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To be or not to be (loyal): Is there a recipe for customer loyalty in the B2B context?☆

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ABSTRACT

The article investigates how firms can achieve high levels of customer loyalty under different configurations of perceived switching costs, returns management, customer value, and customer satisfaction.
In order to better explain the sources of customer loyalty within the B2B context, researchers have already introduced various antecedents and developed several models, however past studies concentrated exclusively on the main 'net effects' of these antecedents. Because of the complex reality in which the phenomena of interest manifests itself, complexity theory tenets can provide a more accurate understanding of what generates customer loyalty. Applying this theory, the current article seeks to determine all the possible "recipes" that build strong customer loyalty in the B2B context.
To address this research question the study employed qualitative comparative analysis (QCA) which assumes that the influence of attributes on a specific outcome (customer loyalty in a B2B context) depends on how the attributes are combined.
Future research can consider other possible combinations and explore how the impact of these antecedents on customer loyalty changes when other variables are considered.

1. Introduction

Business scholars have long proposed that firms with a good understanding of the sources of customer loyalty can gain market advantages (Nathanson & Twitmyer, 1934; Wind, 1970; Womer, 1944) such as increased revenues, lower costs, and increased profitability, to name a few (Lam, Shankar, Erramilli, & Murthy, 2004; Rauyruen & Miller, 2007). Successful firms have realized the importance of customer loyalty, and are investing significant resources toward customer retention. However, customer loyalty can be elusive to understand and create. For example, a recent Bain & Company survey of executive-level managers in business-to-business (B2B) industries throughout 11 countries shows that 68% of respondents believe customers are less loyal than they used to be. Moreover, the same survey reveals that earning loyalty in B2B markets poses unique challenges, often involving complex channel structures, concentrated buyer communities or large accounts, and continuous shifting of perceived value (Michels & Dullweber, 2014). Achieving customer loyalty seems to increasingly require tailored solutions. This highlights the challenges that even top firms have when trying to determine the best "recipe" for customer loyalty.

In order to better explain the sources of customer loyalty within the B2B context, researchers have introduced various antecedents and developed several models. For example, Blocker, Flint, Myers, and Slater (2011) and Blocker (2011) explore the intricate relationship between customer value, customer satisfaction and customer loyalty. Similarly, Lam et al. (2004) and Picón, Castro, and Roldán (2014) investigate the relationship between these variables and perceived switching costs. In addition, the link between customer satisfaction and loyalty is highly variable depending on the industry, the nature of the variables, and the presence of several factors (Kumar, Dalla Pozza, & Ganesh, 2013). The supply chain management literature has also provided evidence that in a B2B context, service attributes such as having a robust product returns management process can play an important role in predicting customer loyalty (Manuj, Esper, & Stank, 2014; Mollenkopf, Rabinovich, Laseter, & Boyer, 2007).

Although the extant literature helps identify various predictors of customer loyalty, past studies concentrate exclusively on the 'net effects' of these antecedents. Yet, there are theoretical reasons to suggest that these effects may be more complicated than they first appear. According to complexity theory, in the real world "Relationships between variables can be non-linear, with abrupt switches occurring, so the same 'cause' can, in specific circumstances, produce different effects" (Urry, 2005, p. 4). Because of the complex reality in which the phenomena of interest manifests itself, complexity theory tenets can help provide a more accurate understanding of what generates customer loyalty. As such, instead

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of analyzing the main effects of certain predictors, the current article seeks to determine configurations (i.e., combinations of antecedents) that help explain customer loyalty in the B2B context.

In line with this theorizing, we investigate how firms participating in B2B markets can achieve high levels of customer loyalty under different configurations of perceived switching costs, returns management, customer value, and customer satisfaction. Specifically, the following question is put forth: What configurations of perceived switching costs, returns management, customer value, and customer satisfaction lead to high customer loyalty? In order to address this research question we employ qualitative comparative analysis (QCA) (Chang, Tseng, & Woodside, 2013; Wu, Yeh, & Woodside, 2014). This method uses Boolean algebra rules to identify which of the attributes combinations, if any, act as sufficient or necessary conditions for the outcome (Fiss, 2007). The QCA method assumes that the influence of attributes on a specific outcome (customer loyalty in a B2B context) depends on how the attributes are combined.

2. Applying complexity theory to customer loyalty within the B2B context

Complexity theory provides a useful theoretical lens for exploring the relationships among the variables of interest. This theory can better drive data analysis because it guides the investigator to account for contrarian cases and go beyond simply pointing out the main effects observed in multiple regression analysis (MRA). Contrarian case analysis indicate that although the data might provide adequate statistical support that X is positively associated with Y, the same data set can include cases of high X and low Y and cases of low X and high Y. As such, complexity theory helps researchers move beyond the dominant approach of using MRA to examine net effects and interaction terms. Accounting for contrarian cases can provide novel and insightful perspectives on the relationships between the variables of interest (Woodside, 2014). The tenets of complexity theory and QCA indicate that multiple possible paths can lead to the same outcome. Different combinations of indicators can help predict an outcome variable, but no combination alone is sufficient for accurately predicting customers' behavior (Wu et al., 2014). The use of asymmetric tools in theory construction and testing allow researchers to create formal, accurate and useful models in B2B marketing (Woodside, 2015).

Popular discussions of complexity theory provide that, “if a system passes a particular threshold with minor changes in the controlling variables, switches occur such that a liquid turns into gas, a large number of apathetic people suddenly tip into a forceful movement for change” (Gladwell, 2002). Such tipping points give rise to unexpected structures and events (Urry, 2005, p.5). This highlights the complexity of the relationship between an antecedent and an outcome variable, and the possibility that the relationship would change based on different configurations. This perspective is supported by the network theory, which is part of complexity theory (Gummesson, 2008). A network is made up of modes (e.g., individuals, firms) and relationships and interaction among the modes. Within a network, numerous variables interact without the constraint of limited unique situations, change is ordinary, and processes are not linear but iterative (Woodside, 2014). Thus, complexity theory provides a more robust tool for assessing customer behavior by accounting for the dynamic and complex relationships among the variables under investigation. Next, we introduce and describe the variables of interest in our model.

3. A configuration model of customer loyalty using perceived switching costs, returns management, customer value, and customer satisfaction

We define B2B customer loyalty consistent with prior literature, as a buyer's intent to repurchase from a given supplier (Oliver, 1999). Operationalized this way, customer loyalty has been previously linked to switching costs (Chebat, Davidow, & Borges, 2011; Lam et al., 2004; Picón et al., 2014). Switching costs represent those costs involved in changing from one supplier to another (Heide & Weiss, 1995), and have traditionally entailed both monetary and non-monetary costs (Dick & Basu, 1994). B2B buyers follow rational buying criteria and have lower commitment to a supplier. B2B buyers also typically invest more in a relationship that lasts longer, which leads to higher switching costs and lower switching rates (Pick & Eisend, 2014). As a result, positive switching costs are foregone benefits from the current relationship when switching to a new supplier, whereas negative switching costs denote actual losses associated with the switching process (Nagengast, Evanschitzky, Blut, & Rudolph, 2014).

Switching costs can also include loyalty benefits that a customer no longer enjoys when the relationship with the service provider is interrupted. When transaction-specific investments have been made in a buyer–supplier relationship, customers are motivated to stay in a relationship to avoid incurring switching costs (Lam et al., 2004; Pick & Eisend, 2014; Picón et al., 2014). When a customer is dissatisfied with the products or services received it would need to establish a new relationship, which would require an investment of time, effort, and money. These required investments constitute a barrier to moving to another supplier. Research has consistently positioned switching costs as a powerful mechanism for influencing customers' actions by deterring them from changing to another supplier (Klemperer, 1995) and encouraging repeat purchase behavior (Weiss & Heide, 1993). Lam et al. (2004) found empirical evidence that switching costs have a positive effect on customer loyalty. Blut, Beatty, Evanschitzky, and Brock (2014) augment prior research that suggests that switching costs represent a viable strategy for retaining customers. Moreover, their findings indicate a stronger effect of switching costs on customer loyalty compared to the findings of Pick and Eisend (2014). However, any single ingredient is insufficient to fully explain the final outcome. For example, switching costs may prevent a customer from switching when satisfaction and customer value are low, so they could be less important for customer loyalty at high levels of satisfaction and value.

In order to enlarge the spectrum of variables that impact customer loyalty, we also examine the role of returns management. Research has increasingly recognized returns management as a strategically important firm process related to loyalty (Griffis, Rao, Goldsby, & Niranjan, 2012; Petersen & Kumar, 2009). Mollenkopf, Frankel, and Russo (2011) found that return policy can affect marketing and operations, enhance customer value and increase supply chain efficiencies. Returns management is a cross-functional and cross-organizational supply chain management process which includes activities such as return organization, reverse logistics, gatekeeping, avoidance, product recovery, disposition and processing, and crediting. At an operational level it involves the physical flow of product, information and finances, while at a strategic level it entails establishing policies, processes and structures to handle these activities (Rogers, Lambert, Croxton, & García-Dastugue, 2002). Moreover managing return product flow is becoming progressively more important to the success of supply chain firms due to high volume of returned products, their value to customers, and the signaling effects of quality such programs implicitly suggest (Huscroft, Hazen, Hall, Skipper, & Hanna, 2013). Although returns management can entail significant operational challenges and high cost, it also represents an often-missed opportunity to manage customer relationships and strengthen customer loyalty (Mollenkopf et al., 2007).

Developing a competency in handling product returns can be an important part of a firm's supply chain strategy and can help transform returns into a profit center just because through improved returns management suppliers can better address customer complaints (Jayaraman & Luo, 2007; Rao, Rabinovich, & Raju, 2014). In industrial marketing there are few studies focusing on the impact of complaint handling when managing product returns. In addition,

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in the B2B context the average transaction value is higher while the number of customers is lower than in consumer market. This enhances the importance of building an effective complaint management system (Brock, Blut, Evanschitzky, & Kenning, 2013). As such, a key premise of the current research is that a robust product returns management could help increase customer loyalty by overwhelming switching behaviors, in the form of a tacit switching cost.

As an additional consideration, research has long demonstrated a positive link between customer satisfaction and customer loyalty (Blocker et al., 2011; Chandrashekaran, Rotte, Tax, & Grewal, 2007; Lam et al., 2004). Customer satisfaction can be defined as a positive affective state resulting from the evaluation of all aspects of a firm's working relationship with another firm (Geyskens, Steenkamp, & Kumar, 1999). Customer satisfaction also reflects a positive affecting state resulting from a business customer's cumulative appraisal of its supplier relationships (Blocker et al., 2011; Lam et al., 2004). It has become apparent that customer satisfaction is not sufficient to achieve customer loyalty, and scholars and practitioners alike have engaged in a quest to identify new ways to build long-term relationships with customers (Haumann, Quaiser, Wieseke, & Rese, 2014).

For this reason when assessing factors that impact customer loyalty, it is important to also account for customer value (Lam et al., 2004). Customer value signifies the trade-off between benefits and sacrifices that stem from a provider's product and relationship resources which customers consider are facilitating their goals (Biggemann & Buttle, 2012; Keränen & Jalkala, 2013; Ulaga & Eggert, 2006; Woodruff, 1997). Substantial empirical evidence indicates that customer value is positively related to customer loyalty (Bolton, 1998; Gao, Sirgy, & Bird, 2005; Lam et al., 2004; Tsai, Tsai, & Chang, 2010). In the B2B context this would result in the business customers' perception of value regulating their firm's behavioral intentions such as loyalty toward the supplier as long as such exchanges offer superior value (O'Cass & Ngo, 2012).

Considering the established significant impact of customer value on customer loyalty (Blocker et al., 2011; Tsai et al., 2010) combining customer value with switching costs, returns management, customer satisfaction the impact of loyalty might be strengthened or be weakened. In fact, it is possible that low/high levels of customer value could mute the positive/negative association between switching costs, returns management, customer satisfaction and customer loyalty.

While the configurations of customer loyalty pertaining to a phenomenon can potentially be numerous, equifinal configurations that effectively explain the phenomenon typically reduce to a few coherent patterns of attributes. Thus, the aim of configuration analysis in regards to our attributes is to discover those few equifinal configurations. Moreover, according with Leischnig and Kasper-Brauer (2015) an analysis of factor configuration is more important than the examination of individual causal condition.

In summary, our conceptual framework seeks to examine whether different combination of attributes (perceive switching costs, returns management, customer value and customer satisfaction) lead to the same outcome (customer loyalty). The general propositions implied in our configurational framework are as follows:

Proposition 1. An individual attribute in a recipe can contribute positively or negatively to customer loyalty depending on the presence or absence of other ingredients in the recipe (perceive switching costs, returns management, customer value and customer satisfaction).

Proposition 2. Simple antecedent conditions can be necessary but insufficient for high customer loyalty.

Proposition 3. Disparate configurations of customer loyalty attributes (perceive switching costs, product returns management, customer value and customer satisfaction) are equifinal in leading to high customer loyalty.

4. Research method

4.1. Data collection, survey development and sampling

Data collection focused on of the evaluation of some loyalty drivers perceived by business customers who operate within the health-care industry in a B2B context. The choice of health care industry was made for several additional reasons. Investigating the health care industry through tools commonly applied in business management research has a wide diffusion (Berry & Bendapudi, 2007; Crié & Chebat, 2013), with the complexity of the product offering driving final customers to search for advice from trustworthy and reliable sources. As such, this industry represents a good example of a changing marketing-channel structure that has emerging actors who have adopted a larger role in the manufacturer/end customer exchange.

Participants were audiologists, who serve as a primary commercial distribution channel for hearing aids manufacturers the audiologist key informants purchase products/services from the hearing aid suppliers and are enabled by law to resell them to hearing-impaired end users. In order to determine the membership of our final sample, we employed the following participant qualification criteria, the volunteer informants were restricted to those health care professionals who were: (a) enabled by law to resell hearing aids, (b) currently operating a business at the retail level, and (c) have freedom of supplier selection. We selected 500 audiologists belonging to the Italian Audiologists Association (ANA) who met the criteria and sent them an email with a link to a secure web survey. This survey was completed after a pre-test that refined the structure of the survey, and the items involved in the survey.

A pilot survey (constructed in Italian by a native Italian speaking researcher, subject to survey design best practice as catalogued by Dillman, 2011) was administered to a convenience assessment sample of 20 potential participants through which some refinements to the survey were applied. Following refinement, the survey was distributed to the remaining qualified participants. We received 317 complete responses, resulting in a 64.4% response rate.

4.2. Measurement of variables

The survey was divided into two main sections. Section A evaluated the demographic characteristics of respondents and characteristics of the audiologist (customer)–key supplier relationship (e.g. experience with hearing-aid products, length of the partnership, total expenditure with their main supplier). Section B contained 7-point Likert scales devised to tap customer value, customer satisfaction, returns management, switching cost, and customer loyalty for the audiologists in the sample frame. All measures were adapted from existing scales (Appendix A). Customer value was measured using three scale items from Blocker (2011) and Ulaga and Eggert (2006). Customer satisfaction was evaluated using three scale items adapted from Lam et al. (2004) and Flint, Blocker, and Boutin (2011). Returns management was assessed using three scale items adapted from Mollenkopf et al. (2007). Perceived switching costs was measured using five scale items evaluating aspects such as time, money, effort and risk associated with change of supplier technology (Lam et al., 2004; Pick & Eisend, 2014). Finally, customer loyalty was assessed using three scale items proposed by Blocker et al. (2011).

4.3. Reliability and validity

Reliability was satisfactory for all scales with alpha values ranging from 0.70 to 0.97. Only one item was dropped due to low Cronbach's, item-to-total correlations and loadings in exploratory factor analysis. In aggregate, the results support construct unidimensionality. In addition, confirmatory factor analysis (CFA) was performed to test the measurement model using LISREL 8.80. The model fit indices were X_2 (94) = 324.906 (p-value < 2.2e − 16),

16), NNFI = 0.93, CFI = 0.95, RMSEA = 0.02 and SRMR = 0.07. Based on these observations, measurement model fit was deemed acceptable (Hu & Bentler, 1999), supporting convergent validity (O'Leary-Kelly & Vokurka, 1998 (see Appendix A for AVE and reliability tests).

5. Analytic approach

In order to develop our proposition we adopt a multi-steps data analysis, starting from the contrarian case analysis for Proposition 1 followed by configural analysis to have a deeper and richer perspective on our data to explore Propositions 2 and 3. In doing so we respectively explored the presence of contrarian cases with cross tabulation and we adopted QCA method to verify the existence of different combination of our "ingredients" which lead to the same output that is in our case reaching a high level of loyalty. In the following section we will provide explanation of these procedures and the main results applied to our context.

5.1. Contrarian case analysis

5.1.1. Can individual loyalty attributes contribute positively or negatively to customer loyalty? (Proposition 1)

This analysis helps provide a better understanding of the complexity of reality, where there might be substantial numbers of cases which display relationships that are counter to a negative (or positive) main effect between X and Y—even when the effect size of the reported X–Y relationship is large. This contrarian cases are mostly ignored by many research as they adopt symmetric analyses which do not consider complexities inherent in realities and apparent in the data sets of academic studies (Woodside, 2013). In fact, the analysis suggested by Woodside (2014) compares and contrasts the use of symmetric (for instance MRA or SEM) versus asymmetric (see for example analysis by quintiles and by fuzzy set QCA) analysis. A symmetric analysis usually considers the accuracy in high values of X (an antecedent condition) indicating high values of Y (an outcome condition) and low values of X indicting low values of Y. On the other hand, asymmetric tests start from the point that the causes of high Y scores usually differ substantially from the causes of low Y scores.

Woodside (2014) and Wu et al. (2014) offer a good example of how to conduct contrarian analysis through quintile analysis applied to the relationship between hospitality employee happiness and their managers' in-role performance (IRP) evaluations (Hsiao, Jaw, Huan, & Woodside, 2015). A quintile analysis includes dividing the respondent cases from the lowest to highest quintile for each measured construct and examining the relationships among two or more constructs (McClelland, 1998). This is helpful in understanding not only the main symmetric relationships between the X and the Y (high levels of happiness of employees lead to high employees productivity while low levels of happiness lead to low levels of productivity) but it also show the other counter combinations effects.

Hsiao et al. (2015) were able to offer asymmetric empirical models via QCA for all four sets of relationships: unhappy and highly unproductive employees, unhappy and highly productive employees, happy and highly unproductive employees, and happy and highly productive employees. The Hsiao et al. (2015) findings on contrarian case responses are illustrative of usual occurrences among large data sets ($n \geq 100$). Even when an effect size is large between two variables, there still exist cases that run counter to the main effects relationship in almost all large data sets.

5.1.2. Main findings: The presence of contrarian cases

Results from the analysis confirm that the main large effect is confirmed for all attributes, except for returns management for which negative contrarian and also positive contrarian cases are present (see Table 1 for returns management and Appendix B for the other elements). Table 1 illustrates the occurrence of contrarian cases that run counter to a large main effect. It reports a quintile analysis of returns management and their relationship with loyalty evaluation. Results confirm loyalty has a "symmetric" relationship with customer value, perceived switching costs and customer satisfaction but negative in several cases with returns management. Regarding returns management we also have the case of positive contrarian analysis. This might mean that when returns receive high evaluation by respondents, this attribute is not sufficient to create high loyalty. Thus, several cases exhibit two relationships counter to the symmetric relationships that high satisfaction with returns management lead to low customer loyalty and low satisfaction with returns management lead to high loyalty.

This provides support for our Proposition 1: the effect of a single element can depend on the recipe it belongs to.

5.2. QCA procedures and configural analysis

5.2.1. Are different recipes to deliver customer loyalty? (Propositions 2 and 3)

Considering the results from the contrarian analysis, we decided to apply complexity theory and configural analysis to have a deeper and richer perspective on our data. This is helpful in order to explore not only the relationship between a single attribute X with the related outcome Y, but also to find the existence of those combinations of attributes that lead to the same level of output Y, that is, in our case, high customer loyalty. That it is the answer of Proposition 2.

As defined by Ordanini, Parasuraman, and Rubera (2014, p. 137), configuration theory posits that "the same set of causal factors can lead to different outcomes, depending on how such factors are arranged. Three principles underlie configuration theory: outcomes of interest rarely result from a single causal factor; causal factors rarely operate in isolation; and, the same causal factor may have different—even opposing—effects depending on the context (Greckhamer, Misangyi, Elms, & Lacey, 2008). This refers to the definition of "equifinality" that occurs when the same outcome can be achieved through different configurations of causal factors (Ragin, 2000). It it true that many configuration of elements can be related to a specific phenomen, however, only fewer combinations of them can effectively represent the phenomenon. The configural analysis helps in doing this and to applying it to our model we adopted QCA software and following the four steps of analysis suggested by Ordanini et al. (2014).

QCA is a set-theoretic method that empirically investigates the relationships between the outcome of interest (customer loyalty in our study) and all possible combinations of binary states (i.e., presence or absence) of its predictors (returns management, perceived switching costs, customer value and customer satisfaction) (Fiss, 2007; Ragin, 2000). This method is growing in marketing and management literature to analize configurations (Chang et al., 2013; Leischnig & Kasper-Brauer, 2015; Ordanini et al., 2014).

In order to test our model we followed these four steps:

1) Defining the property space
   QCA starts by defining the property space, where all possible configurations of drivers of an outcome are identified. In order to find the most relevant drivers, we employed some of the most important loyalty drivers from previous literature. Accordingly, the property space consists of all combinations of binary states, that is, presence or absence, of the four attributes that could influence loyalty (customer value, customer satisfaction, perceived switching costs and returns management) ($2^4 = 16$ combinations).The combinations, or configurations, empirically present in our data appear as rows in Table 2, the Truth Table, where 0 is given to the attribute in case of its "absence" (low scores) and 1 is assigned in case of its "presence" (high scores).
2) Set-membership measures
   As sets are expressed in binary form (presence/absence of attributes), and our variables are not naturally dichotomous; we transformed construct measures into fuzzy-set membership scores,

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Table 1
Two outcomes: returns management (ret) and customer loyalty (loy).

Cases supporting the large main effect: A–>O

Negative contrariaran cases indicating ¯A–>O

			Loy					Total
			1,00	2,00	3,00	4.00	5.00	
ret	1.00	Count	12	5	2	4	10	33
		% within ret	36.4%	15.2%	6.1%	12.1%	30.3%	100.0%
	2.00	Count	38	39	14	24	9	124
		% wi thin ret	30.6%	31.5%	11.3%	19.4%	7.3%	100.0%
	4.00	Count	1	18	15	26	15	75
		% within ret	1.3%	24.0%	20.0%	34.7%	20.0%	100.0%
	5.00	Count	3	10	32	15	25	85
		% within ret	3.5%	11.8%	37.6%	17.6%	29.4%	100.0%
Total		Count	54	72	63	69	59	317
		% within ret	17,0%	22.7%	19.9%	21.8%	18.6%	100.0%

Positive contrariaran cases indicating A–> ¯O

Phi= .550, p<.0000

Note: A= antecedent condition; O = outcome condition

calibrating measures by specifying three qualitative anchors: the threshold for full membership in a set (i.e., value 1), the threshold for full non-membership in a set (i.e., value 0), and the crossover point (i.e., value .5) (Ragin, 2008). As we needed to managed the multiple-item measures, scale items were combined into an average score (Leischnig & Kasper-Brauer, 2015). The endpoints and the midpoint of the 7-point Likert scales served as the three qualitative anchors for calibration of full membership (value 6), full non-membership (value 2), and the crossover point (value 4).

After generating fuzzy-set measures for individual attributes, by applying Boolean algebra rules there is the need to build membership scores for configurations, considering more than one attribute,with can be present or absent. In doing so, each respondents will have some degree of fuzzy membership in every configuration of adoption attributes although, by assumption, in only one configuration, called best-fit case, will his or her membership measure be greater than 0.5 (Longest & Vaisey, 2008; Ordanini et al., 2014).

3) Consistency in set relations

After these steps, the truth table needs preliminary refinement based on two criteria: frequency and consistency (Ragin, 2008). To define the frequency cutoff we considered only those configurations exceeding a minimum number of empirical representations. The treshold for frequency of medium-sized samples (e.g., 10–50 cases) is 1 while it can be higher for large-scale samples (e.g., 150 and more cases) (Ragin, 2008). So we considered only configurations that haveat least three best-fit cases or, in other words, those that at least three customers perceive as characterizing the loyalty.

The column "number" of Table 2 shows the distribution of best-fit cases (customers) across the configurations in our sample. We considered the cases where loyalty is equal to 1, that is when the outcome of high loyalty is present. This allows us to understand the number of potential combinations that lead to the same outcome.The next step is to consider only those combinations that are consistent. According to set theory, a consistent subset relation with fuzzy measures emerges when membership scores in a given causal set of attributes are consistently less than or equal to the membership scores in the outcome set. The consistency measure in this case is thus calculated as the sum of the consistent, or shared, membership scores in a causal set, divided by the sum of all the membership scores that pertain to that causal set.

A configuration is defined sufficient when its consistency measure exceed a treshold, that we set, in line with QCA literature to .8 (Ragin, 2008). From our elaboration the most frequent and consistent combination seem to be the one where high level of perceived switching costs is combined with high customer value and high satisfaction lead in absence of high scores assigned

Table 2
True table of potential combinations.

Edit Truth Table

File Edit Sort

ret	swi	cv	sat	number	loy	raw consist.	PRI consist.	SYM consist
0	1	1	1	177 (58%)		1.000000	1.000000	1.000000
0	0	1	0	93 (89%)		0.567388	0.039699	0.056520
0	1	1	0	6 (91%)		0.999128	0.998196	0.998196
0	1	0	0	6 (93%)		0.991994	0.955300	0.989418
0	0	0	0	6 (95%)		0.870556	0.000000	0.000000
1	1	1	1	5 (97%)		1.000000	1.000000	1.000000
1	0	1	1	5 (99%)		0.981639	0.814570	0.924812
1	0	0	0	3 (100%)		0.898217	0.000000	0.000000
1	1	1	0	0 (100%)				
1	1	0	1	0 (100%)				
1	1	0	0	0 (100%)				
1	0	1	0	0 (100%)				
1	0	0	1	0 (100%)				
0	1	0	1	0 (100%)				
0	0	1	1	0 (100%)				
0	0	0	1	0 (100%)				

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Table 3
Sufficient configuration for customer loyalty.

	raw coverage	unique coverage	consistency
~sat*~cv*~swi	0.120939	0.022568	0.836638
~sat*swi*~ret	0.374329	0.009510	0.994921
cv*swi*~ret	0.812131	0.442806	0.990071
sat*cv*ret	0.107471	0.028028	0.979270
solution coverage: 0.876559			
solution consistency: 0.961423			

~ = this symbol before the variable means that the combination considers low value (absence) of that variable.
sat = customer satisfaction; cv = customer valu`e; swi = perceived switching costs; ret = returns management.

to returns management (frequency = 177; raw consistency = 0.999).

4) Logical reduction and analysis of configuration
After the selection of those consideration that were consistent, a coverage measure is then calculated. Coverage represents the relevance of the combination and reflects the share of consistent memberships as a proportion of total memberships in the outcome set. It is comparable to the R-square value reported in correlational methods (Woodside, 2013).While consistency should be >0.8 the coverage is fixed as >0.01.
The software QCA reports raw and unique coverage scores. Raw coverage indicates the extent of overlap of the size of the configuration set and the outcome set relative to the size of the outcome set; unique coverage controls for overlapping explanations by partitioning the raw coverage. These indicators assist us in assessing the empirical relevance of configural statements (Ragin, 2008).

5.2.2. Findings from the QCA

Table 3 shows the coverage and consistency of the four combinations that the software has selected to be "sufficient" with the four steps following Ordanini's procedure: that is the logical reduction. In addition it report overall solution consistency and coverage.

For the presence of high customer loyalty, configuration 1 reflects a combination of the abscence of satisfaction, customer value and perceived switching. This configuration represents the case where respondents declared to be loyal independetly from their overall evaluation of value, level of satisfaction and perceived switching costs. Configuration 2 combines the presence of perceived switching costs with the absence of satisfaction and returns management. Configuration 3 includes the combination of customer value, perceived switching costs. However, these respondents also experience a very low level of returns management, as indicated by the absence of returns management. Finally, configuration 4 identifies a combination of the presence of satisfaction, customer value and returns management.

The existence of multiple sufficient configurations for customer loyalty indicates equifinality (Fiss, 2011). This result provides support for Proposition 3, Thus, the presence and absence of causal conditions can explain an outcome, depending on how these conditions combine with one or more other causal conditions (Leischnig & Kasper-Brauer, 2015; Woodside, 2014; Wu et al., 2014).

Regarding the coverage, the results indicate an overall solution coverage of .87 and overall consistency of .96, which indicate that a substantial proportion of the outcome is covered by the four configurations. For the particular configurations, the results show that configuration 3 achieves the greatest values for both raw coverage (value .81) and unique coverage (value .44), stating that this combination which combines the presence of high customer value and high perceived switching costs and the absence of returns management represent the most significant and representation of customer loyalty.

5.2.3. Predictive validity

When examining our proposed models, it is important to provide evidence that such models predict a dependent variable in additional samples (Gigerenzer & Brighton, 2009; McClelland, 1998). Holdout samples (i.e., samples that are separate data sets from the data set) can be used to test for predictive validity. As such, we split our sample into a modeling subsample and a holdout sample. The results in Table 4 use the first half of the 317 cases to indicate the patterns of complex antecedent conditions to loyalty. The results for testing model 3 (the most relevant model) predictions on the data in the second sample appear below the models in Table 4. The results suggest a highly consistent model (C1 = 1.000) and high coverage (C2 = 0.767).

6. Discussion, conclusions, limitations, and future research

The role of customer loyalty as a key contributor to firm competitive advantage has been consistently highlighted by business scholars (Kumar et al., 2013; Picón et al., 2014). Past research has identified various predictors of customer loyalty; however, extant studies concentrate exclusively on the main 'net effects' of these antecedents. Using complexity theory as our theoretical lens, we make several noteworthy contributions to the loyalty literature.

Our results indicate that an individual attribute can contribute positively or negatively to customer loyalty depending on the presence or absence of other factors. For example, Blocker et al. (2011) and Blocker (2011) explored the intricate relationship between customer value, customer satisfaction and customer loyalty by evaluating the 'net effects'. Our study is the first in the business to business area of research to indicate that, when others factors are considered (e.g., switching costs and returns management), the impact of these variables on loyalty can change. We have several interesting findings in this area. Our first configuration indicates that a firm can experience high customer loyalty in the abscence of satisfaction, customer value and perceived switching. In essence, some respondents declared to be loyal independent from their overall evaluation of value, level of satisfaction and perceived switching costs. This is a key contribution to the literature and probably the most intriquing configuration as it offers a very different perspective on the sources of customer loyalty, as compared to existing loyalty research. A possible explanation can be found in the B2C service quality literature, where studies indicate that customers can keep coming back and stay loyal simply because of laziness or acting out of habit (Hansemark & Albinsson, 2004; Mauri, 2003). This can have important implications for managers. If companies can successfully profile customers, in terms of habits and "degree of laziness", they could potentially retain some unsatisfied customer although they perceive the value offering and switching costs to be low. Future research can investigate this possibility. Importantly, we are not encouraging companies to offer less to their customers, but rather we seek to offer deeper insights into customer behavior.

Our second configuration indicates that the presence of perceived switching costs with the absence of satisfaction and returns management can lead to customer loyalty. This complements the existing literature investigating the impact of satisfaction on customer loyalty (Lam et al., 2004; Picón et al., 2014). Interestingly, our findings indicate that unsatisfied customers who don't perceive the firm's returns management processes to be adequate can remain loyal if they perceive the switching costs to be high. Suppliers who struggle to improve customer satisfaction and offer little in the area of returns management can try to focus on switching costs to ensure the desired level of customer loyalty is achieved.

Our third configuration suggests that the combination of customer value, perceived switching costs, and perceived inadequate returns management processes can lead to customer loyalty. This complements current research highlighting the overwhelming importance of customer value for customer retention (Blocker, 2011).

Finally, our fourth configuration shows that the presence of satisfaction, customer value and returns management can help retain customers. This finding complements past studies that have explored

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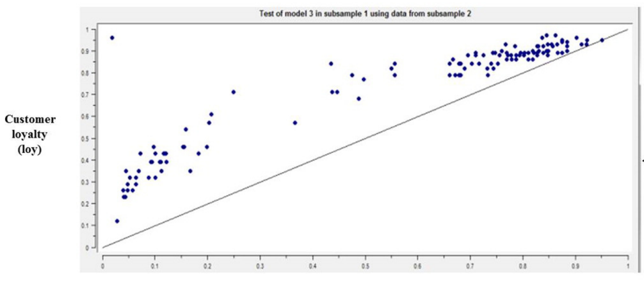
Table 4
Predictive validity testing.

Models from Subsample 1

```
                      raw        unique
                    coverage    coverage    consistency
                   ----------  ----------  ----------
~swi*~cv*~sat      0.136034    0.020670    0.766526
~ret*swi*~sat      0.390503    0.016201    0.990085
~ret*swi*cv        0.788269    0.405029    0.990059
ret*cv*sat         0.145345    0.048976    0.968963
solution coverage: 0.882868
solution consistency: 0.940022
```



XY Plot of Model 3

the 'net effects' of these variables on customer loyalty and found a positive significant relationship (Blut et al., 2014; Chandrashekaran et al., 2007; Pick & Eisend, 2014). Interestingly, this is the only combination in our data set where product returns management was found to positively contribute to customer loyalty. In the other combinations it did not emerge as a factor that can enhance customer loyalty. This finding indicates that this process becomes relevant only when other factors are considered as satisfactory by customers.

In summary, our results indicate that simple antecedent conditions can be necessary but insufficient for high customer loyalty. Furthermore, different combinations of antecedents can lead to customer loyalty. These important findings shed light on the complexity of the process that leads to customer loyalty. In essence, our study provides evidence that customer loyalty can't be accurately explained without acknowledging the complex reality in which this variable manifests itself. The relationships between customer loyalty antecedents can be non-linear with abrupt switches, so the same antecedent can, in certain circumstances, have a different impact on it. As such, our findings indicate that despite the long tradition of customer loyalty research, because of the past methodologies employed and the complexity of the phenomenon, significant work remains to be done to develop a better understanding of how firms can achieve customer loyalty. Future research in this area should be fruitful and can address the inherent limitations associated with any single study.

Our study investigated how firms can achieve high levels of customer loyalty under different configurations of perceived switching costs, returns management, customer value, and customer satisfaction. As such, one limitation of our study is that we considered a limited number of factors that can impact customer loyalty.

Future research should consider other possible combinations and explore how the impact of these antecedents on customer loyalty changes when other variables are considered. For example, it would be interesting to account for the impact of laziness and habit. This would also help better explain our findings, particularly the first proposed combination. Another limitation of our study is that we employed a single method to explore the topic of interest. Consistent with complexity theory, future research can also employ a qualitative approach to better understand the complexity within which the phenomenon of customer loyalty manifests itself. Such an approach can further help with our first suggested avenue for future research as it can help identify additional potential antecedents or factors that impact customer loyalty. Finally, we employed perceptual data to measure the variables of interest. This is a limitation of our study. Future research could incorporate secondary data (e.g., sales data, volume of product returns) to capture some of the constructs of interest.

Appendix A

Measurement item description and confirmatory factor analysis

Item	Coefficient α	Composite reliability	Average variance extracted
Customer value (adapted from Blocker, 2011; Ulaga & Eggert, 2006; level of agreement on a scale from 1 (strongly disagree) to 7 (strongly agree)) - Our main supplier creates greater value for us when comparing all the costs versus benefits in the relationship. - The benefits we gain in our relationship with this provider far outweigh the costs. - Our company gets significant customer value from this provider relationship.	*0.704*	*0.702*	*0.583*
Customer satisfaction (adapted from Lam et al., 2004; Flint et al., 2011; level of agreement on a scale from 1 (strongly disagree) to 7 (strongly agree)) - In general, my company is very satisfied with the services offered by this provider. - Overall, my company is very satisfied with its relationship with this provider. - Overall, how satisfied is your company with this provider?	*0.737*	*0.764*	*0.501*
Perceived switching costs (adapted from Lam et al., 2004; Pick & Eisend, 2014; level of agreement on a scale from 1 (strongly disagree) to 7 (strongly agree)) - It would cost my company a lot of money to switch from this supplier to another one. - It would take my company a lot of effort to switch from this supplier to another one. - It would take my company a lot of time to switch from this supplier to another one. - If my company changed from this supplier to another one, some new technological problems would arise. - My company would feel uncertain if we have to choose a new supplier.	*0.974*	*0.974*	*0.882*
Product returns management (adapted from Mollenkopf et al., 2007; level of agreement on a scale from 1 (strongly disagree) to 7 (strongly agree)) - The main supplier offers a meaningful guarantee on returns product. - The main supplier takes care of problems promptly in the returns flow. - The main supplier allows to take back products for consumer reasons.	*0.765*	*0.782*	*0.550*
Customer loyalty (adapted from Blocker et al., 2011; level of agreement on a scale from 1 (strongly disagree) to 7 (strongly agree)) - Given that there is a need, we intend to continue doing business with this provider for the foreseeable future - Given that there is a need, how likely is it that your firm will continue doing business with this provider during the next year? - Given that there is a need, how likely is it that your firm will continue doing business with this provider during the next 3 to 5 years?	*0.705*	*0.764*	*0.501*

Appendix B

Two outcomes: Switching costs (swi) and customer loyalty (loy)

Cases supporting the large main effect: A->O

Negative contrariaran cases indicating ~A->O

			Loy					Total
			1.00	2.00	3.00	4.00	5.00	
swi	1.00	Count	44	20	0	0	0	64
		% within swi	68.8%	31.2%	0.0%	0.0%	0.0%	100.0%
	2.00	Count	10	42	10	0	1	63
		% within swi	15.9%	66.7%	15.9%	0.0%	1.6%	100.0%
	3.00	Count	0	4	29	15	7	55
		% within swi	0.0%	7.3%	52.7%	27.3%	12.7%	100.0%
	4.00	Count	0	4	17	34	22	77
		% within swi	0.0%	5.2%	22.1%	44.2%	28.6%	100.0%
	5.00	Count	0	2	7	20	29	58
		% within swi	0.0%	3.4%	12.1%	34.5%	50.0%	100.0%
Total		Count	54	72	63	69	59	317
		% within swi	17.0%	22.7%	19.9%	21.8%	18.6%	100.0%

Positive contrariaran cases indicating A-> ~O

Phi= 1.076, p<.0000

Note: A= antecedent condition; O = outcome condition

Two outcomes: Customer value (cv) and customer loyalty (loy)

Cases supporting the large main effect: A->O

Negative contrariaran cases indicating ~A->O

			Loy					Total
			1.00	2.00	3.00	4.00	5.00	
cv	1.00	Count	24	19	25	4	0	72
		% within cv	33.3%	26.4%	34.7%	5.6%	0.0%	100.0%
	2.00	Count	24	12	22	14	0	72
		% within cv	33.3%	16.7%	30.6%	19.4%	0.0%	100.0%
	3.00	Count	5	26	12	30	1	74
		% within cv	6.8%	35.1%	16.2%	40.5%	1.4%	100.0%
	4.00	Count	1	14	1	17	17	50
		% within cv	2.0%	28.0%	2.0%	34.0%	34.0%	100.0%
	5.00	Count	0	1	3	4	41	49
		% within cv	0.0%	2.0%	6.1%	8.2%	83.7%	100.0%
Total		Count	54	72	63	69	59	317
		% within cv	17.0%	22.7%	19.9%	21.8%	18.6%	100.0%

Positive contrariaran cases indicating A-> ~O

Phi= 0.921, p<.0000

Note: A= antecedent condition; O = outcome condition

Two outcomes: Customer satisfaction (sat) and customer loyalty (loy)

Cases supporting the large main effect: A->O

Negative contrariaran cases indicating ~A->O

			Loy					Total
			1.00	2.00	3.00	4.00	5.00	
sat	1.00	Count	50	8	0	0	0	58
		% within sat	86.2%	13.8%	0.0%	0.0%	0.0%	100.0%
	2.00	Count	4	58	3	0	0	65
		% within sat	6.2%	89.2%	4.6%	0.0%	0.0%	100.0%
	3.00	Count	0	4	49	22	1	76
		% within sat	0.0%	5.3%	64.5%	28.9%	1.3%	100.0%
	4.00	Count	0	0	9	36	10	55
		% within sat	0.0%	0.0%	16.4%	65.5%	18.2%	100.0%
	5.00	Count	0	2	2	11	48	63
		% within sat	0.0%	3.2%	3.2%	17.5%	76.2%	100.0%
Total		Count	54	72	63	69	59	317
		% within sat	17.0%	22.7%	19.9%	21.8%	18.6%	100.0%

Positive contrariaran cases indicating A-> ~O

Phi= 1.477, p<.0000

Note: A= antecedent condition; O = outcome condition

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