depending on the type of BDA being utilized. Nevertheless, prior studies have broadly defined BDA use as a single construct and examined its impact on organizational agility (Chatfield & Reddick, 2018; Ghasemaghaei et al., 2017).

Recent BDA studies have categorized BDA into two types: advanced analytics (i.e., predictive and prescriptive analytics) and basic analytics (i.e., descriptive analytics) (Barton & Court, 2012; Bose, 2009; Chatfield & Reddick, 2018; Chin et al., 2017; Díaz et al., 2018; Müller et al., 2016); we used the same classification in this study to enhance our understanding of the impact of BDA use on agility. We defined advanced BDA use as the degree to which predictive and prescriptive analytics are used to predict the future and optimize business models and defined basic BDA use as the degree to which descriptive analytics are used to implement standardized business processes. Because advanced BDA is useful in understanding the business environment, customers, and risks associated with a new product (Banerjee et al., 2013; Chatfield & Reddick, 2018), it is likely to be used to make strategic decisions based on accurate information in a timely manner. On the other hand, basic BDA is often used repetitively and routinely in an organization for daily operations (Banerjee et al., 2013). Being leveraged in a firm's standardized processes, basic BDA use acts as a central function to sustain efficiency and helps a firm to make rapid decisions (Aghina et al., 2015; Sivarajah et al., 2017).

Table 1 lists the key functionalities and illustrative examples of advanced and basic BDA use that could effectively support agility. Many of the example technologies may provide the same functionalities, but these functionalities are key characteristics that can sufficiently reflect what advanced and basic BDA use can achieve and enable one to investigate their roles in achieving agility. Accordingly, our study measures advanced and basic BDA use based on the key functionalities, not on the examples.

Table 1 - Advanced and Basic BDA Use

Type	Key functionalities	Examples
Advanced BDA use	• Predict outcomes of problem solutions or future revenues • Provide 360-degree view of firms' operations and customers • Extract trends and patterns from data • Optimize business process model • Handle information shifts and continuous evolution of business process model	Data mining (e.g., text and web mining), audio/video/social media analytics, machine learning techniques, predictive model development (e.g., decision trees, regression techniques, neural networks), simulation optimization methods
Basic BDA use	• Provide description of knowledge patterns using simple statistics • Repetitively and routinely use for standardized work processes • Routinely generate business metrics to monitor processes over time	Reporting, dashboards, scorecards, data visualization, core applications of traditional business intelligence
Source: Barton & Court, 2012; Bose, 2009; Joseph & Johnson, 2013; Sivarajah et al., 2017		

Organizational Culture

Drawing on a wide spectrum of approaches, the relationship between information technology (IT) and organizational culture has been documented in IS literature (Leidner & Kayworth, 2006). As previously noted in RBV section, organizational culture has attracted attention from IS research because, unlike other resources that fairly easily become commodity-like over time (e.g., physical IT resources or IT skills), it combines with IT resources and creates a sustained competitive advantage (Barney, 1991; Mata et al., 1995). In this sense, the current study focuses on the role of organizational culture and examines it based on three important perspectives on organizational culture – 1) value dimension, 2) differentiation, 3) contextual factor.

First, our study is focused on value dimension of culture. With its growing popularity, researchers have provided a myriad of definitions, dimensions, and conceptualizations of organizational culture (Straub et al., 2002). For example, Schein (2010) proposed a three-level culture model including basic assumptions, values, and artifacts, which becomes more observable as the dimension moves from basic assumptions to artifacts. Likewise, Jermier et al. (1991) proposed that culture has an ideational component that anchors its meaning in

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values, beliefs, and assumptions and a material component that consists of tangible manifestations of the ideational component, such as rituals.

Given these multi-dimensional forms of culture, our study focused on value dimension. In organizational settings, values can be seen as a set of norms that define context for social interaction through which people act and communicate (Delong & Fahey, 2000; Leidner & Kayworth, 2006; O'Reilly & Chatman, 1996). These values affect appropriate ways of relating to others and drive the expected behaviors of organization members, acting as a basis for organizational culture (Leidner & Kayworth, 2006; Schein, 2010). Indeed, the majority of empirical IS research examining the relation between culture and IT employs a value-based approach because values are more easily studied than other dimensions of culture (Leidner & Kayworth, 2006; Schein, 2010). For instance, basic assumptions are the least visible and preconscious and therefore not easily studied, and while cultural artifacts are the most visible dimension of culture, they are not easily decipherable (Schein, 2010). Hence, we assumed that studying culture in the value dimension would effectively measure organizational culture and explain how it leads employees to behave in an expected manner.

There are some well-known measures of organizational culture that are studied in the value dimension, such as the competing values model (CVM) (Quinn & Rohrbaugh, 1983) and the organizational culture profile (O'Reilly et al., 1991). However, the conceptual measurement approach to culture only provides the generic nature of culture, which is not useful for the prediction of specific outcomes (Schneider et al., 2013). Schneider (1975) recognized this issue and recommended that the focus on culture measures should match the outcomes to be predicted. In this regard, to predict specific outcomes from culture measures, our study particularly focused on measures of democratization culture and collectivistic culture. Both cultures are considered to be deeply related to the specific organizational context where BDA use and organizational agility are involved, which we further elaborate on later.

Second, this study is built on differentiation perspective to organizational culture, which notes that an organization has multiple subcultures (Schein, 2009; Schneider et al., 2013). Differentiation perspective is widely adopted for prior research that addresses discussion around organizational culture, not limited to IS studies (Quinn & Rohrbaugh, 1983; Schein, 2009; Von Meier, 1999). As the organization grows and evolves, it adapts specific parts of the organization to their particular environments, thereby creating subcultures (Schein, 1990, 2009). People who occupy subcultures in their organization (by function, by occupation, by gender, and so on) may have different experiences and even attach different meanings to the same events (Schneider et al., 2013). As a representative example, CVM by Quinn and Rohrbaugh (1983), which is one of the most established and cited cultural frameworks, considers that organizations can develop two or more different subcultures that are competing one another in an organization. In prior IS studies, subcultures in CVM are examined by the extent to which they exist in an organization (Gupta et al., 2019; Lin & Kunnathur, 2019). Therefore, consistent with differentiation perspective, we employ democratization culture and collectivistic culture in the same model setting and examine their impacts on the link between BDA use and organizational agility.

Third, in order to examine the impact of organizational culture in a research model, we considered organizational culture as a moderator that explains the link between BDA use and agility. This is because organizational culture is often posited as a contextual factor that moderates the relationship between technology use and its consequences (Schneider et al., 2013). By considering organizational culture as a contextual factor, it appears capable of explaining real-world complexities, which can then be leveraged to elucidate the circumstances under which BDA use translates into organizational agility.

Democratization Culture

In this study, democratization culture is defined as an organizational culture that values the willingness to share information and the acceptance of diversity. We employed the concept of democratization culture from recent industry reports (e.g., McKinsey Quarterly and MIT Sloan Management Review) that place importance on data democratization to effectively utilize BDA and drive positive organizational outcomes (Chin et al., 2017; Díaz et al., 2018; Kiron et al., 2012). When data are democratized, employees can readily draw on information to be better positioned to have seamless interaction with customers and effectively handle market changes across channels (Kiron et al., 2012; Robert & Grover, 2012).

For this approach to work, our study proposes that it is important to create an organizational culture in which members perceive values in democratizing data. Although there may be other factors that are likely to influence data democratization, such as IT infrastructure, this paper focuses on organizational culture because culture is often cited as the biggest challenge to promote information sharing (Ruggles, 1998). Organizations in which culture does not value information sharing will face difficulties in integrating knowledge-based systems into their organizations (Alavi & Leidner, 1999). Therefore, given that culture acts as a primary determinant of people's sharing attitudes and behaviors (Posner & Munson, 1979), we surmised that employees are more likely to democratize data when they are in cultural conditions of democratization. To conceptualize democratization culture, we conducted an extensive literature review based on three main areas: (1) politics; (2) culture, media, and communication; and (3) information technology.

First, from a political perspective, Sawicki & Craig (1996) described democratization as a movement to extend data access to the public. Such movement opens the door for the public to actively participate in debates over policy plans so that they can exert influence on their governments' policy making processes. (Capoccia & Ziblatt, 2010; Dahlum & Knutsen, 2016; Putnam et al., 1994). In addition, policy makers should come from diverse backgrounds to encourage multisector participation and enable different views to thrive (Jiang & Choi, 2018). With a diversity of voices, democratization has its roots in societal conflicts rather than political consensus; thus, democratization requires a willingness to tolerate diversity (Baogang, 1992).

In studies on culture, media, and communication, it has been stated that freedom of the media is one of the most influential factors in determining cultural changes toward democratization because media ensure the free flow of information and the hearing out of different positions on public affairs (Da Silva Lopes, 2014; Powell, 2012). Although allowing citizens to actively engage in debate and open communication might bring out differences in opinions or conflicts, democratization relies on citizens joining each other based on diversification, not on concentration of viewpoints, which in turn contributes to improved decision making (Wu, 2012). Therefore, by facilitating a broader participation of dialog and accepting diverse opinions, freedom of the press could contribute to cultural conditions for democratization (Abbay, 2009; Da Silva Lopes, 2014; Powell, 2012; Wu, 2012).

Finally, in the IT literature, democratization is often related to open access to data (Dutton, 2011; Janssen et al., 2012; Ohemeng & Ofosu-Adarkwa, 2015). For example, the opening of data and information is implemented by a government that acts as an open system and interacts with its environment (Janssen et al., 2012). By allowing the public to know what is being done by the government, people can participate in the decision-making process of government (Ohemeng & Ofosu-Adarkwa, 2015). Because such an open system perceives exchange of information as constructive and accepts new, progressive, or even opposing opinions, it becomes possible to invite diverse perspectives (Janssen et al., 2012; Ohemeng & Ofosu-Adarkwa, 2015). This in turn contributes to improved decision making and other benefits, including stimulating innovation and promoting economic growth (Janssen et al., 2012; Surowiecki, 2004).

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Considering the above studies on democratization, we have deduced two things: (1) the cultural conditions of democratization are closely associated with extended access to information and the acceptance of diverse opinions through open communication and public participation, and (2) the cultural conditions of democratization are not limited to democratizing data, but instead they also encompass democratization of information, opinions, and perspectives. To reflect these findings, we introduce democratization culture that values the willingness to share information and the acceptance of diversity.

Collectivistic Culture

Our paper also adopts collectivistic culture and defines it as an organizational culture that places priority on group goals and values social interaction based on mutual acceptance. The definition is based on studies related to collectivistic culture (Triandis, 2001; Triandis et al., 1988; Wagner III, 1995). Collectivistic culture has been studied in relation to agility and flexibility because it has been proven conducive to cooperation (Lin et al., 2015; Liu et al., 2015; Wagner III, 1995). However, to our knowledge, there has been no research that examines the role of collectivistic culture in the link between BDA use and agility. Further, while collectivistic culture shares similarities with democratization culture in terms of knowledge sharing, they have different stances in terms of diversity acceptance. Collectivistic culture highlights conformity and communal behavior among members, whereas democratization culture values accepting diverse opinions or perspectives from open communication (Baogang, 1992; Janssen et al., 2012; Powell, 2012; Triandis & Gelfand, 1998). In this respect, by comparing the moderating effects of these two types of culture, we expect to clearly identify the features and role of democratization culture in our research model.

Collectivistic culture often appears to be one of the most significant cultural patterns in explaining individual social behaviors, attitudes, and values (Triandis, 2001; Triandis et al., 1988). An essential attribute of collectivistic culture is that individuals must subordinate their personal goals below the goals of their ingroup (Triandis et al., 1988; Triandis & Gelfand, 1998); thus, much of their behavior tends to be consistent with the collective goals (Triandis et al., 1988; Trompenaars, 1996). In this respect, relationships in collectivistic culture induce members to follow primary group norms and beliefs and behave in a communal way, emphasizing compliance with the group (Ali et al., 1997). Moreover, because people in collectivistic culture are supposed to receive social support, resources, and security from their group, they are likely to value social interactions among members and share their knowledge with others (Arpaci & Baloğlu, 2016; Triandis et al., 1988; Triandis, 2001). For these reasons, people in collectivistic culture are inclined to maintain harmony and try to avoid conflicts as much as possible, which in turn contributes to a high level of cooperation (Triandis, 2001; Wagner III, 1995).

Hypotheses Development

The purpose of this study is to investigate the moderating role of organizational culture in the link between BDA use and agility, as illustrated in Figure 2. To this end, we first developed hypotheses that examine the direct relation between BDA use and agility (H1, H2) and the path comparison between advanced and basic BDA use (H3). Subsequently, we constructed hypotheses with the inclusion of organizational culture (H4a, H4b, H5a, H5b) to investigate its moderation effects.

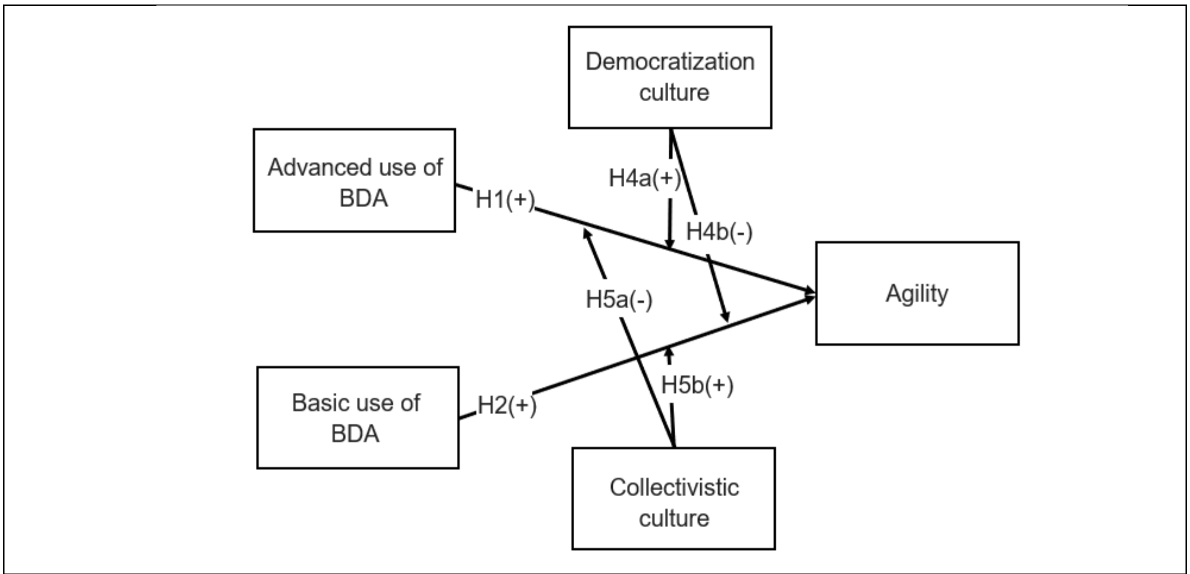

Figure 2 - Proposed Research Model

BDA has recently grown significantly in importance as firms face an unprecedented explosion of big data with the growth of the Internet, social media, and mobile devices (Liu et al., 2016). By effectively processing and analyzing big data, BDA allows firms to quickly sense changes and interpret market-based threats and opportunities, helping them to make more informed and timely decisions (Chen et al., 2012; Ghasemaghaei et al., 2017; Mandal, 2018; Zhou et al., 2018).

Specifically, advanced BDA use is known to assist decision making closer to the point where frontline businesses actually exist, responding to market needs in an adaptive and agile manner (Bose, 2009; Chatfield & Reddick, 2018). For instance, advanced BDA use allows firms to engage in faster and more accurate information processing, providing predictions that give asset managers advanced notice of the need to scale resources up or down (Chen et al., 2015). As such, by directly addressing the demands in sales, service, and product management, advanced BDA use can provide actionable insights for firms to make more informed and timely decisions. Hence, we posit the following hypothesis:

***H1**. Advanced BDA use has a positive effect on organizational agility.*

Basic BDA use is the simplest type of BDA, providing basic statistics or descriptions of data patterns (Ahlbäck et al., 2017; Banerjee et al., 2013; Sivarajah et al., 2017). By connecting data and processes, basic BDA use helps firms to streamline task procedures and effectively operate standardized processes for fast and efficient decision making (Aghina et al., 2015; Banerjee et al., 2013). As such, by supporting firms' internal processes in an efficient manner, basic BDA use can improve organizational agility. Therefore, we posit the following hypothesis:

***H2**. Basic BDA use has a positive effect on organizational agility.*

Further, we attempted to examine the difference between the impacts of advanced and basic BDA use on agility. As previously mentioned, BDA tends to become more complex and valuable as it moves from descriptive (i.e., basic BDA use) to prescriptive analytics (i.e., advanced BDA use), giving us more knowledge, better information, and meaningful insights (Banerjee et al., 2013; Joseph & Johnson, 2013; Sivarajah et al., 2017). Thus, we assume that firms could better understand changing business environments and make more accurate predictions about their markets through advanced BDA use. In turn, this would lead firms to

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make more informed and timely decisions by advanced BDA use compared to its basic use. Hence, we posit the following hypothesis:

***H3**. Advanced BDA use has a stronger effect on organizational agility than basic BDA use.*

Today, advanced BDA use directly influences decision making in frontline businesses, enabling firms to respond to market changes in an agile manner (Barton & Court, 2012; Chatfield & Reddick, 2018). To successfully support frontline businesses through advanced BDA use, we assume that it is important to create democratization culture in which employees are encouraged to share information and willingly accept diverse opinions from others. For example, information sharing allows employees to readily extract necessary data for building more comprehensive analytical models. In turn, this enables employees to make more precise predictions about the markets, customers, and risks associated with new products (Banerjee et al., 2013; Ransbotham & Kiron, 2017; ur Rehman et al., 2016). Further, employees in democratization culture are likely to share diverse views and interpretations of advanced analyses, which facilitates integration of different perspectives on environmental problems and opportunities (Nazir & Pinsonneault, 2012). In such a context, employees are likely to have a better understanding of emerging market trends and issues, improving their chances of noticing opportunities (Nazir & Pinsonneault, 2012). Hence, in democratization culture, employees are likely to obtain valuable and actionable insights about swift market changes and translate them into more informed and timely decision making. Thus, we posit the following hypothesis:

***H4a**. Democratization culture positively moderates the impact of advanced BDA use on organizational agility.*

Basic BDA use generates simple statistics and interpretations of data in the pursuit of efficiency within existing business models (Banerjee et al., 2013; Sivarajah et al., 2017). Embedded in standardized processes, basic BDA use helps firms efficiently manage their daily operations and make rapid decisions, i.e., be agile (Aghina et al., 2015; Banerjee et al., 2013; Wang et al., 2016). As standardized processes are often defined by firms, they are explicitly clarified in terms of roles, responsibilities, and decision-making procedures (Aghina et al., 2015). This allows them to avoid overlapping roles and respond to constant changes in markets with speed (Aghina et al., 2015). However, because democratization culture welcomes open communication for new and diverse opinions or ideas, employees in democratization culture are likely to question firms' best practices or get involved in frequent discussions over the issues that have already been standardized or routinely resolved by their firm (Aghina et al., 2015). This may hinder the firm's agility by causing more confusion over the standardized processes, leading to loss of employees' important time. Hence, we assume that democratization culture may not help employees to effectively use basic BDA to achieve agility. Therefore, we posit the following hypothesis:

***H4b**. Democratization culture negatively moderates the impact of basic BDA use on organizational agility.*

As assumed previously, advanced BDA use potentially better serves organizational objectives by sharing diverse insights across an organization (Kitchens et al., 2018; Ransbotham & Kiron, 2017). However, in collectivistic culture, because employees value conformity and harmony among members, they tend to have low levels of free self-expression (Rokeach, 1973). Employees may not be able to freely engage in open communication and bring new, varied, or sometimes progressive opinions into discussion. This will lead them to have low levels of tolerance for diversity and regard it as a threat that potentially challenges their norms and breaks harmony within their organization (Liu et al., 2015). Therefore, employees in collectivistic culture may be less likely to engage in open communication and explore new, diverse ideas or perspectives. In turn, this will lead to employees having a limited understanding of advanced data-driven analyses (Kitchens et al., 2018), and they therefore may have difficulties in obtaining actionable insights into market changes. Hence, we posit the following hypothesis:

***H5a**. Collectivistic culture negatively moderates the impact of advanced BDA use on organizational agility.*

Because employees in collectivistic culture value conformity and put group goals before individual interests (Wagner III, 1995), it is assumed that they willingly follow standardized work processes through basic BDA use. The standardized processes are often explicitly clarified by firms in terms of task processes, participants' responsibilities, or delegation of direct reports (Aghina et al., 2015; Sivarajah et al., 2017). Thus, a system implemented by a standardized process would work effectively in collectivistic culture, where people tend to behave in a communal way and follow ingroup norms (Wagner III, 1995). Employees are less likely to question firms' best practices and get involved in discussion over the process frameworks explicitly predefined by firms (Aghina et al., 2015). This enables firms to avoid loss of employees' important time or potential inefficiency in task implementation. Therefore, in collectivistic culture, firms are able to sustain efficiency and make fast decisions by having employees engage in standardized processes through basic BDA use. Hence, we posit the following hypothesis:

***H5b**. Collectivistic culture positively moderates the impact of basic BDA use on organizational agility.*

Research Methodology

Sample and Data Collection

We conducted a web questionnaire survey. Data were collected by distributing email messages to an active database of IT professionals managed by a Japanese online survey company. First, an online screening survey was conducted on 60,000 participants to select subjects who are fully aware of what BDA is and currently engage in business affairs that utilize BDA. For the screening survey, we selected participants who are chief executive officers (CEOs) or senior-level managers. This sampling choice was made because opinions from senior-level managers would reasonably reflect the organizational-level, business-related, and technology-related constructs in our research model. After the screening process, the main questionnaire was electronically sent to the selected subjects, and a total of 304 valid questionnaires were submitted. It is important to note that the dataset collected for the current study is limited to Japanese firms. Table 2 presents the sample distribution by respondent profile, industry, and company size.

As previously stated, our study is based on differentiation perspective which asserts that organizations have multiple subcultures rather than one culture shared by all (Schein, 2009; Schneider et al., 2013). Given that an organization has multiple subcultures, we examined the extent to which democratization culture and collectivistic culture exist within an organization, and how they exert influences on the link between BDA use and organizational agility. Thus, the screening survey was conducted targeting senior-level managers who are considered to have enough knowledge about cultural phenomena under the context of our study (i.e., BDA use). This is a predominant approach adopted by prior IS research that empirically examines culture variables (Duan et al., 2020; Dubey et al., 2019a, b; Gupta et al., 2019; Lin & Kunnathur, 2019; Upadhyay & Kumar, 2020).

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Table 2 - Demographic Profile of Respondents			
Demographics	**Categorization**	**Count (N=304)**	**Percentage (%)**
Gender	Female	26	8.6
	Male	278	91.4
Age	Below 30	17	5.6
	30–40	43	14.1
	41–50	68	22.4
	51–60	116	38.2
	Above 60	60	19.7
Respondent's position	Officer (CEO, etc.)	91	29.9
	Head of division/factory	37	12.2
	Senior manager	176	57.9
Industry	ICT (IT and communication)	57	18.7
	Manufacturing	85	28.0
	Service (hotel, restaurant, etc.)	85	28.0
	Wholesale and retail	38	12.5
	Finance	24	7.9
	Medical and welfare	15	4.9
Number of employees	<300	144	47.4
	301–1,000	74	24.3
	1,001–3,000	29	9.5
	>3,000	57	18.8

Measure of Constructs

For each construct in the research model (Figure 2), we either newly developed measures or adapted ones from the IS and management literature, as summarized in Appendix A. The structured questionnaire comprised ten questions, which contained a total of sixty-one measurement items, including a set of demographic questions. All scales were five-point Likert scales, where "1 = strongly disagree" and "5 = strongly agree." The questionnaire was first developed in English, translated to Japanese, and then translated back into English. Three researchers who are versed in both languages compared the translations and made minor modifications.

Consistent with theoretical conceptualization, we operationalized the research constructs using multi-item reflective measures. For new measures of democratization culture, standard scale development procedures were used (MacKenzie et al., 2011), and new items were developed based on a literature review and interviews with IT professionals.

We first developed a conceptualization of democratization culture based on an extensive literature review on democratization. Secondly, we generated a measurement item pool primarily based on the conceptualization to ensure that the items were within the construct's domain. Thirdly, measurement items were iteratively refined and validated by feedback from three IT professionals and two IS researchers. This iterative refinement process was performed to ensure clarity and validity of democratization culture items. Finally, three items were retained after exploratory factor analysis, and each item was reflective of democratization culture without altering the conceptual domain.

For measurement items of other constructs, we primarily adapted ones from prior studies. Advanced and basic BDA use were respectively measured with a three-item reflective scale, focusing on the functionalities of each type (Sivarajah et al., 2017). Further, organizational agility was measured as a reflective construct using four items adapted from Tallon and Pinsonneault (2011). The items reflect firms' abilities to quickly sense and respond to customer needs and the behaviors of competitors by improving products/services or adjusting internal business processes. Finally, collectivistic culture was measured with a three-item reflective scale adapted from Wagner III (1995); the items apply the core features of collectivistic culture, consistent with its conceptualization.

Results

To examine the abovementioned research questions, we proposed a research model (Figure 2). The model was validated through structural equation modeling (SEM) with Amos 25 software.

Measurement Model Validation

First, exploratory factor analysis (EFA) was conducted to determine a factor structure for the constructs. We identified five constructs and a total of sixteen measurement items, as listed in Table 3. All measurement items load most highly on their theoretically assigned constructs with a minimum threshold of 0.6 (Gefen & Straub, 2005).

Secondly, confirmatory factor analysis (CFA) was conducted to evaluate the validity and reliability of the collected data. Overall, the research model fit the data well (CMIN/DF=2.052, [GFI]=0.958; [AGFI]=0.928; [IFI]=0.970; [CFI]=0.970; [RMSEA]=0.059). All constructs proved that Cronbach's α coefficient (α) was higher than the commonly accepted threshold of 0.7 (Bryman, 2016), ranging from 0.85 to 0.91 (see Table 3), which indicates high internal consistency. Furthermore, as shown in Table 3, the composite reliability (CR) scores were higher than the recommended threshold of 0.6 (Bagozzi & Yi, 1988), ranging from 0.77 to 0.85, and the average variance extracted (AVE) for all the constructs was above the limit of 0.5, ranging from 0.53 to 0.58. These results all indicate good convergent validity.

Thirdly, Table 4 shows that discriminant validity is supported because the square root of AVE for each construct (the values on the diagonal) was higher than that construct's correlation with other constructs (Fornell & Larcker, 1981). In addition, the AVE values of all constructs were higher than the maximum shared variance and average shared variance values. To further assess discriminant validity, we employed heterotrait-monotrait ratio of correlations (HTMT). By measuring correlations among items, we found that HTMT values are all lower than 0.85, indicating sufficient distinction between the constructs (Henseler et al., 2015). In particular, Table 4 presents that standard deviation (S.D.) scores range from 0.92 to 1.04 for all variables in our research model. This shows that our sample of firms display a wide range of values for our focal variables (Germann et al., 2013).

Furthermore, because each response came from a single informant, there is a possibility of common method bias. We conducted Harman's single factor test on the measurement items to determine whether there was common method bias (Podsakoff et al., 2003). The results demonstrated that a single factor did not account for the majority of the variances, thereby indicating that there is a low chance of a common method bias in our dataset.

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Table 3 - Factor Loadings, AVE, CR, and Cronbach's Alpha

Variables	Indicators	Factor Loadings	AVE	α	CR	MSV	ASV
Advanced BDA use (AB)	AB 1	0.71	0.53	0.89	0.77	0.22	0.17
	AB 2	0.71					
	AB 3	0.77					
Basic BDA use (BB)	BB 1	0.71	0.55	0.85	0.78	0.22	0.15
	BB 2	0.71					
	BB 3	0.79					
Democratization culture (DC)	DC 1	0.74	0.55	0.86	0.79	0.25	0.18
	DC 2	0.70					
	DC 3	0.79					
Collectivistic culture (CC)	CC 1	0.73	0.53	0.85	0.77	0.29	0.15
	CC 2	0.71					
	CC 2	0.73					
Organizational Agility (OA)	OA 1	0.87	0.58	0.91	0.85	0.29	0.23
	OA 2	0.77					
	OA 3	0.71					
	OA 4	0.70					

AVE = Average Variance Extracted; α = Cronbach's Alpha; CR = Composite Reliability;
MSV= Maximum Shared Variance; ASV = Average Shared Variance

Table 4 - Descriptive Statistics and Correlations

	Mean	S.D.	1	2	3	4	5
1. Advanced BDA use	2.38	0.94	**0.73**				
2. Basic BDA use	2.35	0.97	0.47	**0.74**			
3. Democratization culture	2.31	0.92	0.40	0.36	**0.74**		
4. Collectivistic culture	2.60	1.02	0.30	0.25	0.41	**0.73**	
5. Organizational agility	2.45	1.04	0.45	0.43	0.50	0.54	**0.76**

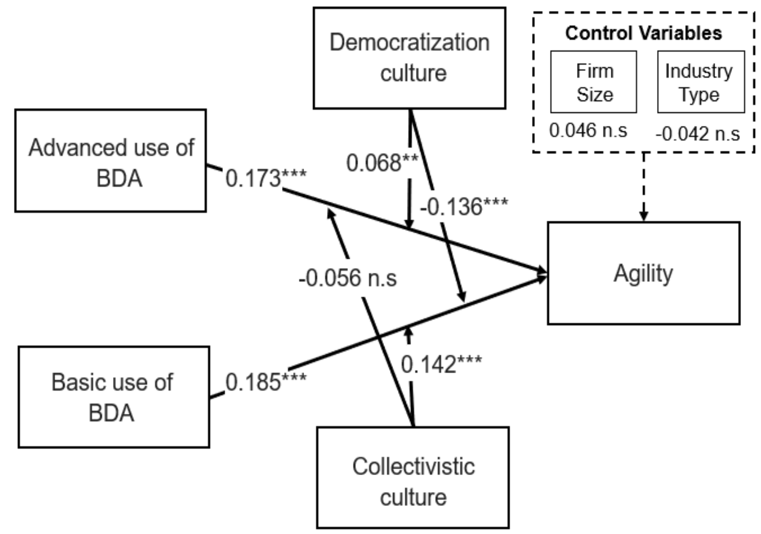
S.D. = Standard Deviation

Notes: Values on the diagonal are the square root of AVEs (Average Variance Extracted).

SEM and Moderation Test

To test the hypotheses, a structural model was estimated with SEM. The overall model provided a good fit to the data (CMIN/DF=2.194; [GFI]=0.967; [AGFI]=0.913; [IFI]=0.964; [CFI]=0.963; [RMSEA]=0.063). Figure 3 shows the analysis results, including standardized path coefficients. The SEM results demonstrate that advanced and basic BDA use are significantly and positively related to organizational agility, respectively (β = 0.173, $p < 0.001$; β = 0.185, $p < 0.001$), which is consistent with H1 and H2. To test H3, we adopted the path comparison method proposed by Cohen et al. (2003). However, we did not find a significant difference between the impacts of advanced and basic BDA use on agility, thereby not supporting H3.

We then examined the moderation links in the research model (i.e., H4a, H4b, H5a, H5b). We first multiplied construct scores to create interaction terms and then added the interaction terms to the model (Goodhue et al., 2007; Tanriverdi, 2006). To minimize potential multicollinearity, we mean-centered the construct scores prior to creating the interaction terms (Aiken et al., 1991). The moderating effect of democratization culture on the link between advanced BDA use and agility was significant (β = 0.068, $p < 0.01$), as anticipated by H4a. The moderating effect of democratization culture was negative and significant on the link between basic BDA use and agility (β = -0.136, $p < 0.001$), thereby supporting H4b. The moderating effect of collectivistic culture on the link between advanced BDA use and agility was not significant, not supporting H5a (β = -0.056, *n.s.*). The moderating effect of collectivistic culture on the link between basic BDA use and agility was significant (β = 0.142, $p < 0.001$), providing evidence for H5b. On the whole, the moderation results support the moderation test hypotheses, except for H5a.



*p<0.05. **p<0.01.***p<0.001, n.s. = non-significant

Figure 3 - Results Estimated by AMOS

Post Hoc Analysis

In addition, control variables were added to the research model to control firm-specific effects. Specifically, we examined the impacts of firm size and industry type on a dependent variable (specifically, organizational agility) because of their potential impacts on organizational agility, as suggested by extant literature (Lu & Ramamurthy, 2011; Tallon & Pinsonneault, 2011). As shown in Figure 3, neither firm size nor industry type are significantly associated with organizational agility (β = 0.046, *n.s.* and β = -0.042, *n.s.*, respectively).

Furthermore, to examine how organizational agility changes by the degree of utilization of each BDA use, we classified the sample firms based on their levels of utilization of each BDA use (i.e., low and high advanced BDA use × low and high basic BDA use). The interaction between advanced and basic BDA use in its impact on organizational agility is visually illustrated in the interaction plot, which was created in R studio (Figure 4). The interaction term of advanced and basic BDA use was found to be significant in its impact on organizational agility.

When an organization has higher levels of advanced BDA use, an increase in basic BDA use does not seem to have a significant impact on higher organizational agility. Although there is a slight increase in organizational agility, the slope of this increase appears to be rather flat without much difference. This result appears to imply that those companies are adept at understanding and predicting market trends and customer behavior through advanced BDA use. Thus, they try to improve their agility primarily through advanced BDA use rather than basic use. However, for an organization with lower advanced BDA use, basic BDA use has a larger amplifying effect on agility. This result suggests that even if an organization has lower levels of advanced BDA use, it is not a barrier to the organization achieving higher agility with higher levels of basic BDA use. The implications of these results will be further elaborated on in the next section.

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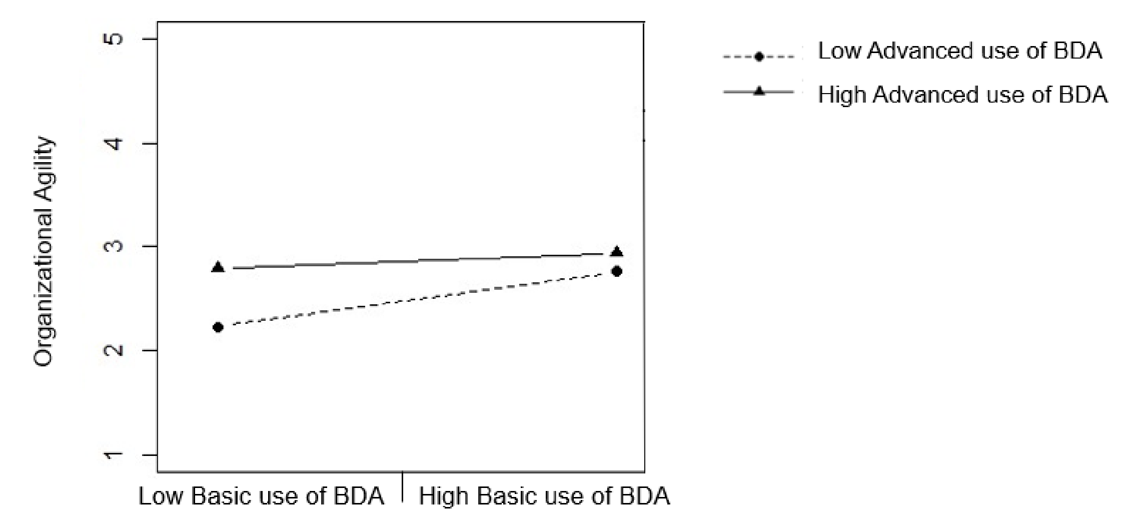

Figure 4 - Interaction Plot

Discussion

The objective of this research is to extend our understanding of the role of organizational culture in shaping the relationship between BDA use and agility. We achieved this by introducing democratization culture and examining its impact on the link between BDA use (advanced and basic) and agility. We also compared the effect of democratization culture with that of collectivistic culture.

Overall, our empirical results showed that democratization culture has significant moderating effects on the link between BDA use (both advanced and basic) and agility. While democratization culture helps advanced BDA use translate into agility ($\beta = 0.068$, $p < 0.01$), it has a negative moderating effect on the link between basic BDA use and agility ($\beta = -0.136$, $p < 0.001$). The results imply that democratization culture is not a one-size-fits-all solution. For example, democratization culture could help employees obtain actionable insights through advanced BDA use by allowing diverse information, ideas, or perspectives to be actively shared (Kitchens et al., 2018; Ransbotham & Kiron, 2017), which in turn enables employees to make more informed and timely decisions. On the other hand, democratization culture could also counteract a firm's efficiency and retard decision-making procedures when standardized work processes are embedded with basic BDA use (Aghina et al., 2015). This is because when task processes are explicitly standardized by a firm, spending much time on discussion or open communication may lead to loss of employees' time and cause more confusion over the firm's best practices by inviting different opinions or interpretations of analytics results.

These findings pose a challenging task for managers to decide how to incorporate democratization culture into their organizations. To avoid potential counter effects accrued from democratization culture, managers should incorporate democratization culture into their organizations with careful consideration of the required functions, task responsibilities, and business processes in which democratization culture can play an effective role. Otherwise, democratization culture could hinder a firm's agility by impeding work process efficiency and retarding decision making.

This study also found that the moderating effects of democratization culture and collectivistic culture are largely different. The results have proven that collectivistic culture has a non-significant moderating effect on the link between advanced BDA use and agility ($\beta = -0.056$, *n.s.*). A possible explanation for this result is that one of the representative features of collectivistic culture is encouragement of interaction among members, which leads to the sharing of knowledge (Arpaci & Baloğlu, 2016; Triandis et al., 1988). This characteristic might help advanced BDA use translate into organizational agility by allowing members to share useful information or insights. Conversely, because collectivistic culture also highly emphasizes conformity and communal behavior within a community (Triandis et al., 1988), it may discourage employees from exploring new ideas or accepting diverse opinions and perspectives, thereby limiting employees' understanding of markets based on advanced data-driven analyses. In this respect, collectivistic culture may weaken the link between advanced BDA use and agility. Hence, it is thought that the impacts of collectivistic culture on the link between advanced BDA use and agility might have been offset. However, we found that collectivistic culture strengthens the link between basic BDA use and agility ($\beta = 0.142$, $p < 0.001$). Because employees in collectivistic culture tend to behave in a communal manner and value group harmony (Wagner III, 1995), they would effectively follow standardized work through basic BDA use and collectively cooperate to achieve group goals, such as efficiency and rapid decision making (i.e., agility).

As described above, the comparison between democratization culture and collectivistic culture clearly identifies the features and role of democratization culture in shaping the relationship between BDA use and agility. For example, both cultures value interaction among members, which could lead to knowledge sharing (Arpaci & Baloğlu, 2016), whereas the acceptance of diversity, which is characterized in democratization culture but not in collectivistic culture, seems to bring about differences in moderating effects between the two types of culture. The results also provide a practical implication that the sharing of knowledge may not be a sufficient element of culture for the firms that attempt to improve their agility through advanced BDA use. Along with knowledge sharing, those firms may need to create cultural conditions where employees recognize value in accepting diverse ideas or perspectives from multiple knowledge sources that reside within the minds and experiences of people throughout the organization (Boland & Tenkasi, 1995; Nold & Michel, 2016; Nonaka & Toyama, 2005). Hence, when diverse ideas, opinions, or insights are effectively shared in democratization culture, employees are more likely to gain actionable insights about market changes, which in turn leads to improved organizational agility.

Finally, with regard to the impact of BDA use on agility, our results show that both advanced and basic BDA use positively influence organizational agility ($\beta = 0.173$, $p < 0.001$; $\beta = 0.185$, $p < 0.001$), which is consistent with findings from prior research that BDA use improves agility (Chatfield & Reddick, 2018; Ghasemaghaei et al., 2017). Further, the path comparison method proved that there was no statistical difference between the impact of advanced and basic BDA use on agility, not supporting H3. Because prior studies have suggested that data analytics give users more precise information, better knowledge and useful insights as it moves from descriptive analytics to prescriptive analytics (Banerjee et al., 2013), we assumed that advanced BDA use has a stronger effect on agility than basic use. However, it was found that using more developed and matured analytics does not necessarily have a stronger effect on organizational agility.

To provide a possible explanation for this, we conducted additional interviews with IT professionals. According to their feedback, some firms, depending on their strategy, data analytics maturity level, and industry type, may be able to employ basic BDA use to deliver functions similar to those of advanced BDA use. For example, some firms may have experienced personnel with sufficient know-how in their business area to enable them to predict market trends or optimize business outcomes by reviewing simple statistical observations from basic BDA use. For those firms, decision making related to market predictions or business optimization (which is normally supported by advanced BDA use) is not necessarily grounded in advanced data analytics. Instead, they would engage in basic BDA use to adjust their business strategies and improve their agility. Thus, which of advanced or basic BDA use is more closely related to agility may hinge on organization-wide characteristics, such as a firm's strategies, skills, age, or industry type.

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Likewise, through post hoc analysis, we further revealed that firms can achieve a higher level of agility with a higher level of basic BDA use, even with lower levels of advanced BDA use. Combining these results, it was found that firms can achieve a high level of agility by either a high level of advanced or basic BDA use. However, we suggest that as the business environment becomes more volatile and increasingly complicated with multiple variables, firms are likely to have difficulties in maintaining their agility by engaging in basic BDA use only. Although firms currently sustain their agility through basic BDA use, from a long-term perspective, they may have to employ advanced BDA use to effectively identify the most profitable customers and analyze market trends more deeply than their less statistically savvy competitors (Barton & Court, 2012; Davenport, 2006). This would help firms to handle unexpected constraints and seize market opportunities in a timely manner (i.e., be agile).

In addition to the practical implications noted above, we now summarize some significant theoretical contributions. First, to the best of our knowledge, our study is one of the first attempts to examine the role of organizational culture in the link between BDA use and organizational agility, addressing an important gap in the IS literature. The empirical work illustrates that organizational culture exerts a subtle yet powerful influence on people and is closely related with effective BDA use to achieve agility.

Secondly, we introduced democratization culture by developing and refining the conceptualization and measurement of the construct. This study also provides useful steps toward determining the role of democratization culture by empirically proving that democratization culture could either promote or impede agility depending on the type of BDA use (i.e., advanced or basic use) it is combined with.

Thirdly, we advance previous research by specifically dividing BDA use into two categories based on the functions and types of BDA being used. This classification is expected to invite a richer understanding of how each BDA use translates into organizational agility.

Table 5 - Summary of Hypotheses and Results

Hypothesis	Relations	Predicted Sign	Results
H1	Direct effect: AB → OA	+	Supported
H2	Direct effect: BB → OA	+	Supported
H3	Path comparison: The impact of AB on OA > the impact of BB on OA	Significant	Not supported
H4a	Moderating effect: AB × DC → OA	+	Supported
H4b	Moderating effect: BB × DC → OA	-	Supported
H5a	Moderating effect: AB × CC → OA	-	Not supported
H5b	Moderating effect: BB × CC → OA	+	Supported

Notes: AB (Advanced BDA use), BB (Basic BDA use), OA (Organizational Agility), DC (Democratization Culture), CC (Collectivistic Culture)

Conclusions

This study is one of a few to examine the role of organizational culture in relation to BDA use and organizational agility, with a particular focus on democratization culture. By conducting an extensive literature review and quantitative research, we have answered three research questions throughout the study. First, we empirically demonstrated the significant moderating effects of democratization culture on the link between BDA use and organizational agility. We found that democratization culture could either promote or hinder agility depending on the type of BDA use (advanced or basic) it is combined with. Second, our study compared the moderating effects of democratization culture with those of collectivistic culture. As we anticipated in our hypotheses, the acceptance of diversity, which is characterized in democratization culture but not in collectivistic culture, appears to engender differences in moderating effects between the two types of culture. For example, democratization culture has a positive moderating effect on the link between advanced BDA use and agility, but it has a negative moderating impact on agility when combined with basic BDA use. Conversely, collectivistic culture shows a non-significant moderating effect on the link between advanced BDA use and agility, but it positively moderates the link between basic BDA use and agility. In this respect, our findings provide useful insights for practitioners in that they should appropriately embed democratization culture into their firms to facilitate effective advanced BDA use without impairing the impact of basic BDA use on agility. Third, we empirically demonstrated that BDA use (both advanced and basic) positively relates to organizational agility. This is consistent with prior research. Yet, unlike our assumption that advanced BDA use would have a stronger impact on organizational agility, as it provides more precise information and useful insights than basic BDA use (Banerjee et al., 2013), there was no statistical difference between impacts of advanced and basic BDA use on organizational agility. This result was further investigated through interviews with IT professionals and post doc analysis, which we elaborated in discussion section. Overall, we addressed three research questions mainly via quantitative research and literature review. We believe that these findings contribute to the IS literature by providing a novel and complementary perspective on the type of cultural condition under which BDA use can be effectively translated into organizational agility.

While we developed our research model and provided theoretical and managerial insights, our study is still subject to several limitations that provide avenues for future research. First, our empirical findings are based on data from Japanese companies that currently utilize BDA. To improve the generalizability of our findings, future research may need to employ a dataset containing a wider range of firms from other countries. Secondly, our post hoc analysis suggests that even with a low level of advanced BDA use, firms can achieve higher organizational agility with a higher level of basic BDA use. However, as business markets become more competitive and turbulent, companies may face increasing needs to employ advanced BDA use to address fast-changing market needs (i.e., be agile). In this respect, it may be worth conducting longitudinal research to examine how the impacts of advanced and basic BDA use on agility change over time. Thirdly, the current study primarily focuses on introducing the role of democratization culture in the link between BDA use and organizational agility. To further clarify the features and role of democratization culture, we compared its moderating impacts with those of collectivistic culture. In this sense, future research can consider developing the current research model by incorporating other organizational culture constructs which would potentially influence BDA use and organizational agility, such as power distance (Hofstede & Bond, 1984). This might provide a more holistic view of organizational culture and deepen our understanding of cultural implications on BDA use and organizational agility. Fourthly, our study has deduced that there might be sub-concepts that comprise democratization culture, such as the willingness to share information and the acceptance of diversity. Future research may need to further develop and refine the democratization culture construct as a second-order formative construct. This could be a useful avenue to extend our work and provide a more comprehensive understanding of democratization culture associated with BDA use and organizational agility.

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Appendix A. Constructs and measurement items

Appendix A – List of Model Constructs and Items

Construct	Indicator	Measurement item	Reference
Advanced use of BDA (AB)		In the organization that I am currently involved in…	Adapted from Sivarajah et al. (2017)
	AB 1	1. BDA is used to derive customers' trends and needs.	
	AB 2	2. BDA is used to predict future possibilities in the market.	
	AB 3	3. BDA is used to perform simulation optimization analysis.	
Basic use of BDA (BB)		In the organization that I am currently involved in …	Adapted from Sivarajah et al. (2017)
	BB 1	1. BDA is used for implementing standardized processes.	
	BB 2	2. BDA is used only in the scope determined by a firm.	
	BB 3	3. BDA is used for producing reports and simple statistics.	
Democratization culture (DC)		In the organization that I am currently involved in…	Newly developed
	DC 1	1. we value the sharing of data, information, and ideas.	
	DC 2	2. we value open communication and active interaction.	
	DC 3	3. we value the acceptance of diverse opinions or perspectives.	
Collectivistic culture (CC)		In the organization that I am currently involved in…	Adapted from Wagner III (1995)
	CC 1	1. we value our group goals more than personal goals.	
	CC 2	2. we value harmony and consensus among members.	
	CC 2	3. we value social interaction based on mutual acceptance.	
Organizational agility (OA)		The organization that I am currently involved in…	Adapted from Tallon and Pinsonneault (2011)
	OA 1	1. proceeds introduction and implementation of new products and services over a short period.	
	OA 2	2. responds quickly to the changes in customers' needs.	
	OA 3	3. reacts promptly when a competitor launches new products or services.	
	OA 4	4. can expand or reduce sales of products and services.	

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About the Authors

Youyung Hyun is a doctoral student in Graduate School of Business Administration at Hitotsubashi University, Tokyo, Japan. Her research interests include big data analytics, IS/human-computer interaction, organizational culture, and organizational agility. She has presented her works in international conferences such as Pacific Asia Conference on Information Systems. Youyung Hyun is the corresponding author who can be contacted at bd181012@g.hit-u.ac.jp

Dr. Taro Kamioka is a Professor in the Graduate School of Business Administration at Hitotsubashi University, Tokyo, Japan. He received his Ph.D. degree in Systems and Information Engineering from Hokkaido University, Japan. His current research interests include Digital Transformation, Big Data Analytics, and the Chief Digital/Data Officer (CDO). He now serves as an advisor of several private companies and CDO Club Japan.

Dr. Ryuichi Hosoya is a Director of IT Innovation Office at KI-Star Real Estate Co., Ltd., Japan. He received his Ph.D. degree in Commerce and Management from Hitotsubashi University, Tokyo, Japan. As a director, he is applying a framework of sense-making through use of big data analytics, which is a major outcome of his Ph.D. study, to lead digital transformation of the organization.