Industrial Marketing Management 86 (2020) 90–98

Contents lists available at ScienceDirect

Industrial Marketing Management

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

Fostering B2B sales with customer big data analytics

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ARTICLE INFO

Keywords:
Big data analytics
Customer analytics
Marketing analytics
Firm performance
Customer relationship management
Big data-enhanced database marketing

ABSTRACT

This study focuses on the use of big data analytics in managing B2B customer relationships and examines the effects of big data analytics on customer relationship performance and sales growth using a multi-industry dataset from 417 B2B firms. The study also examines whether analytics culture within a firm moderates these effects. The study finds that the use of customer big data significantly fosters sales growth (i.e. monetary performance outcomes) and enhances the customer relationship performance (non-monetary performance outcomes). However, the latter effect is stronger for firms which have an analytics culture which supports marketing analytics, whereas the former effect remains unchanged regardless of the analytics culture. The study empirically confirms that customer big data analytics improves customer relationship performance and sales growth in B2B firms.

1. Introduction

A survey in the United States and worldwide reports that 84% of industry-leading firms have started big data analytics initiatives to bring greater accuracy to their decision-making (Statista, 2018). Big data analytics, i.e. the utilization of big data and related analytics methods, is reported to deliver the most value to firms by reducing expenses and creating new avenues for innovation and disruption (NewVantage Partners, 2017). Big data analytics enables firms to strengthen their business operations, for example, in supply chain management (Gunasekaran et al., 2017) and customer relationship management (Nam, Lee, & Lee, 2019; Phillips-Wren & Hoskisson, 2015; Zerbino, Aloini, Dulmin, & Mininno, 2018). In customer relationship management, the emergence of big data analytics will enable a new wave of strategies to support the personalization and customization of sales and customer services (Anshari, Almunawar, Lim, & Al-Mudimigh, 2018), and to build stronger and more personal relationships with customers (De Lima Francisco, Moura, Sabino, Santos, & Esquarcio, 2016). Also, big data is useful to identify what customers actually expect from companies and to predict their future demands (Perera, Dilini, & Kulawansa, 2018) utilizing big data technologies and tools (Emtiyas & Keyvanpour, 2011).

The main motive behind the exploitation of big data analytics is the creation of business knowledge (Davenport, 2014), i.e. information and understanding related to business processes and the business environment (Wang, Xu, Fujita, & Liu, 2016) to support decision-making in firms. Big data analytics can enable better-informed decision-making and can be used for the optimization of business processes and enhanced understanding of customers (Wamba et al., 2017). It can additionally reveal hidden behavioral patterns (Erevelles, Fukawa, & Swayne, 2016). Furthermore, big data analytics can use real-time data and provide instant information, creating real-time knowledge of markets (Xu, Frankwick, & Ramirez, 2016) and thus when properly implemented it can increase sales. Customer big data analytics can be used to generate valuable information about customers, but the challenge for marketers is to transform the information into a market advantage (Erevelles et al., 2016). Companies will only benefit from customer big data analytics if they succeed to effectively address this managerial challenge (McAfee & Brynjolfsson, 2012). Practical examples suggest that a vital ingredient for success in using analytics effectively is not solely to do with the technology, but also involves having a data-driven organizational culture (Diaz, Rowshankish, & Saleh, 2018; Tao, 2018). McKinsey research suggests that a healthy data culture, i.e., an organizational culture that accelerates the application of data analytics, is becoming increasingly important for leading and lagging companies alike (Diaz et al., 2018). When describing a healthy data culture they refer to organizations wherein data initiatives aim to deploy data for better organizational decision-making, and that data initiatives are a constant process within the organization rather than periodical projects (Diaz et al., 2018). Also, the deployment of data aims to provide accurate and timely information throughout the organization and from the top to the bottom (Diaz et al., 2018).

In discussing emerging topics and the future of B2B marketing, Wiersema (2013) identifies big data analytics as one of the emerging

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https://doi.org/10.1016/j.indmarman.2019.12.005
Received 30 June 2018; Received in revised form 10 October 2019; Accepted 14 December 2019
Available online 24 December 2019

areas in the domain of B2B marketing. Previously, firms were limited mainly to quantitative and transactional data such as purchase quantities (Erevelles et al., 2016). Recent developments have made the collection of data more feasible and cost-effective (Frizzo-Barker, Chow-White, Mozafari, & Ha, 2016), and data can be obtained from both internal and external data sources (Lilien, 2016). A great potential exists in big data analytics for B2B firms, but nonetheless B2B practitioners seem to lack the tools and the guidance to realize the potential (Lilien, 2016). Moreover, organizations lack the knowledge of how big data can enhance their business activities and how they would benefit from those changes (Lycett, 2013), and academic research has, so far, failed to provide this information (Frizzo-Barker et al., 2016). As stated in recent studies (Sivarajah, Kamal, Irani, & Weerakkody, 2017; Wang & Hajli, 2017), this is due because academic research on the topic is only emerging, and much of the present discussion has focused on simulations, technical views, and experiments rather than strategic and managerial implications. Indeed, the research on big data lacks confirmed empirical evidence on the effect of big data analytics on customer relationship performance and the financial performance of firms.

Consequently, the present study focuses on the question: *How does big data analytics enable B2B firms to manage their customer relationships, thereby driving their sales?* In doing so, the study examines the impacts of customer big data analytics on customer relationship performance (non-monetary performance outcomes) and sales growth (monetary performance outcomes). Additionally, the study proposes that an analytics culture, i.e. an organizational culture that supports the utilization of analytics (Germann, Lilien, & Rangaswamy, 2013), is a significant enabler of these effects. The study suggests that firms with an established data analytics culture, i.e. firms which have an overall supportive stance toward the use of data analytics and who consider clear benefits in it, are more likely to benefit from customer big data analytics in managing their customer relationships, compared to firms which do not have such an established culture. Additionally, differences are expected in relation to the firm size, because previous results suggest that the ways in which big data strategies are developed and executed depend on the firm size, among other factors (Mikalef, Boura, Lekakos, & Krogstie, 2019). As such, the study contributes to the existing academic discussion in several ways. First, while a growing body of research is interested in the impact that big data analytics can have on business performance (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Gunasekaran et al., 2017; Wamba et al., 2017), the present study is among the first *empirical* studies to shed light on the phenomenon in managing B2B customer relationships. Second, an analytics culture is suggested to act as an enabler moving a firm from competitive parity to a competitive advantage when it comes to gaining profits from big data analytics (Kiron, Prentice, & Ferguson, 2014), however empirical results are needed to support the proposition. Third, when it comes to big data analytics, B2B is considered to be falling behind B2C (Lilien, 2016), and this study provides empirical evidence of the role of big data analytics in customer relationship management and sales growth for B2B firms. This is a research area that is practically non-existent in the current academic literature.

2. Theoretical background and hypotheses development

2.1. B2B relationships in the era of big data

The study builds on the theory of relationship marketing, which is concerned with how companies manage and improve their customer relationships for long-term profitability (Ryals & Payne, 2001). Relationship marketing emphasizes the central role of customers for the strategic positioning of the company and it includes activities such as training employees to develop personal relationships with customers, establishing loyalty programs and communicating with customers through multiple channels (Jones et al., 2015). Indeed, it is well known that companies should strive to keep existing customers rather than acquire new ones (Jahromi, Stakhovych, & Ewing, 2014). This is especially the case in B2B markets where the number of customers is often smaller than in B2C markets but given the customers' much greater purchase amount and value in the B2B setting, there are great rewards for those suppliers who succeed in creating and maintaining B2B customer relationships (Rauyruen & Miller, 2007). Therefore, it is essential to approach B2B customers with tailored offers and incentives (Jahromi et al., 2014), and big data analytics enables new opportunities for providing more personalized customer experiences (Morgan, 2018).

Today, customer relationship management, i.e., the use of information technology for implementing relationship marketing strategies (Ryals & Payne, 2001), has become one of the key enablers for relationship marketing. Database marketing, which is a subdimension of relationship marketing with the focus on exploiting data in marketing (Möller & Halinen, 2000), represented a step toward a more sophisticated means of achieving targeted communication and segmentation in the late 1990s and early 2000. Database marketing was concerned with using information about customers and markets to improve the efficiency of firm activities (Cespedes & Smith, 1993). Marketing databases, when implemented wisely, were considered to provide useful assistance to marketing managers in various tasks ranging from daily operations, resource allocation, and budget planning, to strategic decision-making processes (Tao & Yeh, 2003). Further, database marketing utilized advanced information technology to provide recognition and services to customers for the purpose of increasing customer loyalty and to generate repeat sales (Tao & Yeh, 2003). Hence it provided a way to learn about the characteristics of individual customers (Petrison, Blattberg, & Wang, 1997) instead of the masses. Today, customer big data analytics enables even more sophisticated marketing actions and therefore the study proposes that the use of big data in customer relationship management may be the next step in database marketing for managing customer relationships.

2.2. Customer big data analytics in B2B customer relationship management

Big data here refers to a collection of large, heterogeneous and complex datasets that are difficult to process using conventional tools and applications. Typically, big data is described through its features: volume (the scale and quantity of data), velocity (the rate at which the data is generated and the speed at which it should be analyzed) and variety (different formats of unstructured and structured data) although additional characteristics such as value (extracting knowledge from data), veracity (data assurance, accuracy of data), variability (the constantly changing meaning of data) and visualization (presenting the data in a readable manner) are commonly associated with the definition of big data (Erevelles et al., 2016; Lycett, 2013; Sivarajah et al., 2017; Wamba et al., 2017). However, big data alone is not a key but rather it can be considered a raw material that needs to be further transformed into business insights (Xu et al., 2016). Analytics, in general, refers to extracting hidden insights from data (Gandomi & Haider, 2015) with the purpose of creating business knowledge, referring to enhanced information and understanding with regard to business processes and business environments (Wang et al., 2016). Customer big data analytics used in this study, thus, refers to acquiring, storing, processing and analyzing an immense volume, variety and velocity of customer-related data, aimed at creating meaningful information for the firm's decision-making, and to discover business value and insights in a timely fashion (Wang & Hajli, 2017).

Customer relationship management data is among the most important information available in many organizations, and according to Stein, Smith, and Lancioni (2013), this is particularly the case in B2B marketing. In managing B2B customer relationships, big data analytics can be useful to extract knowledge and gain insights from various sources of data. Orenga-Roglá and Chalmeta (2016), for instance, suggest that Web 2.0 technologies together with big data analytics will enhance customer relationship management, as they enable the company to generate better product recommendations, understand the competitive environment and predict upcoming trends. Additionally, big data analytics in customer relationship management can be used to automatically categorize and route customer interactions, and to generate a better overall view of customer behavior through different channels (Orenga-Roglá & Chalmeta, 2016). Overall, big data analytics enhances the firm's dynamic and adaptive capabilities, reflecting the firm's ability to respond to change (Erevelles et al., 2016). This is in line with what marketers attempted in the late 1990s through database marketing activities.

Compared to traditional database marketing, big data-enhanced database marketing provides improved opportunities for B2B customer relationship management as big data analytics enables customer data to be converted to knowledge, and further transformed in an effective, secure and scalable way into real business value (Orenga-Roglá & Chalmeta, 2016). Big data analytics can thus provide crucial information for marketers and it ultimately enables the firm to move toward a customer-focused strategy (Orenga-Roglá & Chalmeta, 2016) to better answer rapidly changing customer needs and preferences (Xu et al., 2016). Big data analytics enables, for example, better-personalized product recommendations, offerings and price optimizations (Martin & Murphy, 2017), allowing the firm to operate in a more customer-oriented way, to build highly personalized customer relationships (Erevelles et al., 2016). Additionally, big data analytics can enable the firm to optimize its marketing activities based on real-time information and to do so in a timely manner (Xu et al., 2016).

2.3. Customer big data analytics and firm performance

The question of whether a firm's marketing efforts are directed effectively toward the right customers remains one of the main difficulties for marketers (Iyer, Soberman, & Villas-Boas, 2005). With customer big data analytics, marketers can better understand the heterogeneity in their customer base and respond to specific customer needs, enabling a more accurate targeting of marketing activities and hence better firm performance. In line with Wamba et al. (2017), this study suggests that the use of customer big data analytics can improve firm performance. The study operationalizes firm performance through two constructs: 1) *customer relationship performance*, capturing non-monetary outcomes such as achievement of customer satisfaction, and 2) *sales growth*, describing a firm's financial performance and achievement of monetary objectives.

Customer relationship performance is an outcome of a firm's customer relationship management (CRM), composed of people, processes and technology (Öztayşi, Kaya, & Kahraman, 2011) with a strategic target to develop long-term relationships with customers (Mendoza, Marius, Pérez, & Grimán, 2007). Zablah, Bellenger and Johnston (2004, p. 480) define customer relationship management as "an ongoing process that involves the development and leveraging of market intelligence for the purpose of building and maintaining a profit-maximizing portfolio of customer relationships". This process view of customer relationship management suggests that buyer-seller relationships develop over time, and success is dependent on the firm's ability to detect and respond to evolving customer needs and preferences (Zablah et al., 2004). Indeed, it is a basic dogma in relationship marketing that maintaining long-term customer relationships is more beneficial than short-term customer relationships (Morgan & Hunt, 1994; Sheth & Parvatiyar, 1995). Recent studies (Choudhury & Harrigan, 2014; Trainor, Andzulis, Rapp, & Agnihotri, 2014) suggest that social media, for example, may enhance customer relationship management in firms. New sources of customer big data can enable more and possibly better data for CRM decision-making (Phillips-Wren & Hoskisson, 2015). Customer big data together with big data analytics enables marketers to fill gaps in their knowledge of customer behavior that could not have been detected before (Erevelles et al., 2016) and enhances the key activities of database marketing such as targeting, segmenting and retaining customers (Fan, Lau, & Zhao, 2015). Consequently, it is hypothesized:

H1. Big data analytics has a positive effect on a B2B firm's customer relationship performance.

The actual pay-off from investments in customer relationship management has been an on-going debate among business practitioners as well as academics (Reimann, Schilke, & Thomas, 2010; Ryals, 2005). Several studies have found a positive relationship between customer relationship management and firm performance, while others report an insignificant or a negative effect (Reimann et al., 2010). The challenge with intangible assets, such as those of customer relationship management, is the generally acknowledged fact that the outcomes are seldom directly measurable in short-term performance measures, but rather are accumulated over a longer period (Homburg, Vomberg, Enke, & Grimm, 2015; Mizik, 2014). Stakeholder theory provides a theoretical framework to examine the relationship between customer relationship performance and firm performance as it suggests that meeting the needs of customers and other stakeholders leads to an increased financial performance (Preston & O'bannon, 1997; Van der Laan, Van Ees, & Van Witteloostuijn, 2008). With regard to customer relationship performance and sales growth, it is hypothesized that:

H2. Customer relationship performance has a positive effect on a B2B firm's sales growth.

Many firms lack the knowledge and understanding of how big data analytics relates to their business activities and how to benefit from it (Lycett, 2013). Based on the resource-based view of the enterprise (Wernerfelt, 1984), prior research draws a direct link between general information technology investments and firm performance (Huang, Ou, Chen, & Lin, 2006; Melville, Kraemer, & Gurbaxani, 2004) and recently also between investments in big data analytics and firm performance (Akter et al., 2016; Nam et al., 2019; Wamba et al., 2017; Wang & Hajli, 2017). Akter et al. (2016) find a strong alignment between a firm's capability to utilize big data analytics and business strategy alignment, in achieving improved firm performance. We suggest that because customer big data analytics enables firms to exploit real-time information about customers and respond to their needs almost instantly (Xu et al., 2016), it is likely that in addition to the indirect effect via customer relationship performance, big data analytics has also a positive direct effect on sales. Therefore, it is hypothesized that:

H3. Big data analytics has a positive effect on a B2B firm's sales growth.

2.4. Moderating effect of a firm's analytics culture

An analytics culture reflects the pattern of shared values and beliefs within a firm (Germann et al., 2013), and it unites business and technology around a common goal through a specific set of behaviors, values, decision-making norms and outcomes (Kiron et al., 2014). Germann et al. (2013) propose that the analytics culture of a firm plays a key role in incorporating insights gained from marketing analytics into the firm's decision making. With regard to big data analytics, Kiron et al. (2014) suggest that an analytics culture acts as an enabler moving a firm from competitive parity to a competitive advantage when it comes to generating profits from customer big data analytics. The *analytics culture* of an organization here refers to the extent to which an organization is supportive of marketing analytics in general (Germann et al., 2013) and finds it useful, and encourages fact-based decision-making relying on data (Thirathon, Wieder, Matolcsy, & Ossimitz, 2017). Such a stance can act as a significant enabler for using customer big data for the benefit of the firm (Lismont, Vanthienen, Baesens, & Lemahieu, 2017), whereas a lack of it can form a significant barrier (Alharthi, Krotov, & Bowman, 2017). Lismont et al. (2017) found that an organization's data analytics culture is one of the key characteristics for disruptive analytics innovative firms, enabling them to exploit big

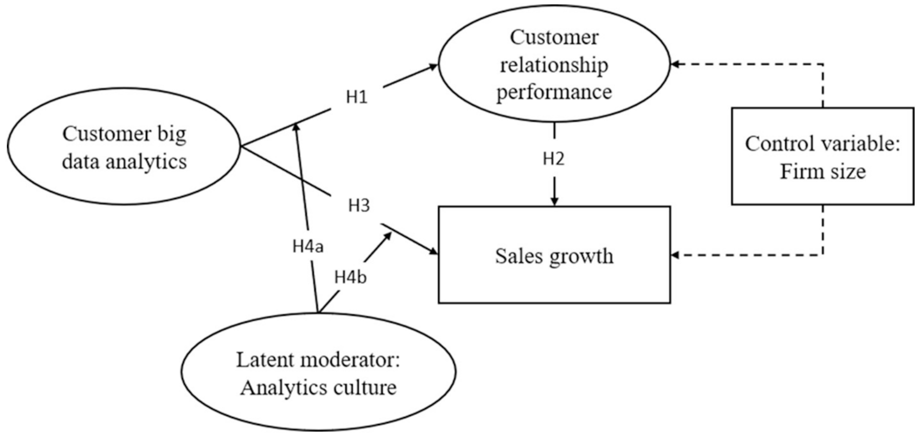

Fig. 1. Conceptual model.

data as an enabler for the management of their key strategic business processes. The key to helping a business benefit from customer big data is for it to have an organizational culture that invests in big data analytics and has confidence in the benefits of such investments (Germann et al., 2013). Consequently, the following hypotheses are presented:

H4a. An analytics culture positively moderates the relationship between big data analytics and customer relationship performance in B2B firms.

H4b. An analytics culture positively moderates the relationship between big data analytics and sales growth in B2B firms.

Finally, as the performance metrics may vary significantly depending on the firm size, the study controls for the size of the firm in terms of the number of employees, in the model Fig. 1.

3. Data and method

In order to answer the research question, a questionnaire was designed and sent to CEOs and high-level managers to test the hypotheses. The data gathered was then examined and latent moderated structural equation was used to test the hypotheses. This section describes the design of the questionnaire, the measurement scales used and the data collection procedure.

3.1. Measurement scales

Validated measurement scales from prior research were used in the design of the questionnaire. The seven-item scale for big data analytics was derived from Jayachandran, Sharma, Kaufman, and Raman (2005) and it captures different purposes for which customer-related big data can be used in firms, in order to create meaningful information for the firm's decision-making. The scale was slightly modified to measure big data use specifically instead of the original and more generic customer information use.

The firm performance, composed of customer relationship performance (i.e. non-monetary performance outcomes) and sales growth (monetary performance outcomes), were measured using firm performance metrics adopted from Homburg et al. (2015). These are relational measures where the respondent is asked to evaluate how their firm has performed relative to their competitors. The customer relationship performance was measured with five items (Table 2), while sales growth was a single-item variable asking: “Relative to your competitors, how did your company perform in growth in sales within the last year?”

The moderating variable of the analytics culture was measured using three items from Germann et al. (2013). We used a five-point Likert scale ranging from *1 = Strongly disagree* to *5 = Strongly agree* for customer big data analytics and analytics culture. A five-point Likert scale ranging from *1 = Much worse* to *5 = Much better* was used for the customer relationship performance and sales growth. The research was conducted in Finland and, therefore, before the data collection, the questionnaire was translated into the local language by the authors. The translated version was then provided to a professional language office to be back translated into English (Douglas & Craig, 2006). Thereafter, the researchers scanned the questionnaire to detect any possible changes in the wording and made a few minor changes to the translations.

3.2. Data collection and sample

Large firms have an advantage over small and medium-sized firms when it comes to big data analytics, since big data analytics may require organizational resources (Erevelles et al., 2016) as well as investments in applicable technology and infrastructure (Xu et al., 2016). Therefore, in the data collection we purposefully targeted at firms with a minimum of 10 employees and a private corporate information company was used to provide a nationwide listing of all firms in Finland that met the criteria. To empirically test the research hypotheses, we collected a dataset from CEOs and other high-level managers with knowledge and understanding of the firm's strategy, performance metrics and big data analytics. A link to the questionnaire was emailed to the senior managers in the firms, which resulted in 551 valid responses within the two-week research period.

As Gummesson (2004) notes, almost all companies are a blend of B2B and B2C. Therefore, the respondents were asked to indicate whether their company *primarily* operated in B2B markets or B2C markets. Out of the 551 companies, 417 reported to primarily operate in B2B markets, forming the dataset for the study. The collected dataset is male dominated with an average age of 34 and this group mainly represents senior management and entrepreneurs (Table 1). Following Armstrong and Overton's (1977) recommended procedure of comparing early and

Table 1
Respondent demographics.

	n	(%)
Job level		
Senior management	330	79.1
Middle management	2	0.5
Entrepreneur	80	19.2
White – /blue-collar	5	1.2
Gender		
Women	44	10.6
Men	373	89.4
Age (average)	34	

Table 2
Constructs and measurement items.

	Std. loadings	AVE	Construct reliability	Cronbach's α
Customer big data analytics (Jayachandran et al., 2005)		0.729	0.949	0.949
1. We use big data to develop customer profiles.	0.893			
2. We use big data to segment markets.	0.859			
3. We use big data to assess customer retention behavior.	0.859			
4. We use big data to identify appropriate channels to reach customers.	0.831			
5. We use big data to customize offers.	0.745			
6. We use big data to identify our best customers.	0.848			
7. We use big data to assess the lifetime value of our customers.	0.776			
Customer relationship performance (Homburg et al., 2015)		0.524	0.814	0.813
1. Achievement of customer satisfaction.	0.693			
2. Retaining present customers.	0.761			
3. Customer structure (e.g. stable customer relationships).	0.761			
4. Quality of the products and services (e.g. greater customer benefit)	0.615			
Analytics culture (Germann et al., 2013)		0.756	0.861	0.856
1. If we reduce our marketing analytics activities, our company's profits will suffer.	0.801			
2. We are confident that the use of marketing analytics improves our ability to satisfy our customers.	0.910			

late respondents, the data was examined for non-response bias, referring to a systematic bias between the respondents and those who were invited but did not participate. No significant differences emerged between the first and the last quartiles of the respondents, suggesting no significant influence due to non-response bias.

4. Results

4.1. Measurement model

A confirmatory factor analysis indicated that the measurement model was adequate ($\chi^2(87) = 243.559$, $p < .001$, CFI = 0.955, TLI = 0.946, RMSEA = 0.066, SRMR = 0.041). With two exceptions, all standardized factor loadings were statistically significant and > 0.60 (Table 2). After removing these two items (the third item on customer relationship performance, and the third item on analytics culture), the model shows a slightly improved fit with ($\chi^2(62) = 206.076$, $p < .001$, CFI = 0.958, TLI = 0.947, RMSEA = 0.075, SRMR = 0.035).

The composite reliability estimates range between 0.814 and 0.949. AVE estimates, indicating the average amount of variation that a latent construct is able to explain the observed variables to which it is theoretically related (Farrell, 2010) are all > 0.50. Additionally, the square roots of the AVE values exceed the between-construct correlations (Table 3) confirming discriminant validity.

The study accounted for the chance of common method variance, referring to variance that is attributable to the measurement method rather than to the theoretical constructs of interest (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Specifically, the study employed both ex ante and ex post procedures recommended by Podsakoff et al. (2003). Ex ante procedures included, for example, ensuring the anonymity of the respondents throughout the data collection and data analysis process, and using theory-driven and previously established measures. An ex post procedure, in which a common method factor is introduced to the measurement model, shows no significant influence of common method variance. Following Lindell and Whitney (2001), the study also used a marker variable, i.e. a variable that is theoretically unrelated to the model variables, and for which correlations with the constructs of interest are expected to be 0 (Williams, Hartman, & Cavazotte, 2010). Market turbulence, reflecting a fluctuation in the composition of customers and their preferences (Jaworski & Kohli, 1993), served as the marker variable. The correlation of the marker variable was 0.039, 0.032 and 0.086 with big data analytics, customer relationship performance and analytics culture, respectively, and thus common method variance seems not to be an issue in the study (Lindell & Whitney, 2001).

Table 3
Discriminant validity.

	AVE	1	2	3
1. Customer big data analytics	0.729	**0.854**		
2. Customer relationship performance	0.524	0.089	**0.724**	
3. Analytics culture	0.756	0.618	0.103	**0.870**

Note: the square root values of the AVEs are on the diagonal and correlations between construct are below the diagonal.

4.2. Structural model

A baseline model (Model 1) with only simple effects (i.e. excluding the interaction effects of the analytics culture) was first estimated. The results show that big data analytics had a positive effect on the firms' customer relationship performance ($\beta = 0.057$, $p < .05$) supporting H1. The customer relationship performance had a highly significant effect on sales growth ($\beta = 0.543$, $p < .001$) supporting H2. The data also supports H3 as big data analytics increased the firms' sales performance ($\beta = 0.173$, $p < .001$). Consequently, hypotheses H1-H3 are all supported (Table 4).

Thereafter the study estimated the hypothesized interaction effect of the analytics culture on the customer relationship performance (Hypothesis 4a; Model 2) and sales growth (Hypothesis 4b; Model 3) using a latent moderated structural equations method in Mplus 8. Traditional goodness-of-fit indices, such as the Comparative Fit Index (CFI), Bentler-Bonett Index or Normed Fit Index (NFI), and Root Mean Square Error of Approximation (RMSEA), are not available for latent moderated structural equations (Maslowsky, Jager, & Hemken, 2015) and consequently we compared the hypothesized model with an alternative model using Satorra-Bentler scaled chi-square difference tests (Satorra & Bentler, 2001).

Hypothesis 4a predicts that the relationship between customer big data analytics and customer relationship performance would be stronger for firms with a strong analytics culture. This effect was supported by the data (Model 2) as the interaction term [customer big data analytics x analytics culture] was positive and significant ($\beta = 0.095$, $p < .01$). Fig. 2 further illustrates the effect in which customer big data analytics has a stronger effect on the customer relationship performance when the analytic culture in the firm is strong. A comparison between a model without and with the interaction effect shows that adding the hypothesized interaction effect of the analytics culture to the path between big data analytics and customer relationship performance significantly improves the model fit (Satorra-Bentler scaled chi-square test ($\Delta\chi^2(1) = 24.992$ $p < .001$).

Hypothesis 4b predicted that the relationship between customer big data analytics and sales growth would be stronger for firms with a

Table 4
Estimated unstandardized path coefficients.

	Model 1	Model 2	Model 3
Model paths			
H1: Customer big data analytics ➔ CR performance	0.057 *	0.006 ns.	0.057 *
H2: CR performance ➔ Sales growth	0.543 ***	0.542 ***	0.552 ***
H3: Customer big data analytics ➔ Sales growth	0.173 ***	0.174 ***	0.168 **
H4a: Customer big data analytics x analytics culture ➔ CR performance	–	0.095 **	–
H4b: Customer big data analytics x analytics culture ➔ Sales growth	–	–	−0.039 ns.
Model characteristics			
Log-likelihood	−5542.906	−6563.926	−6567.921
Scaling factor	1.2171	1.1906	1.1912
Free parameters	38	47	47

Note: Model 1: baseline model without interaction effects.
Model 2: model with the moderating effect of the analytics culture on the path between customer big data analytics and CR performance.
Model 3: model with the moderating effect of analytics culture on the path between customer big data analytics and sales growth.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

strong analytics culture. A comparison between a model without and with the interaction effect shows that adding the hypothesized interaction effect of the analytics culture to the relationship between customer big data analytics and sales growth significantly improves the model fit (Satorra-Bentler scaled chi-square test ($\Delta\chi^2(1) = 21.912$ $p < .001$). However, we do not find evidence for a moderating effect of the analytics culture on the relationship between customer big data analytics and sales growth ($\beta = -0.039$, $p > .05$) and hence hypothesis 4b is rejected (Model 3). Fig. 3 further illustrates the interaction effect of customer big data analytics and analytics culture on a firm's sales growth.

An additional analysis was performed to control for the effect of the firm size on the dependent variables, that is the customer relationship performance and sales growth. The results show that the effect of the firm size on the customer relationship performance and sales growth is statistically non-significant.

5. Discussion and conclusion

5.1. Theoretical contribution

This study is among the first to empirically examine whether big customer data analytics enables B2B companies to enhance their customer relationship performance and foster sales, as conceptual papers suggest. Hence, the study adds to the ongoing discussion on the relationship between big data assets and firm performance (e.g. Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Müller, Fay, & vom Brocke, 2018), and provides fine-grained results from the viewpoint of B2B firms' customer relationship management. The theoretical contribution of the study is salient, as much of the existing academic discussion is focused on the technical side (Wang & Hajli, 2017) and empirical studies are scarce.

The study focuses on how the use of customer big data analytics in managing customer relationships impacts company performance metrics, comprised of customer relationship performance (non-monetary outcomes) and sales growth (monetary outcomes). The results of the study show that customer big data analytics enhances customer relationship performance and sales growth, the direct effect being stronger for the latter. Additionally, we find that customer relationship performance supports sales growth. These results are in line with prior studies related to big data analytics and company performance (Akter et al., 2016; Nam et al., 2019; Wamba et al., 2017) while also providing new information about the influence of big data analytics on non-monetary outcomes in the form of customer relationship performance, as existing studies model company performance mainly through monetary outcomes such as profitability, return on investment (ROI) and sales growth. Big data analytics may enhance company performance in various ways, providing improved opportunities in

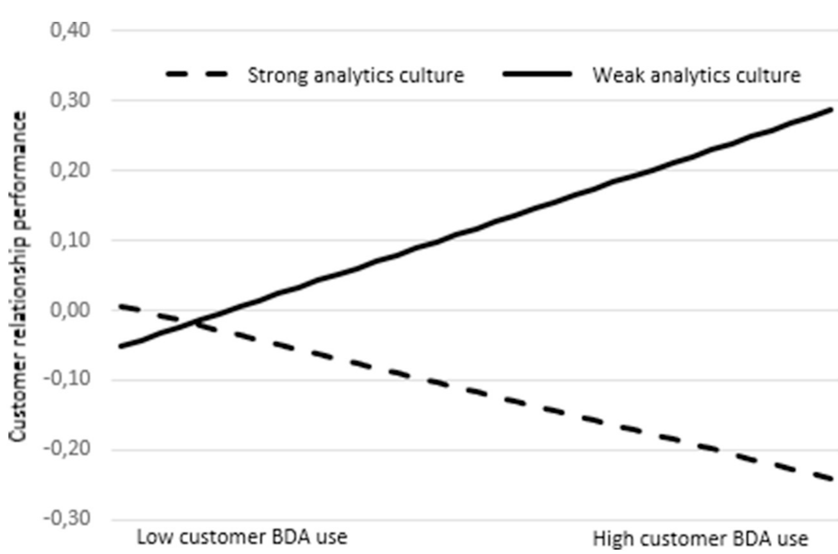

Fig. 2. The moderating effect of the analytics culture on the customer relationship performance.

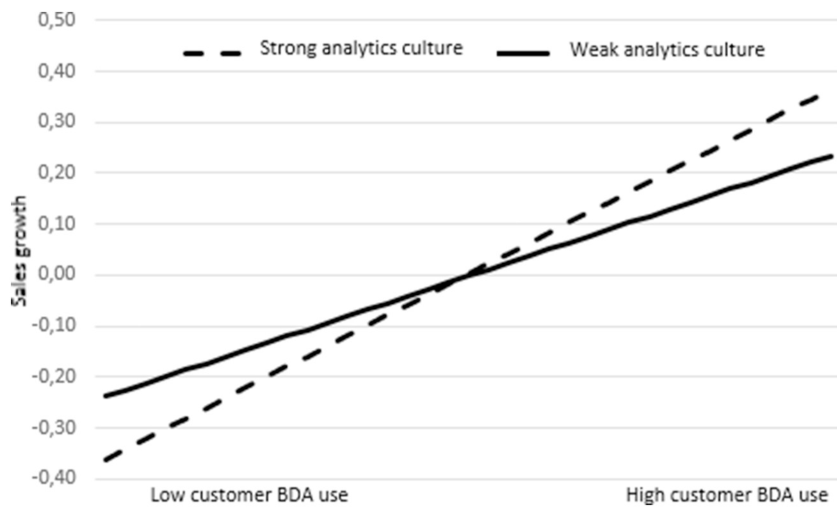

Fig. 3. The moderating effect of an analytics culture on sales growth.

segmenting and profiling customers (Fan et al., 2015), generating recommendations (Fan et al., 2015) and dynamic pricing (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011) for different microsegments, for example.

Although there exists some tentative evidence of the influence of the analytics culture in terms of gaining profits through big data analytics, the present study confirms that a supportive analytics culture is indeed crucial for gaining a competitive advantage from customer big data. Thus, the relation between customer big data analytics and customer relationship performance is stronger for companies with a strong analytics culture than companies with a weak analytics culture. This is in line with the findings by Dubey et al. (2019) reporting that an organizational culture which is supportive of big data has a significant positive moderating influence on the paths leading from human skills and tangible resources to the use of big data analytics. In practice, an analytics culture impacts how well knowledge derived from customer big data is interpreted in practice (Germann et al., 2013) and a weak analytics culture can thus form a considerable barrier (Alharthi et al., 2017). An analytics culture reflects the organizational culture within the company, and an organizational culture which is supportive of big data analytics can accelerate the application of data analytics and related initiatives (Diaz et al., 2018). Factors pertinent to organizational culture are indeed crucial as recent research reports that a data-driven orientation (Troisi, Maione, Grimaldi, & Loia, 2019) and top management support (Sun, Hall, & Cegielski, 2019) are key factors when it comes to big data use in B2B companies. On the other hand, the study did not find support for the moderating effect of the analytics culture on the path between big data analytics and sales growth, and thus the implications of a strong analytics culture pertain mainly to the use of customer big data analytics for managing customer relationships rather than direct impacts on sales growth.

Overall, based on an extensive literature review on the existing big data analytics research, the present study evokes the database marketing paradigm and suggests that big data-enhanced marketing should be reconsidered in managing B2B customer relationships, as it has several improvements compared to database marketing back in the 1990s. Big data-enhanced marketing enables companies to gain an enhanced understanding of their customers, competitors, markets and business operations in almost real-time, and to develop highly personalized relationships with their stakeholders (Orenga-Roglá & Chalmeta, 2016). A competitive advantage may not arise from the data itself, but rather from the speed of generating knowledge based on data, and such activities may act as a driver for incremental and radical innovation (Erevelles et al., 2016). Consequently, we suggest that big data analytics represents the next wave of database marketing in the relationship marketing domain.

5.2. Practical contribution

The practical contribution of this research is significant, as statements about the potential benefits of big data analytics are mainly based on anecdotal evidence rather than empirical results. The results of the study are of particular interest for B2B practitioners, as the present study is among the first in the B2B domain to provide empirical results on the effect of customer big data analytics on company performance metrics. In their big data analytics initiatives, these findings provide guidance to the company management and consultants, particularly as investments in big data initiatives are considered difficult to justify (Lee, 2017) as proof of the benefits is often lacking (Phillips-Wren & Hoskisson, 2015).

According to a recent Salesforce report (2018), 72% of business customers expect vendors to personalize the customer experience and adjust the engagement to customer needs. For B2B sales, big data analytics provides potential in this respect. According to Marr (2017), big data can be particularly useful in B2B lead generation, predictive account management and monitoring customer behavior, and overall big data analytics can free up B2B salespeople to do what they do the best. Hence, recent interest in customer big data has led many B2B companies to invest and develop their capabilities with big data analytics in order to enhance company performance, although it seems that investments in customer big data pay off for some companies but not for others (Akter et al., 2016). Erevelles et al. (2016) suggest that particularly early adopters can gain sustainable competitive advantages through big data analytics. However, being ahead does not provide a competitive advantage in the long run, as big data analytics is becoming mainstream. Therefore, understanding the conditions under which big data analytics can provide a competitive advantage is highly relevant.

The results of this study show that a firm's investment in big data analytics does pay off. Additionally, in order to investments in big data being supportive of customer relationships, firms need to build an analytics culture. Indeed, in a big data executive survey > 85% of firms reported to have started projects to enhance a data-driven culture, but only 37% reported success (NewVantage Partners, 2017). Based on our findings we suggest that a data-driven analytics culture will support the use of customer big data analytics to enhance customer relationships, and, thus, may become a competitive advantage. Values, norms and practices affect how data is shared and exploited within a company, and a strong analytics culture, like an organizational culture that is supportive of analytics (Germann et al., 2013), seems to be one of the characteristics for those companies who succeed in their big data initiatives. With respect to the firm size, the control variable in the model, it seems that contrary to previous studies (e.g. Mikalef et al., 2019), the firm size does not have an effect on the customer relationship performance and sales growth.

Overall, the study forms a holistic view of the relation between customer big data analytics and company performance, as the data collection obtained results from various industry sectors rather than focusing on big data analytics within a specific industry. Consequently, we believe the results of the study are generalizable for different fields of industry and B2B practitioners within different industries will find the results useful. The existing studies on the relation between big data analytics and company performance were carried out using data collected from mainly business analysts (Akter et al., 2016; Wamba et al., 2017) and IT managers (Wamba et al., 2017). Business analysts and IT managers may not have clear knowledge of the company's performance metrics, and hence, we believe that these results collected from senior managers strengthen the understanding of the interrelationship.

5.3. Limitations and future research

The scope of this study was limited to exploring the use of customer big data in managing B2B customer relationships and modelling the impact of big data analytics on company performance with an analytics culture as a moderator. The study was conducted using data collected from several industry sectors, and future studies could deepen our findings and examine whether these results are generalizable to specific industry sectors, such as manufacturing or retailing. Future studies could extend the model by including additional constructs, such as management and team advocacy, an IT orientation and IT flexibility to better understand the moderating conditions under which big data analytics can provide competitive advantages for companies. The study adopted subjective and relative measures of customer relationship performance and sales growth, which could be replaced by objective measures in future studies to present a more pervasive picture of the impact of big data analytics on company performance. Additionally, the data for the present study was collected from senior managers, while previous studies on the relation between firm performance and big data analytics have been conducted mainly among business analysts and IT professionals (Akter et al., 2016; Wamba et al., 2017). Although senior managers have the best understanding of the company's strategic objectives and performance metrics, they may have a limited picture of the exploitation of big data analytics at the operational level of the company. Thus, a multilevel study combining the views of the senior management and business analysts, could potentially provide further insights.

Acknowledgments

The authors wish to thank Business Finland, funding decision 2715/31/2016, for funding this research.

References

Salesforce (2018). State of the Connected Customer. https://www.salesforce.com/content/dam/web/en_us/www/documents/e-books/state-of-the-connected-customer-report-second-edition2018.pdf, Accessed date: 5 August 2019.

Statista (2018). Big Data Initiatives and Success Rate Among Corporations in the United States and Worldwide. https://www.statista.com/statistics/742935/worldwide-survey-corporate-big-data-initiatives-and-success-rate/, Accessed date: 19 June 2018.

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

Alharthi, A., Krotov, V., & Bowman, M. (2017). Addressing barriers to big data. *Business Horizons, 60*(3), 285–292.

Anshari, M., Almunawar, M. N., Lim, S. A., & Al-Mudimigh, A. (2018). Customer relationship management and big data enabled: Personalization & customization of services. *Applied Computing and Informatics, 15*(2), 94–101.

Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse Bias in mail surveys. *Journal of Marketing Research, 14*, 396–402.

Cespedes, F. V., & Smith, H. J. (1993). Database marketing: New rules for policy and practice. *Sloan Management Review, 34*(4), 7–22.

Choudhury, M. M., & Harrigan, P. (2014). CRM to social CRM: The integration of new technologies into customer relationship management. *Journal of Strategic Marketing, 22*(2), 149–176.

Davenport, T. (2014). *Big Data at Work: Dispelling the Myths, Uncovering the Opportunities.* Harvard Business Review Press.

De Lima Francisco, L., Moura, W. F., Sabino, L. R., Santos, V. F. D., & Esquarcio, R. B. (2016). Big data as a customer management relationship tool. *International Journal of Business Administration, 7*(6), 91–95.

Diaz, A., Rowshankish, K., & Saleh, T. (2018). Why data culture matters. *McKinsey Quarterly*. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/why-data-culture-matters (September 2018).

Douglas, S. P., & Craig, C. S. (2006). On improving the conceptual foundations of international marketing research. *Journal of International Marketing, 14*(1), 1–22.

Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., & Papadopoulos, T. (2019). Big data and predictive analytics and manufacturing performance: Integrating institutional theory, resource-based view and big data culture. *British Journal of Management, 30*(2), 341–361.

Emtiyas, S., & Keyvanpour, M. (2011). Customers behavior Modeling by semi-supervised learning in customer relationship management. *Advances in Information Sciences and Service Sciences, 3*(9), 229–236.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big data consumer analytics and the transformation of marketing. *Journal of Business Research, 69*(2), 897–904.

Fan, S., Lau, R. Y., & Zhao, J. L. (2015). Demystifying big data analytics for business intelligence through the Lens of marketing mix. *Big Data Research, 2*(1), 28–32.

Farrell, A. M. (2010). Insufficient discriminant validity: A comment on Bove, Pervan, Beatty, and Shiu (2009). *Journal of Business Research, 63*(3), 324–327.

Frizzo-Barker, J., Chow-White, P. A., Mozafari, M., & Ha, D. (2016). An empirical study of the rise of big data in business scholarship. *International Journal of Information Management, 36*(3), 403–413.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management, 35*(2), 137–144.

Germann, F., Lilien, G. L., & Rangaswamy, A. (2013). Performance implications of deploying marketing analytics. *International Journal of Research in Marketing, 30*(2), 114–128.

Gummesson, E. (2004). Return on relationships (ROR): The value of relationship marketing and CRM in business-to-business contexts. *Journal of Business & Industrial Marketing, 19*(2), 136–148.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research, 70*, 308–317.

Homburg, C., Vomberg, A., Enke, M., & Grimm, P. H. (2015). The loss of the marketing Department's influence: Is it really happening? And why worry? *Journal of the Academy of Marketing Science, 43*(1), 1–13.

Huang, S. M., Ou, C. S., Chen, C. M., & Lin, B. (2006). An empirical study of relationship between IT investment and firm performance: A resource-based perspective. *European Journal of Operational Research, 173*(3), 984–999.

Iyer, G., Soberman, D., & Villas-Boas, J. M. (2005). The targeting of advertising. *Marketing Science, 24*(3), 461–476.

Jahromi, A. T., Stakhovych, S., & Ewing, M. (2014). Managing B2B customer churn, retention and profitability. *Industrial Marketing Management, 43*(7), 1258–1268.

Jaworski, B. J., & Kohli, A. K. (1993). Market orientation: Antecedents and consequences. *Journal of Marketing, 57*, 53–70.

Jayachandran, S., Sharma, S., Kaufman, P., & Raman, P. (2005). The role of relational information processes and technology use in customer relationship management. *Journal of Marketing, 69*(4), 177–192.

Jones, M. A., Reynolds, K. E., Arnold, M. J., Gabler, C. B., Gillison, S. T., & Landers, V. M. (2015). Exploring Consumers' attitude towards relationship marketing. *Journal of Services Marketing, 29*(3), 188–199.

Kiron, D., Prentice, P. K., & Ferguson, R. B. (2014). The analytics mandate. *MIT Sloan Management Review, 55*(4), 1–25.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review, 52*(2), 21–31.

Lee, I. (2017). Big data: Dimensions, evolution, impacts, and challenges. *Business Horizons, 60*(3), 293–303.

Lilien, G. L. (2016). The B2B knowledge gap. *International Journal of Research in Marketing, 33*(3), 543–556.

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in Cross-Sectional Research Designs. *Journal of Applied Psychology, 86*(1), 114–121.

Lismont, J., Vanthienen, J., Baesens, B., & Lemahieu, W. (2017). Defining analytics maturity indicators: A survey approach. *International Journal of Information Management, 37*(3), 114–124.

Lycett, M. (2013). "Datafication": Making sense of (big) data in a complex world. *European Journal of Information Systems, 22*(3), 381–386.

Marr, B. (2017). Why AI, Machine Learning and Big Data Really Matter to B2B Companies. https://www.forbes.com/sites/bernardmarr/2017/11/03/why-ai-machine-learning-and-big-data-really-matter-to-b2b-companies/#2148bde81f2a, Accessed date: 5 August 2019.

Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in marketing. *Journal of the Academy of Marketing Science, 45*(2), 135–155.

Maslowsky, J., Jager, J., & Hemken, D. (2015). Estimating and interpreting latent variable interactions: A tutorial for applying the latent moderated structural equations method. *International Journal of Behavioral Development, 39*(1), 87–96.

McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard*

Business Review, 90(10), 1–9.
Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly, 28*(2), 283–322.
Mendoza, L. E., Marius, A., Pérez, M., & Grimán, A. C. (2007). Critical success factors for a customer relationship management strategy. *Information and Software Technology, 49*(8), 913–945.
Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research, 98*, 261–276.
Mizik, N. (2014). Assessing the Total financial performance impact of brand equity with limited time-series data. *Journal of Marketing Research, 51*(6), 691–706.
Möller, K., & Halinen, A. (2000). Relationship marketing theory: Its roots and direction. *Journal of Marketing Management, 16*(1–3), 29–54.
Morgan, B. (2018). Marketing Needs to Do These Three Things to Better Leverage Big Data. https://www.forbes.com/sites/blakemorgan/2018/08/14/marketing-needs-to-do-these-three-things-to-better-leverage-big-data/#615e09037484, Accessed date: 5 August 2019.
Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of Marketing, 58*(July), 20–38.
Müller, O., Fay, M., & vom Brocke, J. (2018). The effect of big data and analytics on firm performance: An econometric analysis considering industry characteristics. *Journal of Management Information Systems, 35*(2), 488–509.
Nam, D., Lee, J., & Lee, H. (2019). Business analytics use in CRM: A Nomological net from IT competence to CRM performance. *International Journal of Information Management, 45*, 233–245.
Orenga-Roglá, S., & Chalmeta, R. (2016). Social customer relationship management: Taking advantage of web 2.0 and big data technologies. *SpringerPlus, 5*(1), 1462.
Öztayşi, B., Kaya, T., & Kahraman, C. (2011). Performance comparison based on customer relationship management using analytic network process. *Expert Systems with Applications, 38*(8), 9788–9798.
NewVantage Partners (2017). Big Data Executive Survey 2017. http://newvantage.com/wp-content/uploads/2017/01/Big-Data-Executive-Survey-2017-Executive-Summary.pdf, Accessed date: 19 June 2018.
Perera, W. K. R., Dilini, K. A., & Kulawansa, T. (2018). A review of big data analytics for customer relationship management. *2018 3rd International Conference on Information Technology Research*.
Petrison, L. A., Blattberg, R. C., & Wang, P. (1997). Database marketing: past, present, and future. *Journal of Interactive Marketing, 11*(4), 109–125.
Phillips-Wren, G., & Hoskisson, A. (2015). An analytical journey towards big data. *Journal of Decision Systems, 24*(1), 87–102.
Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in Behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903.
Preston, L. E., & O'bannon, D. P. (1997). The corporate social-financial performance relationship: A typology and analysis. *Business & Society, 36*(4), 419–429.
Rauyruen, P., & Miller, K. E. (2007). Relationship quality as a predictor of B2B customer loyalty. *Journal of Business Research, 60*(1), 21–31.
Reimann, M., Schilke, O., & Thomas, J. S. (2010). Customer relationship management and firm performance: The mediating role of business strategy. *Journal of the Academy of Marketing Science, 38*(3), 326–346.
Ryals, L. (2005). Making customer relationship management work: The measurement and profitable Management of Customer Relationships. *Journal of Marketing, 69*(4), 252–261.
Ryals, L., & Payne, A. (2001). Customer relationship Management in Financial Services: Towards information-enabled relationship marketing. *Journal of Strategic Marketing, 9*(1), 3–27.
Satorra, A., & Bentler, P. M. (2001). A scaled difference Chi-Square test statistic for moment structure analysis. *Psychometrika, 66*(4), 507–514.
Sheth, J. N., & Parvatiyar, A. (1995). Relationship in consumer markets: Antecedents and consequences. *Journal of the Academy of Marketing Science, 23*(4), 255–271.
Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of big data challenges and analytical methods. *Journal of Business Research, 70*, 263–286.
Stein, A. D., Smith, M. F., & Lancioni, R. A. (2013). The development and diffusion of customer relationship management (CRM) intelligence in business-to-business environments. *Industrial Marketing Management, 42*(6), 855–861.
Sun, S., Hall, D. J., & Cegielski, C. G. (2019). Organizational intention to adopt big data in the B2B context: An integrated view. *Industrial Marketing Management* (In Press).
Tao, A. L. (2018). Data analytics is about culture, not technology. *Computer Weekly*. https://www.computerweekly.com/news/252440068/Data-analytics-is-about-culture-not-technology, Accessed date: 28 July 2019.
Tao, Y. H., & Yeh, C. C. R. (2003). Simple database marketing tools in customer analysis and retention. *International Journal of Information Management, 23*(4), 291–301.
Thirathon, U., Wieder, B., Matolcsy, Z., & Ossimitz, M. L. (2017). Big data, analytic culture and analytic-based decision-making: Evidence from Australia. *Procedia Computer Science, 121*, 775–783.
Trainor, K. J., Andzulis, J. M., Rapp, A., & Agnihotri, R. (2014). Social media technology usage and customer relationship performance: A capabilities-based examination of social CRM. *Journal of Business Research, 67*(6), 1201–1208.
Troisi, O., Maione, G., Grimaldi, M., & Loia, F. (2019). Growth hacking: Insights on data-driven decision-making from three firms. *Industrial Marketing Management* (In Press).
Van der Laan, G., Van Ees, H., & Van Witteloostuijn, A. (2008). Corporate social and financial performance: An extended stakeholder theory, and empirical test with accounting measures. *Journal of Business Ethics, 79*(3), 299–310.
Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356–365.
Wang, Y., & Hajli, N. (2017). Exploring the path to big data analytics success in healthcare. *Journal of Business Research, 70*, 287–299.
Wang, H., Xu, Z., Fujita, H., & Liu, S. (2016). Towards felicitous decision making: An overview on challenges and trends of big data. *Information Sciences, 367–368*, 747–765.
Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal, 5*(2), 171–180.
Wiersema, F. (2013). The B2B agenda: The current state of B2B marketing and a look ahead. *Industrial Marketing Management, 42*(4), 470–488.
Williams, L. J., Hartman, N., & Cavazotte, F. (2010). Method variance and marker variables: a review and comprehensive CFA marker technique. *Organizational Research Methods, 13*(3), 477–514.
Xu, Z., Frankwick, G. L., & Ramirez, E. (2016). Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. *Journal of Business Research, 69*(5), 1562–1566.
Zablah, A. R., Bellenger, D. N., & Johnston, W. J. (2004). An evaluation of divergent perspectives on customer relationship management: Towards a common understanding of an emerging phenomenon. *Industrial Marketing Management, 33*(6), 475–489.
Zerbino, P., Aloini, D., Dulmin, R., & Mininno, V. (2018). Big data-enabled customer relationship management: A holistic approach. *Information Processing & Management, 54*(5), 818–846.