Submission for:

GIKA Conference 2016

and

Journal of Business Research

Special Issue on "Qualitative Comparative Analysis, Crisp and Fuzzy Sets, in Knowledge and Innovation"

Digital analytics and high organizational performance: a fuzzy-set QCA approach

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Abstract

Empirical evidence and previous literature on the effect of customer analytics on organizational performance demonstrate contrasting results. The enormous expansion of digital customer-related data, which is accessible almost freely and in real time, has made this a critical issue for contemporary marketing managers. Employing fuzzy-set qualitative comparative analyses (fsQCA), this study examines which configurations of digital analytics and organizational customer-related culture, processes and capabilities drive high market performance. The evidence finds certain conditions are necessary for achieving high market performance, and other conditions constitute a path of sufficient conditions, depending on the level of environmental dynamisms.

Keywords: digital analytics; analytics skills, customer knowledge; customer responsiveness; fuzzy-set qualitative comparative analysis

1. Introduction

The “digital era” of marketing is leading to significant changes in marketing channels and to new challenges for firms (Leeflang, Verhoef, Dahlström, & Freundt, 2014) because of the massive expansion of customer data available online. Data are now dispersed in different virtual environments (e.g. blog, forums and social media) and are often freely accessible to firms, potentially in real time. Marketers are challenged by this “deluge of data” (Day, 2011, p. 183) relating to customers, as well as the concomitant increasing fragmentation and complexity of the market, and the growing number of customer touch points (Day, 2011).

The focus in the managerial literature on the importance of coping with the rapidly changing environment is not new, and is highlighted by the seminal studies on hypercompetition (D’Aveni & Gunther, 1994) and dynamic capability (DC) (Teece, Pisano, & Shuen, 1997). However, the expansion of social media, the Internet and mobile technologies is causing further acceleration in the rate of change, particularly in relation to firm–consumer interactions (Yadav & Pavlou, 2014).

The proliferation of customer data, marketing channels, customer touch points and media is a double-sided coin. While it creates greater complexity and renders traditional marketing strategies and capabilities obsolete (Day, 2011), it provides the opportunity to improve firms’ capabilities to “sense opportunities” (Teece, 2007, p. 1323) through employing customer analytics and responding to environmental changes.

The effect of the use of customer analytics on performance represents an enduring debate in the managerial literature that is characterized by polarized perspectives. From the older claim of “paralysis through analysis” (Peters & Waterman, 1982), which claims that an overload of data and analysis slows the decision-making process, to more recent studies that demonstrate the positive effects of analytics on performance (Germann, Lilien, Fiedler, & Kraus, 2014; Germann, Lilien, & Rangaswamy, 2013; Kannan, Pope, & Jain, 2009).

Germann, Lilien, Fiedler, and Kraus (2014), Germann et al. (2013) and Kannan, Pope, and Jain (2009) demonstrate that deploying analytics directly and positively affects performance because “analytics can also significantly improve a firm’s ability to identify and assess alternative courses of action [allowing firms to] offer products and services that are better aligned with customer needs” (Germann et al., 2013, pp. 115–116). However, information availability and analytics are not sufficient for generating organizational responsiveness without the “interaction of several subsystems within the organization” (Homburg, Grozdanovic, & Klarmann, 2007, p. 19).

The marketing literature suggests that customer-related knowledge processes (Jaworski & Kohli, 1990; Jayachandran, Hewett, & Kaufman, 2004) and organizational culture in relation to information processing (Homburg et al., 2007; Narver & Slater, 1990) are strongly related to customer responsiveness.

Given the empirical verification that analytics of digital customer data can increase the strategy performance of digital business (Oestreicher-Singer & Zalmanson, 2013), this study focuses on "digital analytics" and customer-related culture, knowledge processes and capabilities, and their effect on market performance. In addition, given the particular context of the use of digital analytics and the consequent need for specific analytics tools (Chen, Chiang, & Storey, 2012) and skills (Leeflang et al., 2014), this study also considers the constructs of analytics skills and marketing and information-technology (IT) integration.

The relationships between organizational capabilities, culture, systems and performance outcomes are difficult to analyze because of the high level of complexity of these factors. As such, "organizational structures and management systems are best understood in terms of overall patterns rather than in terms of analyses of narrowly drawn sets of organizational properties" (Meyer, Tsui, & Hinings, 1993, p. 1181).

To understand which configurations of these constructs can yield high market performance and in line with calls to approach organizational and marketing research using configural analysis—particularly when analyzing complex relationships (Woodside, 2013, 2014)—the authors decided to employ fuzzy-set qualitative comparative analysis (fsQCA) (Ragin, 1987, 2008; Woodside, 2015).

Section 2 provides the theoretical framework for the study and outlines the development of the tenets derived from prior theoretical and empirical literature. Section 3 presents the data-collection process, methodology and analyses, which follow established procedures in fsQCA applied to management and marketing research. Section 4 presents the discussion and conclusions.

2. Theoretical framework

When the market is highly dynamic (Teece, 1997) and characterized by high velocity dynamics (Eisenhardt & Martin, 2000) firms must develop DC to gain a sustainable competitive advantage (Teece, 1997) or at least to obtain a series of short-lived competitive advantages (D'Aveni & Gunther, 1994; Peteraf, Di Stefano, & Verona, 2013).

To clarify the role of DC, Teece (2007) proposed the microfoundations framework categorizing processes and structures that undergird DC. The DC microfoundation perspective and the marketing literature related to information processing and market responsiveness (Homburg et al., 2007; Jayachandran et al., 2004; Li & Calantone, 1998) provide the theoretical background for this study, with the aim of analyzing specific processes and competences that constitute the microfoundations

of DC and finding configurations that lead to high market performance.
To complete the overall theoretical framework and the development of the study's tenets (Hsiao, Jaw, Huan, & Woodside, 2015; Woodside, 2014), the authors also rely on Information Systems (IS) and marketing-analytics literature.

2.1. Digital data and analytics: a necessary clarification

The first step to defining what constitutes digital analytics is to specify which type of digital data is the object of this study. The study focuses on the all the data that can represent a customer's data footprint (Alaimo & Kallinikos, 2015; Chi, Ravichandran, & Andrevski, 2010), following Alaimo and Kallinikos's (2015) distinction by considering both "online transaction data" and "social data".
Online transaction data refer to all the customer data that represent customer online behaviors (e.g. clicking behavior, page visits, time spent on page) and transactions (e.g. records generated online), but do not represent relationships, opinions, tastes or sentiments (Alaimo & Kallinikos, 2015). Social data can be defined as the "data footprint of social interaction and participation in the online environments of what is now commonly referred to as 'social media'" (Alaimo & Kallinikos, 2015) and represent customer relationships and opinions.
The immense amount of available data, which is particularly widespread in different digital environments, must be managed through the correct analytics so that it is possible to make sense of the data and use them strategically (e.g. Chen et al., 2012; Davenport, 2006; Leeflang et al., 2014).
Following the literature on business intelligence and analytics (BI&A) (e.g. Chen et al., 2012), this study focuses on three typologies of BI&A: web, social-media, and mobile analytics.
Although social-media analytics are categorized under web analytics in the BI&A framework proposed by Chen et al. (2012), given the extremely different natures of social data and online transaction data (Alaimo & Kallinikos, 2015), this study treats web and social-media analytics as separate technologies: the first principally operates on online transaction data and the second on social data.
Web analytics refers to the BI&A 2.0 tools (Chen et al., 2012) developed following the Web 2.0 revolution, which have generated a vast amount of customer data on the web. The use of web analytics allows the understanding of online customer behavior and responses to online marketing stimuli (Järvinen & Karjaluoto, 2015) through performing customer-transaction analysis and market-structure analysis (Chen et al., 2012).
The analysis of social-media data requires a distinct set of tools (i.e. social-media analytics), which have already been considered in the previous literature because of the specific features that permit

them to run different types of analyses, for example, sentiment analysis relating to customers and competitors (Fan & Yan, 2015), social-networking analysis, and communities and influencer identification (Fan & Gordon, 2014).

Mobile analytics is the third type of analytics to be treated in this study. While “research on mobile BI [Business Intelligence] is still in an embryonic stage” (Chen et al., 2012, p. 1168), the coming of Web 3.0, which is mainly location and sensor based, is creating great opportunities for location-aware and person-centered analysis, and the significant expansion of the app market is fostering the rise of mobile analytics tools (Chen et al., 2012; Ghose & Han, 2014). In this study, mobile analytics can be defined as the category of digital analytics that permits the analysis of mainly online transaction data deriving from mobile web navigation and all the data stemming from the usage of apps.

2.2. Customer-knowledge process as microfoundation of sensing capability

Sensing capabilities refer to a firm’s capacity to discover new opportunities using scanning, creative, learning, and interpretative activities (Teece, 2007). Firms need differential access to existing information, fostering research activities and “the probing and reprobing of customer needs” (Teece, 2007, p. 1322). The ability of “interpreting the available information in whatever form it appears [and even] the angst expressed by a frustrated customer” (Teece, 2007, p. 1323) can be considered important information for sensing opportunities.

The development of customer online behaviors such as leaving comments on social media and rating online products and services is creating a vast amount of dispersed data from which firms can gain useful information about customers’ needs and market trends through digital analytics (Du, Hu, & Damangir, 2015).

As organizational learning theory suggests (Sinkula, 1994; Slater & Narver, 1995), the simple availability of information is not sufficient for building advantage. There is also a need for organizations to have customer-knowledge processes to learn about and respond to customer needs (Jayachandran et al., 2004).

The idea of customer-knowledge processes is a construct rooted in marketing literature (Li & Calantone, 1998; Jayachandran et al., 2004) and derived from the market-orientation literature (Kohli & Jaworski, 1990; Narver & Slater, 1990) focusing on the capabilities aspect of this construct.

Customer-knowledge processes can be defined as “the activities within an organization focused on the generation, analysis, and dissemination of customer-related information for the purpose of strategy development and implementation” (Jayachandran et al., 2004, p. 220). In the theoretical background of this study, these processes are framed as the microfoundational processes behind a firm's sensing capabilities. They are grounded in organizational processes devoted to opportunity discovery, and their purpose is to scan and monitor technological developments and customer needs (Teece, 2007) to gain competitive advantage.

Besides the theoretical importance of customer-knowledge processes, empirical studies have verified the positive effect of customer-knowledge processes on new product development and market performance (Durmuşoğlu & Barczak, 2011; Jayachandran et al., 2004; Li & Calantone, 1998).

2.3. Enhancing customer-information processing: marketing/IT integration and analytics skills

As previous research suggests, the integration between marketing and IT could lead to various benefits such as enhancing collaboration and information sharing in the organization (Tanriverdi, 2005); higher departmental market orientation (Borges, Hoppen, & Luce, 2009); improving customer acquisition and retention (Brodie, Winklhofer, Coviello, & Johnston, n.d.); and developing specific marketing capabilities that positively affect organizational performance (Trainor, Rapp, Beitelspacher, & Schillewaert, 2011).

Today, the need to integrate marketing and IT is even more pronounced given the differences between traditional marketing practices and digital marketing practices. Marketers face many new challenges brought by the computer-mediated environment (Yadav & Pavlou, 2014). The digital era is changing the structure and content of marketing managers' job (Germann et al., 2013), and is creating a "talent gap" (Leeflang et al., 2014, p. 8) in analytical skills.

The importance of analytics skills in the digital era is highlighted in Leeflang et al. (2014), who state that "hiring more analytically skilled individuals is seen as a strategic asset" (p. 8). This is even more true in the context of analytics implementation and use, where analytics skills are essential for gaining meaningful insight from analytics tools (Järvinen & Karjaluoto, 2015). In the context of marketing analytics, both tacit individual-level skills and more technical-related skills are directly related with a superior deployment of analytics and indirectly to performance (Germann et al., 2013).

2.4. Affective organizational systems and customer responsiveness

Customer-knowledge processes are not the only necessary condition for enhancing organizational responsiveness. Organizational culture also plays a fundamental role in supporting intensive information processing in companies (Leeflang et al., 2014; Peltier, Zahay, & Lehmann, 2013).

There is evidence that the customer-related affective organizational system—defined as "the extent to which attention to customer needs is anchored in an organization's values, belief structures, and norms" (Homburg et al., 2007 p. 20)—is more important in driving customer responsiveness than customer-related organizational information processes.

Given the importance of customer orientation in the affective organizational system in enhancing customer responsiveness and increasing performance (Germann et al., 2013; Homburg et al., 2007; Narver & Slater, 1990; Peltier et al., 2013), this study also considers the orientation of the affective organizational system, relying on Homburg et al.'s (2007) definition.

The concept of market responsiveness dates back to the seminal studies on marketing-orientation, and is framed as the firm's responsiveness to market intelligence in relation to customer needs (Jaworski & Kohli, 1990; Kohli & Jaworski, 1990).

More recent studies have demonstrated that information processing and market intelligence affect organizational responsiveness, and that organization responsiveness in turn mediates the positive effects of information processing and market intelligence on firm performance (Bhatt, Emdad, Roberts, & Grover, 2010; Hult, Ketchen, & Slater, 2005).

This study focuses on customer-related responsiveness following Jayachandran et al.'s (2004) definition of customer-response capability as the "competence in serving customer needs through effective and quick actions" (p. 220), and recognizes customer-related responsiveness as a critical capability for firm performance (Homburg et al., 2007; Jayachandran et al., 2004).

To be responsive, organizations need to adapt rapidly (Haeckel, 2013) to match changing customer needs and the market environment.

From the perspective of the DC microfoundations, customer-response capability can be seen as the firm's competence that undergirds its capability to seize opportunities (Teece, 2007) and part of its "ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece et al., 1997, p. 516). This ability is particularly necessary in high-velocity markets (Eisenhardt & Martin, 2000).

Considering all the theoretical and empirical premises discussed thus far, this study formulated the following tenet:

T1: digital-analytics use, analytics skills, and marketing/IT integration combined with customer-oriented affective organizational systems, customer-knowledge processes and customer responsiveness will be associated with high market performance in a highly dynamic environment.

The literature on strategic management (e.g. Eisenhardt & Martin, 2000; Teece et al., 1997) and marketing (e.g. Jayachandran et al., 2004; Yadav & Pavlou, 2014) underlines the importance of real-time and intensive customer-related information processing when the level of environmental dynamism is high. In contrast, in a moderately dynamic environment there is less need for real-time information (Eisenhardt & Martin, 2000). As such, this study analyzes (using exploratory logic) the following tenet, which is not rooted in theoretical and empirical evidence, but can be indirectly derived from such evidence:

T2: digital-analytics use, analytics skills, and marketing/IT integration combined with customer-oriented affective organizational systems, customer-knowledge processes and customer responsiveness will be not associated with high market performance in a medium-low dynamic environment.

3. Methods and results

3.1. Sample and data collection

The data for this research were obtained using a sample frame from a database of the most important Italian firms. The authors identified managers inside these organizations that have roles of responsibility in marketing or related activities as potential respondents. This study focused particularly on marketing managers because they are most involved in and informed about activities relating to customer sensing and response (Roberts & Grover, 2012). The resulting frame of potential respondents was a random sample of 500 firms from a wide variety of industries.

The respondents were assured of anonymity and the aggregated use of data and compliance to Italian privacy laws. As incentive to participate, the authors offered to provide them with a report with the study results and extended an invitation to attend a workshop related to the study. The responses were collected in approximately eight weeks, and one phone follow-up was performed to test for non-response bias. A total of 108 responses were received, which equaled a response rate of 21.6%.

For the data analysis, 46 questionnaires that had not been fully completed were excluded. As such, the final data frame comprised 62 complete questionnaires.

The authors checked for non-response bias, and the tests conducted to compare early and late respondents did not show significant differences.

The organizational respondents represented a wide and equilibrated variety of industries, for example, services (18%), manufacturing (16%), fashion and clothing (16%), information and telecommunications (14%) and food and beverage (10%). The firm sizes in the sample are in line with the statistics of Italian firm sizes, which report a great majority of small and medium enterprises

(SMEs). That is, our sample had 24% of firms with 10 to 50 employees, 34% of firms with 50 to 249 employees and 15% of firms with 250 to 499 employees.

3.2. Measures

Almost all the multi-item scales used were adapted from previous literature, and have been tested in survey research. All were based on a 7-point Likert-type scale. To measure web, social-media and mobile analytics use, the authors developed a specific multi-item scale adapted to each type of digital analytics. The constructs are presented below.

Web/social media/mobile analytics customer-related use (WACU, SMACU and MACU): to test the use of customer-related web, social-media and mobile analytics, this study partially follow previous approaches for measuring technology use (Jayachandran, Sharma, Kaufman, & Raman, 2005; Trainor, Andzulis, Rapp, & Agnihotri, 2014), but instead of creating a single-item index, this study used a multi-item scale based on the possible functions and use of digital analytics that emerged from a literature analysis and six expert interviews. The items, tested with exploratory factor analysis (EFA), demonstrate consistent loading only on two factors, but given the peculiarities of fsQCA analysis, the authors decided to keep three constructs and test them with confirmatory factor analysis (CFA) and Cronbach's alpha. Each of the three constructs contains one reverse item, and the alphas are above 0.8 (see Table 1).

[Table 1 here]

Customer-knowledge process (CKP): the scale is adapted from Li and Calantone (1998) and Jayachandran et al. (2004), representing the processes of acquiring, analyzing and disseminating inter-departmental customer-related knowledge inside the organization. Six items (one reverse) measure the construct (α=0.76).

Marketing and IT integration (MII): the five-item construct by Peltier et al. (2013) is adapted to measure the level of integration between marketing and IT functions and the level of collaboration in developing IT projects (α=0.93).

Analytics skills (AS): this construct from Germann et al. (2013) is adapted to digital analytics to measure both technical and individual-level skills of marketing personnel in relation to analytics. The construct was measure with three items (α=0.96).

Customer orientation of the affective organizational system (COA): this construct, based on five items adapted from Homburg et al. (2007), measures the orientation of the organizational culture toward customers and related information-processing activities (α=0.71).
Customer-response capabilities (CRC): the scale has five items from Homburg et al. (2007), which measure the organization's capability in responding quickly to customer-related changes. After dropping one item, the scale was found to be reliable (α=0.85).
Market performance (MP): the authors employed the concept of market performance as the effectiveness of marketing activities in relation to market goals (i.e. revenues, growth and market share) compared to competitors using the three-item construct from Homburg et al. (2007), which has demonstrated a high reliability (α=0.94).
Environmental dynamism (ED): five-item construct from Jayachandran et al. (2005) is employed to account for the level and speed of changes in relation to customer preferences and technological innovation (α=0.78).
A correlation matrix (Table 2) demonstrates that all nine indexes are not significantly related to market performance.

[Table 2 here]

According to Ragin (1987), the distribution of cases is not random because the $\chi 2$ value is 129.61 and the level of significance is less than 0.001.

3.3. Calibration and analysis

FsQCA preserves information by allowing gradual set membership. It requires the substantiation of the method of "calibration", that is, the transformation of original data to a continuous value interval from 0 to 1 (Ragin, 2008). According to Woodside (2015, p. 252), "the software program at fsQCA.com includes a sub-routine for calibrating continuous values into membership scores for a logarithmic function (whereby values distant from the median are nearly equal to one another and values near the median are not equal to one another)." The study follows this approach to transform 7-point Likert-type scale into variables ranging from 0 to 1.
To verify the two tenets, the full sample of 62 observations was divided into two sub-samples following the approach used in Fiss (2011), which considers the seventy-fifth percentile the threshold for a high value of the variable. This procedure led to two sub-samples of medium–low (n=30) and high (n=32) environmental dynamism. This choice also derives from the DC framework in which the

emphasis is on a high level of environmental dynamism, and there is less emphasis on differentiating between medium and low dynamism. The two sub-samples were calibrated and analyzed using fsQCA 2.5 (Ragin & Sean, 2014). To validate the calibration, the authors also used the "fuzzification" model presented by Li (2013, pp. 1613).

The authors first checked for the necessary conditions. In both sub-samples, *COA* and *CRC* are necessary conditions (consistency above 0.9) and in the sub-sample of high environmental dynamism also *CKP* is a necessary condition.

The authors then constructed the truth table. Given the low number of observations, the minimum number of cases was set at 1 and the raw consistency threshold was at 0.9. The standard analyses provided the results presented in the following section.

3.4. Results and discussion

The results of the sub-samples analyses are presented in Table 3 (high level of environmental dynamism) and Table 4 (medium–low level of environmental dynamism). Both the tables use Fiss's (2011) approach and symbolism to present results: the black circle indicates the presence of the condition, the circle with a cross indicates the absence of the condition, and the empty table cell indicates the "don't care" response, in which the condition may be either present or absent. The bigger circle indicates a core condition, which is present both in the intermediate solution and in the parsimonious solution, and the smaller circle indicates a peripheral condition, which is not present in the parsimonious solution (Fiss, 2011).

In analyzing the results presented in both tables, the authors weighed their considerations with the value of unique coverage, as suggested in Ragin (2008), which represents the coverage of the single path purified by the overlapping coverage with other paths. In the two sub-samples (Table 3 and Table 4), the solution coverage of sufficient combinations is 0.79 (medium–low environmental dynamism), and 0.83 (high environmental dynamism), which means that the configuration of included attributes captured the 79%, and the 83% of set membership. For each sub-sample (high and medium–low level of environmental dynamism), the software fsQCA 2.5 (Ragin & Sean, 2014) identified equifinal configurations associated with this outcome (market performance): four in the first sub-sample and five in the second.

[Table 3 here]

Solution S1a (unique coverage=0.34) partially supports T1. That is, in an environment of high environmental dynamism, the use of web and social-media analytics, combined with marketing/IT integration (and with *COA*, *CKP* and *CRC*, which are necessary conditions) lead to high market performance. S2a also supports T1 despite the fact that its unique coverage is not high (0.01). However, S1a and S2a show that the presence of analytics skills is not part of the path, and moreover, S2a provides the absence of *AS*.

The paths S3a and S4a suggest that in some cases, different paths can be followed to achieve high market performance in the absence of the use of digital analytics, but the two solutions do not converge for *AS* or *MII*, which in S4a must be present and in S3a are both absent.

To evaluate T2 (which as stated, is an exploratory attempt because it is not explicitly supported by the literature), the authors analyzed the resulting configurations in a medium–low dynamic environment.

[Table 4 here]

Table 2 presents five paths with comparable raw coverage of approximately 40%, but the first path demonstrates the highest unique coverage (0.13). T2 is supported by S1b which provides the absence of *WACU, SMACU, MACU*, *MII* and *AS* in the path to achieving high market performance. S2b partially supports T2, providing the absence of *WACU, SMACU and MACU*. Some contrarian paths are also relevant, in particular, in S3b and S5b (S4b has a quite low unique coverage of 0.005) demonstrate alternative paths, which contemplate the presence of digital analytics customer-related use.

4. Limitations and conclusions

This study has some limitations related to the single-informant and subjective measure of performance. However, the use of such forms of data collection is widely employed in marketing and organizational literature.

The principal contribution of this study is to highlight the complex interactions among customer-related digital analytics use, organizational capabilities, knowledge processes and customer-oriented culture in achieving high market performance.

The findings suggest that in highly dynamic environments versus medium–low dynamic environments, different paths can be followed to achieve high market performance. In particular, the results partially support the tenet (T1) that in a highly dynamic environment, firms must rely on a structured customer-related information process that uses digital analytics and data from web and social media.

The same partial support is found for the need to integrate marketing and IT in a highly dynamic environment.

The analysis of solutions in medium–low dynamic environment partially supports the tenet (T2) that the use of customer-related digital analytics is not part of the path toward high market performance.

The strongest evidence in the study related to the customer orientation of the affective organizational system and customer responsiveness, which were found to be necessary conditions for high market performance in both sub-samples.

The results of this study have interesting managerial implications for decisions relating to budget allocation, particularly in Italian organizations in which the effect of organizational culture is sometimes underestimated.

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TABLE 1

Properties of Measures

Construct	Labels	Items (N)	Mean	SD	Alpha	Source
Web analytics customer-related use	WACU	4	4.46	1.78	0.85	
Social-media analytics customer-related use	SMACU	4	4.29	1.93	0.87	
Mobile analytics customer-related use	MACU	4	3.79	1.89	0.84	
Customer-knowledge process	CKP	6	5.16	1.34	0.76	Jayachandran et al. (2004)
Marketing and IT integration	MII	5	4.52	1.49	0.93	Peltier et al. (2013)
Analytics skills	AS	3	4.05	1.70	0.96	Germann et al. (2013)
Customer orientation of the affective organizational system	COA	5	6.44	0.77	0.71	Homburg et al. (2007)
Customer-response capabilities	CRC	4	5.80	1.05	0.85	Homburg et al. (2007)
Market performance	MP	3	4.84	1.27	0.94	Homburg et al. (2007)
Environmental dynamism	ED	5	4.84	1.41	0.78	Jayachandran et al. (2005)

TABLE 2

Correlation matrix

		COA	WACU	SAMCU	MACU	CKP	CRC	AS	MII	ED	MP
COA	Pearson correlation	**1**	.399**	.383**	.317*	.202	.163	.290*	.192	.259*	.213
	Sign. (two-tailed)		.001	.002	.012	.116	.206	.022	.134	.042	.096
	N	62	62	62	62	62	62	62	62	62	62
WACU	Pearson correlation	.399**	**1**	.946**	.833**	.142	.125	.639**	.452**	.366**	0.281
	Sign. (two-tailed)	.001		.000	.000	.269	.333	.000	.000	.003	.272
	N	62	62	62	62	62	62	62	62	62	62
SAMCU	Pearson correlation	.383**	.946**	**1**	.787**	.147	.164	.634**	.465**	.402**	0.264
	Sign. (two-tailed)	.002	.000		.000	.254	.203	.000	.000	.001	.381
	N	62	62	62	62	62	62	62	62	62	62
MACU	Pearson correlation	.317*	.833**	.787**	**1**	.145	.098	.623**	.451**	.324*	.247
	Sign. (two-tailed)	.012	.000	.000		.259	.450	.000	.000	.010	.053
	N	62	62	62	62	62	62	62	62	62	62
CKP	Pearson correlation	.202	.142	.147	.145	**1**	.457**	.242	.412**	.301*	0.26
	Sign. (two-tailed)	.116	.269	.254	.259		.000	.058	.001	.018	.411
	N	62	62	62	62	62	62	62	62	62	62
CRC	Pearson correlation	.163	.125	.164	.098	.457**	**1**	0.287	.341**	.052	0.295
	Sign. two-tailed)	.206	.333	.203	.450	.000		.238	.007	.687	.200
	N	62	62	62	62	62	62	62	62	62	62
AS	Pearson correlation	.290*	.639**	.634**	.623**	.242	.287*	**1**	.460**	.373**	.219
	Sign. (two-tailed)	.022	.000	.000	.000	.058	.024		.000	.003	.087
	N	62	62	62	62	62	62	62	62	62	62
MII	Pearson correlation	.192	.452**	.465**	.451**	.412**	.341**	.460**	**1**	.401**	.152
	Sign. (two-tailed)	.134	.000	.000	.000	.001	.007	.000		.001	.237
	N	62	62	62	62	62	62	62	62	62	62
ED	Pearson correlation	.259*	.366**	.402**	.324*	.301*	.052	.373**	.401**	**1**	.018
	Sign. (two-tailed)	.042	.003	.001	.010	.018	.687	.003	.001		.889
	N	62	62	62	62	62	62	62	62	62	62
MP	Pearson correlation	.213	0.281	0.264	.247	0.26	0.295	.219	.152	.018	**1**
	Sign. (two-tailed)	.096	.272	.381	.053	.411	.200	.087	.237	.889	
	N	62	62	62	62	62	62	62	62	62	62

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

TABLE 3

Configurations for achieving high market performance in a highly dynamic environment

	Solutions			
Configuration	**S1a**	**S2a**	**S3a**	**S4a**
Web analytics customer-related use	•		⊗	⊗
Social-media analytics customer-related use	●	●	⊗	⊗
Mobile analytics customer-related use		•	⊗	⊗
Marketing and IT integration	●	●	⨂	●
Analytics skills		⨂	⨂	●
Customer orientation of the affective organizational system	•	•	•	•
Customer-knowledge process	•	•	•	•
Customer-response capabilities	•	•	•	•
Consistency	0.91	0.97	0.91	0.99
Raw coverage	0.79	0.38	0.27	0.33
Unique coverage	0.34	0.01	0.02	0.02
Solution consistency	0.89			
Solution coverage	0.83			

Legend

● = Core causal condition present

⨂ = Core causal condition absent

• = Complementary causal condition present

⊗ = Complementary causal condition absent

TABLE 4

Configurations for achieving high market performance in medium–low dynamic environment

	Solutions				
Configuration	**S1b**	**S2b**	**S3b**	**S4b**	**S5b**
Web analytics customer-related use	⊗	⊗	●	●	●
Social-media analytics customer-related use	⊗	⊗	●		●
Mobile analytics customer-related use	⊗	⊗	⊗	●	●
Marketing and IT integration	⊗	●	●	●	
Analytics skills	⊗			●	●
Customer orientation of the affective organizational system	●	●	●	●	●
Customer-knowledge process		●	●	●	●
Customer-response capabilities	●	●	●	●	●
Consistency	0.93	0.97	0.91	0.99	0.99
Raw coverage	0.47	0.43	0.42	0.40	0.41
Unique coverage	0.13	0.07	0.05	0.005	0.02
Solution consistency			0.89		
Solution coverage			0.79		

Legend

● = Complementary causal condition present

⊗ = Complementary causal condition absent

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