Industrial Marketing Management 91 (2020) 483–494

Contents lists available at ScienceDirect

Industrial Marketing Management

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

Research paper

Linking big data analytical intelligence to customer relationship management performance

Chubing Zhang [a,1], Xinchun Wang [b,*], Annie Peng Cui [b], Shenghao Han [c]

[a] School of Business, Tianjin University of Finance and Economics, Tianjin 300222, China
[b] John Chambers College of Business and Economics, West Virginia University, Morgantown, WV 26506, United States of America
[c] School of Business, Shanghai University of Finance and Economics, Shanghai 200433, China

ARTICLE INFO

Keywords:
Big data
Data-driven culture
Competitive pressures
Mass customization
Marketing capability
CRM performance

ABSTRACT

This study investigates the driving forces of a firm's assimilation of big data analytical intelligence (BDAI) and how the assimilation of BDAI improve customer relationship management (CRM) performance. Drawing on the resource-based view, this study argues that a firm's data-driven culture and the competitive pressure it faces in the industry motivate a firm's assimilation of BDAI. As a firm resource, BDAI enables an organization to develop superior mass-customization capability, which in turn positively influences its CRM performance. In addition, this study proposes that a firm's marketing capability can moderate the impact of BDAI assimilation on its mass-customization capability. Using survey data collected from 147 business-to-business companies, this study finds support for most of the hypotheses. The findings of this study uncover compelling insights about the dynamics involved in the process of using BDAI to improve CRM performance.

1. Introduction

With the rapid development of the digital economy and the enhancement of data analytics technologies, organizations are placing increasingly more emphases on using applications of big data technology, such as big data analytics, to improve their performance (Chen, Preston, & Swink, 2015). For example, by analyzing GPS data, United Partial Service successfully reduced its drivers' driving distance by one million miles in 2017, which significantly reduced delivery time, improved its customer satisfaction, and lowered its operational costs (Samuels, 2017). In business-to-business (B2B) markets, one purpose of utilizing big data analytics is to better understand customer needs, which can help firms improve their customer relationship management (CRM) performance (e.g., McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012; Salehan & Kim, 2016; Wamba et al., 2017). Table 1 provides a brief summary of recent research on big data analytics in the B2B context. While increasingly more managers have recognized the importance of big data–related technologies, knowledge is still limited due to a few gaps existing in current literature.

First, although previous studies have well documented the positive impact of big data strategy on firm performance (e.g., McAfee et al., 2012; Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015), firms still vary in their levels of implementation of big data intelligence in business practices. In other words, understanding of the driving forces behind a firm's big data analytics strategy remains incomplete. Drawing on the resource-based view (RBV) (Barney, 1991; Wernerfelt, 1984), this study examines one important organization resource — namely, big data analytical intelligence (BDAI) and the driving forces behind the assimilation of such resource in business practices. BDAI assimilation reflects the extent to which a firm implements BDAI in its business operations (Chen, Chiang, & Storey, 2012; Gunasekaran et al., 2017). In terms of the driving forces behind BDAI assimilation, a firm's decision to implement BDAI may be influenced by both internal and external conditions. From the internal perspective, prior research suggests that a firm's culture drives its strategy (Lau, David, & Zhou, 2002). In the big data context, a firm's data-driven culture might be an internal "pushing" factor that motivates management to adopt BDAI in business practices. From the external standpoint, firms may increasingly devote efforts to promote BDAI assimilation, given competitive pressure from leading or peer companies that are apt to convert BDAI into competitive advantage.

Second, prior research suggests that a firm's resources, such as BDAI, need to be embedded within organizational processes to develop capabilities that can create competitive advantage for the firm (Zhou & Wu, 2010). However, few studies have investigated the mechanism of how

* Corresponding author.
E-mail addresses: zcb@tjufe.edu.cn (C. Zhang), xinchun.wang@mail.wvu.edu (X. Wang), annie.cui@mail.wvu.edu (A.P. Cui), hanshh96@163.com (S. Han).
[1] The first author acknowledges the financial support provided by the Youth Project of Ministry of Education Humanities Social Science Fund (No. 16YJC630166).

https://doi.org/10.1016/j.indmarman.2020.10.012
Received 29 October 2019; Received in revised form 28 October 2020; Accepted 29 October 2020
Available online 11 November 2020

BDAI can assist firms in developing unique capabilities and enhancing firm performance. This study proposes that the assimilation of BDAI enables a firm to obtain valuable insights into customers' unique and specific needs and to deliver customized products or services to meet those needs at a relative low cost. As a result, the firm will enhance its mass-customization capability, which tends to rely heavily on large-scale market intelligence (Duray, Ward, Milligan, & Berry, 2000; Wedel & Kannan, 2016) and leads to superior CRM performance. Moreover, given the focus of mass customization (i.e., providing customized products at low cost), a firm's marketing capability may interact with the intelligence provided by big data analytics on developing mass-customization capability to satisfy customers' heterogeneous needs. Overall, this study aims to investigate two research questions: (1) What are the drivers of a firm's assimilation of BDAI? and (2) What is the mechanism by which BDAI improves CRM performance in B2B markets?

To answer these questions, we develop a theory-based model (Fig. 1) and test it using survey data collected from 147 Chinese industrial firms actively trading on a B2B online platform. By examining the proposed research questions, this study aims to make several contributions. First, this study answers recent calls for research on how, why, and when big data can be a valuable resource for organizations to develop competitive advantages (Elia, Polimeno, Solazzo, & Passiante, 2020). By investigating the drivers of BDAI assimilation, this study brings supplemental insights to how and why firms devote efforts to implement BDAI. Second, this study contributes to the mass-customization literature by identifying BDAI as a key organizational resource that can significantly improve a firm's mass-customization capability, thereby enhancing its CRM performance. Third, by introducing mass-customization capability as a strategic means to transform a firm's BDAI into superior CRM

Table 1
Summary of recent research of big data in B2B marketing.

Citation	Independent variable	Mediator	Moderator	Dependent variable	Key findings
Sun, Hall, and Cegielski (2020)	Relative advantage, technology competence, technology resources, management support, firm size, competitive pressure, trading partner readiness, regulatory environment	/	/	Intention to adopt big data	A firm's intention to adopt big data is driven by its relative advantage, technological competence, technology resources, support from top management, competitive pressure, and the regulatory environment.
Hallikainen, Savimäki, and Laukkanen (2020)	Customer big data analytics	CRM	Analytics culture	Sales growth	The use of customer big data significantly fosters sales growth and enhances the customer relationship performance, especially for firms with an analytical focus.
Demirkan and Delen (2013)	Data intelligence	Data management	/	Information and operation management	Information can be obtained from various data sources. Large-scale data can help firms improve information and operation management efficiency.
Zhang and Xiao (2020)	Customer involvement as data provider and as data analyst	/	Customer need tacitness and customer need diversity	New product performance (NPP)	Customer involvement facilitates NPP. These effects are contingent on customer need tacitness and diversity.
Gunasekaran et al., 2017	Big data predictive analytics (BDPA)	Supply chain management performance	/	Organization performance	BDPA can improve a firm's performance by enhancing its supply chain efficiency.
Liu (2020)	User-generated content (UGC) from social media platforms, consumers' sentiment	/	/	B2B and B2C firms' stock performance	UGC has a significant impact on firms' stock performance, and its impact on stock performance is much stronger among B2C than B2B firms.
Yang et al. (2020)	/	/	/	/	How widely available data, such as emails, which all companies have, can be used to underpin new methods for the early identification and monitoring of product demand trends, informing marketing strategies.
Jahromi, Stakhovych, and Ewing (2014)	Data-mining models	/	/	Non-contractual customer churn	Data-mining approach can help firms retain current customers more efficiently.
Sena and Ozdemir (2020)	Upstream investment in big data analytics (BDA)	/	The availability of graduate workforce in the local area	Retailers' technical efficiency, technical progress	Retailers located in regions with a larger proportion of graduate workforce benefit more from inter-industry upstream investment in BDA as they tend to be more efficient on average. Upstream investment in BDA is positively associated with frontier shifts over time (i.e., technical progress).
Gupta, Drave, Dwivedi, Baabdullah, & Ismagilova (2020)	Managerial skills and technical skills required in big data predictive analytics	/	/	Operational performance, market performance, financial performance	Managerial and technical skills required in big data predictive analytics have positive impacts on market, financial, and operational performance.
This study	Data-driven culture and competitive pressure	Mass-customization capability	Marketing capability	CRM performance	A firm's BDAI can be driven by its data-driven culture and competitive pressure but in different ways. A firm's BDAI can improve its CRM performance by enhancing its mass-customization capability, especially if it has superior marketing capabilities.

Note: B2C = business-to-consumer.

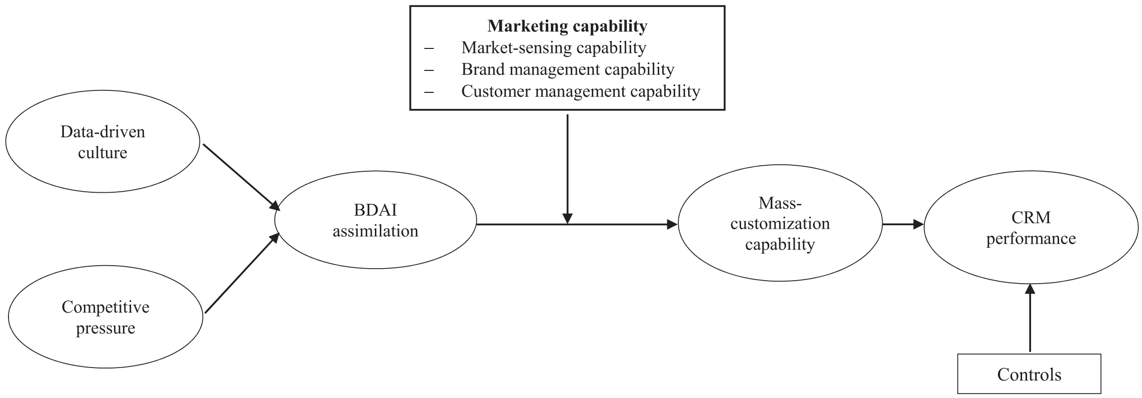

Fig. 1. Theoretical model.

performance, this study adds to the big data analytics literature by uncovering the mechanism by which BDAI contributes to B2B performance.

of our study. Then, we introduce the methodology employed by the present study, including the sampling and data collection procedure and the measures of key constructs. Next, we present the data analysis results. The paper concludes with discussions on research findings and implications for both theory and managerial practices.

2. Theoretical background and hypotheses

Developing and implementing BDAI is a complex process, but it may produce valuable resources that enable a firm to develop firm capabilities, which in turn lead to superior CRM performance. In this section, we draw on the RBV to discuss the antecedents of BDAI assimilation and the mechanism by which BDAI improves a firm's CRM performance.

2.1. BDAI: A resource-based view

The RBV emphasizes that a firm's competitive advantage comes from its resources (Barney, 1991; Wernerfelt, 1984). However, not all resources are a source of competitive advantage. Instead, only resources and/or capabilities that are valuable, rare, inimitable, and non-substitutable bring competitive advantage to a firm (Barney, 1991). Moreover, recent research drawing on the RBV and dynamic capability perspective argues that resources should be embedded within organizational processes so that firms can transform the resources into actionable capabilities that enable them to gain a competitive advantage in market competition (Zhou & Wu, 2010).

As organizations are increasingly employing Internet-based techniques to improve CRM-related business processes, accumulating large-scale data is no longer a taxing task (McAfee et al., 2012). However, the data accumulated are of little value to the organization without further analytical processing, such as data mining (Liu & Shih, 2005) and machine learning (Bose & Mahapatra, 2001). Although big data have the potential to become valuable resources for firms, they also require a substantial amount of management and analysis (Tien, 2013; Wamba et al., 2015). For example, while big data brings valuable information to organizations, this information often contains high velocity and variety (Elia et al., 2020). Therefore, organizations must have sophisticated data management, data analysis, and data processing technology to extract inherited insights from the data and obtain operable value creation insights (Sivarajah, Kamal, Irani, & Weerakkody, 2017; Wamba et al., 2015).

In this study, BDAI refers to the valuable information and insights extracted from large-scale datasets using various statistical and analytical techniques (Dubey et al., 2017; Gunasekaran et al., 2017; Gupta, Qian, Bhushan, & Luo, 2018). Big data-related strategies usually consist of three components: descriptive analysis to interpret data, predictive analysis to depict future insights, and prescriptive analysis to optimize or simulate organizational decision results (Gupta et al., 2018). Previous studies (e.g., Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Elia et al., 2019; Gupta & George, 2016) suggest that BDAI can be viewed as an organizational resource based on RBV logic. For example, Dubey et al. (2017) define big data predictive analytics as an organizational capability that relies on the binding of strategic resources. In addition, prior research suggests that intelligence obtained from big data analytics can lead to superior firm capabilities (Gunasekaran et al., 2017; Mishra, Luo, & Hazen, 2018). For example, Schoenherr and Speier-Pero (2015) find that firms that employ big data analytics can expect better demand-planning capability. Similarly, Wamba et al. (2017) integrate RBV logic and contingency theory into a model and suggest that big data analytics can affect a firm's financial performance by improving its process-oriented dynamic capability. Consistent with these arguments, this study proposes that BDAI can be viewed as an organizational resource that enables a firm to develop competitive advantage by using intelligence obtained from big data analytics and developing firm capabilities.

Though the importance of big data intelligence has been well established in previous literature, firms still vary in their levels of implementing big data analytical intelligence in their business practices. In this study, we aim to provide more insights into this problem by specifically investigating the antecedents and outcomes of BDAI assimilation, which refers to the degree to which a firm implements BDAI in its business practices. We present the related hypotheses in the following sections.

2.2. Antecedents of BDAI assimilation

2.2.1. Data-driven culture

Data-driven culture refers to the beliefs, attitudes, and opinions regarding data-driven decision making in management practices and operational processes (Aho, 2015; Gupta & George, 2016). A firm with a data-driven culture has three characteristics (Kiron & Shockley, 2011): (1) it treats data as an intangible asset that has value to the organization, (2) leaders or top management members emphasize and support data analytics when making decisions, and (3) the firm uses big data technology to gain data-driven insights. Therefore, a data-driven corporate culture can help management make forward-looking decisions that yield high operational effectiveness and superior firm performance by improving competitiveness (Gupta et al., 2018; Sistla & Babu, 2013). Thus, this study argues that a data-driven corporate culture serves as an internal driver for an organization's assimilation of BDAI.

First, in general, organizational culture reflects "corporate personality," which contains the collective values, beliefs, behaviors, and principles of organizational members (Khazanchi, Lewis, & Boyer, 2007; Liu, Ke, Wei, Gu, & Chen, 2010; White, Hill, McGovern, Mills, &

Smeaton, 2003). It helps organizational members understand the organizational functions and supports organizations in their efforts to gain competitive advantages for sustainable growth and prosperity. Therefore, as a corporate culture, a data-driven culture can motivate organizational members (including top management, middle managers, and frontline employees) to work together and explore the potentials of big data (Gupta et al., 2018), which assists BDAI assimilation.

Second, a data-driven culture helps managers improve decision making by developing knowledge that is less subjective and more reliable. With the knowledge and beliefs in BDAI, management will have more confidence and trust in using big data technologies throughout the organization (Chatterjee, Grewal, & Sambamurthy, 2002). Because data-driven decision making yields improved and reliable outcomes, managers will be more willing to use big data techniques to develop market intelligence that helps them better understand customers' needs and solve their problems. Therefore, we expect a data-driven culture will lead to the assimilation of BDAI. Thus.

H1. An organization's data-driven culture has a positive impact on its BDAI assimilation.

2.2.2. Competitive pressure

In this study, competitive pressure refers to an organization's perceived pressure to catch up with its peer firms' technological advancements so that it can keep a competitive advantage in market competition (Chen et al., 2015). Research drawing on institutional theory suggests that organizational structure and behavioral changes are driven not only by competition and the desire for efficiency but also by the demand for organizational legitimacy (e.g., DiMaggio & Powell, 1983). The drive for legitimacy promotes the adoption of organizational practices and the process of institutionalization, which eventually make organizations more similar (Hirsch, 1975).

In this study, we consider the competitive pressure from peer competitors that exerts an external "pulling" force that drives a firm's BDAI assimilation. First, implementing BDAI usually involves complex processes and organizational changes (McAfee et al., 2012). As a result, the return on investment of BDAI is often uncertain (Tingling & Parent, 2002). Under the condition of high uncertainty, organizations are more inclined to benchmark their behaviors against those of peer organizations and to mimic behaviors that appear legitimate and progressive (DiMaggio & Powell, 1983). For example, organizations often follow peer firms to adopt new technology to reduce technological uncertainty (Tingling & Parent, 2002). In addition, competitive pressure along with uncertainty can lead to the bandwagon effect of organizations imitating successful ones (Staw & Epstein, 2000), which will directly influence organizational decisions and practices. The less specific the technical information a company has, the more likely it will follow existing practices to adopt new technologies (Kwon, Lee, & Shin, 2014).

As El-Kassar and Singh (2018) suggest, compared with other innovations, the uncertainty of big data benefits and implementation barriers (e.g., lacking sufficient knowledge in using big data resources) may make organizations more susceptible to follow other leading firms' big data practices. Moreover, for management, it is often a difficult, risky, and expensive decision to choose one of the focal technologies until the market has given sufficient signals that such technology can indeed contribute to firm success (Tingling & Parent, 2002). Thus, to reduce the risks associated with decisions and search costs, organizations are more willing to defer to others' successful practices (Banerjee, 1992). As such, we expect that organizations are likely to follow how leading firms adopt and assimilate BDAI in their data-related strategies and practices. (Srinivasan & Swink, 2018). Thus.

H2. Competitive pressure has a positive impact on an organization's BDAI assimilation.

2.3. Linking BDAI assimilation to CRM performance: The mediating role of mass-customization capability

CRM performance refers to the extent to which a customer is loyal to its supplier and thus is willing to maintain a long-term relationship with it (Trainor, Andzulis, Rapp, & Agnihotri, 2014). Superior CRM performance not only helps a firm maintain long-term relationships with its customers but also generates more relationship-specific assets for both parties (Heide & John, 1988; Weiss & Kurland, 1997). As a result, firms that have superior CRM performance can often expect better financial outcomes (Keramati, Mehrabi, & Mojir, 2010).

As technology rapidly advances, computing- and network-empowered customers have a higher demand for customized products and services to satisfy their changing needs (Tu, Vonderembse, Ragu-Nathan, & Ragu-Nathan, 2004). In this uncertain environment, a traditional standardization strategy can no longer ensure a firm's success when competing with rivals (Liu, Shah, & Babakus, 2012). As a result, customizing products to satisfy the heterogeneous needs of customers is an important capability that enables a firm to develop competitive advantage. However, customization requires significant resource commitment and often involves deep customer engagement when developing new products (Lai, Zhang, Lee, & Zhao, 2012; Tu et al., 2004). Consequently, the cost of individual customization tends to be high. Mass customization, in which "customized products or services [are quickly produced] on a large scale and at a cost that is comparable to non-customized products or services" (Tu, Vonderembse, & Ragu-Nathan, 2001, p. 203), becomes an effective way to address the increasing demand of customization at a relative low cost. Specifically, mass customization enables organizations to produce customized products on a large scale, while maintaining relative cost-efficiency (Duray et al., 2000). Thus, mass-customization capability can help a firm achieve better performance by reducing uncertainty and complexity in product offerings and by lowering the overall cost for both the manufacture and the customers (Sanchez & Mahoney, 1996). With improved product or service flexibility and cost-efficiency, customers will be more likely to develop a long-term relationship with the supplier and have higher levels of customer satisfaction. Therefore, we anticipate that mass-customization capability will help a firm achieve better CRM performance.

As Zipkin (2001) suggests, not every firm can easily develop mass-customization capability. In general, mass customization needs organizational-level support. For example, Huang, Kristal, and Schroeder (2010) propose that flat and decentralized organizational structures can facilitate the development of mass-customization capability. Other studies argue that modularity is one of the key organizational resources that can help firms build mass-customization capability (Wang, Chen, Zhao, & Zhou, 2014). Overall, to improve mass-customization capability, organizations need to (1) involve their customers in the product development process, and (2) obtain timely knowledge and intelligence on customers' changing needs (Huang et al., 2010).

As De Bellis, Hildebrand, Ito, Herrmann, and Schmitt (2019) suggest, mass customization requires a firm to match the interface to customers' specific processing styles. BDAI can help a firm achieve this goal by improving effectiveness and efficiency in mass customization. First, BDAI provides organizations with the resources and capabilities to acquire valuable information about market trends, which helps a firm improve effectiveness in understanding customers' specific needs. For example, Zhang and Xiao (2020) suggest that by using big data intelligence provided by customers, firms can significantly improve the effectiveness of understanding customer needs. Second, BDAI assimilation requires managers to use BDAI in decision making and enables organizations to constantly interact with customers in strategic activities, such as new product development, so that the customized products or services better fit customers' needs and expectations. The evolution of three-dimensional (3-D) printing provides a good example of using big data intelligence to improve mass-customization capability. Specifically, data-driven 3-D printing technologies can significantly improve a firm's ability to provide customized products for customers on a large scale but at a relatively low cost (Jin & Ji, 2013; Kusiak, 2017). Thus, we expect BDAI assimilation to help a firm improve its mass-customization capability. Overall, we posit that.

H3. Mass-customization capability mediates the relationship between BDAI assimilation and CRM performance.

2.4. Interactive effect of marketing capability and BDAI on mass-customization capability

Marketing capability refers to a firm's ability to transform organizational resources into valuable marketing offerings for its customers (Vorhies & Morgan, 2005). Prior research drawing on the RBV suggests that firms need to integrate the "know-what" knowledge with their "know-how" deployment capabilities (e.g., Grant, 1996; Morgan, Vorhies, & Mason, 2009). Marketing capability, which contributes to a firm's dynamic capability (Morgan, Vorhies, and Mason, 2009), enables a firm to efficiently manage its marketing-related processes, such as product development, pricing, and channel management.

As Morgan, Slotegraaf, and Vorhies (2009) suggest, a firm's marketing capability can be realized through three organizational capabilities, namely market-sensing capability, brand management capability, and customer management capability. Market-sensing capability captures a firm's ability to learn about customer needs and the market trend (Day, 1994). Thus, with enhanced market-sensing capability, a firm can better understand customers' heterogenous needs and thus develop proper marketing offerings to satisfy their needs (Bharadwaj & Dong, 2014). As O'Cass and Weerawardena (2010) suggest, to improve firm performance, firms with a high level of marketing capability are likely to accumulate and utilize knowledge inputs provided by market-focused learning to understand customer needs and develop customized products. Similarly, Kotabe, Srinivasan, and Aulakh (2002) suggest that when companies enter global markets to leverage cross-culture knowledge, their performance is highly dependent on their marketing expenditure intensity. To be successful in mass customization, a firm not only needs to provide customized products or service at a lower cost, but also must effectively identify the needs for customization. Therefore, we expect market-sensing capability to interact with BDAI so that the firm can best use the valuable knowledge obtained from big data analytics to improve its ability to provide mass customization for its customers. Specifically, we posit that:

H4. Market-sensing capability positively moderates the relationship between BDAI assimilation and mass-customization capability.

Brand management capability refers to a firm's ability "not only to create and maintain high levels of brand equity but also to deploy this resource in ways that are aligned with the market environment" (Morgan, Slotegraaf, and Vorhies, 2009, p. 286). With enhanced brand management, firms can provide additional value to customers with branded products. Because premium brand assets are often associated with positive customer attitude and purchase intention (e.g., Keller, 1993), we expect that a firm's brand management capability can serve as a substitute for the resources provided by BDAI in mass customization. Specifically, firms with strong brands can develop and maintain superior brand awareness among their customers and thus differentiate themselves from competing brands (Hulland, Wade, & Antia, 2007). Under this condition, firms will develop a better understanding of customer needs than those that do not have strong brand management capability (Santos-Vijande, del Río-Lanza, Suárez-Álvarez, & Díaz-Martín, 2013). As a result, mass-customization capability is less important for firms with strong brand management capability as these firms are able to fulfill customer needs with superior brand offerings and distinctive benefits other than mass-customization options. In addition, our interviews with managers reveal that because of the comparative advantage obtained from premium brand management, firms may lack motivation to leverage benefits from BDAI to improve operational efficiency, such as improving mass-customization capability. Consequently, the dependence on BDAI to improve mass-customization capability will be lower. Therefore, we posit that:

H5. Brand management capability mitigates the positive impact of BDAI assimilation on mass-customization capability.

Customer management capability reflects a firm's ability to identify valuable customers, establish and maintain relationships with those customers, and leverage benefits from the relationships by increasing customer-level profits (Morgan, Slotegraaf, and Vorhies, 2009). Firms with high customer management capability recognize that not all customers are equal in terms of value generation and the relationships with valuable customers can provide long-term benefits for both customers and the suppliers. Prior research argues that involving customers in the product development process might be helpful in ensuring the success of mass customization (Duray et al., 2000). Mass customization requires firms to constantly identify and meet customers' changing needs (Tu et al., 2001), and thus it is imperative for firms to develop their customer management capability to face these heightened challenges. Therefore, we expect that customer management capability can provide supplemental support when using BDAI to improve mass-customization capability. Therefore, we suggest that.

H6. Customer management capability positively moderates the relationship between BDAI assimilation and mass-customization capability.

3. Method

To investigate our research questions, we employed a survey research design and collected data from B2B firms in China. We discuss the sampling procedure and data collection, along with measures of the key constructs in the following sections.

3.1. Sample and data collection

This study uses the Chinese B2B market as the research context. As one of the fastest-growing economies, the Chinese B2B market presents compelling dynamics (Dong, Ma, & Zhou, 2017). In addition, with a relationship-oriented culture, the Chinese market offers a good source for obtaining CRM-related data. We obtained an initial sample frame by searching B2B companies registered on the Alibaba platform. According to its own statistics, Alibaba is one of the largest B2B electronic platforms in the world and serves buyers from more than 190 countries and regions with over 10 million monthly customer logins. More importantly, Alibaba provides CRM services with big data analytical tools for its customers (i.e., selling companies). For example, it provides information about customers' analytical statistics (e.g., site visitor demographic information analysis, behavior trajectory analysis, click/payment conversion rate analysis), customer reception diagnosis (e.g., intelligent management of customer service personnel's initiative, success rate, service level), and inquiry management (e.g., real-time tracking of buyers, timely inquiry follow-up). Thus, companies on the Alibaba platform can form a closer relationship with customers through the social platform, as well as increase marketing effectiveness and reduce marketing and sales costs by leveraging analytical tools provided by Alibaba. Therefore, Alibaba provides an ideal pool of organizations for this study.

For data collection, we worked with a leading marketing research company in China. Senior managers or owners of B2B selling firms on the Alibaba platform were targeted and surveyed. To ensure data quality, we added two screening questions to the survey to rule out unqualified informants (e.g., non-B2B firms, lower-level executives). In total, 147 completed surveys were returned. Appendix A provides the demographic profile of the sample.

3.2. Measures

To measure the constructs included in the model, we adapted measurement scales from existing studies (see Appendix B for details). To ensure that the measurement items fit the research context well, we used a back-translation technique with the help of two marketing strategy researchers fluent in both English and Chinese. In addition, we invited managers and business professionals with similar backgrounds as the informants to evaluate the appropriateness of the survey design. With their feedback, we further improved the questionnaire design by re-ordering the question flow and re-wording the sentences to make them more intuitive and easier for the informants to understand. All scales are measured on 5-point Likert scales (1 = *strongly disagree*, 5 = *strongly agree*).

To measure *data-driven culture*, we adapted a scale from Gupta and George (2016). We assessed data-driven culture with three items that capture the degree to which an organization values big data analytics.

We measured *competitive pressure* with three items adapted from Dubey et al. (2017).[2] These items assessed the reputation, role models, and methodological research of leading companies in big data practices.

We measured *BDAI assimilation* with a scale adapted from previous studies (Gunasekaran et al., 2017; Liang, Saraf, Hu, & Xue, 2007). These items reflect the extent to which an organization uses BDAI in business practices, especially marketing-related activities.

We measured *mass-customization capability* with a scale adapted from Keramati et al. (2010). This measure assesses a firm's ability to provide customized products or services for its customers on a large scale.

We measured *marketing capability* as a second-order construct using twelve items adapted from Morgan et al. (2009a),[3] among which four items were used to measure a firm's market-sensing capability, four items were used to capture a firm's brand management capability, and another four items were used to measure a firm's customer management capability.

To measure *CRM performance*, we adapted a scale from Trainor et al. (2014). The scale consists of three items that reflect managers' assessment of their organizational performance relative to competitors in terms of customer satisfaction, customer loyalty, and new customer acquisition.

Finally, we included a set of control variables to capture the extraneous effects on a firm's mass-customization capability and CRM performance. Specifically, *firm size*, *firm age*, *industry type*, *technology capability, environmental dynamism, relationship length, a service dummy*, and *R&D intensity* serve as control variables in the model.

4. Results

4.1. Descriptive analysis

Table 2 lists the descriptive statistics and the correlation matrix among the key constructs. Overall, the results show that mass-customization capability is positively correlated with CRM performance. In addition, BDAI assimilation is positively related to mass-customization capability. The average employee size of the firms in the sample is 101–500, and the average length of the relationship is 6 years (see Appendix A).

4.2. Common method variance

As the data came from a single source, common method variance (CMV) can potentially bias the results. To examine this threat, we performed two additional analyses. First, following Podsakoff and Organ's (1986) approach, we performed the Harman one-factor test. The underlying assumption of this technique is that if one factor can explain a large proportion of the total variance, bias likely exists because of common method. The results reveal eight factors, with the first one explaining 21.97% of the total variance. This evidence suggests that CMV is unlikely to be a threat in this study.

Second, following Lindell and Whitney (2001), we use the partial correlation approach to further investigate the potential threat of CMV. This technique uses a marker variable, which in theory should be uncorrelated with at least one key construct in the model to compare the partial correlations among all the constructs with the original correlation matrix. In this study, inter-functional conflict[4] serves as a marker variable, as it is not necessarily related to competitive pressure. The initial correlation matrix confirms this assumption ($\gamma = -0.02$, $p > 0.10$). After we subtract the lowest positive correlation coefficient (0.02), the correlation matrix remains statistically consistent. This evidence further confirms that CMV is not a threat in the study.

4.3. Model assessment

To examine the reliability of the measurement, we computed the composite reliability for each construct (Hair, Sarstedt, Ringle, & Mena, 2012). The results show that all the composite reliability values are greater than 0.80. Furthermore, to investigate the validity of the measurements, we obtained the average variance extracted (AVE) values for each variable. All the AVE values are greater than 0.5, indicating that the measurement model has acceptable convergence validity (Hair et al., 2012). Finally, the results indicate acceptable discriminant validity, as the square roots of the AVEs are greater than the correlation coefficients between constructs (Fornell & Larcker, 1981).

4.4. Hypotheses testing results

To test H1–H3, we performed a partial least square (PLS) analysis. H1 posits that data-driven culture has a positive impact on a firm's BDAI assimilation. The results show a positive relationship between data driven culture and BDAI assimilation ($\beta = 0.31$, $p < 0.01$). Thus, H1 is supported. H2 proposes that competitive pressure positively affects a firm's BDAI assimilation. The results provide support for this hypothesis ($\beta = 0.20$, $p < 0.001$) (See Table 3.).

H3 proposes that by enhancing its mass-customization capability, a firm's BDAI assimilation can positively affect its CRM performance. We applied Hayes's (2013) PROCESS macro to test the mediation effect of mass-customization capability. With 5000 bootstrap samples, PROCESS produces estimates and bias-corrected 95% bootstrap confidence intervals (CI) for the indirect effect. As Table 4 shows, the direct effect of BDAI assimilation on CRM performance is not statistically significant ($\beta = 0.15$; CI = [−0.001, 0.29]), but the indirect effect is significant ($\beta = 0.07$; CI = [0.01, 0.14]). Overall, the results suggest that a firm's mass-customization capability mediates the relationship between its BDAI and its CRM performance. Therefore, H3 is supported.

To test the moderating effects of marketing capability on the relationship between BDAI assimilation and mass-customization capability (i.e., H4 – H6), a regression analysis was used. Specifically, we first computed the factor scores for each variable and used the factor scores in the regression analysis to capture the different weights of the items (DiStefano, Zhu, & Mindrila, 2009). Table 5 summarizes the results

[2] In Dubey et al.'s (2017) study, they used a slightly different term (mimetic pressures) to define? definite this construct.

[3] The original scale provided by Morgan, Slotegraaf, and Vorhies (2009) includes fifteen items. We dropped three items due to the poor factor loadings, which significantly worsen the model fitness.

[4] Inter-functional conflict is measured using a scale adapted from Arnett and Wittmann (2014).

Table 2
Correlation matrix and descriptive statistics.

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
CRM performance	4.10	0.44	1.00	0.29	0.24	0.26	0.06	0.29	0.34	0.24	0.09	0.28	0.09
Mass customization	4.00	0.48	0.31	1.00	0.35	0.33	0.30	0.44	0.46	0.38	0.18	0.25	0.00
BDAI_assimilation	4.11	0.50	0.26	0.37	0.34	0.32	0.22	0.34	0.45	0.42	0.20	0.28	−0.03
Data-driven culture	4.15	0.37	0.28	0.35	0.24	1.00	0.21	0.21	0.24	0.19	0.10	0.21	−0.03
Competitive pressure	3.95	0.65	0.08	0.32	0.36	0.23	1.00	0.03	0.23	0.08	0.18	0.15	−0.16
Market-sensing capability	4.15	0.39	0.31	0.46	0.47	0.23	0.05	1.00	0.46	0.49	0.07	0.27	0.06
Brand management capability	4.08	0.42	0.36	0.48	0.44	0.26	0.25	0.48	1.00	0.56	0.06	0.34	−0.01
Customer management capability	4.08	0.40	0.26	0.40	0.22	0.21	0.10	0.51	0.58	1.00	0.19	0.21	−0.01
Environmental dynamism	3.85	0.63	0.11	0.20	0.30	0.12	0.20	0.09	0.08	0.21	1.00	0.06	0.00
Technology capability	4.07	0.39	0.30	0.27	−0.01	0.23	0.17	0.29	0.36	0.23	0.08	1.00	−0.01
Relationship length	6.07	3.00	0.11	0.02	0.24	−0.01	−0.14	0.08	0.01	0.01	0.02	0.01	1.00

Note: Correlations that have an absolute value greater than 0.17 are significant at the $p < 0.05$ level. The zero-order correlations are listed below the diagonal, and the adjusted correlations are listed above the diagonal.

Table 3
Results of main effects.

Path	Coefficient		R^2
	Estimate	SE	
CRM performance			0.14
Mass-customization capability → CRM performance	0.27	0.10	
BDAI assimilation → CRM performance	0.16	0.08	
Mass-customization capability			0.18
BDAI assimilation → Mass-customization capability	0.44	0.07	
BDAI assimilation			0.16
Data-driven culture → BDAI assimilation	0.31	0.10	
Competitive pressure → BDAI assimilation	0.20	0.06	

Table 4
Bootstrapped mediation results.

Path	Coefficient		Bias-corrected 95% CI	
	Estimate	SE	Lower	Upper
a. Total effect model				
BDAI assimilation → CRM performance	0.21	0.07	0.07	0.35
b. Multiple mediation mode				
Direct effects				
BDAI assimilation → CRM performance	0.15	0.07	−0.001	0.29
Indirect effects				
BDAI assimilation → Mass-customization capability → CRM performance	0.07	0.03	0.01	0.14

Note: Results obtained using 5000 bootstrap samples. SE = standard error; CI = confidence interval. Covariates include R&D, Firm size, Firm age, industry dummies, service dummy.

Table 5
Results of moderating effects.

DV: Mass-customization capability	B	S.E.	p
Intercept	0.18	0.58	0.75
BDAI_assimilation	0.13	0.08	0.09
MSC	0.20	0.08	0.02
BMC	0.20	0.09	0.03
CMC	0.05	0.09	0.59
BDAI_assimilation * MSC	−0.12	0.08	0.16
BDAI_assimilation * BMC	−0.22	0.09	0.02
BDAI_assimilation * CMC	0.17	0.09	0.07
Environmental dynamism	0.07	0.07	0.31
Technology capability	0.09	0.07	0.23
Service	−0.17	0.16	0.29
R&D	0.07	0.05	0.17
Industry dummies	Included		
Firm age	0.03	0.08	0.71
Firm size	0.11	0.09	0.23
Manager position	−0.34	0.15	0.03
N	147		
F-statistics	7.68		
Adjusted R^2	0.41		

Note: MSC = market-sensing capability; BMC = brand management capability; CMC = customer management capability.

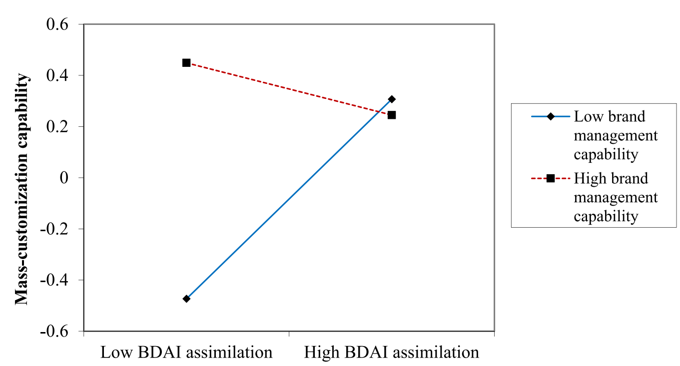

Fig. 2. Moderating effect of brand management capability.

obtained from the regression analysis. H4 proposes that market-sensing capability strengthens the positive relationship between BDAI dissimilation and mass-customization capability. The results show that the interactions of market-sensing capability with BDAI assimilation is not statistically significant ($\beta = -0.12, p > 0.10$). Thus, H4 is not supported.

In H5, we posit that brand management capability will mitigate the positive impact of BDAI assimilation on mass-customization capability. The results from Table 5 show that the interaction of BDAI assimilation and brand management capability is negatively significant (β = −0.22, $p < 0.05$). This effect is plotted in Fig. 2. As shown in the figure, when brand management capability is higher (one standard deviation higher than the mean value), the slope shows a downward trend. However, when brand management capability is lower (one standard deviation below the mean value), the slope shows an upward trend. This result indicates that brand management capability may serve as a substitute mechanism that helps a firm improve its mass-customization capability. Therefore, H5 is supported.

In H6, we posit that a firm's customer management capability will positively moderate the relationship between BDAI assimilation and mass-customization capability. The results from Table 5 show that the interaction of BDAI assimilation and customer management capability is positively significant ($\beta = 0.17$, $p = 0.07$). Therefore, H6 is supported. To further probe this effect, we plot it in Fig. 3. As shown in Fig. 3, when customer management capability is higher (one standard deviation above the mean), the slope shows an upward trend. In comparison, when customer management capability is lower (one standard deviation below the mean), the line shows a negative slope. This evidence indicates that a firm's customer management capability can serve as a supplemental mechanism that helps a firm better utilize BDAI to

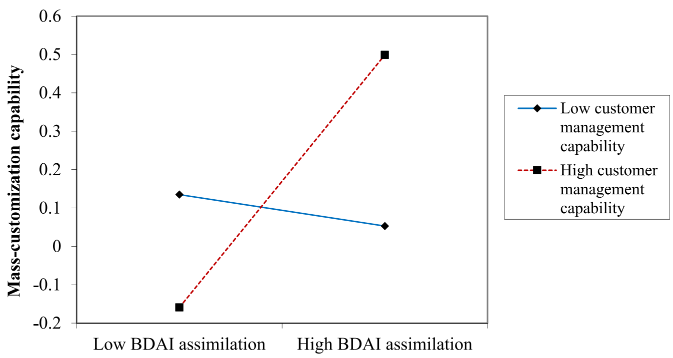

Fig. 3. Moderating effect of customer management capability.

improve mass-customization capability.

4.5. Supplemental evidence from in-depth interviews

To glean more insights into our research findings, we conducted 16 in-depth interviews with managers who have similar backgrounds to the informants in our large-scale survey. The interviews were guided by a semi-structured question list along with probing questions throughout the interview process. Each interview lasted from 30 min to one hour on average. During the interviews, we asked the informants to provide information about the big data practices in their firms and to elaborate on the drivers and implications of big data strategy. Overall, we found evidence supporting our key hypotheses. Appendix C summarizes the research findings from the interviews.

5. Discussion

While big data plays an increasingly important role in firms' business operations, such as CRM (Davenport, Barth, & Bean, 2012), research has just begun to examine the mechanisms through which big data techniques contribute to business success (Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Gunasekaran et al., 2017). This study aims to add insights by exploring the antecedents of BDAI assimilation and the influence of BDAI assimilation on CRM performance in B2B markets.

The first research question in this study asked what the drivers of a firm's BDAI assimilation are. The findings reveal that a data-driven culture and competitive pressure are two key factors affecting the assimilation of BDAI. From an internal perspective, a data-driven culture can positively affect the assimilation of BDAI by influencing managers' commitment to an analytics-based vision and orientation for employees. From an external standpoint, competitive pressure urges organizations to follow leading companies or competitors to use and employ BDAI so that they can lower search costs and improve business performance (Dubey et al., 2019).

The second research question explores the mechanism by which BDAI improves CRM performance in B2B markets. The results reveal that BDAI assimilation does not directly affect CRM performance; instead, it indirectly influences CRM performance by improving mass-customization capability. This result uncovers the underlying mechanisms of BDAI to improve CRM performance and helps explain why there are significant differences in the performance levels of companies relying on similar big data technological platforms. As the findings suggest, implementing BDAI without considering the improvement of related business processes (e.g., mass customization) will lead to inefficient resource allocation, which in turn will result in unfavorable performance outcomes.

Furthermore, the findings indicate that a firm's marketing capability can potentially influence the level of benefits firms can get from using BDAI to improve mass-customization capability. Specifically, a firm's brand management capability can provide a substituting effect for BDAI on enhancing mass-customization capability. Superior brand management requires a better understanding of customer needs, which indirectly reduces the dependence on BDAI to improve mass-customization capability. In addition, firms with superior brand management may also lack motivation in using BDAI to improve business effectiveness due to the competitive advantage obtained from superior brand management. However, our findings reveal that customer management capability supplements the effect of BDAI on improving mass-customization capability. Superior customer management provides more channels to identify and understand customer needs. As a result, firms can better transform big data resources into developing marketing offerings that can satisfy customers' changing needs.

5.1. Theoretical contributions

This study offers important theoretical contributions to several research streams. First, though previous studies have provided substantial evidence supporting the importance of big data-related strategies in achieving firm success, our knowledge is limited in understanding why and when a firm actually implements big data intelligence in its business practices. To bring new insights into solving this problem, this study explores the antecedents of BDAI assimilation by examining both internal and external environmental factors. Specifically, we propose that a data-driven culture serves as an internal pushing driver and that competitive pressure works as an external pulling force that motivates organizations to adopt and assimilate BDAI in their strategic activities.

Second, this study contributes to the big data literature by exploring the mechanism by which BDAI affects firm performance outcome. Our findings highlight that BDAI assimilation itself cannot directly lead to superior B2B firm performance (i.e., CRM performance), but through the enhanced mass-customization capability. This finding yields an important implication for the theoretical framework examining big data-related strategies by linking BDAI (as a firm resource) to firm performance through an organizational capability.

Third, this study identifies marketing capability as a potential firm capability that can influence the transformation of BDAI assimilation into superior firm dynamic capabilities, such as mass-customization capability. More importantly, this finding highlights that different aspects of marketing activities may play differential roles in influencing the effectiveness of BDAI assimilation. As the results reveal, superior brand management capability serves as a substitute for BDAI while customer management capability supplements BDAI in enhancing mass-customization capability. This finding provides supplemental insights into the boundary conditions through which BDAI can generate more benefits for a firm.

5.2. Managerial implications

The findings provide compelling implications for managerial practice. First, managers should realize that the assimilation of BDAI could contribute to their CRM performance. While managers strive to maintain relationships with valuable customers, they often lack sufficient knowledge for understanding customer needs. This study suggests that managers should devote significant organizational resources to developing big data analytics intelligence and assimilating BDAI in all possible practices to manage their customer relationships. For example, managers can encourage cloud computing and data-driven customer needs analysis when profiling customers. In addition, they can develop databases to help predict customer needs so they can provide better marketing offerings.

Second, managers should be aware that BDAI is driven not only by external competitive pressure; it also needs internal support from a data-driven culture. Thus, managers should strive to promote such a culture within their organizations. For example, managers should emphasize that relying solely on traditional experiences and intuition to make decisions may not be reliable or efficient, especially in CRM. Rather, it is important to convert as much customer data as possible into valuable information. In addition, managers should provide training and supporting resources for employees so that they can cultivate and process data-specific technologies and skills.

Finally, managers should realize that BDAI is not a panacea. They also need to pay attention to the improvement of marketing capability and mass-customization capability. As the results suggest, BDAI does not directly affect CRM performance; instead, it indirectly affects CRM performance through mass-customization capability. Managers should leverage the insights from BDAI to define specific processes that fit their customers' needs and to identify the necessary ways to build mass-customization capabilities, so as to facilitate the transfer of BDAI investments into superior CRM performance. For example, BDAI can be used to enable data-driven 3-D printing technology, which may significantly improve a firm's mass-customization capability (Kusiak, 2017). In addition, managers need to use proper marketing strategies so they can better absorb and transform BDAI resources.

5.3. Limitations and future research

This study has several limitations that pave the way for future research. First, the data come from informants' self-reports, which may lead to potential bias of the results. Although management teams likely have a good understanding of their companies' industry background, corporate culture, resource deployment, and process design, they are likely to exaggerate their companies' BDAI usage, mass customization, marketing capabilities, and even CRM performance. Moreover, self-reporting technology usage may be different from what is employed in practice (Ahearne, Jones, Rapp, & Mathieu, 2008). For example, respondents might report that they use relevant big data technologies, but the actual use of this technology may be rare. Therefore, future research should try to collect feedback from individuals who are more directly involved in daily operations to capture the actual use of technologies, such as BDAI, and link this information to other sources of performance data, such as the company's archival data and customers' views, to obtain a more accurate and comprehensive picture of usage. In addition, some firms included in our sample are not manufacturing firms but service-oriented firms. Although BDAI assimilation and mass customization are equally important for service-oriented firms and for manufacturing firms, we acknowledge that the process of how BDAI affects CRM performance might be different in service firms from that in manufacturing firms. Thus, future research can further look into this problem and provide more insights by examining the differences between different types of firms.

Second, as prior research suggests, BDAI can also benefit from routinization of big data–related activities (Chen et al., 2015; Gunasekaran et al., 2017). For example, a firm can provide dedicated resources, such as budgets for BDAI, specific business units, and related training to facilitate the development of BDAI. In this study, routinization is less connected with the research context than assimilation because firms in the sample are operating on the Alibaba platform and big data technical support generally comes from Alibaba. Future research could examine this problem further and extend the research findings by considering the role of routinization in this process.

Furthermore, research suggests that a firm's marketing capability can directly affect its performance, including the CRM performance (e.g., Chang, Park, & Chaiy, 2010). A post-hoc analysis of this study shows that marketing capability does have a positive impact on CRM performance. In this study, we only consider the moderating effect of marketing capability on the relationship between mass customization capability and CRM performance. However, this process can be very complicated as marketing capability can in turn influences a firm's big data strategy as a performance-based learning process. Therefore, future research can benefit from looking further into other roles played by marketing-related capabilities in enhancing a firm's big data capability and firm performance.

Finally, the finding on the impact of BDAI on firm performance demands further exploration. For example, this study explores only the mediating effect of marketing capability and mass-customization capability on the relationship between BDAI and CRM performance. However, BDAI might bring more benefits to firms by enhancing many other firm capabilities, such as dynamic capability (Wamba et al., 2017) and sustainable capability (Singh & El-Kassar, 2019). In addition, investing in BDAI does not come without cost. Therefore, future research could explore whether risks are associated with BDAI. For example, BDAI may improve firm performance but also open up the possibility for information leakage risk due to hacking and moral hazard from obtaining customer information through BDAI.

6. Conclusion

As market intelligence generated by big data has been increasingly used by firms to build competitive advantage, this study offers some initial insights into how firms can develop BDAI and use it to improve their CRM performance. We highlight the important roles marketing capability and mass-customization capability play in transforming a firm's BDAI into superior CRM performance. However, we caution that firms need to consider their organizational context when utilizing BDAI in business practices.

Appendix A. Sample profile

Item		Frequency	%
Number of employees	21–100	41	27.9
	101–500	70	47.6
	501–1000	27	18.4
	>1000	9	6.1
Industry	Manufacturing	69	47.0
	Wholesale	70	47.6
	Transportation	2	1.4
	Information Service	3	2.0
	Others	3	2.0
Firm age	<3	20	13.6
	6–10	69	46.9
	11–15	35	23.8
	>15	23	15.6
R&D intensity	<5%	20	13.6
	6% - 10%	52	35.4
	11%–20%	45	30.6
	>20%	30	20.4

Appendix B. Measurement scales

Constructs and measurement items	Loading
Data-driven culture (CR = 0.839, AVE = 0.568) (Gupta & George, 2016)	
– We consider data a tangible asset.	0.810
– We base our decisions on data rather than on instinct.	0.645
– We are willing to override our own intuition when data contradict our viewpoints.	0.724
– We continuously coach our employees to make decisions based on data.	0.821
Competitive pressure (CR = 0.865, AVE = 0.681) (Dubey et al., 2017)	
– Our competitors who have adopted big data and predictive analytics have greatly benefitted.	0.886
– Our competitors who have adopted big data and predictive analytics are favorably perceived by the others in the same industry.	0.838
– Our competitors who have adopted big data and predictive analytics are favorably perceived by their suppliers and customers.	0.746
BDAI assimilation (CR = 0.829, AVE = 0.621) (Gunasekaran et al., 2017; Liang et al., 2007)	
– BDAI is used as an important tool in every department.	0.862
– BDAI is used for decision making in every functional area.	0.823
– BDAI is used in developing new products and other marketing-related activities.	0.665
Mass-customization capability (CR = 0.809, AVE = 0.515) (Keramati et al., 2010)	
To what extent can your firm achieve the following situation with most customers?	
	0.749
– We are highly capable of large-scale product customization.	
– We can easily add significant product variety without increasing cost.	0.680
– We can customize products while maintaining high volume.	0.657
– Our capability for responding quickly to customization requirements is very high.	0.777
Marketing capability (Morgan, Slotegraaf, and Vorhies, 2009)	
Market-sensing capability (CR = 0.825, AVE = 0.543)	
– Learning about customer needs and requirements.	0.800
– Discovering competitors' strategies and tactics.	0.657
– Identifying and understanding market trends.	0.678
– Learning about the broad market environment.	0.801
Brand management capability (CR = 0.837, AVE = 0.563)	
– Using customer insights to identify valuable brand positioning.	0.799
– Maintaining a positive brand image relative to competitors.	0.749
– Achieving high levels of brand awareness in the market.	0.711
– Tracking brand image and awareness among target customer.	0.740
Customer management capability (CR = 0.831, AVE = 0.552)	
– Identifying and targeting attractive customers.	0.755
– Getting target customers to try our products/services.	0.680
– Maintaining loyalty among attractive customers.	0.837
– Enhancing the quality of relationships with attractive customers.	0.691
CRM performance (CR = 0.802, AVE = 0.577) (Trainor et al., 2014)	
Relative to your competitors:	
– Our customers are very loyal to our firm.	0.779
– Our customers work with our firm for a long time.	0.664
– Our customers are satisfied with our company.	0.826

Note: CR = composite reliability; AVE = average variance extracted.

Appendix C. Summary of interview findings

Item	Summary of findings
BDAI and mass customization	• "To develop a product, especially for those customized products, we need first to learn about what our customers would prefer in terms of design, the purchase intention, etc." (M1) • "We have a database that can track our transaction flow. With the data provided by our database, we can offer customized products for our customers, which will best fit their needs and perhaps will sell well on the market." (M4) • "Once we have identified those VIP customers [using big data analytics], we will adjust our service strategy and to meet their specific needs." (M16) • "One of our key competitive advantages is our ability to promote customized content to our customers using machine learning." (M15) • "We typically use the industry data to predict and research our customers' needs, then we will provide customized products to meet their needs." (M12)
Competitive pressure and BDAI	• "Using big data in business practices is a trend in the industry. If we do not follow the trend and explore its value, we will fall behind the competition." (M2) • "We have advantage in the area of RFID, so we want to capitalize on what we are good at." (M9) • "I can picture that big data will play a significant role in future market competition." (M7) • "If we do not follow others to build advantage on data intelligence, we could lose our advantage on the market competition." (M16)
Data-driven culture and BDAI	• "The primary reason for our focus on big data is that our company has the resources and tradition in using data-enabled decision-making in our business practices." (M3) • "Some other companies who do not adopt big data believe they are traditional manufacturing firms and thus there has little to nothing to do with big data, which is wrong. I believe the intelligence obtained from big data can significantly improve our business growth." (M9) • "Some firms are not comfortable with risk and thus are not willing to use unknown information." (M10) • "We believe big data could be the future power that drives productivity." (M16)

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