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Alternative pathways to utilizing customer knowledge: A fuzzy-set qualitative comparative analysis

Simos Chari, University of Leeds

Anssi Tarkiainen, Lappeenranta University of Technology

Hanna Salojärvi, Lappeenranta University of Technology

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Abstract

This study explores alternative configurations of causes to customer knowledge utilization using a set theoretic approach with fuzzy set qualitative comparative analysis. The study uses a previous empirical dataset of Salojärvi, Sainio, and Tarkiainen (2010) to assess organizational factors that enhance customer knowledge utilization. The results show that use of key account management teams and customer relationship management systems are core predictors for high degrees of customer knowledge utilization. However, these core causes are not sufficient on their own; they need to be accompanied by different degrees (i.e. high/low) and combinations of other peripheral antecedents, such as customer relationship orientation, top management involvement, and formalization. This study shows that many firms make trade-off decisions regarding the use of these core and peripheral conditions. The present study identifies alternative pathways to customer knowledge utilization, discuss their differences, and suggest managerial implications and future research directions.

Keywords: customer knowledge utilization; qualitative comparative analysis, fuzzy-set, fsQCA.

1. Introduction

Customer knowledge – comprising knowledge about and from customers – is increasingly being recognized as a strategic asset for firms and a predictor of customer and new product performance (e.g. Salojärvi, Sainio, & Tarkiainen, 2010; Rollins, Bellenger, & Johnston, 2012b; Joshi & Sharma, 2004). However, customer knowledge is complex to manage, dynamic in nature, and quickly goes out of date (Rollins et al., 2012b). Prior studies indicate that in general, firms tend be better at generating new customer knowledge than at utilizing it (Campbell, 2003), and yet, the need for customer knowledge generation and utilization is of utmost importance in business markets and in the context of key account management (KAM). This is because key account customers are often complex to manage and are associated with high costs and risks (Stein, Smith, & Lancioni, 2013).

The marketing literature categorizes customer knowledge utilization (CKU) into two knowledge types: enhancing and action-oriented (e.g. Jayachandran, Sharma, Kaufman, & Raman, 2005). Knowledge-enhancing utilization refers to long-term oriented learning about customers' needs and behaviour and may not result in immediate action, whereas, the nature of action-oriented utilization is short term and refers to knowledge utilization for resolving customer-specific problems (Rollins et al., 2012b). However, CKU has been studied empirically either as one-dimensional, covering both knowledge types (i.e. enhancing and action), or modelled as separate dimensions. Regardless, overall, CKU has been found to be positively related to customer performance as it supports systematic management of customer relationships and value creation for customers (Rollins, Bellenger, & Johnston, 2012a; Salojärvi & Sainio, 2010).

Various organizational processes, systems, and managerial actions affect utilization of knowledge (Moorman, 1995). Drawing on Homburg, Workman, and Jensen (2002), the Salojärvi et al. (2010) (hereafter SST) study argues that CKU is a central activity in KAM. The

SST proposes different KAM dimensions as drivers of CKU and provides several implications for managers overseeing key account relationships. Specifically, it asserts that CKU can enhanced by: increasing the level of top management involvement (TMI) in managing key account relationships, implementing KAM teams (TEAMS), adopting customer relationship orientation (CRO), investing in customer relationship management technologies (CRMI), and formalizing KAM rules and procedures (FORM). While realization of factors that drive CKU is of paramount importance, the implications suggested by the SST study may be limited. The SST study considers individual and not combinatory effects of drivers of CKU; thus, its findings may be oversimplified to be reflective of the strategic reality facing firms. This issue of oversimplification raises further questions. Should managers consider investing in all of the suggested drivers or just some of them? If only some are sufficient for high CKU, then which ones?

In fact, recent studies on KAM show that firms use different combinations of organizational factors in their attempt to reach desirable performance outcomes (Marcos-Cuevas, Nätti, Palo, & Ryals, 2014). In the same vein, it appears highly likely that firms may adopt different configurations of organizational practices in their pursuit of high CKU. Potential reasons for different configurations may vary; such as, firms may need to take resource allocation and trade-off decisions between which organizational factors to invest in (Le Breton-Miller & Miller, 2015). Alternatively, firms may opt to use different configurations of drivers, depending on what their objectives are. For instance, while firms strive to reach high levels of CKU, they may attempt to eliminate factors that could lead to undesirable outcomes. Theory argues (e.g., Guesalaga, 2014) that under specific circumstances, high levels of TMI and FORM may deter relationship quality and hinder KAM effectiveness, respectively. Whatever the underlying reason is, the firms are likely to adopt different combinations of organizational factors. Therefore, researchers should consider studying causes of CKU with an approach that assesses combinations of antecedents for higher CKU levels. Thus, the present study uses the dataset of the SST study and aims to re-examine the SST study's hypotheses (see Figure 1) and clarify its findings by implementing a fuzzy-set qualitative comparative analysis (fsQCA). This study aims to highlight how different antecedents interplay or combine to predict CKU. As a technique, fsQCA has been attracting increasing interest due to its ability to provide increased understanding of the configurational pathways needed for reaching an outcome (Fiss, 2011).

The present study aims to contribute to prior research in multiple ways. First, the present study provides a methodological contribution by highlighting the benefits of fsQCA technique. The present study shows that in comparison to traditional correlation-based methods (e.g. multiple regression analyses, MRA); fsQCA proposes a configurational perspective to associations between independent and dependent variables. Second, this study contributes to the prior literature on KAM and CKU by expanding the findings of SST. The main objective of the study is to identify solutions and combinations of causes (e.g. TMI, TEAMS, CRO, CRMI, and FORM) leading to high levels of CKU in the context of KAM. Knowledge of such solutions serves as the starting point to understand better how predictors of CKU intertwine. In addition, the findings of this study provide managerial implications for ensuring higher levels of CKU.

2. Customer Knowledge Utilization: SST study

Key account customers are those that suppliers regard as strategically important based on their attractiveness and strength of business relationship (McDonald, Millman, & Rogers, 1997). As firms cannot afford to lose key accounts, they strive to find ways – through customized customer service or by having in place processes to support and enhance relationships – to provide additional value to key accounts (Gounaris & Tzempelikos, 2014). Prior studies in the field of KAM (e.g. Shi, Zou, White, McNally, & Cavusgil, 2005) highlight the need for indepth key account–related knowledge. Efficient knowledge processes facilitate decision-making (SST). Despite its increasing strategic importance, there is little research focusing on the intra-organizational aspects of customer knowledge processing. In order to address this gap, the SST study draws on Homburg et al. (2002) and proposes a conceptual model in which CKU is a central activity within the dimensions of KAM. The conceptual framework of the SST study and associations is shown in Figure 1.

Figure 1 here

The data for the SST study consists of a cross-industrial sample of 169 firms of 200 employees and more. The sampling frame is drawn from the Amadeus database; 361 firms were identified initially. After contacting each firm by telephone, 171 were eligible to participate. Each firm had business-to-business sales coordinated from Finland and KAM practices in place. A single informant approach (i.e. key account managers) was used for collecting data. Key respondents were mainly sales managers (37%), key account managers (27%), or leaders of business units (13%). Each respondent answered the survey from the perspective of the most important strategic key account relationship for which he/she is personally responsible. Data collection resulted 169 received responses from 97 companies. Multiple key informants represented different business units and answered the questionnaire from the perspective of different key account customers. Of a total of 395, 169 questionnaires were received (42.8% response rate). The measurement scales were adapted from prior studies and modified to fit the context of the SST study (see Appendix). The SST study used MRA to test hypotheses and its findings reveal that the strongest predictor of CKU is CRMI; FORM, TEAMS, and TMI, follow. Contrary to the authors' expectations, the SST study fails to support the effects of CRO. The present study re-examines the proposed relationships of the SST study using a set-theoretic approach with fsQCA.

3. The need for set-theoretic approaches: fsQCA

Conventional multivariate methods (e.g. MRA) are less able to capture complex interdependent relationships between a set of predictors and an outcome (Fiss, 2011). Hypotheses testing that relies on such methods cannot always be trusted. For instance, MRA follow net effect estimations and its findings can be affected by the existence of high multicollinearity (Skarmeas, Leonidou, & Saridakis, 2014). Even when researchers control for high multicollinearity, net effects may change direction and level of significance when additional predictors are added in the equation (Armstrong, 2012). Furthermore, in a given dataset, some cases may not always support an exclusive positive or a negative association between the predictor and outcome variables (Woodside, 2013).

In addition, MRA make assumptions of the following characteristics among associations: (a) symmetry – that is, low (high) degrees of the independent variable always correspond to low (high) degrees of the dependent variable; and (b) linearity – that is, an increase (decrease) in an independent variable will result in a corresponding increase (decrease) in the dependent variable (Skarmeas et al., 2014). However, in reality, relationships could be asymmetric and non-linear. Scholars (e.g. Armstrong, 2012) demonstrate that most observed relationships are in fact non-linear. Ragin (2000, 2008) argues that high degrees of the dependent variable may also occur when the independent variable display low values.

By contrast, fsQCA is uniquely suitable for exploring intertwined relationships between multiple predictors. In effect, fsQCA is an analysis of sets of relationships among causes. Contrary to MRA, fsQCA models the concept of conjunctural causation. In other words, it allows a detailed analysis of how alternative conditions of causes combine and contribute to high membership scores of the outcome (Rihoux & Ragin, 2009). Instead of one predictor condition alone, fsQCA may detect multiple solution paths that can lead to high levels of the same outcome. Thus, it fully captures the concept of equifinality (Katz & Kahn, 1978). The fsQCA findings provide necessary (i.e. those that produce the outcome but by themselves may not be enough) and sufficient (i.e. those that always lead to the outcome) conditions and combinations that are associated with high degrees of the outcome (Ragin, 2000, 2008).

4. The fsQCA procedure

This section outlines how fsQCA proceeds in four steps: (1) calibration of data; (2) construction of a truth table; (3) identification of relevant causal combinations; and (4) simplification of combinations and assessment of solutions.

4.1. Calibration of data

The first step in performing a fsQCA is calibrating all variables involved into sets. Unlike conventional techniques that treat all variance as equal, data calibration aims to identify meaningful groupings of cases (Crilly, 2011). Sets represent the degree of membership that a particular variable (e.g. a predictor) takes in a specific category; sets may take any value between 0 and 1 (Woodside & Zhang, 2013). Variables in the dataset can be calibrated to either crisp sets (i.e. the membership of a variable in the category is binary: 0 for non-membership and 1 for membership) or fuzzy sets (i.e. variables take varying degrees of memberships from 0 to 1) (Skarmeas et al., 2014). Fuzzy set analysis usually uses three threshold breakpoints for set calibration: 0.05 for full non-membership, 0.50 as the crossover point of maximum ambiguity, and 0.95 for full membership (Ragin, 2008).

4.2. Construction of the truth table

The second step comprises the construction of the truth table to identify causal combinations of predictors with the outcome (Crilly, 2011). The truth table has 2^k rows, where k is the number of causal conditions used in the analysis. Rows on the truth table are associated with specific combinations of causes with the outcome and the entire table represents all possible combinations (Ragin, 2008). The dataset cases are sorted into rows according to the values they display on these cause variables; it is expected that some rows may have many cases, some rows may have a few cases, and other rows no cases whatsoever (Fiss, 2011).

4.3. Identification of relevant causal combinations

The next step involves identifying relevant combinations that are associated with at least one observation between the predictors and outcome. The number of rows of the truth table are reduced on the basis of (a) minimum number of cases needed for a solution to be deliberated and (b) minimum consistency level needed for a particular solution (Ragin, 2000). Consistency represents the "degree to which a combination of causal conditions is reliably associated with the outcome" (Crilly, 2011, p. 705). Consistency ranges from 0 to 1; it should be close to 1 to enable inferences that a subset relationship exists, indicating that all cases (when consistency = 1) sharing a condition also share the outcome (Greckhamer, 2011). In other words, consistency indicates whether the derived solution as a whole and separate pathways are indeed subsets of the outcome (Ragin, 2008).

4.4. Simplification of combinations and assessment of solutions

According to Fiss (2011, p. 402), fsQCA uses Boolean algebra and algorithms that allow a "logical reduction of numerous, causal conditions into a reduced set of configurations that lead to the outcome". The truth table algorithm generates a range of plausible solutions; to speculate about these, the algorithm uses counterfactual analysis (Fiss, 2011), which allows classifications of core and peripheral connections between causes and the outcome (Ragin, 2008). Core refer to the essential causes that have a strong causal relationship with the outcome of interest, whereas peripheral are more expendable or exchangeable, as they reveal a weaker causal relationship with the outcome (Fiss, 2011).

Distinguishing between easy and difficult counterfactuals, fsQCA provides three types of solutions: complex, intermediate, and parsimonious (Rihoux & Ragin, 2009). Each solution provides pathways for high membership of the outcome of interest (Skarmeas et al., 2014). A complex solution reflects only the empirically observed combinations of causal conditions; the remainders (i.e. those lacking empirical instances) are omitted from the reduction process (Schneider, Schulze-Bentrop, & Paunescu, 2010). An intermediate solution distinguishes between easy and difficult counterfactuals and integrates only simplifying assumptions of easy cases (Greckhamer, 2011). An intermediate solution results in both core and peripheral conditions (Crilly, 2011). The parsimonious solution is the simplest; it contains only core conditions and takes into consideration a number of simplifying assumptions, regardless whether they are based on easy or difficult counterfactuals (Fiss, 2011).

The derived solutions of fsQCA are assessed on the basis of two measures: consistency and coverage. Adequate consistency is a precondition for examining set-theoretic coverage. A consistency threshold of at least 0.75 and up to 0.95 is recommended (Ragin, 2008). Researchers may choose a consistency threshold by observing the distribution scores of consistency and selecting the one that corresponds to a gap (Schneider et al., 2010). In the final solution, researchers should retain all the combinations of causes that demonstrate values above the selected consistency threshold point. Apart from consistency measures, coverage statistics are used to interpret fsQCA findings (Ragin, 2008). Coverage gauges the empirical importance of solutions for reaching the outcome of interest; specifically, it demonstrates how much of the outcome is explained by the solution as a whole and by each solution pathway separately (Skarmeas et al., 2014). A model solution is perceived as explanatory when coverage is between 0.25 and 0.65 (Rihoux & Ragin, 2009). The higher the consistency threshold chosen, the lower the respective coverage will be (Elliott, 2013).

5. Results

5.1. Analysis of results

Table 1 depicts construct correlations and key descriptive statistics. Correlations among constructs are below the recommended threshold of 0.60 (see Hair, Black, Babin, Anderson, & Tatham, 2006), which indicates that the associations between constructs are asymmetric. Evidently, asymmetry implies the existence of alternative conditions and combinations of predictors that may lead to the same outcome (Woodside, 2013). Thus, there is a need for alternative analytical methods to examine such effects.

Table 1 here

Prior to implementing fsQCA, all cases in the dataset (i.e. N = 169) were calibrated into fuzzy-sets. The three recommended threshold breakpoints (i.e. 0.95, 0.50, and 0.05) were used for set calibration. The truth table was then constructed, with 2^5 possible combinations for high degrees of CKU; the rows of the truth table were reduced by applying a consistency threshold of 0.937. Table 2 shows the derived alternative solutions for high membership of CKU. For the purposes of this study, it is appropriate to use complex solutions, as they make no particular assumptions and include neither easy nor difficult counterfactuals (Elliott, 2013).

Table 2 here

The fsQCA demonstrate three solution pathways that lead to high membership of CKU. The solution as a whole reveals acceptable consistency (i.e. $\geq$ .80) and explains a satisfactory number of cases in high CKU (i.e. $\geq$ .25 coverage $\leq$ .65). The first pathway indicates that the use of TEAMS, high levels of CRMI and TMI, and low levels of CRO leads to high degrees of CKU. The second pathway indicates that a combination of TEAMS, high levels of CRMI and FORM, and low levels of CRO leads to high degrees of CKU. On the other hand, the third pathway indicates that a combination of TEAMS with high levels of CRMI, FORM, and TMI lead to high degrees of CKU.

The fsQCA findings demonstrate core and peripheral conditions that lead to high CKU memberships. The use of TEAMS and high CRMI are necessary – although not sufficient on their own – conditions to obtain high levels of CKU. On the other hand, CRO, TMI, and FORM are peripheral for reaching the same outcome. Specifically, high levels of FORM and TMI and low levels of CRO appear in two of three pathways. This finding implies that TEAMS and high levels of CRMI need to co-exist with different combinations and levels (i.e. high/low) of FORM, TMI, and CRO. The following subsection discusses these findings.

5.2. Interpretation of results

The original SST study suggests that managers should consider allocating resources to TMI, TEAMS, CRMI, and FORM for generating desirable levels of CKU. However, in modern business environments, managers are often challenged to choose between different alternatives scenarios and make decisions about where scarce resources should be allocated. This study uses fsQCA to understand further the findings of the SST and seeks to deepen current understanding of how different conditions intertwine to lead to higher levels of CKU. The strength of the fsQCA technique is that it examines and provides complex causal combinations of predictors that lead to high levels of the same outcome. Table 3 draws a comparison between the MRA results of the original SST study and the fsQCA findings of the present study.

Table 3 here

The main conclusion from the fsQCA analysis is that TEAMS and high levels of CRMI are core conditions for ensuring high levels of CKU. The existence and deployment of teams that manage key accounts and investments in CRM systems are essential. TEAMS serve as an integrative mechanism between customer-specific knowledge and CRM activities (Katzenbach

& Smith, 2005). This mechanism works through efficient knowledge sharing among team members (Geiger & Turley, 2005). Furthermore, TEAMS offer a forum for discussing customer-specific issues (Nätti et al., 2006). On the other hand, use of TEAMS ensures discussion of customer-related issues, and CRM systems provide the needed customer-specific knowledge for these discussions. The more available knowledge there is, the more it is actually used. Thus, the fact that both TEAMS and high CRMI are core conditions for high degrees of CKU imply that both are needed, so that there is a large base of customer-specific knowledge available in the CRM systems and this knowledge is discussed within KAM teams. These findings are consistent with the SST study (i.e. original H2 and H4).

However, the fsQCA findings suggest that while teams and CRMI are necessary conditions for high levels of CKU, their existence alone is not sufficient for high CKU. The original SST study found TMI (i.e. original H1) and FORM (i.e. original H5) are significant predictors of CKU, whereas the effect of CRO (i.e. original H3) is not supported. However, the individual pathways of the derived fsQCA solutions provide partial support for the effects of TMI and FORM; in addition, it appears that CRO is not entirely irrelevant to CKU. This part of the fsQCA findings expands current understanding of the factors that lead to high CKU.

In addition to core conditions, the first two pathways include low levels of CRO as a peripheral condition for high levels of CKU. In the first pathway, low levels of CRO are combined with high levels of TMI; in the second pathway, low levels of CRO are combined with high levels of FORM. This finding suggests that under certain conditions, CRO may actually be harmful for the achievement of high levels of CKU. The first pathway, in which CRMI and TEAMS are accompanied with high levels of TMI and low levels of CRO, illustrates one such condition. Guesalaga (2014) notes that high levels of TMI may under certain circumstances deter relationship quality, which in turn creates conflict in KAM teams with high levels of CRO; thus, it may prevent utilization of customer knowledge. The second pathway, in which CRMI and TEAMS are accompanied with low CRO and high levels of FORM, illustrates another case of conditions that may harm CKU. FORM may impede flexibility and thereby limit a firm's ability to give special attention to key accounts, which again may create conflict in KAM teams showing high levels of CRO; consequently, this may prevent CKU.

Even though levels of FORM and TMI often go hand in hand in KAM organizations (see Homburg et al., 2002), sometimes companies may need to choose between one of these two approaches to maximize CKU. Firms may adopt the second pathway (e.g. high levels of FORM and varying levels of TMI) for higher CKU levels, if top management do not have sufficient time to be involved in all relationships with key account customers or when intensive involvement may have negative consequences. According to Homburg et al. (2002), this configuration is referred to as operating-level KAM. Alternatively, firms may adopt the first pathway (e.g. high levels of TMI and varying levels of FORM) if key account coordinators are locally based (i.e. isolated KAM in the taxonomy of Homburg et al., 2002).

The third pathway suggests that for high levels of CKU, the use of teams and high levels of CRMI need to be accompanied with high levels of both TMI and FORM. In this pathway, the level of CRO is irrelevant. Examples in Homburg et al.'s (2002) taxonomy include top-management and cross-functional, dominant KAM. This finding implies that the best way to achieve high levels of CKU is to use highly formalized KAM programs with high levels of top management support, together with TEAMS and high levels of CRMI.

7. Conclusions and future research directions

This study assesses configurations of causes for high CKU, using empirical data from the SST study. Three solution pathways are identified. The first conclusion that can be drawn from the fsQCA results is that CRMI and TEAMS are necessary (core) conditions for high CKU. Thus, firms should invest in CRM technologies and assign teams of experts for managing key accounts. The second conclusion reflects the differences identified between the three solutions. The first two pathways suggest that firms can achieve high levels of CKU even when they lack a company-wide CRO; in these cases, managers need to accompany CRMI and TEAMS with high levels of either TMI or FORM. Interestingly, the third pathway describes a configuration in which firms accompany CRMI and TEAMS with both TMI and FORM. These pathways are examples of firms that have made trade-off decisions between TMI and FORM.

The findings of the present study open up several interesting directions for future research. First, since firms can reach high levels of CKU with different configurations of causes, there is a need to understand the underlying logic of resource allocation for each solution pathway. Second, if there are potential suboptimal consequences of causes (e.g. FORM or TMI), it is possible that the path with which CKU is created dictates its performance implications. It is reasonable to argue that CKU is not a firm's final goal but rather a means to an end, such as key customer performance (see Salojärvi & Sainio, 2010). Thus, the future research should examine how the pathway with which firms have created CKU impacts account performance outcomes.

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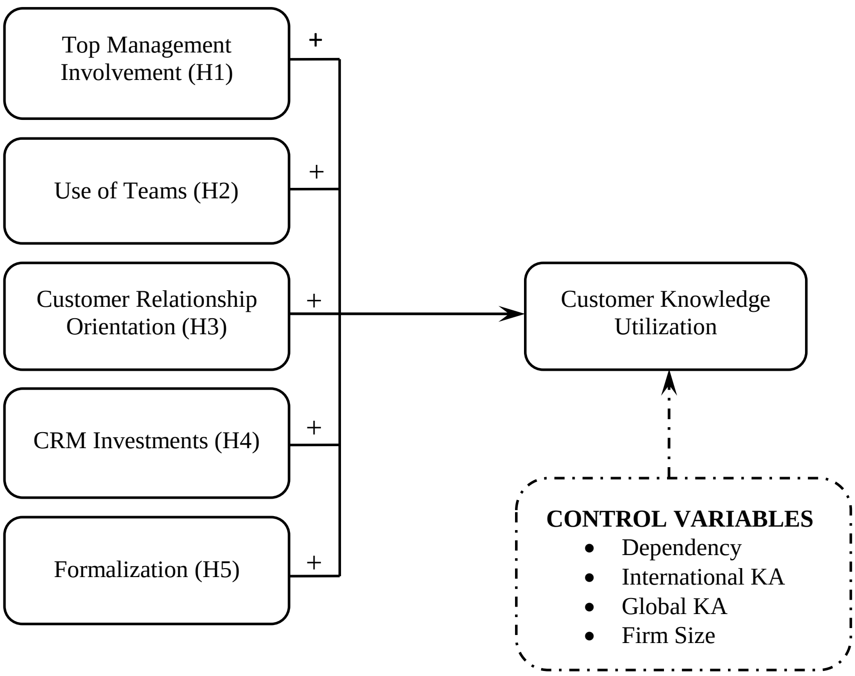

Note: H1: Top management involvement is positively related to CKU; **H2:** The use of teams is positively related to CKU; **H3:** Customer relationship orientation is positively related to CKU; **H4:** Investment in CRM technology is positively related to CKU; **H5:** Key account management formalization is positively related to CKU.

Figure 1. Conceptual framework and hypotheses of the SST study

Table 1. Correlation matrix and summary statistics

Variable	1.	2.	3.	4.	5.	6.
1. Top Management Involvement	1					
2. Use of Teams	.07	1				
3. Customer Relationship Orientation	.29	.25	1			
4. CRM Investments	.15	.12	.28	1		
5. Formalization	.23	.28	.30	.27	1	
6. Customer Knowledge Utilization	.29	.33	.33	.42	.43	1
Number of Items	4	1	4	3	4	4
M	4.6	NA	5.0	3.8	4.5	4.4
SD	1.24	NA	1.12	1.70	1.36	1.10

Notes: (1) Sample size = 169.
(2) Correlations greater than |± .23| are significant at the $p < .001$ level.
(3) NA = not applicable, as TEAMS is a binary variable of 0 (i.e. no use) and 1 (i.e. use)

Table 2. Complex solutions for high CKU

Complex Solution	Raw Coverage	Unique Coverage	Consistency
Configurations for achieving high CKU Model: f_CKU = f(f_tmi, f_teams, f_cro, f_crmi, f_form)			
~cro_cal*tmi_cal*crmi_cal*team	0.198179	0.017274	0.926856
~cro_cal*form_cal*crmi_cal*team	0.216153	0.035247	0.921852
tmi_cal*form_cal*crmi_cal*team	0.272409	0.091503	0.941889
Solution coverage: 0.324930; solution consistency: 0.913086 Frequency cutoff: 1.000000; consistency cut-off: 0.937058			

Note: tmi = top management involvement; teams = use of KAM teams; cro = customer relationship orientation; crmi = customer relationship management investments; form = formalization.

Table 3. Comparison of SST's MRA with fsQCA findings

Customer Knowledge Utilization								
MRA results in STS				fsQCA solutions and pathways				
		Std. Coefficient	Conclusions	1st	2nd	3rd	Core or Peripheral	Conclusions
H1	TMI	0.134*	Supported	•		•	ø	ℂ
H2	TEAMS	0.210***	Supported	•	•	•	●	√
H3	CRO	0.082	Not supported	○	○		ø	×
H4	CRMI	0.303****	Supported	•	•	•	●	√
H5	FORM	0.221****	Supported		•	•	ø	ℂ

Notes: (1) R^2 of MRA analysis = 0.367; * p < .10; *** p < .01; **** * p < .001.

(2) Small black and white circles represent high and low presence of an antecedent condition, respectively. Blank spaces represent a situation in which a causal condition may be either present or absent (i.e. 'do not care' situation). In the Conclusions column, large black circles represent necessary (i.e. core) conditions; ø represents a peripheral condition. √ indicates a situation in which the fsQCA findings support the STS results. ℂ indicates that fsQCA findings partially (or conditionally) support the STS results, and × indicates that the finding is not supported.

Appendix: Measurement Development

Scales	Std. Loadings
Customer relationship orientation (α = 0.82)	
The people involved in the management of the key account *relationship….*	
are willing to put extra effort beyond expected to make key account management successful	0.833
consider retaining the key account relationship as their top priority	0.854
consider the key account relationship as a valuable asset	0.798
Top management involvement (α = 0.74)	
Top management often deals with the management of the key account relationship	0.848
Top management have close relationships with the key account's top management	0.790
Top management encourages employees to pay special attention to the key account relationship	0.669
The key account manager is often left alone when key account-related decisions need to be made	0.605
Formalization (α = 0.80)	
To coordinate parts of our organization working with key accounts, standard operating procedures have been established	0.825
We have put a lot of effort into developing guidelines for working with our key accounts	0.774
Within our organization, formal internal communication channels are followed when working on key accounts	0.725
We have established criteria for selecting key accounts	0.774
CRM investment (α = 0.80)	
We have invested in technology to acquire and manage 'real time' customer-related information	0.863
We have dedicated CRM technology in place for analysing customer information	0.858
Our CRM technology does not meet our needs	0.763
Customer knowledge utilization (α = 0.84)	
We constantly assess our key account relationship strategy with the help of new key account-related knowledge	0.830
We regularly assess our sales processes to ensure it meets the key account's expectations	0.798
We exploit key account-related knowledge actively in developing new value-added solutions for the key account	0.781
We continually exploit the key account-related knowledge when assessing our successes and failures in managing the key account relationship	0.692

Note: Use of teams is measured with a categorical dummy variable (i.e. 0 = no team and 1 = team).