BIG DATA ANALYTICS USE IN CUSTOMER RELATIONSHIP MANAGEMENT: ANTECEDENTS AND PERFORMANCE IMPLICATIONS

Key words (5): *big data analytics, customer information use, information quality (IQ), organizational culture, performance*

Abstract

Customer information plays a key role in managing successful relationships with valuable customers. Big data analytics use (BD use), i.e., the extent to which customer information derived from big data analytics guides marketing decisions, helps firms better meet customer needs for competitive advantage. This study aims to (1) determine whether organizational BD use improves customer-centric and financial outcomes, and (2) identify the factors influencing BD use. Drawing primarily from market information use theory, we advance a model to explain how information quality (IQ), customer orientation and big data analytics culture predict BD use, which in turn influences customer relationship and financial performance.

Empirical findings from a survey of 301 senior marketing executives, representing large US-based firms in B2C industries, support our conceptualization of the performance outcomes and antecedents of BD use. All seven hypotheses received empirical support.

The results highlight that the characteristics of the customer information (IQ) and the characteristics of the user organization (customer orientation and big data analytics culture) strongly predict BD use. The findings also reveal the relative importance of different customer information characteristics to marketing decision-makers.

Practitioners may significantly improve firm performance with BD use, but only if certain antecedent factors facilitate BD use in the organization. We offer managers advice

how to overcome challenges specific to BD use by managing the quality aspects of customer information, and by fostering shared customer-oriented and analytics-oriented cultures.

To the best of our knowledge, this study is the first to examine the role of big data analytics use in managing customer relationships. We hope that this contribution motivates more academic research to address the impact of big data on marketing and customer strategies.

INTRODUCTION

Firms' ability to generate, disseminate and utilize superior customer information and, consequently, to deliver superior value to its customers is regarded as key to superior performance (Day 1994; Kohli & Jaworski 1990; Narver & Slater 1990; Webster 1988). Recent advances in "big data" technologies, and greater willingness of consumers to share their personal information through web-based channels, offers firms unprecedented opportunities to generate customer insight that was not previously possible (Chen et al. 2012: Nunan and DiDomenico 2013). Specifically, big data refers to techniques, technologies, systems, practices, methodologies, and applications related to the acquisition, storage, integration, analysis, and deployment of massive amounts of diverse data to support business decision-making (Chen et al. 2012, Jelinek and Bergey 2013; McAfee and Brynjolfsson 2012).

An increasing number of firms are making decisions based on customer insights derived from using big data analytics, with human expertise remaining critical but in a supporting role (LaValle et al. 2011; McAfee and Brynjolfsson 2012). In this study, we define "*big data analytics use*" as the extent to which customer information derived from big data analytics guides customer-focused marketing decisions (Germann et al. 2013; Jayachandran et al. 2005; Menon and Varadarajan 1992). Academic research has not examined the performance outcomes of organizational big data analytics use and, by extension, the factors that influence its application. To address this critical knowledge gap, this paper aims to conceptualize and examine the antecedents and customer performance impacts of big data analytics use. We believe that the findings have both academic importance and managerial relevance by incorporating big data analytics into the customer relationship management.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

In framing our investigation, we draw from market information use theory and related CRM research (Jayachandran et al. 2005; Menon and Varadarajan 1992; Moorman 1995), information quality (IQ) research (Wang et al. 1996; Lee et al. 2002), cultural customer orientation (Deshpande et al. 1993; Narver and Slater 1990), and data analytics (Chen et al. 2012; Germann et al. 2013; McAfee and Brynjolfsson 2011) to examine how informational and organizational factors act to enhance big data analytics use, and, ultimately customer and financial performance.

Big data analytics use

Market information use theory posits that firms' effective use of customer information is a crucial driver of performance. Building on this research, CRM studies have found that the creation, dissemination and consequent use of customer information plays a key role in managing customer relationships (Becker et al. 2009; Jayachandran et al. 2005; Reinartz et al. 2004; Srinisavan and Moorman 2005). We extend prior CRM research by focusing on big data analytics use, i.e., customer information derived from big data analyses to guide marketing decisions. Big data analytics use (hereafter referred to as BD use) enables firms to analyze vast amounts of diverse customer data from external sources to better understand their customers, develop more customized and personalized offerings, and identify high-value customers (Jayachandran et al. 2005). As such, BD use holds great promise for improving decision making related to customer relationship strategy. Next, we discuss the factors that may lead to greater organizational BD use.

Antecedents of big data analytics use

Organizational BD use depends on informational (characteristics of the information itself) and organizational (characteristics of the organization) factors that facilitate or inhibit its deployment in a firm (Menon and Varadarajan 1992). In this study, we conceptualize the former as information quality (IQ), and the latter as customer orientation and big data analytics culture, respectively.

Information quality

Information perceived as credible and useful is more likely to be utilized by organizations (Menon and Varadarajan 1992). We lend support from *information quality* (IQ) research that refers to IQ as the desired characteristics of the information output produced by an IT (Bailey and Pearson 1983). IQ is recognized as a multidimensional concept the composition of which depends on specific information usage context (Fehrenbacher and Helfert 2012; Lee et al. 2002; Wang and Strong 1996),

In the case of big data-driven customer information, and what distinguishes it from prior customer information stored in customer relationship management (CRM) and other enterprise information systems, is the sheer volume, velocity and variety of data (the three V's) from which customer insights are gained (Chen et al. 2002). Specifically, big data analytical tools can process massive amounts of multi-structured data (varieties of data formats and data types) in real-time. Recently, delivering customer insights in understandable form to executives to support decision-making, i.e., visualization, has also been put forward as a fourth crucial element of IQ in the big data context (Chen et al. 2012; Jelinek and Bergey 2013; Manyika et al. 2011*;* Nunan and DiDomenico 2013).

In a similar vein, prior IQ research has identified currency, accuracy, completeness and format as the key dimensions of IQ (Wixom and Todd 2005; Xu et al. 2013). *Currency* refers to the degree to which the information is up to date. *Accuracy* represents the degree to which the information is correct. *Completeness* expresses the degree to which all relevant information is provided. *Format*, in turn, refers to how well the information is presented to the decision-maker (Wixom and Todd 2005; Zheng et al. 2013). While their relative importance depends on the specific IT system setting, the afore-mentioned four dimensions have high general applicability and relevance to the IT context such as BD use (Wixom and Todd 2005).

Based on the preceding exposition, we posit that big data –driven IQ is determined by its timeliness (velocity), accuracy (volume), completeness (variety) and format (visualization). Big data analytics is expected to provide firms with customer insight (IQ) that is accurate (from large volumes of data), complete (from various types of data), and timely (from real-time parallel processing). Furthermore, customer insights are delivered to business decision-makers who are unfamiliar with the analytics process, suggesting that the format in which such insights are presented (visualization) is an important dimension of overall IQ. Hence we hypothesize that:

H1a: Currency has a positive effect on Information Quality (IQ)

H1b: Accuracy has a positive effect on Information Quality (IQ)

H1a: Completeness has a positive effect on Information Quality (IQ)

H1a: Format has a positive effect on Information Quality (IQ)

As we alluded to earlier, customer information perceived as high quality enhances its utilization by organizations. In the BD use context, customer information that is timely, accurate, complete, and presented in understandable format, jointly influence overall IQ that in turn drives decision-makers' choice of information use (Menon and Varadarajan 1992). We put forward the following hypothesis:

H2: IQ has a positive effect on BD use.

Customer Orientation

Organizational culture promotes expected behaviors through embedded structures of shared values and norms (Deshpande et al. 1993). In this study, we propose that two elements of the firm's overall organizational culture are closely associated with BD use, namely, customer orientation and big data analytics culture.

Customer orientation reflects an organization-wide culture to collect, share and use customer information to provide superior value to customers (Deshpande et al. 1993; Narver and Slater 1990). Customer orientation also entails that customer performance is an organizational priority that dictates the implementation of necessary activities to achieve this goal (Jayachandran et al. 2005). Because superior customer information is the means to better understand customers, and to design offerings that meet their preferences and needs, a firm's customer orientation motivates the utilization of big data analytics (Jayachandran et al. 2005). Stated differently, we expect that:

H3: Customer Orientation has a positive effect on Big Data Analytics Use (BD use).

Big data analytics culture

Big data analytics culture refers to shared values, beliefs and norms that encourage decision-makers to utilize customer insights provided by big data analytics (Germann et al. 2013). A favorable culture embeds BD use as part of daily operations, which is reflected as an openness to systematically adopt big data analytics to solve business problems (Barton and Court 2012; McAfee and Brynjolfsson 2012).

However, marketing executives are not naturally inclined to trust or understand data-based models, and reluctant to allow BD use to over-rule managerial experience and intuition (LaValle et al. 2011; McAfee and Brynjolfsson 2012). Managerial resistance may be even stronger because BD use necessarily involves various people from different departments to first create customer insight, and then to act upon it (Germann et al. 2013). Industry surveys have thus reported that BD use is greater in firms where the importance of data analytics is appropriately communicated and encouraged by top management (Brown et al. 2012; Bloomberg 2012; Cap Gemini 2012; Manyika et al. 2011).

We similarly anticipate that big data analytics culture is a key driver of BD use to support customer-focused decision-making. Hence:

H4: Big Data Analytics Culture has a positive effect on Big Data Analytics Use (BD use).

Performance impacts of big data analytics use

We examine two performance outcomes in this study, customer relationship performance and financial performance. We expect that BD use improves customer relationship performance in terms of customer satisfaction, retention, and acquisition.

Prior CRM literature suggests that customer information derived from CRM systems helps firms interact with customers more efficiently and effectively (Becker et al. 2009; Jayachandran et al. 2005; Mithas et al. 2005; Srinisavan and Moorman 2005). Web-based big data technologies enable firms to access unfiltered customer opinions, understand customer behavior, and converse with customers unlike traditional one-way marketing such as CRM (Chen et al. 2012; Day 2011). With web, text, sentiment, social network, mobile and sensor-based analytical tools, multi-structured customer data can be analyzed to build predictive models that help firms tap into customer attitudes and behavior, and innovate and optimize marketing activities to improve customer-centric outcomes (Chen et al. 2012; Einav and Levin 2013; Jelinek 2013). Person- , context-, and location-specific product offerings can be tailored based on data collected from mobile and sensor devices, resulting in higher customer satisfaction and retention (Chaudhuri et al. 2011). In addition, customer information is often available in real-time, and at a significantly lower cost than traditional means to understand customers' needs (Jelinek and Bergey 2013).

In sum, BD use puts managers are in a superior position to design highly personalized offerings that are better aligned with customer needs in real-time, leading to higher customer acquisition, satisfaction and retention (Einav and Levin 2013; Germann et al. 2013). Thus:

H5: Big Data Analytics Use (BD use) has a positive effect on Customer Relationship Performance.

We also expect that BD use influences financial performance in terms of sales, profitability and market share. Academic studies have shown that data analytics use in decision making is associated with better financial performance (Brynjolfsson et al. 2011; Germann et al. 2013), which is supported by various industry reports (Bloomberg 2012; Brown et al. 2012; Cap Gemini 2012; Manyika et al. 2011). In addition to more sales, we posit that BD use lowers costs by automating customer information and marketing processes (Chen et al. 2012; Einav and Levin 2013; Jelinek 2013). Therefore, BD use is expected to have a dual direct effect on financial performance through higher customer relationship performance as well as through lowering costs (Rust et al. 2002). We thus hypothesize that:

H6: Big Data Analytics Use (BD use) has a positive effect on Financial Performance.

Prior research has also found a positive relationship between customer relationship and financial performance. Customer outcomes are antecedent to sales growth, market share and profitability (e.g., Ahearne et al. 2005; Day and Wensley 1988).

H7: Customer Relationship Performance has a positive effect on Financial Performance.

Control variables

The volatility of the firm's environment increases the need for information use (Menon and Varadarajan 1992). Changes in competitors' strategies, customer needs or technologies increase the need for customer information to alleviate uncertainty in decision making (Kohli and Jaworski 1990).

In addition, environmental factors may decrease customer relationship performance as customer retention becomes more difficult, thereby also affecting financial performance (Jayachandran et al. 2005; Kirca et al. 2005). We include competitive intensity, market turbulence and technological turbulence as control variables.

METHODOLOGY

Data collection and sample

We employed a survey study methodology and administered an online questionnaire for data collection. All of our measures are directly adopted from or based substantially on scales validated by prior studies (see Table 1), and were measured on a 7-point Likert scale. Our sampling frame focuses on strategic business units (SBUs) in large (>1000 employees), US-based, B2C manufacturing and service firms who have invested in big data analytics to support marketing decision making.

We set forth these sample criteria for the following reasons. Firstly, due to considerable initial investment and expertise required, large firms are more likely to have implemented big data initiatives. Second and similar to prior marketing studies, the focus of this study is at the SBU level (Homburg et al. 1999; Workman et al. 1998). If there were no distinct SBUs, respondents were instructed to answer at the firm level. Third, B2C sectors are more prevalent in terms of big data investment because understanding the needs of a large customer base is more complicated than in B2B sectors, where the number of customers is lower, and the salesforce is more knowledgeable about individual customers' needs.

Using a commercial research panel provider, we targeted senior marketing executives in SBUs across a range of B2C industries. Prior marketing studies have also adopted a multi-industry approach (e.g., Song et al. 2007; Vorhies and Morgan 2005). The survey was sent to senior marketing executives in 2497 SBUs, and after a rigorous screening process, 301 usable responses (12% response rate) were received in return. Appendix 1 summarizes the sample characteristics. The data was cleared for non-response biases, which included screening for possible differences in variable means between early and late responders with an independent samples t-test (Armstrong and Overton 1977). No significant differences were found among early and late responders.

RESULTS

Measurement Model

We used PLS-SEM (Smart-PLS 2.0 M3; Ringle et al. 2005) to test the measurement model and structural model. Item descriptions and indicator reliabilities are presented in Table 1. Descriptive statistics, construct-level validation, and latent variable correlations are summarized in Table 2. Reflective measures were assessed in terms of item-level reliability, construct reliability, and convergent and discriminant validity. We eliminated two items (Accu2 and Co3) after which all item loadings, composite reliability, and average variance extracted (AVE) exceed acceptable reliability criteria (Hair et al. 2011) and all measures discriminate well (Fornell and Larcker 1981). Formative measures were validated via multicollinearity (VIF values) and construct validity (item weights and loadings) testing (MacKenzie et al. 2011; Petter et al. 2007). All VIF values were below 1.5, and formative measures showed acceptable psychometric properties for structural model assessment.

Table 1. Study measures and indicator reliability

Measure / item	Item description	Loading	Source
Accuracy			Wixom and Todd 2005
accu1	The Big Data analyses performed in our SBU produce correct customer insight.	0.77 **	
accu2∞	There are few errors in the customer insight our SBU derives from Big Data analyses.	0.47 **	
accu3	The customer insight our SBU derives from Big Data analyses is accurate.	0.82 **	
Completeness			Wixom and Todd 2005
comp1	Big Data analyses provide our SBU with complete customer insight.	0.80 **	
comp2	Big Data analyses provide our SBU with comprehensive customer insight.	0.76 **	
comp3	Big Data analyses provide our SBU with all the customer insight we need.	0.69 **	
Currency			Wixom and Todd 2005
curr1	Big Data analyses provide decision-makers within our SBU the most recent customer insight.	0.83 **	
curr2	Big Data analyses in our SBU produce the most current customer insight.	0.78 **	
curr3	The customer insight our SBU achieves from Big Data analyses is not timely. (R)	0.74 **	
Format			Wixom and Todd 2005
frmt1	The customer insight our SBU derives from Big Data analyses is presented to decision-makers in an easy to follow format.	0.71 **	
frmt2	The customer insight our SBU derives from Big Data analyses is presented to decision-makers in a well laid out format.	0.80 **	
frmt3	The customer insight our SBU derives from Big Data analyses is clearly presented to decision-makers.	0.78 **	
Information Quality			Wixom and Todd 2005
iq1	Overall, the customer insight derived from Big Data analyses in our SBU is of high quality.	0.79 **	
iq2	Overall, the customer insight derived from Big Data analyses in our SBU achieves a high rating in terms of quality.	0.79 **	
iq3	In general, our SBU's Big Data analyses provide decision-makers with high-quality customer insight.	0.75 **	
Customer Orientation			Narver and Slater 1990
co1	Our SBU constantly monitors its level of commitment and orientation to serving customer needs.	0.73 **	
co2	Our SBU's strategy for competitive advantage is based on a superior understanding of customers' needs.	0.75 **	
co3*	Our SBU measures customer satisfaction systematically and frequently.	0.66 **	
co4	Our SBU exists primarily to serve customers.	0.69 **	
Big Data Analytics Culture			Germann et al. 2013
cul1	If our SBU reduces its Big Data analytics activities, its profits will suffer.	**0.20** *	
cul2	The use of Big Data analytics improves our SBU's ability to satisfy its customers.	**0.72** **	
cul3	Most people in our SBU are skeptical of Big Data-based results and recommendations. (R)	**0.35** **	
Big Data Analytics Use			Jayachandran et al. 2005
use1	Our SBU regularly uses Big Data analytics to develop customer profiles.	**0.18** **	
use2	Our SBU regularly uses Big Data analytics to segment markets.	**0.21** **	
use3	Our SBU regularly uses Big Data analytics to assess customer retention.	**0.13** *	
use4	Our SBU regularly uses Big Data analytics to identify appropriate channels to reach customers.	**0.15** **	
use5	Our SBU regularly uses Big Data analytics to customize our offers.	**0.21** **	
use6	Our SBU regularly uses Big Data analytics to identify our best customers.	**0.14** *	
use7	Our SBU regularly uses Big Data analytics to assess the lifetime value of our customers.	**0.21** **	
use8	Our SBU regularly uses Big Data analytics to personalize the marketing mix.	**0.29** **	
Customer Relationship Performance	In the most recent year, relative to your major competitors, how has your SBU performed with respect to:		Rust et al. 2002
crp1	Achieving customer satisfaction?	0.80 **	
crp2	Keeping current customers?	0.79 **	
crp3	Attracting new customers?	0.77 **	
Financial Performance	In the most recent year, relative to your major competitors, how has your SBU performed with respect to:		Rust et al. 2002
fp1	Sales?	0.80 **	
fp2	Profitability?	0.82 **	
fp3	Market share?	0.77 **	
Competitive Intensity			Kohli and Jaworski 1990
ci1	Competition in our industry is cutthroat.	0.71 **	
ci2	There are many 'promotion wars' in our industry.	0.75 **	
ci3	Price competition is a hallmark of our industry.	0.77 **	
ci4	One hears of a new competitive move in our industry almost every day.	0.71 **	
Market Turbulence			Kohli and Jaworski 1990
mt1	In our kind of business, customers' product preferences change quite a bit over time.	0.72 **	
mt2	It is very difficult for our SBU to predict changes in the marketplace.	0.85 **	
Technological Turbulence			Kohli and Jaworski 1990
tt1	A large number of new product ideas have been recently made possible through technological breakthroughs in our industry.	0.86 **	
tt2	The technological changes in this industry are frequent.	0.82 **	

∞ eliminated after measure validation testing
formative item weights in **bold**
*p<.05 ** p<.01

Table 2. Descriptive Statistics, Measure Validation, and Latent Variable Correlations

Construct	Mean	SD	CR	AVE	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Accuracy	5.33	.95	.81	.68	**.83**												
2 Completeness	5.32	1.01	.80	.57	.63	**.75**											
3 Currency	5.35	1.03	.83	.61	.66	.60	**.78**										
4 Format	5.50	.98	.81	.59	.60	.59	.63	**.77**									
5 Information Quality	5.49	1.02	.82	.60	.70	.64	.71	.72	**.77**								
6 Big Data Analytics Culture	5.36	1.06	.80	**NA∞**	.60	.52	.52	.55	.54	**NA**							
7 Customer Orientation	5.27	.94	.81	.58	.47	.50	.55	.63	.68	.42	**.76**						
8 Big Data Analytics Use	5.40	.93	.84	**NA∞**	.66	.69	.70	.65	.73	.59	.62	**NA**					
9 Customer Relatonship Performance	5.38	1.05	.83	.62	.44	.54	.50	.50	.52	.34	.46	.54	**.79**				
10 Financial Performance	5.23	1.05	.84	.63	.43	.47	.40	.41	.45	.35	.40	.52	.68	**.79**			
11 Competitive Intensity	5.04	1.06	.82	.54	.36	.44	.38	.42	.43	.36	.40	.49	.33	.25	**.73**		
12 Market Turbulence	4.84	.94	.77	.62	.47	.47	.49	.49	.52	.36	.47	.55	.41	.36	.42	**.79**	
13 Technological Turbulence	4.95	1.04	.83	.71	.46	.51	.50	.52	.55	.41	.52	.58	.39	.34	.51	.54	**.84**

∞ formative construct
√AVE in bold

Common Method Bias

Since both independent and dependent measures are obtained from the same source, we used CFA and Harman's single-factor test to assess common method bias (Podsakoff et al. 2003). Eight factors had eigenvalues greater than one, and together they accounted for 56% of the total variance; the first factor accounted for 32% of the total variance. We concluded that common method bias is not likely to be a concern in this study but caution that Harman's test does not completely rule out the risk of common method bias.

Structural Model

The results of our hypothesis testing, the structural path estimates (standardized effects), significance tests, and explained variances are summarized in Table 3. We assessed the adequacy of the structural model by examining explained variances and standardized beta coefficients and we also assessed significance levels (t-statistics) and standard errors using 5000 bootstrap iterations (Hair et al. 2011).

Table 3. Structural model results

			Dependent variable			
Predictor variables	**Hypothesis**	**Supported?**	**Information Quality**	**Big Data Analytics Use**	**Customer Relationship Performance**	**Financial Performance**
Currency	H1a	Yes	.25** (4.71)			
Accuracy	H1b	Yes	.26** (4.43)			
Completeness	H1c	Yes	.13* (2.25)			
Format	H1d	Yes	.34** (5.60)			
Information Quality	H2	Yes		.38** (4.79)		
Customer Orientation	H3	Yes		.13* (2.44)		
Big Data Analytics Culture	H4	Yes		.21** (3.89)		
Big Data Analytics Use	H5	Yes			.44** (6.28)	
Big Data Analytics Use	H6	Partial				.12 (1.62)
Customer Relatonship Performance	H7	Yes				.58** (6.44)
Control variables						
Competitive Intensity				.12* (1.96)	.02 (.26)	-.04 (.70)
Market Turbulence				.13* (1.99)	.11 (1.40)	.07 (1.09)
Technological Turbulence				.07 (1.06)	.08 (.90)	.03 (.34)
Explained variance R2			**.68**	**.66**	**.33**	**.47**

Structural model results reveal that all four IQ characteristics are statistically significant antecedents to overall IQ, together explaining 68% of its variance. Hypotheses

H1a-d are thus supported. IQ (.38, *p*<.01), customer orientation (.13, *p*<.05), and big data analytics culture (.34, *p*<.01) are significant predictors of big data analytics use (R^2=.66), providing support for H2, H3 and H4. In addition, competitive intensity (.12, *p*<.05) and market turbulence (.13, *p*<.01) positively influence big data analytics use.

Big data analytics use (BD use) is a strong predictor (.44, *p*<.01) of customer relationship performance, explaining 33% of its variance when competitive intensity, market and technological turbulence are controlled for. Hence, H5 received empirical support. Customer relationship performance, in turn, is positively associated (.58, *p*<.01) with financial performance, providing support for H7. BD use has a significant direct effect on financial performance at 10% level (.12, t=1.62). When the effect of customer relationship performance on financial performance is not controlled for, BD use predicts financial performance at 1% significance level (.38, *p*<.01), suggesting that H6 is partially supported. Finally, control variables have no significant effects on customer relationship performance and financial performance.

Since our research model implicitly suggests that BD use mediates the relationships between antecedents information quality (IQ), customer orientation, big data analytics culture, and the outcome customer relationship performance, we carried out additional analyses. In addition, we tested whether customer relationship performance mediates the relationship between BD use and financial performance.

Specifically, we tested indirect effects using bootstrapping (see Table 4), which is currently regarded as the most advanced method for mediation testing, and is also not restricted by normality assumptions (Edwards and Lambert 2007; Kenny 2008; Preacher and Hayes 2008). We carried out separate bootstrapping tests with Preacher and Hayes' SPSS macros for each possible mediation path (2008; see http://www.afhayes.com/spss-sas-and-mplus-macros-and-code.html) using 5000 bootstrap resamples. Their macro also enabled us to control for covariates. The results, summarized in Table 4, includes unstandardized regression coefficients of direct paths (a, b, c, and c'), and the indirect path *ab* with significance levels, bias-corrected 95% confidence intervals, and standard error (Zhao et al. 2010). The indirect effect is assessed solely based on the strength of path *ab* (Edwards and Lambert 2007; Preacher and Hayes 2008; Shrout and Bolger 2002). Finally, type of mediation was determined based on Zhao et al.'s (2010) refined classification of Baron and Kenny (1986) into complementary, competitive, and indirect-only type of mediation (see Appendix 2 for a detailed description). We also accounted for the effects of control variables. Control variables were included in mediation bootstrapping tests as covariates, which are treated like independent variables in the estimation, with paths to mediator and outcome.

Table 4. Mediation testing with bootstrapping

Mediation path	**IQ→BDU→CRP**	**CO→BDU→CRP**	**BDAC→BDU→CRP**	**BDU→CRP→FP**
a	0.38**	0.13**	0.21**	0.32**
b	0.32**	0.32**	0.32**	0.57**
c	0.27**	0.15*	0.04	0.23**
c'	0.15	0.11	-0.03	0.05
ab [a]	**0.12****	**0.04****	**0.07****	**0.18****
SE	0.044	0.020	0.028	0.066
Bias-C. CI 99% Lower	0.027	0.003	0.012	0.043
Bias-C. CI 99% Upper	0.266	0.122	0.163	0.387
R^2	0.35	0.35	0.35	0.48
Controls	**Control→BDU**	**Control→BDU**	**Control→BDU**	**Control→CRP**
Competitive Intensity	0.12**	0.12**	0.12**	0.02
Market Turbulence	0.13**	0.13**	0.13**	0.08
Technological Turbulence	0.07	0.07	0.07	0.03
Information Quality		0.38**	0.38**	0.15
Customer Orientation	0.13**		0.13**	0.11
Big Data Analytics Culture	0.21**	0.21**		-0.03
	Control→CRP	**Control→CRP**	**Control→CRP**	**Control→FP**
Competitive Intensity	0.02	0.02	0.02	-0.05
Market Turbulence	0.08	0.08	0.08	0.06
Technological Turbulence	0.03	0.03	0.03	0.01
Information Quality		0.15	0.15	0.04
Customer Orientation	0.11		0.11	0.04
Big Data Analytics Culture	-0.03	-0.03		0.08

** p<.01; * p<.05
Legend:
Path a: from independent variable to mediator.
Path b: from mediator to dependent variable.
Path c: direct effect.
Path ab: indirect effect.
Path c': direct effect when ab is controlled for

Legend:
IQ: Information Quality, BDU: Big Data Analytics Use, CRP: Customer Relationship Performance, CO: Customer Orientation, BDAC: Big Data Analytics Culture, FP: Financial Performance

The bootstrapping tests in Table 4 show that BD use fully mediates the effects of IQ, customer orientation, and big data analytics culture on customer relationship performance. Customer relationship performance also fully mediates the effect of BD use on financial performance. Hence, all bootstrapping tests revealed indirect-only effects (the indirect effect *ab* is significant and no significant direct effect *c'* exists when *ab* is controlled for) through proposed mediators.

In sum, all hypotheses received empirical support, and the model explains 33% and 47% of the variance in customer relationship performance and financial performance, respectively. Furthermore, BD use is a key mediator between antecedents and performance outcomes. These findings are discussed in the following section.

DISCUSSION

Customer information plays a vital role in managing successful long-term relationships with valuable customers (Jayachandran et al. 2005). The utilization of customer information through big data analytics use (BD use) holds potential for competitive advantage. Our research objective was to determine to what extent organizational BD use improves customer-centric and financial outcomes, and to identify the factors that influence BD use. We discuss the results regarding these two research objectives and offer implications for research and practice.

Research implications

Firstly, the results highlight information quality (IQ) as the most important predictor of BD use. By modeling IQ as a multifaceted construct, our findings shed light on how customer information characteristics to influence BD use in customer-focused decision making. While currency, accuracy, completeness and format are all valuable facets of overall IQ in the big data context, format emerges as the most important aspect for marketing executives. This finding underscores the notion that only easily interpretable customer insights are likely to be used by non-technical business decision-makers, regardless how high-quality such customer information is in substance. It is also noteworthy that the completeness of customer information is the least important dimension of big data-related IQ. This possibly reflects the pace at which markets and consumers are changing, favoring less in-depth analyses that provide rapid, moderately accurate and easily understandable results to respond to market changes as soon as they occur.

Second, the results confirm that a favorable organizational culture toward customers as well as big data analytics lead to higher levels of BD use. Customer-oriented firms are more open to pursuing superior customer information with novel analytics technologies. Big data analytics culture, in turn, helps overcome skepticism and distrust toward BD use. We posit that the effect of big data analytics culture on BD use is further enforced by its special usage context. More specifically, the people who carry out big data analyses (data scientists) are not the same people who use resulting customer information (marketing executives) to guide customer-focused decisions. Under such circumstances, we speculate that big data analytics culture may play a key role in promoting shared norms that different groups adopt to foster BD use in the organization (Germann et al. 2013).

Third, this study confirms that BD use positively influences customer relationship performance and financial performance. Furthermore, we found that BD use affects customer relationship performance directly, and financial performance indirectly via improved customer-centric outcomes. While the positive relationship between BD use and firm performance measures is not surprising, the strength of these relationships underscores the the potential of BD use for competitive advantage.

Finally, study results indicate that firms who operate in markets characterized by unpredictable customer needs and intense competition are more likely to use BD. Under volatile market conditions, external contingencies lead to a greater need to depend on data-based insights to make well-informed decisions related to customer relationship management.

Managerial implications

Based on study results, we highlight to practitioners that big data analytics use (BD use), provided that certain informational and organizational conditions are met, may form a stern foundation on which customer-driven competitive advantage can be established. In particular, we stress the importance of the quality of data-driven customer information. Marketing decision-makers demand easily understandable and up-to-date customer insights to make swift decisions. IT management should be aware that the format in which customer information is delivered to marketing executives is highly important. Firms should thus pay special attention to visualization and simulation tools that meet the requirements of decision-makers despite visualization still lagging behind big data-related storage, management, integration and analytics technologies. We also recommend that data scientists focus on delivering customer insights that are timely and sufficiently accurate, and if necessary, at the expense of more exhaustive predictive models.

Furthermore, we urge top management to ensure that an organization-wide commitment to serving customer needs and trusting analytics is implemented to facilitate BD use throughout the entire process that ranges between big data collection and information use. Across functional boundaries, C-level executives should make every effort to encourage IT managers, data scientists, and front-office management in marketing, sales and customer service to buy into BD use. With such shared values and norms in place, better customer relationship performance and, ultimately, higher financial returns are achievable with BD use.

Limitations

This study has several limitations, some of which point to opportunities for future research. First, the data in this research was gathered in a cross-sectional format and causal relationships between constructs cannot be asserted with complete confidence. We recommend that future studies adopt longitudinal research designs for confirming and extending our findings. Second, we used a single-informant design with self-reported subjective data that may be a source of common method bias, though our tests show that it should be minimal. Third, the generalizability of results is restricted to large US-based firms/SBUs operating in B2C industries. Future studies may explore BD use in SMEs, B2B sectors and other geographical contexts. Fourth, this study focused on BD use in customer relationship management. Future research may seek to improve understanding about how BD use influences firms' general capabilities in marketing, operational and R&D (Krasnikov and Jayachandran 2008). Finally, we examined organizational BD use as a single dimension concept. Future research efforts may apply more fine-grained levels of analysis to investigate offline vs online BD use, BD use for automated decision support vs strategic decision making, and the performance implications of BD use across web, text, sentiment, social network, mobile and sensor-based analytics.

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APPENDICES

Appendix 1. Sample Characteristics (N=301)

Industry	**N**	**%**	**Position of respondent**	**N**	**%**
Finance & Insurance	68	22.6	CMO	47	15.6

B2C Manufacturing	60	19.9
Retail	52	17.3
IT	32	10.6
Hospitality	19	6.3
Wholesale	19	6.3
Professional services	18	6.0
Healthcare / Pharmaceuticals	11	3.7
Media & Advertising	10	3.3
Telecom	7	2.3
Other	5	1.7
Total	301	100

SBU revenue (m$)	**N**	**%**
less than 10	72	23.9
10-100	103	34.2
101-1000	62	20.6
over 1000	64	21.3
Total	301	100

Marketing Director	67	22.2
Senior Marketing Manager	66	21.9
Marketing VP	29	9.6
CEO	24	7.8
CRM Director/Manager	68	22.6
Total	301	100

Tenure (years)	**N**	**%**
3-5 years	67	22
6-9 years	130	43
10-20 years	97	32
over 20 years	7	2.3
Total	301	100

Number of subordinates	**N**	**%**
10-20	89	30
21-50	140	47
51-100	41	14
over 100	31	10
Total	301	100

Appendix 2. Mediation Testing Using the Bootstrapping Method

The most advanced method for examining indirect effects is bootstrapping (Edwards and Lambert 2007; Kenny 2008; Preacher and Hayes 2008; Zhao et al. 2010). Adopting Preacher and Hayes' (2008) bootstrapping macros for SPSS, each mediation path was assessed in the structural model. The bootstrapping procedure is a non-parametric test without normality assumptions which creates confidence intervals (CI) for the indirect effect. We used 5000 bootstrapping resamples with 95% bias-corrected confidence intervals to test our hypotheses.

Significant paths X→M (path a) and M→Y (path b) are necessary prerequisites for the indirect effect X→M→Y (path ab) to occur. In contrast with Baron and Kenny's (1986) third condition for mediation, a significant direct effect X→Y (path c) is not necessary to establish mediating effects. X→Y's direct effect c does not represent the effect to be mediated but the *total effect*, which is the zero-order effect of simultaneous direct and indirect effects c = c' + ab (c' is the direct path when ab is controlled for). If the direct effect c' is negative, the indirect effect ab may be significant when the total effect c is not. Thus, the indirect effect is assessed solely based on the strength of X→M→Y (path ab) (Edwards and Lambert 2007; Preacher and Hayes 2008; Shrout and Bolger 2002).

Zhao et al. (2010) refined Baron and Kenny's (1986) four tests of mediation. Following Zhao et al's (2010) classification of mediation and non-mediation types, we analyze mediation effects as (1) complementary (significant and positive ab and c'), (2) competitive (significant ab and c' with opposite signs), (3) indirect-only (significant ab , no direct effect c'), (4) direct-only non-mediation (significant c', no indirect effect ab), and (5) no-effect non-mediation (no direct or indirect effect exists). Baron and Kenny's (1996) third and fourth condition tests (significance of c and c' paths) are used to determine the type of mediation taking place, which provides additional information regarding the validity of mediators in the research model. Complementary mediation overlaps with partial mediation, indirect-only mediation with full mediation, and no-effect non-mediation with no mediation (Zhao et al. 2010). Competitive mediation, in turn, may be partial or full mediation where the opposite sign of direct effect c' indicates the possibility of alternative mediators.