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USE OF BIG DATA ANALYTICS FOR CUSTOMER RELATIONSHIP MANAGEMENT: POINT OF PARITY OR SOURCE OF COMPETITIVE ADVANTAGE?

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USE OF BIG DATA ANALYTICS FOR CUSTOMER RELATIONSHIP MANAGEMENT: POINT OF PARITY OR SOURCE OF COMPETITIVE ADVANTAGE?

Firms' ability to generate, disseminate and utilize customer information and, consequently, to deliver superior value to its customers is regarded as key to firm performance (Day 1994; Kohli and Jaworski 1990; Narver and Slater 1990; Webster 1988). Recent advances in *big data*[2] technologies, and greater access to customer information through web-based channels including e-and m-commerce, social media, sensors (the Internet of Things), and loyalty programs, offers firms unprecedented opportunities to generate customer insight not previously possible (Chen et al. 2012: Nunan and DiDomenico 2013). Consequently, big data initiatives offer much promise for improving firms' customer relationship management (CRM) efforts, and are thus commonly championed by firm's marketing function (Gartner 2013; Wedel and Kannan 2016).

According to the Boston Consulting Group (Gerbert et al. 2016), data analytics is expected to transform firm CRM strategy in all key areas encompassing marketing effectiveness, pricing and revenue management, segmentation and personalization, customer lifecycle assessment, and customer loyalty and churn analysis. Unlike traditional CRM systems, big data technologies enable firms to collect and analyze unfiltered customer opinions, understand customer attitudes and behaviors, and engage in a two-way dialogue with their customers (Chen et al. 2012; Day 2011). Web, text, sentiment, social network, mobile, and sensor-based analytics can be used to analyze multi-structured customer data to build predictive models that outperform those that can be generated using legacy CRM tools (Chen et al. 2012; Jelinek 2013; Wedel and Kannan 2016), thus enabling firms to offer its customers highly personalized products and

[2] 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).

services that meet their needs better than rivals, often in real-time, and at a lower cost (Einav and Levin 2013; Jelinek and Bergey 2013; LaValle et al. 2011; McAfee and Brynjolfsson 2012).

For the majority of firms, however, a disconnect exists between the collection of data, and the actual usage of data in decision-making. This disconnect, or "utilization gap," is regarded as big data's greatest challenge (Moorman 2013). Despite virtually unlimited access to diverse customer data, and advances in sophisticated data management tools, only an estimated 35% of marketing decisions are made based on analytics-driven customer information (CMO Survey 2016). To explore the drivers and consequences of this utilization gap, we introduce the term *big data customer analytics use* to refer to 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).

Unlike legacy CRM tools – which are user-intensive and often deployed across organizational levels to support interactions at the customer-firm interface (Mithas et al. 2005; Srinisavan and Moorman 2005) – big data customer analytics programs rely far less on human involvement to enhance customer outcomes (Chen et al. 2015). Specifically, big data technologies enable firms to automate CRM processes ranging from customer data collection, management, integration and analysis, to customer information use in decision-making (Chen et al. 2015) because they are enhanced with real-time, machine learning algorithms that render human judgment unnecessary.

Given its advanced functionality (relative to legacy CRM systems), scholars have argued that big data-driven decision-making leads to better managerial decisions, and is thus a potential source of competitive advantage (Chen et al. 2012; Gillon et al. 2014). While big data success stories of first movers turned industry leaders provide compelling evidence to support this claim

(Chen et al. 2015; Wedel and Kannan 2016), it is unclear whether the advantage provided by big data customer analytics use is sustainable over time, or can be competed away by rivals to become a necessary pre-requisite for firm survival rather than lead to a sustainable competitive advantage (e.g., Clemons and Row 1991; Kumar et al. 2011).

In sum, prior research suggests that big data customer analytics use is expected to dramatically improve CRM decision-making, consequently leading to higher performance and competitive advantage. However, extant research is silent about what determines whether firms use big data analytics to guide CRM strategy and, by extension, the extent to which big data customer analytics use impacts customer relationship outcomes and firm financial performance. In addition, it remains unclear whether the competitive advantage, if any, afforded by big data customer analytics use is sustainable when its use is highly prevalent in the firm's industry, i.e., whether big data customer analytics use is vulnerable to imitation by rivals. To remedy these crucial knowledge gaps, this study addresses three research questions:

1. What are the key antecedents of big data customer analytics use?
2. How, and to what extent, does big data customer analytics use influence customer relationship performance, and, ultimately, financial performance?
3. Is competitive advantage, if any, achieved through big data customer analytics use contingent upon its prevalence within an industry?

To answer these questions, we primarily build on market information use theory and related CRM research (e.g., Jayachandran et al. 2005; Menon and Varadarajan 1992; Moorman 1995), with additional support drawn from business analytics studies (Chen et al. 2012; Germann et al. 2013; McAfee and Brynjolfsson 2011), information quality (IQ) research (Wang et al. 1996; Lee et al. 2002), and cultural customer orientation (Deshpande et al. 1993; Narver and Slater 1990). We advance a theoretical framework to examine how informational and

organizational factors act to enhance big data customer analytics use, which in turn influences customer relationship and financial performance. More specifically, we posit and find that information quality (IQ), big data analytics culture, and customer orientation are key antecedents of big data customer analytics use, which in turn is a critical driver of CRM and firm performance outcomes. Finally, our findings reveal that the performance benefits of big data customer analytics use vary depending on the prevalence of big data customer analytics use in the firm's industry.

This research makes three important contributions to CRM literature. First, this study extends the CRM literature by synthesizing knowledge from diverse theories to show how informational and organizational factors act as critical antecedents to enhance big data customer analytics use. In particular and in contrast with prior CRM research, the results highlight the role of information quality (IQ) in predicting big data customer analytics use. By applying well-established IQ research into the big data (4V's) context, the findings reveal the relative importance of different IQ dimensions for CRM decision-makers, with the format (visualization) of customer information being most critical. The results also indicate that customer orientation and big data analytics culture are key antecedents of big data customer analytics use. The study's findings thus suggest that both firm-wide cultures are necessary to facilitate the formation of collective values, beliefs and norms to adopt a successful big data-driven CRM strategy.

Second, this study introduces a new measure adopted from prior CRM literature that captures the primary set of CRM activities for which firms use big data customer analytics to better understand, classify, and prioritize their customers, and offer them products and services that match their individual needs (Gerbert et al. 2016; Jayachandran et al. 2005; Wedel and Kannan 2016). The findings confirm big data customer analytics use as a key predictor of firm

performance, and more specifically, that big data customer analytics use primarily influences financial performance indirectly via customer relationship performance. The results also underscore the personalization of the marketing mix as the key dimension of big data customer analytics use.

Third, this study suggests that the performance impacts of big data customer analytics use are highly contingent on the prevalence of big data customer analytics use within an industry. The findings reveal that big data customer analytics use only leads to superior financial performance directly when big data analytics use is low among industry competitors. When the industry prevalence of big data analytics use is high, firms may still achieve sustainable competitive advantage indirectly through better customer outcomes. Thus, the results indicate that while some of the competitive advantage afforded by big data can be imitated away by rivals, the hyper-personalization afforded by big data makes the firm's customers less vulnerable to competitor moves, allowing the firm to partially escape the game of competition and imitation (McGahan and Ghemawat 1994).

CONCEPTUAL FRAMEWORK AND HYPOTHESES

In framing our investigation, we primarily build on market information use theory and related CRM research (Jayachandran et al. 2005; Menon and Varadarajan 1992; Moorman 1995) to examine how informational and organizational factors act to enhance big data customer analytics use, which in turn influences customer relationship and financial performance. Furthermore, we assess whether the prevalence of big data analytics use within an industry moderates the relationships between big data customer analytics use and outcome variables of interest. When applicable, market information theory is complemented with business analytics (BI) studies

(Chen et al. 2012; Germann et al. 2013; McAfee and Brynjolfsson 2011), information quality (IQ) research (Wang et al. 1996; Lee et al. 2002), and cultural customer orientation (Deshpande et al. 1993; Narver and Slater 1990). The research framework that guides our inquiry is illustrated in Figure 1.

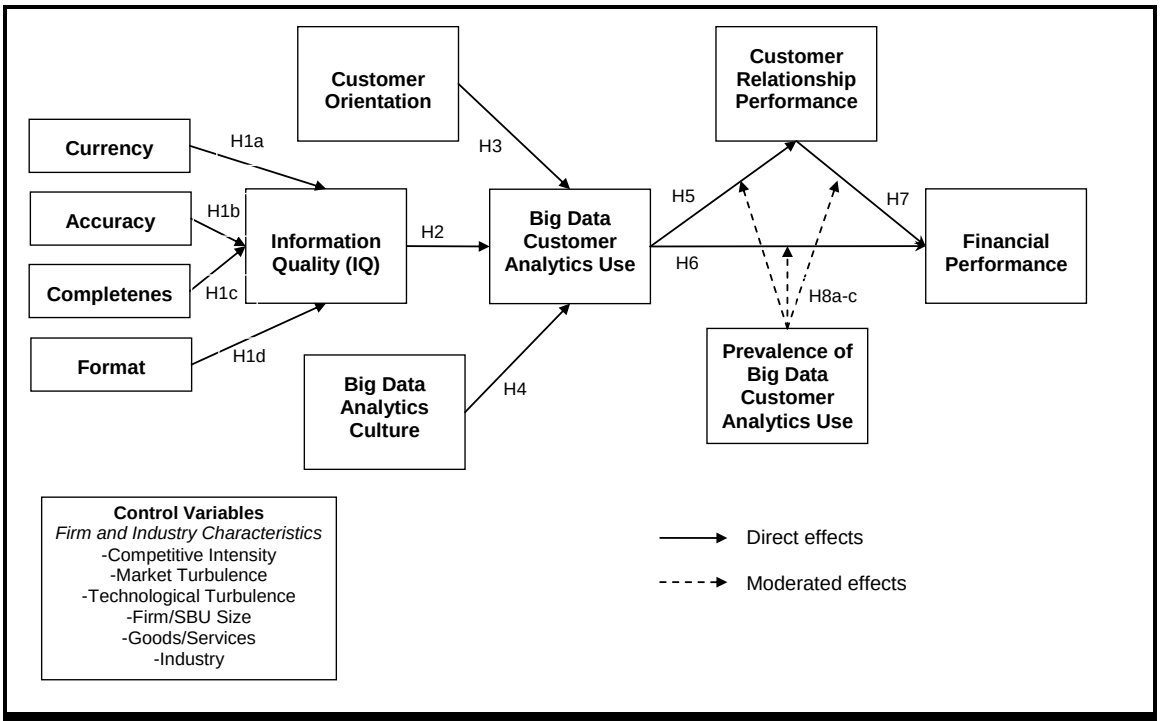

Figure 1. Research Model

Big Data Customer Analytics Use

Market information theory posits that firms' effective use of customer information is a crucial driver of performance (Menon and Varadarajan 1992). 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). Firm CRM strategy relies on the analysis of diverse customer information from external sources to better understand their customers, identify high-value customers, and offer new products and services accordingly (Jayachandran et

al. 2005). CRM technology tools have thus far been the primary IT's used to support the firm's customer information processes (Mithas et al. 2005; Srinisavan and Moorman 2005). For example, CRM tools are used to exploit big databases of customer purchase histories to forecast customer lifetime value (CLV), improve marketing resource allocation to profitable customers, and personalize firm offerings (e.g. Kumar et al. 2008; Rust et al. 2011; Schulze et al. 2012).

We extend prior CRM research by focusing on big data customer analytics use, i.e., customer information derived from big data analyses to guide marketing decisions. By definition, big data customer analytics use (hereafter referred to as *CA use*) builds on the assumption that the actual usage of IT, as opposed to the level of IT investment, is the key driver of improved performance (Devaraj and Kohli 2003). Marketing decisions are typically complex tasks, dictating that a greater amount of information needs to be processed to reach better decisions (Brynjolfsson et al. 2011). The actual usage of IT denotes that customer information influences the decision-making process through its knowledge-enhancing and action-oriented use (Menon and Varadarajan 1992). Building on this theory, knowledge-enhancing CA use improves marketing decision-makers' ability to understand customer needs and behaviors. Predictive modeling and algorithms can analyze big data to develop finely-grained customer profiles and customer segments, for personalization as well as to assess customer churn and retention, and to identify the firm's best customers in terms of CLV (Chen et al. 2012; Einav and Levin 2013; Jelinek 2013). With a wealth of in-depth customer information, action-oriented CA use leads to better decisions related to the profiling, segmentation and prioritization of customers, the identification of appropriate channels to reach customers, the customization of product and service features, and the personalization of the different elements of the marketing mix (e.g., Chaudhuri et al. 2011; Jayachandran et al. 2005; Jelinek and Bergey 2013; Roberts et al. 2014).

Prior research offers several examples of how customer relationships could be further enhanced with the application of big data analytics methods (Chen et al. 2012; Manyika et al. 2011; Lycett 2013; Sung-Hyuk et al. 2012). In comparison, traditional CRM tools are used to exploit customer purchase histories that reside in firm databases. This data is required for CLV management actions in order to increase marketing resource allocations to profitable customers, and to put forward personalized offerings (e.g., Bolton et al. 2004; Gupta et al. 2004; Kumar and Reinartz 2006; Kumar et al. 2008; Rust et al. 2011; Schulze et al. 2012). With the application of non-relational big data technologies, however, transactional data from firm databases can now be combined with rich, multi-structured data from a variety of other sources including retailers, e- and m-commerce, the "Internet of Things (IoT)", and social media, to make far more accurate customer-focused decisions (Balasubramanian et al. 2002). Similarly CA use in the areas of customer selection and segmentation, consumer key decision processes, and repeat purchases forecasting, is considered to add substantial value for customer relationships (Glady et al. 2015; Sahoo et al. 2012; Snijders et al. 2012; Roberts et al. 2014). In sum, prior theory indicates that CA use holds great potential for improving decision making related to customer relationship strategy. Next, we discuss the antecedent factors that may influence organizational CA use.

Antecedents of Big data Customer Analytics Use

Market information use theory suggests that organizational CA 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). Based on a review of relevant literature, 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 borrow 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),

Big data-driven customer information can be distinguished from prior customer information stored in legacy CRM systems by the sheer volume, velocity, and variety of data (the three V's) that are used to generate customer insights (Chen et al. 2002; Wedel and Kannan 2016). Specifically, big data analytical tools can process massive amounts of multi-structured data (varieties of data formats and data types) in real-time. More recently, visualization has been put forward as a fourth "V" because the complexity of big data-driven customer insights should be delivered in understandable form to executives to support decision-making (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 CA 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).

H1c: Completeness has a positive effect on information quality (IQ).

H1d: 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 CA use context, customer information that is timely, accurate, complete, and presented in understandable format, jointly influence overall IQ, which, in turn, drives decision-makers' choice of information use (Menon and Varadarajan 1992). We put forward the following hypothesis:

H2: Information quality (IQ) has a positive effect on big data customer analytics 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 CA 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 entails that customer satisfaction is an organizational priority that dictates the implementation of necessary activities to achieve this goal (Jayachandran et al. 2005). Customer-oriented firms strive to create and respond to customer information of their expressed and unexpressed needs to achieve competitive advantage (Deshpande et al. 1993; Narver and Slater 1990). 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 customer analytics (Jayachandran et al. 2005). Stated differently, we expect that:

H3: Customer orientation has a positive effect on big data customer analytics 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 CA 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 CA use to over-rule managerial experience and intuition (LaValle et al. 2011; McAfee and Brynjolfsson 2012). Managerial resistance may be particularly strong because CA 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 CA 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). Consistent with this research, we anticipate that big data analytics culture is a key driver of CA use to support customer-focused decision-making. Hence:

H4: Big data analytics culture has a positive effect on big data customer analytics use.

Performance Impacts of Big Data Customer Analytics Use

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

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 with CRM technologies (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 as well as CLV, 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, CA use puts managers in a superior position to design highly personalized offerings that are better aligned with customer needs in real-time, leading to higher CRM performance, such as customer acquisition, satisfaction and retention (Einav and Levin 2013; Germann et al. 2013). Thus:

H5: Big data customer analytics use has a positive effect on customer relationship performance.

We also expect that CA 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 CA use lowers costs by automating customer information and marketing processes (Chen et al. 2012; Einav and Levin 2013; Jelinek 2013). Therefore, CA use is expected to have a dual effect on financial performance through higher customer relationship performance as well as through increased sales and lower costs (Rust et al. 2002). We thus hypothesize that:

H6: Big data customer analytics use has a positive effect on firm financial performance.

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

H7: Customer relationship performance has a positive effect on firm financial performance.

Moderating Effect of Industry Prevalence of Big Data Customer Analytics Use

We also examine whether the prevalence of CA use in the firm's industry influences the relationship between CA use, customer relationship performance, and firm financial performance. Stated differently, we use industry prevalence as a proxy to examine whether CA use provides a sustainable competitive advantage in the face competitive imitation over time.

While no studies have specifically investigated whether CA use prevalence moderates the effects of CA use on firm performance, prior research has shown that when traditional CRM tools became more prevalent, they were no longer considered sources of competitive advantage but necessary pre-requisites for competitive parity and firm survival (Clemons and Row 1991; Dowling and Uncles 1997). For example, loyalty programs within CRM strategy are characterized more by imitation and isomorphic effects than innovation because all industry players typically adopt the same management practices, enabling them to achieve a situation of competitive stability (Dowling and Uncles 1997). In sum, CRM tools became necessary but non-differentiating assets as their industry prevalence increased.

In a similar vein, the firm's differential advantage afforded by CA use is also exposed to competitive imitation. When industry prevalence is low, first-mover advantages afforded by CA use through a superior understanding of customer needs, and more personalized product offerings compared to rivals, may lead to sustainable competitive advantage (Day 2011; McAfee and Brynjolfsson 2012). Furthermore, difficult-to-copy tacit knowledge requires a learning curve that gives first movers a highly advantageous position that may discourage other firms in the industry, rendering CA use among imitators ineffective (Day 2011). Conversely, in industries where the prevalence of CA use is high, such as retail and e-commerce, the potential of CA use to sustain differential advantage may be more difficult (Brown et al. 2012). For example, big data-driven firms have an equal opportunity to collect external customer data from web-based

sources, decreasing the differential advantages of CA use. Competition is also likely to have copied the imitable explicit knowledge related to successful big data technologies and practices, further undermining the performance impacts of CA use (Germann et al. 2013).

The preceding logic suggests that CA use may only provide for sustainable competitive advantage in industries where CA use is not prevalent. However, we posit that CA use may lead to sustainable competitive advantage due to its unprecedented potential in matching customer needs with products and services, in real-time, and at lower costs through process automation and optimization. More specifically, firms are able to retain relationship-oriented customers through emotional exit barriers with hyper-personalization and individualized offers (Morgan and Hunt 1994). As hyper-targeted customers become resistant against counter persuasion of competitors, they can be isolated from competitive pressures to create internal captive, "domesticated markets (McGahan and Ghemawat 1994)". With differentiation through personalization, big data-driven firms may thus be able to build isolating mechanisms against competition and imitation that creates a sustainable competitive advantage (Arndt 1979; Kahn et al. 1988; Fader and Schmittlein 1993; Shapiro and Varian 1999). Furthermore, the sustainability of this advantage from CA use may be even more sustainable because the majority of firms do not utilize the full potential of their investments into big data technologies (CMO Survey 2016; Moorman 2013).

In sum, we expect that the prevalence of CA use influences the relationships between CA use and firm performance. In the context of big data, there are opposing arguments that suggest that competitive advantage from CA use is either immune or exposed to the industry prevalence of CA use. There is no empirical evidence to inform how the two opposing forces (isolation mechanism from differentiation versus competitive imitation) play out against each other. Thus,

the direction of the moderating effect of CA use prevalence on the relationships between CA use and firm outcomes is not hypothesized. Hence:

H8a: The positive effect of big data customer analytics use on customer relationship performance is moderated by the prevalence of big data customer analytics use.

H8b: The positive effect of big data customer analytics use on financial performance is moderated by the prevalence of big data customer analytics use.

H8c: The positive effect of customer relationship performance on financial performance is moderated by the prevalence of big data customer analytics use.

Control Variables

We control for firm and industry characteristics that may influence the action mechanisms between market information use, its antecedents and consequences. Control variables (1) firm size, (2) goods versus services firms, (3) industry, (4) competitive intensity, (5) market turbulence, and (6) technological turbulence are included to partial out any noise in the variance (e.g., Homburg et al. 1999; Kohli and Jaworski 1990; Menon et al. 1999).

Firm/SBU size is controlled for in terms of the number of employees because larger business units may benefit from scale and scope economies that influence CA use and financial performance (Germann et al. 2013). Differences in CA use and financial performance between goods and services firms are also controlled with a dummy variable (Homburg et al. 1999; Verhoef and Leeflang 2009). Three industry dummies are employed to account for differences between the largest big data-driven industry sectors in our dataset, namely, B2C manufacturing, finance and insurance, and retail. In some industries, firms may use big data analytics less or benefit less from it due to limited access to data, dispersion of data sources, and data privacy and

protection laws, for instance (Brown et al. 2012; Cap Gemini 2012; Gartner 2013; Manyika et al. 2011).

We include two-item scales for competitive intensity, market turbulence and technological turbulence as controls to account for the effects on model endogenous variables (Kohli and Jaworski 1990). The volatility of the firm's environment increases the need for market information use (Homburg et al. 1999; Menon and Varadarajan 1992). Changes in competitors' strategies, customer needs or technologies increase the need for customer information use to alleviate uncertainty associated with decision-making (Kohli and Jaworski 1990; Menon et al. 1999). These three factors may also decrease customer relationship performance as customer retention becomes more difficult, thereby also affecting financial performance (Jayachandran et al. 2005; Kirca et al. 2005). Prior marketing research also indicates that these environmental factors may have direct effects on firm performance (Homburg et al. 1999; Menon et al. 1999; Olson et al. 2005; Vorhies and Morgan 2005).

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 Appendix B), and were measured on a 7-point Likert scale. Following established measurement model specification guidelines (Petter et al. 2007), we determined that two scales modeled in prior studies as reflective were actually formative (Big Data Analytics Culture, Big Data Customer Analytics Use)[3]. Based on our literature review, an

[3] We carried out additional tests following Chwelos et al. (2001) to test whether measurement model specification affects structural model results. We tested two other versions of the model (one with all constructs formative (Mode B) and another with all constructs reflective (Mode

additional item (use8, personalization of the marketing mix) was added to the Big Data Customer Analytics Use scale that is based on Jayachandran et al.'s (2005) original seven-item scale measuring customer information use in CRM. Our sampling frame focuses on strategic business units (SBUs) in large (>1000 employees), US-based, B2C manufacturing and service firms that have invested in big data analytics for the marketing department.

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[4]. To ensure that the final informants possessed adequate knowledge, respondent competency was assessed through a separate question in the survey instrument (Kumar et al. 1993). Appendix A summarizes the sample characteristics. The data was cleared for non-response biases, which included screening for

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A). The results of the structural model were qualitatively similar with no path coefficients gaining or losing statistical significance, and no significant paths changed in sign. In sum, measurement model specification decisions, which are always judgment calls made by authors, do not affect the results of the study.

[4] Due to personal data protection laws, it was not possible to match the collected data with survey data from other informants or with objective financial data.

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 (SmartPLS 3; Ringle et al. 2015) to test the measurement model and structural model. Item descriptions, indicator reliabilities and references are summarized in Appendix B. Descriptive statistics, construct-level validation, and latent variable correlations are shown in Appendix C. 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, 2017) 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.

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. However, Harman's test does

not completely rule out the risk of common method bias so we carried out additional common method tests with a marker variable (Lindell and Whitney 2001).

Ideally, the marker variable should be theoretically unrelated to other substantive variables in the study, chosen *a priori*, and similar to the substantive variables in content and format (i.e., in this case latent variables, perceptual/subjective measures) (Richardson et al. 2009; Simmering et al. 2015). To provide a plausible *a priori* assumption of a zero correlation between the marker and other study variables, the marker variable was adopted from another discipline. Following these criteria, the 4-item perceptual "Astrology interest (Mowen et al. 2009)" scale was chosen *a priori* and included in the survey instrument. Pearson correlations and significance levels between the marker and substantive variables are shown in Table 1.

Table 1. Marker Variable Analysis

Construct	1	2	3	4	5	6	7	8	9	10	11
1 Accuracy	1.000										
2 Completeness	.631**	1.000									
3 Currency	.656**	.601**	1.000								
4 Format	.603**	.586**	.629**	1.000							
5 Information Quality	.703**	.636**	.705**	.723**	1.000						
6 Big Data Analytics Culture	.585**	.515**	.534**	.563**	.568**	1.000					
7 Customer Orientation	.473**	.498**	.548**	.630**	.677**	.423**	1.000				
8 Big Data Analytics Use	.650**	.649**	.697**	.701**	.741**	.601**	.619**	1.000			
9 Customer Relatonship Performance	.445**	.542**	.502**	.502**	.515**	.347**	.462**	.556**	1.000		
10 Financial Performance	.434**	.470**	.402**	.414**	.451**	.350**	.401**	.477**	.674**	1.000	
11 Astrology Interest	.021	.023	-.062	-.024	-.096	-.077	.008	-.059	.075	.159**	1.000

The correlations between all predictor and criterion variables, ranging between .347 and .741, are highly significant. Astrology interest, in turn, has a significant correlation of .159 with the criterion variable "Financial performance". However, the marker has no significant correlations with the other nine substantive variables.

This correlation of the marker with the criterion scale is then used to partial out the common method effect from other correlations to assess the extent of method bias. The partial

correlations between all predictor and criterion variables remain highly significant, indicating that correlations in the model are not resulting from common method bias (Lindell and Whitney 2001). In sum, common method bias is not likely to be a concern in this study.

Structural Model

The results of our hypothesis testing, the structural path estimates (standardized effects), significance tests, and explained variances are summarized in Table 2. 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, 2017).

Table 2. Structural Model

			Dependent variable			
Predictor variables	**Hypothesis**	**Supported?**	**Information Quality**	**Big Data Analytics Use**	**Customer Relationship Performance**	**Financial Performance**
Currency	H1a	Yes	.26** (4.53)			
Completeness	H1c	Yes	.13* (2.37)			
Accuracy	H1b	Yes	.25** (4.88)			
Format	H1d	Yes	.34** (5.49)			
Information Quality	H2	Yes		.36** (4.51)		
Customer Orientation	H3	Yes		.13* (2.47)		
Big Data Analytics Culture	H4	Yes		.22** (4.25)		
Big Data Analytics Use	H5	Yes			.40** (5.43)	
Big Data Analytics Use	H6	No				.10 (1.34)
Customer Relatonship Performance	H7	Yes				.54** (8.83)
Moderating effects						
Big Data Analytics Use * Prevalence of Big Data Analytics Use	H8a	No			-.04 (.80)	
Big Data Analytics Use * Prevalence of Big Data Analytics Use	H8b	Yes				-.26** (5.39)
Customer Relationship Performance * Prevalence of Big Data Analytics Use	H8c	Yes				.19** (3.64)
Control variables						
Competitive Intensity				.08 (1.60)	.07 (.96)	-.03 (.22)
Market Turbulence				.12 (1.88)	.15* (2.34)	.11 (1.80)
Technological Turbulence				.11 (1.69)	.06 (.74)	-.01 (.10)
Firm Size				-.02 (.45)		.04 (.87)
Goods versus Services				.00 (.04)		.04 (.98)
Industry: B2C Manufacturing				-.10* (2.25)		-.02 (.67)
Industry: Finance and Insurance				.00 (.01)		-.03 (.83)
Industry: Retail				.05 (1.48)		.01 (.06)
Explained variance R2			**.68**	**.66**	**.34**	**.55**

** p<.01 * p<.05 (t-value in brackets)

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 (.36, $p<.01$), customer orientation (.13, $p<.05$), and big data analytics culture (.22, $p<.01$) are significant predictors of big data customer analytics use, providing support for H2, H3 and H4.

Big data customer analytics use (CA use) is positively associated (.40, $p<.01$) with customer relationship performance, explaining 34% of its variance when competitive intensity, market and technological turbulence are controlled for. Hence, H5 received empirical support. As expected, customer relationship performance is a strong predictor (.54, $p<.01$) of financial performance, providing support for H7. CA use, in turn, has a non-significant direct effect (.10, t=1.34) on financial performance, indicating that H6 is not supported. When the indirect effect of CA use via customer relationship performance on financial performance is not controlled for, however, CA use predicts firm financial performance (.28, $p<.01$).

The hypotheses on whether the prevalence of CA use moderates the relationships between CA use, customer relationship and financial performance received mixed support. The interaction term between CA use and prevalence of CA use had no significant effect on customer relationship performance (-.04, t=.80) but had a highly significant negative effect on financial performance (-.26, t=5.39, $p<.01$). Thus, H8a is rejected and H8b is supported by the data. In support of H8c, we find that prevalence of CA use has a positive moderating effect (.19, t=3.64, $p<.01$) on the relationship between customer relationship performance and financial performance.

Control variables had some minor direct effects on the endogenous constructs. The industry dummy for B2C manufacturing is negatively associated with CA use (-.10, $p<.05$)

suggesting that manufacturing firms have lower levels of CA use than other industries. Market turbulence also positively influences customer relationship performance (.15, $p<.05$) but there were no significant controlled paths to financial performance. Finally and as an additional test, the control variables did not moderate any of the relationships proposed in the structural model.

Additional Mediation and Moderation Analyses

Since the research model implicitly suggests that CA use mediates the effects of the three antecedents, information quality (IQ), customer orientation, and big data analytics culture, on the outcome customer relationship performance, we carried out additional analyses. In addition, we apply a more robust test to determine whether customer relationship performance mediates the relationship between CA use and financial performance.

Specifically, we tested indirect effects using bootstrapping (see Table 3), 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 3, include 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 D for a detailed description). In order to perform the most stringent test, control variables were included in mediation bootstrapping tests as covariates that were treated like independent variables in the estimation, with all possible paths to mediator and outcome.

Table 3. Mediation Testing with Bootstrapping

Mediation path	**IQ→CAU→CRP**	**CO→CAU→CRP**	**BDAC→CAU→CRP**	**CAU→CRP→FP**
a	.36**	.13**	.22**	.29**
b	.29**	.29**	.29**	.56**
c	.25**	.15**	.04	.21**
c'	.14	.11	-.02	.05
ab [a]	**.11****	**.04****	**.06****	**.16****
SE	.041	.019	.028	.063
Bias-C. CI 99% Lower	.021	.015	.010	.036
Bias-C. CI 99% Upper	.234	.081	.164	.368
R^2	.34	.34	.34	.49
Controls	**Control→CAU**	**Control→CAU**	**Control→CAU**	**Control→CRP**
Information Quality		.36**	.36**	.14
Customer Orientation	.13**		0.13**	.11
Big Data Analytics Culture	.22**	.22**		-.02
Competitive Intensity	.08*	.08*	.08*	.07
Market Turbulence	.12**	.12**	.12**	.11
Technological Turbulence	.11*	.11*	.11*	.02
Firm Size	-.02	-.02	-.02	-.08
Goods vs Services	.00	.00	.00	-.08
Industry: B2C manufacturing	-.10*	-.10*	-.10*	.06
Industry: Finance&Insurance	.00	.00	.00	.00
Industry: Retail	.05	.05	.05	.06
	Control→CRP	**Control→CRP**	**Control→CRP**	**Control→FP**
Information Quality		.14	.14	.02
Customer Orientation	.11		.11	.02
Big Data Analytics Culture	-.02	-.02		.08
Competitive Intensity	.07	.07	.07	-.03
Market Turbulence	.11	.11	.11	.11
Technological Turbulence	.02	.02	.02	.00
Firm Size	-.08	-.08	-.08	.02
Goods vs Services	-.08	-.08	-.08	-.05
Industry: B2C manufacturing	.06	.06	.06	.00
Industry: Finance&Insurance	.00	.00	.00	-.05
Industry: Retail	.06	.06	.06	.00

** 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, CAU: Big Data Customer Analytics Use, CRP: Customer Relationship Performance, CO: Customer Orientation, BDAC: Big Data Analytics Culture, FP: Financial Performance

The bootstrapping tests suggest that CA 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 CA 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.

Next, we carried out an additional test to further examine the opposing significant moderating effects of big data analytics prevalence on the relationships between CA use and financial performance, and between customer relationship performance and financial performance. Specifically, we calculated the conditional direct effects between CA use, customer relationship performance, and financial performance at different levels of big data analytics prevalence with the bootstrapping method, controlling for all three moderating effects (H8a-c) simultaneously (Preacher and Hayes 2008). The analyses revealed that when big data analytics prevalence is low (one standard deviation below mean value), the indirect effect of CA use via customer relationship performance on financial performance is significant (.11, $p<.01$), and the direct effect of CA use on financial performance is also significant (.31, $p<.01$). Conversely, when big data analytics prevalence is high (standard deviation above mean value), the indirect effect increases to .18 ($p<.01$) but the direct effect becomes significant of the opposite sign (-.21, $p<.05$). The conditional direct effect of CA use on customer relationship performance remained insignificant across all possible values of the moderator.

In order to facilitate the interpretation of these moderating effects, Figure 2 illustrates the direct effects of CA use and customer relationship performance on financial performance across different industry conditions (low vs high industry prevalence). Figure 2 suggests that when industry prevalence of CA use is low (one standard deviation below mean value), CA use and

customer relationship performance are associated with financial performance to a similar degree (.38, *p<.01*). However, the direct relationship between CA use and financial performance is always more important (i.e., higher financial performance) than the indirect relationship through customer relationship performance under low industry prevalence.

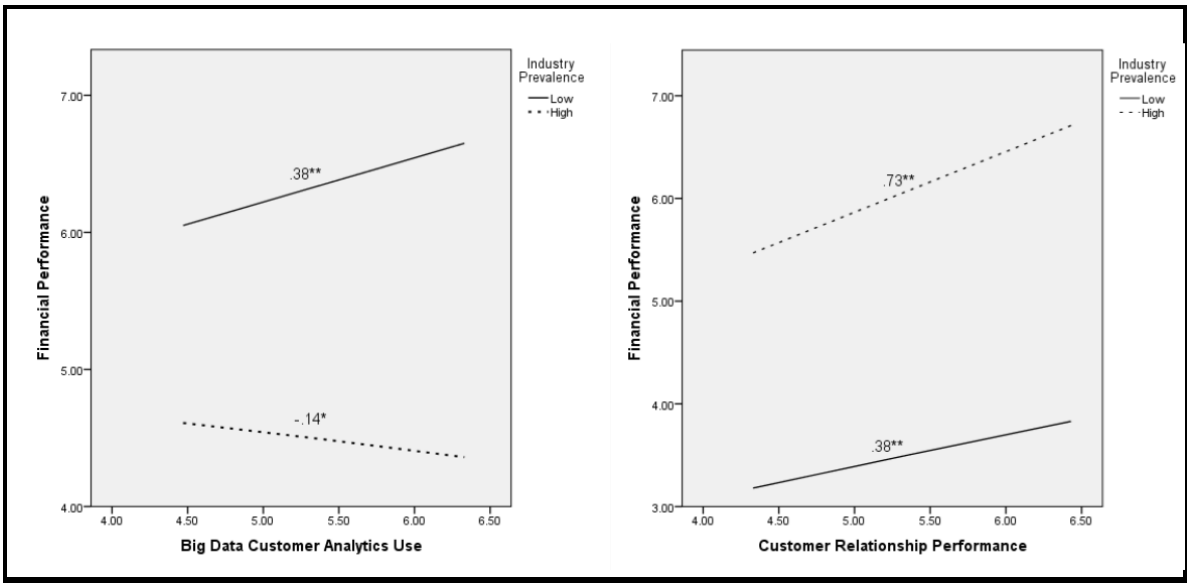

Figure 2. Direct Effects of Big Data Customer Analytics Use and Customer Relationship Performance on Financial Performance under Low and High Industry Prevalence

When industry prevalence is high, the CA use is negatively associated with financial performance (-.14, *p<.05*). In stark contrast, the positive relationship between customer relationship performance and financial performance becomes stronger (.73, *p<.01*) in high prevalence conditions. As a consequence, the indirect relationship between CA use and financial performance through customer relationship performance is more important (i.e., higher financial performance) than the direct relationship when industry prevalence of CA use is high.

In sum, six out of eight hypotheses received full empirical support, and moderation hypotheses H8a-c were partially supported. The model explains 34% and 55% of the variance in customer relationship performance and financial performance, respectively. 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). Our research objective was to determine to what extent organizational big data customer analytics use (CA use) improves customer-centric and financial outcomes, and to assess how antecedent factors influence CA use. In addition, we examined whether the performance of CA use is conditioned by its industry prevalence among competition. We discuss the results regarding these research objectives and offer implications for research and practice.

Research Implications

Information Quality (IQ) and its Visualization Dimension are Key Antecedents of Big Data Customer Analytics Use

The study advances CRM theory in at least three important ways. First, this study applies well-established quality dimensions from IQ research into the big data analytics (4V's) context, and highlights information quality (IQ) as the most important predictor of CA use. By modeling IQ as a multifaceted construct, our findings shed light on how customer information characteristics influence CA use in customer-focused decision-making. While currency (velocity), accuracy (volume) and completeness (variety) are all valuable facets of overall IQ in the big data context, format (visualization) emerges as the most important characteristic of customer information 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. Another possible explanation is that in managerial or theoretical modeling practices, the length of the estimation period might be limited by data availability, time and costs. Prior research has shown that short estimation periods with reduced information and data volume are sufficient to ensure adequate predictive validity or data veracity (Casteran et al. 2017). This important finding confirms that, even in contexts in which available data are lacking (e.g., left-censored data, unknown customer entries, insufficient customer purchase histories, lack of costly CRM infrastructure), managers can use incomplete data residing in the firm's big customer databases to derive reliable forecasting indicators, such as CLV.

In addition, the results confirm that a favorable organizational culture toward customers as well as big data analytics lead to higher levels of CA use. Customer-oriented firms are more open to pursuing superior customer information with novel analytics technologies (Deshpande et al. 1993; Jayachandran et al. 2005; Narver and Slater 1990). Big data analytics culture, in turn, helps overcome skepticism and distrust toward CA use. We posit that the effect of big data analytics culture on CA 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, big data analytics culture may play a critical role in promoting shared norms that different organizational groups adopt to foster CA use in the organization (Germann et al. 2013).

Big Data Customer Analytics Use is a Critical Driver of Firm Performance

Second, empirical studies focusing on the business value of big data analytics use are scant in academic research and non-existent in CRM (Chen et al. 2015; Corte-Real et al. 2017; Fosso Wamba et al. 2017; Janssen et al. 2017). This study introduces a new measure adopted from prior CRM literature that captures the primary set of CRM activities for which firms use big data customer analytics to better understand, classify, and prioritize their customers, and to offer them products and services that match their individual needs (Jayachandran et al. 2005). The findings confirm that CA use is a key driver of CRM strategy (e.g., Gerbert et al. 2016; Wedel and Kannan 2016). The results also show that CA use primarily affects financial performance indirectly via improved customer-centric outcomes. While the positive relationships between CA use and performance measures are not surprising, the strength of the relationships on the CA use-customer relationship performance-financial performance continuum underscores the potential of CA use for competitive advantage. In addition, while all eight dimensions of big data customer analytics use are significant, the results show that personalization of the marketing mix is the key application area of big data customer analytics in predicting superior performance. This finding supports the notion that highly individualized product and services are at the core of big data-driven competitive advantage (Einav and Levin 2013; Jelinek and Bergey 2013; LaValle et al. 2011; McAfee and Brynjolfsson 2012).

Industry Prevalence Erodes Competitive Advantage of Big Data Customer Analytics Use

Third, the results show that the performance impacts of big data customer analytics use depend on the prevalence of big data customer analytics use within an industry. The findings reveal that big data customer analytics use only leads to superior financial performance directly when big

data analytics use is low among industry rivals. When the industry prevalence of big data analytics use is high, customer-oriented firms may still achieve sustainable competitive advantage indirectly through customer relationship performance. Thus, the results indicate that the differential advantage driven by CA use, through increased sales and reduced operating costs through customer process automation and optimization, can be imitated away by rivals unless the firm is customer-oriented. Stated differently, building strong customer relationships as an isolation mechanism is critical to financial performance in big data-driven industries because data-driven attacks by competitors are more likely. Therefore, the findings suggest that CA use is both necessary for competitive parity and firm survival but can also be used to build a sustainable competitive advantage if CA use differentiates firm CRM strategy through micro-segmentation, hyper-personalization and individualized marketing mix to make customers immune to competing offers.

Implications for Practice

Based on study results, we highlight to practitioners that -- provided certain informational and organizational conditions are met -- CA use may provide a solid foundation on which customer-driven competitive advantage can be built. 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. The IT function should ensure that the format in which customer information is delivered to marketing executives is a priority. Developments in big data visualization tools lag behind non-relational storage, management, integration and analytics technologies, underlining the need to pay special attention to meeting the format requirements of business decision-makers. 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.

We encourage top management to ensure that an organization-wide commitment to serving customer needs and trusting analytics is implemented to facilitate CA 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 CA use as an integral part of firm CRM strategy. With such shared values and norms in place, better customer relationship performance and, ultimately, higher financial returns can be expected from CA use.

Finally, firms should be aware that the business value of big data analytics is vulnerable to competitive imitation. When considering big data investment in a specific industry, we urge managers to take into account the potential upside of first-mover advantages, or the potentially detrimental effect of competing against big data-driven rivals. On the one hand, firms should be aware that in industries where using big data analytics is a widely-adopted business practice, automating and optimizing CRM processes do not always yield differential advantages over rivals but may still be necessary to ensure competitive parity. On the other hand, managers should also know that CA use can differentiate firm CRM strategy and provide sustainable competitive advantage when it is utilized to build stronger relationships with customers.

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 CA use in SMEs, B2B sectors and other geographical contexts. Fourth, this study focused on CA use in customer relationship management. Future research may seek to improve understanding about how CA use influences firms' general capabilities in marketing, operations and R&D (Krasnikov and Jayachandran 2008). Finally, we examined CA use as an organization -level concept. Future research efforts may apply more fine-grained levels of analysis to investigate the business impacts of offline vs online CA use, CA use for automated decision support vs strategic decision making, and of CA use across various web, text, sentiment, social network, mobile and sensor-based analytical tools (Chen et al. 2012).

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APPENDIX A: ONLINE SUPPLEMENT

Sample Characteristics

Table A1. Sample Characteristics (N=301)

Industry	N	%
Finance & Insurance	68	22.6
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 size (# of employees)	N	%
less than 500	63	20.9
501 - 1,000	59	19.6
1,001 – 5,000	106	35.2
5,001 – 10,000	48	15.3
over 10,000	25	8.4
Total	301	100

Position of respondent	N	%
CMO	47	15.6
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 B: ONLINE SUPPLEMENT

Measure Descriptions and Item Reliability

Table B1. Measure Descriptions and Item 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-	0.75	**	

	quality customer insight.			
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 Customer Analytics Use	Our SBU regularly uses Big Data analytics to…			Jayachandran et al. 2005
use1	develop customer profiles.	**0.19**	**	
use2	segment markets.	**0.23**	**	
use3	assess customer retention.	**0.12**	*	
use4	identify appropriate channels to reach customers.	**0.14**	**	
use5	customize our offers.	**0.21**	**	
use6	identify our best customers.	**0.13**	*	
use7	to assess the lifetime value of our customers.	**0.20**	**	
use8	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.	0.79	**	
ci2	One hears of a new competitive move in	0.83	**	

	our industry almost every day.			
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	**	
Prevalence of Big Data Customer Analytics Use	Big Data analytics are used extensively in our industry.	NA		Germann et al. 2013
Firm Size	What is the total number of fulltime employees in your business unit (SBU)? Less than 500=1; 501-1,000=2; 1,001-5,000=3; 5,001-10,000=4; 10,001-50,000=5; 50,001-100,000=6; over 100,000=7	NA		Homburg et al. 1999
Goods versus Services	Is your business unit's (SBU) offering primarily a good or service?	NA		Mithas et al. 2005
Industry	What is your business unit's (SBU) industry sector?	NA		

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

APPENDIX C: ONLINE SUPPLEMENT

Descriptive Statistics, Measure Validation, and Latent Variable Correlations

Table C1. 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	13	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∞	.59	.52	.53	.56	.57	**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∞	.65	.65	.70	.70	.74	.60	.62	**NA∞**							
9 Customer Relatonship Performance	5.38	1.05	.83	.62	.45	.54	.50	.50	.52	.35	.46	.56	**.79**						
10 Financial Performance	5.23	1.05	.84	.63	.44	.47	.40	.42	.45	.35	.40	.48	.67	**.79**					
11 Competitive Intensity	5.04	1.06	.82	.54	.27	.38	.34	.37	.37	.30	.32	.41	.31	.24	**.73**				
12 Market Turbulence	5.38	1.05	.77	.62	.47	.46	.52	.50	.55	.40	.50	.56	.43	.43	.36	**.79**			
13 Technological Turbulence	5.23	1.05	.83	.71	.46	.51	.50	.52	.55	.41	.52	.56	.39	.34	.43	.49	**.84**		
14 Firm Size	3.46	1.75	NA	NA	.00	.04	.00	-.02	.05	.03	.08	.00	-.07	-.02	-.03	-.01	-.05	**NA**	
15 Prevalence of Big Data Analytics Use	5.49	1.01	NA	NA	.43	.39	.37	.43	.47	.31	.37	.43	.26	.29	.25	.35	.39	.02	**NA**

∞ formative construct

√**AVE in bold**

APPENDIX D: ONLINE SUPPLEMENT

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 analyzed 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.

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