A roadmap for applying qualitative comparative analysis in supply chain research
The reverse supply chain case

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Abstract

Purpose – The purpose of this paper is to introduce qualitative comparative analysis (QCA) to the field of supply chain management and provide a detailed roadmap that supply chain researchers can utilize when applying this methodology.

Design/methodology/approach – Data collection focused on the evaluation of product returns management practices as perceived by business customers who operate in a supplier–customer context. In order to analyze the data using the QCA approach, a multi-step analysis was developed.

Findings – The results indicate five solutions that lead to high levels of customer satisfaction. The existence of multiple sufficient configurations for customer satisfaction indicates equifinality because multiple alternative solutions can lead to the same outcome.

Research limitations/implications – The authors make a methodological contribution by applying the QCA method to the field of supply chain management and providing a detailed roadmap that supply chain researchers can utilize.

Practical implications – The authors provide managers five different and novel combinations of antecedents that lead to higher levels of customer satisfaction.

Originality/value – This study offers supply chain researchers a better understanding of when it is appropriate to use QCA and how to apply this methodology. From a theoretical perspective, past studies focused exclusively on the "net effects" of these antecedents, thus, did not capture the complexity of the relationships between these various antecedents and customer satisfaction. This is a noteworthy contribution as it highlights the complexity of the amalgam of relationships and factors that impact customer satisfaction within the context of reverse supply chain.

Keywords Customer satisfaction, QCA, Complexity theory, Qualitative comparative analysis,
Configural analysis, Reverse supply chain, Supply chain research

Paper type Research paper

Introduction

In today's complex and dynamic business environment, supply chain managers must consider multiple factors when making decisions (Gligor *et al.*, 2015). Consider the following scenario, in which a customer reports being very satisfied with the supplier's on-time delivery, responsiveness, order accuracy and reverse logistics, yet does not intend to buy again from the supplier; while another customer reports not being satisfied with the supplier's on-time delivery but satisfied with the supplier's responsiveness, order accuracy and reverse logistics, yet he intends to purchase again from the supplier. Traditional research methods would be limited in their ability to shed light on such apparently

confounding results, as these approaches are usually symmetric and do not encompass different "solutions" to account for the complex situations that firms might experience. To address this limitation, we introduce qualitative comparative analysis (QCA) to the field of supply chain management and provide detailed steps that supply chain researchers can follow when utilizing this methodology.

QCA is a technique that combines qualitative investigation with quantitative analysis through a configural analysis to explain complex situations, such as the one described above (Kraus *et al.*, 2018). In detail, QCA helps identify how various causal attributes combined into different configurations lead to an outcome of interest (conjunctural causation) and assess whether multiple sufficient configurations lead to the same outcome (equifinality) (Rihoux and Ragin, 2008; Fiss, 2011; Greckhamer *et al.*, 2008). Moreover, when a variable leads to an output, this does not mean that its reverse leads to the reverse output (asymmetry) (Wu *et al.*, 2014; Schneider and Wagemann, 2010). This method also allows researchers to identify contrarian cases. For example, in our anecdotal story, the satisfied customer reports no intention to repurchase from the supplier although he reports being satisfied with various aspects of the logistics service. The first anecdotal scenario is an example of a "negative contrarian case" where different positive associations result in a negative outcome, while the second one is an example of a "positive contrarian case" where a specific combination of negative and positive associations result in a positive outcome. As such, QCA allows analysts to uncover that within one data set, there can exist instances where one variable can relate to another positively, negatively or not at all; yet the overall relationship between the two variables may be significant and positive (Misangyi *et al.*, 2017; Ordanini *et al.*, 2014). In sum, this method allows data analysts to gain a richer and deeper perspective on small data samples going beyond the "all-or-nothing" association presumed by traditional statistical models such as multiple regression analysis or structural equation modeling (Rihoux and Ragin, 2008; Schneider and Wagemann, 2006; Woodside, 2018a, b). Traditional methodological approaches employ symmetric statistical tests that report the net effects of independent variables on dependent variables and do not take into consideration asymmetric relationships among independent variables and dependent variables (Fiss, 2011; Rihoux and Grimm, 2006).

Complexity theory prompts the consideration of QCA when evaluating complex supply chain phenomena. That is, compared to regression analysis, QCA can better explain phenomena when relationships between variables appear to be non-linear, inconsistent or statistically insignificant (Armstrong, 2012). 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). Thus, scholars in other disciplines (e.g. political science, sociology, organization studies, general management and marketing) have started to develop models via configural analysis of "recipes" of independent variables (i.e. QCA) to provide more granular explanations for cases where X affects Y positively, X affects Y negatively, and X is not relevant to the state of Y (Fiss, 2011; Greckhamer *et al.*, 2008, 2013; Kan *et al.*, 2016; Kent, 2005; Miethe and Drass, 1999; Ordanini *et al.*, 2014; Ragin, 1987, 2000; Ragin and Fiss, 2008; Rihoux *et al.*, 2013; Rihoux and Grimm, 2006; Rihoux and Ragin, 2008; Schneider *et al.*, 2010; Kraus *et al.*, 2018; De Villiers, 2017; Gabriel *et al.*, 2018). More recently, this methodology has also been introduced to the purchasing and supply management domain (Karatzas *et al.*, 2016; Kosmol *et al.*, 2018; Timmer and Kaufmann, 2017). QCA uses Boolean algebra rules that assign a membership to cases across a configuration of conditions where variables can be coded with "0" or "1," and thus must be dichotomized in "no membership" or "full membership," respectively, (e.g. when measuring "satisfaction" using a 1–7 Likert scale, an answer between 1 and 3 would be assigned to "unsatisfied" while 5–7 would indicate "satisfied"). This method allows researchers to identify how different combinations of

antecedents, rather than individual antecedents, act as sufficient or necessary conditions for the outcome (Fiss, 2007; Hsiao *et al.*, 2015; Schneider *et al.*, 2010).

One area within supply chain management that can greatly benefit from the rich explanatory power of QCA lies in the realm of the reverse supply chain (RSC). After two decades of evolution, RSC remains an increasing challenge for companies because it represents both a cost driver and an opportunity to improve customer service. Scholars have proposed several models for how managers can better manage product returns to increase satisfaction across the supply chain (i.e. Govindan *et al.*, 2015; Wang *et al.*, 2017). Although these models help identify various predictors of specific outcomes, previous studies concentrate exclusively on the net effects of these antecedents. Yet, complexity theory suggests that these relationships can be more complex than a simple positive or negative correlation would indicate. To explore this possibility, we employ the QCA methodology to a complex phenomenon to examine whether firms can achieve high levels of customer satisfaction by employing different configurations of specific reverse flow and operational antecedents. This offers richer insights into RSC operations and practices than conventional methods, such as regression analysis. Specifically, the following research question is put forward:

RQ1. What configurations of distinct RSC operations lead to customer satisfaction?

We seek to make both methodological and theoretical contributions within the domain of logistics and supply chain management. First, we make an important methodological contribution by applying the QCA method to the field of supply chain management. This method allows scholars to go beyond exploring the net effects of independent variables on dependent variables. In conjunction with complexity theory, this method helps provide a deeper understanding of the relationship between variables. QCA allows researchers to explore how different combinations of the same antecedents can lead to the same outcome. Crafting and testing theories of main and interaction effects alone might not always capture the complexity of the relationships among various supply chain phenomena. We make a significant methodological contribution by providing detailed steps that researchers can follow to execute the QCA method. Thus, we hope this study will lead supply chain scholars to adopt QCA, primarily in situations where the phenomenon under investigation is complex and/or the research sample is too small for the application of multiple regression analysis (QCA allows data analysis for smaller samples than regression analysis).

Second, by applying this method to the RSC area, we contribute to the literature by offering a more comprehensive understanding of the factors that help firms achieve a competitive advantage. Specifically, we explore how combinations of different attributes related to RSC lead to customer satisfaction. QCA allows us to move beyond the analysis of the net effects of each variable. The focus on net effects is derived from the assumption that the antecedents/predictors are independent and additive in their ability to influence the outcome (Ragin, 2008). In addition, net effects do not reveal all aspects of reality because not all cases lead to an exclusive negative or positive relationship between the independent and dependent variables. Further, QCA allows researchers to uncover possible asymmetrical relationships (Woodside and Baxter, 2013; Timmer and Kaufmann, 2017). As such, QCA allowed us to identify five distinct configurations that lead to customer satisfaction and, thus, offer a more granular understanding of the value creation process in RSC management. Relevant managerial implications are also derived from our findings.

The rest of the paper is organized as follows. The following section presents the main tenets of complexity theory to ground our theoretical approach and highlight its relevance to supply chain research. Next, we introduce the attributes related to returns management that are considered in the model. The study continues with an overview of the QCA method. Finally, we discuss the findings, contributions, and then conclude with limitations and opportunities for future research.

Background literature

Applying complexity theory in the supply chain context

Complexity theory argues that multiple paths (e.g. on-time delivery, responsiveness, order accuracy) can lead to the same outcome (e.g. customer satisfaction). Specifically, different combinations of indicators can be sufficient, but no single combination must occur to predict an outcome. This principle is also referred to as "equifinality" (Woodside, 2015). In addition, models that predict a certain outcome (e.g. high customer satisfaction) are not the mirror opposite of models that predict the opposite of that outcome (e.g. low customer satisfaction). Both outcomes can occur as a consequence of different sets of complex antecedent configurations. Further, no one condition (e.g. on-time delivery, responsiveness) is sufficient for either outcome to occur (Woodside, 2015). Interestingly, complexity theory also recognizes that the plethora of necessary conditions can never be fully explained (Byrne, 1998). According to this theory, reality is too complex to be fully captured by any single model. Researchers should strive to capture as many elements as possible in their explanatory models, but also acknowledge the impossibility of accounting for all the factors that might influence their outcome variable(s).

The degree of complexity is derived from the structural properties of the system, as determined by the number and variety of elements defining the supply chain and their interactions (e.g. the number of participants, facilities, and warehouses, stock keeping units, transportation links and the distance, information, product and financial flows, multichannel and/or omni-channel) (Nilsson and Gammelgaard 2012; Carter *et al.*, 2015; Russo and Confente, 2017). Applying complexity theory allows scholars to have a deeper and richer perspective of the data, and superior predictive accuracy using algorithms vs regression models, particularly in social sciences (Gigerenzer and Brighton, 2009; Sterman and Wittenberg, 1999; Woodside, 2018b).

Supply chain management in general, and the area of returns management in particular, examines complex phenomena where different combinations of indicators can yield similar outcomes. This makes the application of QCA to this area fruitful. Examples of such "causal complexity" (Ragin, 2000) are identified and empirically examined in this study.

A configuration model of customer satisfaction deriving from returns management operations and practices

To identify the various combinations of returns management-related antecedents that result in high levels of customer satisfaction, we review the literature to uncover different aspects of returns management that have been previously suggested to impact customer satisfaction. Table I provides a summary of the literature review supporting this premise.

Construct	Main references
Product returns practices (PRP)	Rogers *et al.* (2008), Mollenkopf *et al.* (2011) and Huang *et al.* (2016)
Product returns recovery practices (PRECP)	Thierry *et al.* (1995), Stock and Mulki (2009) and Huang *et al.* (2016)
Product returns recovery responsiveness (RECRESP)	Parasuraman *et al.* (2005) and Russo *et al.* (2017)
Commitment of resources to managing returned products (COMMRES)	Richey *et al.* (2005) and Huang *et al.* (2016)
Returns satisfaction (RETSAT)	Mollenkopf *et al.* (2007)
Customer satisfaction (SAT)	Cannon and Perreault (1999) and Homburg *et al.* (2014)

Table I.
Dimensions
considered
in the study

Customer satisfaction and returns satisfaction
The concept of customer satisfaction has been widely explored in the marketing and service disciplines over the last few decades. Nevertheless, it is not possible to identify a generally accepted definition, partly because there are different interpretations of the concept: one linked to single transactions, and one associated with cumulative transactions. We conceptualize customer satisfaction as a cumulative evaluation of the purchase and consumption of products and services from a supplier (Anderson *et al.*, 1994; Cannon and Perreault, 1999; Homburg *et al.*, 2014; Parasuraman *et al.*, 2005).

From a logistics perspective, customer satisfaction is defined as the result of a cognitive and affective evaluation, based on the overall purchase and consumption experience with the logistics service over time; several scholars explore why, how and when the relationship between customer service and customer satisfaction holds and has a positive impact on performance (Davis-Sramek *et al.*, 2008; Ellinger *et al.*, 1999; Leuschner *et al.*, 2014). A recent study by Pellathy *et al.* (2018) described how different elements of middle-range theorizing could be applied to examine logistics customer service and called for more research on reverse logistics, considering product returns a critical determinant of logistics customer service. Most firms experience returns, but few firms manage them successfully or are able to recognize the hidden value of proper returns management as a means to enhance customer satisfaction (Griffis *et al.*, 2012). One popular method for assessing the success of returns processes is to evaluate return satisfaction, which encompasses the customer's perceptions of the specific process of performing a return – the instructions, the return process itself, and the credit process (Govindan *et al.*, 2015; Mollenkopf *et al.*, 2007; Rao *et al.*, 2018).

Returns management plays a key role in the positioning of a company's customer service and also represents a way to improve supplier and customer relationships. At a strategic level, firms need to develop procedures to identify avoidance opportunities through improved product design, testing and quality control. Similarly, gatekeeping rules can limit products from entering the returns flow by setting appropriate returns policies and procedures. While at an operational level firms should seek to identify and eliminate unnecessary returns managed by the supply chain and try to recover value (Mollenkopf *et al*, 2016), better planning at the strategic level can pre-empt returns.

Although previous research has explored the importance of returns management, the extant studies have not investigated how combinations of different conditions related to returns management may affect customer satisfaction. Rather, past studies focused on these distinct conditions in isolation from one another. Identifying the different combinations of returns management conditions that lead to high customer satisfaction helps integrate this fragmented body of literature on returns management and also offers a more comprehensive and complex perspective on the phenomenon.

Product return practices and product recovery practices
Consistent with Huang *et al.* (2016), we divide returns management into product returns practices and product recovery practices. This allows us to gain a more detailed understanding of the factors that impact customer satisfaction. We consider product returns practices to be composed of returns avoidance, receiving and processing a used or defective product with the goal of remanufacturing, reuse or destruction. Specifically, returns avoidance entails preventing returns from occurring at the downstream level. For example, one way to minimize the number of returns is by improving product quality, creating products that are easy to use, and training frontline staff to better assist customers (Rogers *et al.*, 2008; Mollenkopf *et al.*, 2011). Receiving refers to the unloading, distributing and sorting of product returns at processing centers. Processing includes activities aimed at sorting returns into groups based on their SKU number so that they can ultimately be

returned to inventory if they are in saleable condition, as well as other activities such as data entry and the issuing of customer credits (Stock and Mulki, 2009).

Product recovery practices refer to the recovery of the value of used or defective products by repairing, reconditioning and remanufacturing/recycling methods. These practices entail allocating and moving items according to their determined destinations in the supply chain (i.e. return-to-stock, return-to-vendor, repair/refurbish/remanufacture and salvage/scrap) (Stock and Mulki, 2009). Customers increasingly demand warranties, take-backs, changes and repairs, therefore, presenting firms with both challenges and opportunities to enhance customer satisfaction (Blackburn *et al.*, 2004; Röllecke *et al.*, 2017). As such, product recovery practices are the first element considered in our recipes of RSC elements that can lead to customer satisfaction.

Product recovery responsiveness
Recovery responsiveness is an important topic within supply chain research. A supply chain's ability to respond to, and recover from, unpredictable changes in demand and supply within a short amount of time is a significant source of competitive advantage (Gunasekaran *et al.*, 2015; Ponomarov and Holcomb, 2009). Product recovery practices are defined as the management of the phases related to the remanufacture of returned items: the choice of whether to repair the product, recondition or remanufacture it, or to proceed with a recycling method (Ferguson *et al.*, 2011; Guide and Van Wassenhove, 2009; Thierry *et al.*, 1995). Thus, product recovery responsiveness refers to the speed with which these phases are executed and the time that customers have to wait before a prompt response (Mollenkopf *et al.*, 2007). This aspect of RSC has been noted as a source of satisfaction in the extant literature. For example, Guide *et al.* (2006) use queuing networks to highlight the value of speed of recovery for time-sensitive consumer returns such as consumer electronics and argue that unsatisfactory speed of recovery can lead to customer dissatisfaction (Rogers *et al.*, 2012). On the contrary, effective returns processing through timely returns management can contribute to customers' perception of value creation (Mollenkopf *et al.*, 2011). Thus, product recovery responsiveness is the second element considered in our recipes of RSC elements that can lead to customer satisfaction.

Commitment of resources to managing returns
The RSC literature has explored the role of commitment of resources in managing returns. The concept captures the extent of effort and expenditures devoted to managing returns. Li and Olorunniwo (2008, p. 384) state that "commitments in terms of leadership support, financial and personnel resources as well as investment in technological innovation in reverse logistics are important to the success of a firm." These resources can be described as the capital equipment needed for the recovery, availability of financial resources, employees' skills in managing returned items, and management's efforts in planning and investing in technological innovation (Morgan *et al.*, 2016).

Richey *et al.* (2004) divide the commitment of resources into three components: technological, managerial and financial. Later, Daugherty *et al.* (2005) highlighted the relevance of commitment of resources to the development of returns and reverse logistics capabilities. More recently, Huang *et al.* (2016) show that commitment of resources (e.g. technological, managerial and financial) positively and significantly moderates the relationship between institutional pressure and product returns practices. Thus, commitment of resources to managing returns is the third element considered in our recipes of RSC elements that can lead to customer satisfaction.

Different studies have focused on these distinct elements in isolation and explored how they individually impact returns management performance and customer satisfaction. Our study considers these elements together and seeks to determine the various

combinations (i.e. recipes) that lead to customer satisfaction. However, according to complexity theory, different elements in a recipe can positively or negatively impact the outcome variable depending on the presence or absence of other elements in the recipe (Woodside, 2015). Thus, we consider the following:

P1. An individual attribute in a recipe can contribute positively or negatively to customer satisfaction, depending on the presence or absence of other ingredients (product returns practices, product returns recovery practices, product returns recovery responsiveness, commitment of resources to managing returns product, returns satisfaction, percentage of returns rate and level of expenditure with respect to the main supplier).

In addition, complexity theory argues that any single element can be necessary, but is not necessarily sufficient to predict the outcome variable; rather, any element must be combined with other elements (Wu *et al.*, 2014). Thus, we explore the following:

P2. A single ingredient can be necessary but insufficient for high customer satisfaction and it must be combined with other ingredients.

Further, complexity theory posits that multiple paths or different combinations of elements can lead to the same outcome (Woodside, 2015). That is, different recipes of RSC attributes can exist for customer satisfaction. Thus, we empirically investigate the following:

P3. Disparate configurations of RSC attributes (product returns practices, product returns recovery practices, product returns recovery responsiveness, commitment of resources to managing returns product, returns satisfaction, percentage of returns rate and level of expenditure with respect to the main supplier) are equifinal in leading to high customer satisfaction.

Research method
Data collection, survey development and sampling
Data collection focused on the evaluation of product returns management practices as perceived by business customers who operate within the health care industry in a supplier–customer context.

The health care industry was chosen for several reasons. Investigating the health care industry through tools commonly applied in business management and supply chain management research has a wide diffusion (Russo *et al.*, 2016; Abdulsalam *et al.*, 2015; Simpson *et al.*, 2015). This industry has complex product offerings, and buyers within this industry (i.e. audiologists) require reliable suppliers (Kochkin *et al.*, 2010). Buyers frequently have to return products to suppliers, which make this field ripe for the exploration of returns management and its impact on customer satisfaction.

The study participants were selected from independent retailers in Italy who served as a primary commercial distribution channel for hearing aid manufacturers. Independent retailers are often audiologists who act as key informants and purchase products/services from the hearing aid suppliers (the manufacturer) and re-sell them to patients. To define the potential participants of our final sample, we used the following criteria. Participants were health care professionals who: were permitted by law to re-sell hearing aids, were operating a business at the retail level, were entrepreneurs running their own business, and had the freedom to choose their suppliers. Based on these criteria, we selected 500 customers belonging to the Italian Audiologists Association (FIA).

In 2017, a personalized survey packet was presented to each audiologist during the most important National Hearing Conference in Italy (Società Italiana Otorinolaringoiatria).

The survey packet included a cover letter from the researchers and a self-administered questionnaire with instructions. We received 280 completed responses, a 56 percent response rate. Although collecting data in person at the conference using paper surveys resulted in a high response rate, these data collection approach did not allow us to contact non-respondents to fully assess non-response bias. However, considering the homogeneity of the population sampled (i.e. nationality, profession, expertise and business model employed) non-response bias was examined by comparing the answers of early and late respondents. No statistical difference was found between these two groups. We recognize this approach – although used extensively in the literature – is a limitation and note it accordingly. In addition, although we could not contact non-respondents, we obtained the list of all 500 delegates from the FIA and collected information related to these companies (turnover, demographics and size). Our analysis of these dimensions revealed that the 220 non-respondents had similar characteristics to those of the 280 respondents, as no statistically significant differences were detected.

Measurement of variables

The survey encompassed several topics related to the overall perceptions business customers have of their suppliers. An introductory section evaluated the main characteristics of the respondents (i.e. audiologists), such as their gender, age and years of experience. In addition, respondents were asked to provide information about their key supplier relationship (e.g. length of the partnership, total expenditure with their main supplier). A second section prompted respondents to evaluate the constructs of interest on a seven-point Likert scale.

All measures were adapted from existing scales, as illustrated in Table AI. A summary of the descriptive statistics is offered in Table II.

Customer satisfaction was assessed using a six-item scale adapted from Homburg *et al.* (2014), returns management satisfaction was assessed using a four-item scale from Mollenkopf *et al.* (2007), while for returns management the dimension was split into two constructs, as suggested by Huang *et al.* (2016): product returns practices and product recovery practices. To measure these two latter constructs we used the three-item scales proposed by Huang *et al.* (2016). Commitment of resources to returns management was measured using a three-item scale adapted from Huang *et al.* (2016), while for recovery responsiveness we utilized the four-item scale proposed by Parasuraman *et al.* (2005). In addition to these variables, we also evaluated the length of partnership with the supplier dimension (the number of years the participant had been a customer of this supplier) and the return rate, operationalized as the percentage of returns over the total sales that customers return to their suppliers.

Reliability was satisfactory for all scales, with α values ranging from 0.70 to 0.85. In aggregate, the results support construct unidimensionality.

Variables	N	Min.	Max.	Mean	SD
SAT	280	1.83	7.00	5.31	1.06
RETSAT	280	2.50	7.00	5.52	0.97
PRP	280	1.00	7.00	5.76	0.88
PRECP	280	1.33	7.00	5.15	1.29
COMMRES	280	2.00	7.00	5.84	0.88
RECRESP	280	1.50	7.00	5.45	1.04
Total respondents	280				

Table II.
Descriptive statistics

An asymmetric approach: qualitative comparative analysis

QCA is a set-theoretic method that empirically investigates the relationships between the outcome of interest (customer satisfaction in our study) and all possible combinations of binary states (i.e. presence or absence) of its predictors (Fiss, 2007; Ragin, 2000).

QCA is based on the principles of set theory, formal logic and Boolean and fuzzy algebra, and has gained importance in management studies for its role in performing configuration analyses (Greckhamer *et al.*, 2013; Ordanini *et al.*, 2014; Russo *et al.*, 2016; Schneider and Wagemann, 2006; Woodside, 2014).

Considering QCA's principles, our aim is not to exhaustively explain the basis of this analysis from a theoretical and epistemological perspective, but rather to provide an example of its use within the supply chain management field. QCA was initially implemented for small samples (15–40 cases), but recent studies have extended its application to larger samples (e.g. Kraus *et al.*, 2018; Leischnig *et al.*, 2017).

In order to analyze our data using the QCA approach, multi-step analysis is required. First, the contrarian case analysis is needed to verify the presence of contrarian cases by cross-tabulation. Second, a configural analysis is performed using fuzzy set QCA (fsQCA) software, to explore the existence of different combination of antecedents that lead to the same output (i.e. high levels of customer satisfaction). Next, we describe these phases in detail.

Contrarian case analysis

This analysis facilitates the understanding of the complexity of a phenomenon as it shows the existence of cases where the relationship among variables is not symmetric. For example, when X associates positively with Y with high correlation, the same data set may include cases of high X and low Y as well as cases of low X and high Y. However, most of the time, scholars ignore these contrarian cases in their research, considering only the main effect (Woodside, 2014).

Contrarian case analysis starts with a quintile analysis, which divides the respondent cases from the lowest to highest quintile for each measured construct and explores the relationships among two or more constructs (McClelland, 1998). To demonstrate the existence of contrarian cases, a contingency table considering quintiles needs to be created. This computation was performed using SPSS software. We considered customer satisfaction (SAT) and its relationship with all the antecedents illustrated in the "measurement of variables" section. Our results in Figure 1 indicate that the majority of these relationships are symmetric.

However, negative contrarian cases (see Figure 1, "negative contrarian cases" box) or positive contrarian cases (see Figure 1, "positive contrarian cases" box) may occur. The latter relationship (positive contrarian cases) is considered as symmetrical, but in the opposite direction. That is, a low degree of PRP leads to higher SAT, and a high degree of PRP leads to a lower degree of SAT. Some negative contrarian and positive contrarian cases are present within this relationship. The presence of contrarian cases can also be observed through the fuzzy XY plot (Figure 2), which indicates that the relationship between PRP and SAT is in some cases asymmetric. These contrarian cases impact the remainder of the cases that constitute the large main effect (high values of X that lead to high values of Y and low values of X that lead to low values of Y). This provides support for $P1$.

Next, we compare our results obtained using QCA with those obtained using a more traditional method, such as regression analysis. As illustrated in Table AII, the regression analysis results fail to provide a detailed perspective on the relationships between the variables of interest. Specifically, these results simply indicate a significant and positive correlation between the variables of interest, except for the returns rate and customer satisfaction. This further illustrates that such traditional methods do not have the ability to identify asymmetrical relationships. In addition, as we will detail in the next section,

SAT×PRP

			PRP					Total
			1.00	2.00	3.00	4.00	5.00	
SAT	1.00	Counts	52	5	9	3	4	73
		% in SAT	71.2%	6.8%	12.3%	4.1%	5.5%	100.0%
		% of total	18.6%	1.8%	3.2%	1.1%	1.4%	26.1%
	2.00	Counts	18	18	12	5	6	59
		% in SAT	30.5%	30.5%	20.3%	8.5%	10.2%	100.0%
		% of total	6.4%	6.4%	4.3%	1.8%	2.1%	21.1%
	3.00	Counts	4	5	9	12	13	43
		% in SAT	9.3%	11.6%	20.9%	27.9%	30.2%	100.0%
		% of total	1.4%	1.8%	3.2%	4.3%	4.6%	15.4%
	4.00	Counts	2	4	25	21	10	62
		% in SAT	3.2%	6.5%	40.3%	33.9%	16.1%	100.0%
		% of total	0.7%	1.4%	8.9%	7.5%	3.6%	22.1%
	5.00	Counts	1	6	14	7	15	43
		% in SAT	2.3%	14.0%	32.6%	16.3%	34.9%	100.0%
		% of total	0.4%	2.1%	5.0%	2.5%	5.4%	15.4%
Total		Counts	77	38	69	48	48	280
		% in SAT	27.5%	13.6%	24.6%	17.1%	17.1%	100.0%
		% of total	27.5%	13.6%	24.6%	17.1%	17.1%	100.0%

Cases supporting the large main effect: A→O

Positive contrariaran cases indicating A→~O

Negative contrariaran cases indicating ~A→O

Figure 1.
Two outcomes:
product return
practices and
customer satisfaction

Notes: A=antecedent condition; O=outcome condition

QCA provides multiple paths, or recipes, for the same outcome, while regression analysis only offers one (Woodside, 2015).

After performing the contrarian analysis, the next step within the QCA method is to apply configural analysis to generate a deeper understanding of the data. This allows researchers to identify the combinations of variables that lead to the same level of output (Y). Our output is SAT and the aim is to identify the different recipes or combinations of ingredients (antecedents) that lead to a higher degree of customer satisfaction.

The procedure of qualitative comparative analysis
The four-step procedure, as suggested by Fiss (2011), is described below.

Defining the property space
QCA starts by defining the property space, where all possible configurations of the drivers of an outcome are identified. To find the most relevant drivers, we selected some of the most
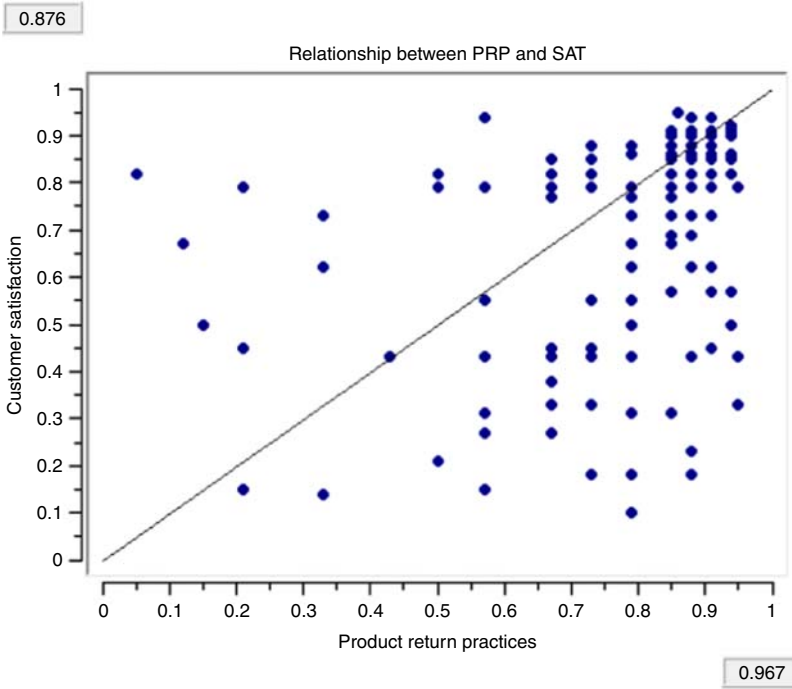
0.876

Relationship between PRP and SAT

0.967

important satisfaction drivers from the extant RSC literature. The property space consists of all combinations of binary states; that is, the presence or absence of the influence attributes that impact satisfaction. In our study these are return satisfaction (RETSAT), product returns practices (PRP), product recovery practices (PRECP), commitment of resources to managing product recovery (COMMRES), recovery responsiveness (RECRESP), length of partnership (LENGTH), returns rate. These combinations, or configurations, appear as rows in Table III (the truth table), where 0 is assigned to the attribute in the case of its absence (low scores) and 1 is assigned in the case of its presence (high scores). For instance, as illustrated in Table III, the first configuration in row 2 that leads to high levels of satisfaction contains all the attributes considered in our study (indicated by the number "1" assigned to them in row 2), except for the length of partnership variable (a score of "0" is assigned). This means that this potential recipe for reaching a high level of customer satisfaction is composed by high levels of all these attributes, but does not require a long-term relationship between the supplier and the customer.

Set membership measures
As our variables are not naturally dichotomous, we transformed them into fuzzy set membership scores, 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 0.5) (Ragin, 2008). As we needed to manage multiple item measures, the scale items were combined into an average score (Leischnig *et al.*, 2017). The endpoints and the midpoint of the seven-point Likert scales served as the three qualitative anchors for calibration of full membership (value 7), full non-membership (value 1) and the crossover point (value 4).

Table III.
Truth table

prp	precp	recresp	commres	retsat	returnsrate	lenght	number	sat	raw consist.	PRI consist.	SYM consist
1	1	1	1	1	1	0	97 (58%)	1	0.995498	0.993653	0.998065
1	1	1	1	1	0	1	13 (66%)	1	0.976014	0.925849	0.957707
1	0	1	1	1	1	0	9 (72%)	1	0.984135	0.919949	0.919950
1	1	1	1	0	1	0	5 (75%)	1	0.998052	0.990642	0.990642
1	1	0	1	1	1	0	5 (78%)	1	0.981127	0.866800	0.866800
1	0	1	1	1	0	1	4 (80%)	1	0.987070	0.927693	0.937792
1	0	0	1	1	1	1	4 (83%)	1	0.942776	0.459703	0.476782
1	1	1	1	1	1	1	2 (84%)	1	0.989635	0.976542	0.985965
1	1	1	1	1	0	0	2 (85%)	1	0.985234	0.943798	0.943799
1	1	1	0	0	1	1	2 (86%)	1	0.958233	0.482587	0.487438
1	1	0	1	1	0	1	2 (87%)	1	0.973953	0.796917	0.796917
1	0	1	1	1	1	1	2 (89%)	1	0.963411	0.731603	0.737992
1	0	1	1	0	1	1	2 (90%)	1	0.955116	0.537415	0.537416
1	0	0	1	0	1	1	2 (91%)	1	0.958781	0.493619	0.493619
0	0	1	1	1	0	1	2 (92%)	1	0.980400	0.807274	0.807271
1	1	1	0	1	1	1	1 (93%)	1	0.970236	0.785340	0.785342
1	1	0	1	1	1	1	1 (93%)	1	0.983558	0.825175	0.825174
1	0	1	0	1	1	1	1 (94%)	1	0.958113	0.455884	0.455884
1	0	1	0	0	1	1	1 (95%)	1	0.958796	0.369700	0.369700
1	0	0	1	0	0	1	1 (95%)	1	0.967598	0.549223	0.549224
0	1	1	1	1	1	1	1 (96%)	1	0.982201	0.681159	0.681157
0	1	1	1	1	0	0	1 (97%)	1	0.992822	0.896174	0.959064
0	1	1	0	0	0	0	1 (97%)	1	0.982963	0.181813	0.533327
0	1	0	1	1	0	1	1 (98%)	1	0.967679	0.601943	0.601943
0	0	1	1	1	1	0	1 (98%)	1	0.992438	0.801887	0.801888
0	0	1	0	1	0	1	1 (99%)	1	0.981858	0.596156	0.596154
0	0	0	1	1	1	1	1 (100%)	1	0.954458	0.186209	0.203009

After generating fuzzy set measures for individual attributes by applying Boolean algebra rules, membership scores must be determined for configurations by considering more than one attribute, which can be present or absent. In doing so, each respondent will have some degree of fuzzy membership in all configurations of the attributes, although it is assumed that there is only one configuration, called the best-fit case, where the membership measure is greater than 0.5 (Ordanini *et al.*, 2014).

Consistency in set relations
Next, we refined our truth table (Table III) using two preliminary criteria: frequency and consistency (Ragin, 2008). To define the frequency cut-off, we considered only those configurations exceeding a minimum number of empirical representations. The threshold for the frequency of medium-sized samples (e.g. 10–50 cases) is 1; this can be higher for large-scale samples (e.g. 150 or more cases) (Ragin, 2008). We kept only configurations that had at least three best-fit cases.

The column "number" in Table III shows the distribution of best-fit cases (customers) across the configurations in our sample. We considered the cases where SAT is equal to 1; that is, when the outcome of high satisfaction 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 the 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 (Russo *et al.*, 2016; Ordanini *et al.*, 2014). A configuration is defined as sufficient when its consistency measure exceeds a threshold, which we set in line with the QCA literature to 0.8 (Ragin, 2008).

Logical reduction and analysis of configurations
After the selection of the configurations that were consistent, a coverage measure is 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^2 value reported in correlational methods (Woodside and Baxter, 2013). While consistency should be greater than 0.8, coverage should exceed 0.01.

Main findings from the qualitative comparative analysis

The study results are reported in Table IV, which shows the number of combinations/solutions we obtained for each combination. Our findings indicate that five solutions/combinations lead to high levels of customer satisfaction. This supports P3, indicating equifinality in reaching high levels of customer satisfaction.

Following the guidelines suggested by Ragin and Fiss (2008), a useful way to represent the presence and absence of the variables in each combination can be realized as reported in Table IV, where black circles (●) indicate the presence of a condition, and circles with a cross (⊗) indicate its absence. In addition, as can be noted in the table, some circles are larger than others. These latter circles represent the "core conditions" that are included in the parsimonious solutions that must be included in any representation of the results, as they are the decisive causal ingredients. Conversely, smaller circles represent peripheral conditions within a recipe. This in line with P2, which states that no single ingredient alone can lead to the outcome, but that it must be combined with other ingredients. As a consequence, a necessary condition (larger circles) is not a sufficient one. Furthermore, a blank cell indicates the "do not care" condition, which means a specific condition is not considered in a solution.

With regard to the coverage, the findings indicate an overall solution coverage of 0.77 and an overall consistency of 0.96, suggesting that a substantial proportion of the outcome is covered by the five configurations. Of the five configurations, Solutions 2 and 4 are the ones with the highest raw coverage (values of 0.61 and 0.60, respectively), highlighting that this combination of attributes provides the best representation of customer satisfaction.

Solution 1 reflects a combination of the presence of returns satisfaction, product returns practices, commitment of resources to managing product returns, product returns recovery practices, length of partnership (all these variables are reported in Solution 1 with a black circle, indicating that to reach high customer satisfaction, these variables must be present in the solution) and the absence (a low percentage, represented by a circle with a cross) of a returns rate. That is, this configuration represents the case where respondents experience overall customer satisfaction when they are satisfied with return practices, they are

Configurations	Solutions				
	1	2	3	4	5
Return satisfaction	●	●	●		●
Product returns practices	●	●	●	●	●
Product recovery practices			●	●	⊗
Commitment of resources	●	●	●	●	●
Recovery responsiveness	●	●		●	⊗
Length of partnership	●	⊗	⊗	⊗	●
Returns rate	⊗	●	●	●	●
Consistency	0.97	0.99	0.98	0.99	0.94
Raw coverage	0.22	0.61	0.59	0.60	0.14
Unique coverage	0.10	0.01	0.01	0.01	0.01
Solution coverage	0.77				
Solution consistency	0.96				

Notes: ●, core causal condition present; ⊗, core causal condition absent

Table IV.
Configurations for achieving high customer satisfaction

long-term business partners, and they do not return many products. For this reason, they may not need a satisfying recovery practice as there is no urgency related to returns.

From Solutions 2 to 5, we have four clusters of cases where the returns rate is high and a high level of satisfaction depends on different combinations of antecedents. For instance, Solution 2 is constituted by a cluster of short-term business customers (this is represented in Solution 2 using a circle with a cross (⊗) for the variable "length of partnership", which means that this condition is not present in this solution) that return a lot (expressed in Table III with the use of a black circle when referring to "returns rate," meaning that this group of respondents, who have a high perception of satisfaction for the supplier, are also heavy returners), and value returns satisfaction, product returns practices, commitment of resources to managing product returns and product returns recovery responsiveness; this is illustrated in Solution 2 by the presence of black circles for each of these variables.

Solution 3 adds the presence of product recovery practices, which in some way substitutes for the role of recovery responsiveness in Solution 2 and is absent in Solution 3. That is, the presence of product recovery practices offsets the lack of recovery responsiveness, thus leading to a high level of satisfaction.

Solution 4 is the only one that contains overall return management satisfaction as a "do not care" variable (illustrated in Table III with a blank cell for the variable "return satisfaction"), while all the other dimensions related to specific return practices are relevant for achieving high customer satisfaction (reported in Table III with black circles) for respondents that are not long-term customers (length of partnership reports a circle with a cross, which means that the variable is absent).

Solution 5, along with Solution 1, includes the cluster of long-term customers who, in this case, return a lot (presence of the length of partnership plus high returns rate, both illustrated with a black circle); they are very satisfied with return practices and the commitment of resources involved in returns management, but are not concerned about recovery practices (as indicated by circles with a cross for these two variables, which means that for this combination these attributes are not necessary for customers to be highly satisfied). The variables that are present in each of the solutions are product returns practices and commitment of resources to managing product returns. This indicates that customers consider that both of these practices must be present in order to experience high levels of satisfaction with their suppliers.

Discussion, conclusions, limitations and future research
The goal of this study was to make both methodological and theoretical contributions within the domain of logistics and supply chain management. From a methodological perspective, this study provides a detailed perspective of the QCA approach. First, we describe the benefits of QCA as compared to traditional regression methods (Ordanini *et al.*, 2014; Woodside, 2015). QCA does not provide an explanation of the outcome; instead, it provides a statement of what is part of the explanation of an outcome (Baumgartner and Thiem, 2017). This offers supply chain researchers a better understanding of when it is more appropriate to use QCA. Second, we offer a detailed description of the steps involved when conducting QCA. Supply chain researchers can follow the roadmap provided in this study when executing a QCA analysis. Third, we offer a specific example of how to execute each step, and provide a detailed interpretation of the findings. As such, this study should spur additional research utilizing the QCA methodology within the domain of supply chain management.

Our study also makes some noteworthy contributions to the RSC management literature. Specifically, we concomitantly examined the impact of several factors previously considered within the RSC literature on customer satisfaction. While previous studies have presented disparate efforts to better understand sources of customer satisfaction (Wang *et al.*, 2017), the current study identifies how different combinations of these antecedents lead to high

levels of customer satisfaction. Further, past studies have focused exclusively on the net effects of these antecedents, and, thus, do not capture the complexity of the relationships between them and customer satisfaction. The current study offers a comprehensive perspective on these relationships. Specifically, five different combinations were found to lead to the same outcome (i.e. high customer satisfaction). This is an important finding, as it highlights the complexity of the amalgam of relationships and factors that impact customer satisfaction within the context of returns management.

The current study also makes important managerial contributions. By identifying five different combinations of antecedents that lead to customer satisfaction, managers are offered alternatives when exploring ways to increase their customers' satisfaction levels through returns management. Different firms have different resources available to them, and by offering managers several paths that lead to the same destination, they can better allocate their limited resources to select the path that is more appropriate for their firm, while considering their particular constraints. Further, our findings send a clear message to managers: there is flexibility in how they can configure their returns management operations. While some factors must be present within their firms' returns management (e.g. product returns practices, commitment of resources) some are not necessary (e.g. recovery responsiveness) and can be substituted with other factors (e.g. product recovery practices). As such, our paper's message contrasts with past studies suggesting that firms must possess certain reverse logistics factors for customers to be satisfied, while offering no alternatives to managers.

As with any study, ours has limitations, some of which can be addressed through future research. First, we explored the impact of seven antecedents on customer satisfaction. Further research can consider the role of additional antecedents. For example, future research should examine the type of returns (i.e. customers returns, returns because of damage and recall products), previous service experience, service recovery quality, perceived value and customer effort (Mollenkopf *et al.*, 2007). This should provide a better understanding of the sources of customer satisfaction within a returns management context. Such future studies would make important managerial contributions, primarily in the e-commerce business and omni-channel retail environments where product returns management processes are becoming increasingly critical (Mola *et al.*, 2017; Rao *et al.*, 2018).

Second, we utilized a sample of Italian firms within the audiology industry. Future research should test these relationships within different industries to provide additional evidence of generalizability for the findings. In addition, while our data collection method allowed us to achieve a relatively high response rate, it also negatively impacted our ability to test non-response bias. Future research replicating our study in a different context could help address this limitation. In addition, study replication can provide further evidence to support the robustness of our results and also explore the possibility of identifying more parsimonious solutions (Wagemann *et al.*, 2016). Moreover, results may be different in other countries with their unique cultures, habits and business practices. Accordingly, future research aimed at gaining a broader understanding of the effects of national characteristics and cultural distance in the context of global operations is important (Griffis *et al.*, 2014). More research is particularly warranted in this area given the trend toward globalization of supply chains and the importance of understanding how to manage global returns when accounting for factors such as cultural and regulatory differences across countries.

Third, configurational studies have underplayed the longitudinal dimension and how configurations can evolve over time. The investigation of possible ways to incorporate time into QCA is encouraged, particularly within the context of unstable environments (Misangyi *et al.*, 2017). Fourth, future research should employ a qualitative approach using interviews; only a few studies (Forkmann *et al.*, 2017) have undertaken this type of analysis, and have provided a major contribution on how to conduct QCA starting with interview results.

Fifth, this study focused on returns management. QCA can benefit several other areas of research within the domain of supply chain management. Thus, we encourage researchers to apply QCA to other areas as well, primarily when examining complex phenomena, such as agility, resilience, flexibility and innovation for smart technology.

Finally, QCA has its own limitations and constraints. For example, the method is not ideal when dealing with very large sample sizes (i.e. thousands of observations) as it can provide better insights when applied to medium/smaller samples. Scholars are still refining the guidelines utilized in the process of data calibration. Additional research is needed to provide more evidence regarding the rigor of these guidelines. Further, data analysis errors can be difficult to identify (Maggetti and Levi-Faur 2013; Thomann and Maggetti, 2017). For example, when performing binary data calibration a case can be "in" (present = 1) or "out" (absent = 0); a single wrong coding of a case could significantly alter the results, particularly when dealing with small samples; this is the main reason we recommend the use of fuzzy set analysis with different degrees of membership in the data sets (calibration process). Lastly, the method does not lend itself to situations when researchers seek to establish specific causal relationships, such as mediation and moderation.

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Appendix 1

Construct	Items	References
Product returns practices (PRP) (7-point scale: 1 = not at all to 7 = extensive implementation)	Company adopts measures to prevent returns occurring Company accepts product returns from customers Our company processes returned product effectively	Huang *et al.* (2016)
Product returns recovery practices (PRECP) (7-point scale: 1 = not at all to 7 = extensive implementation)	Company tests, sorts and classifies returned product Company repairs, reconditions and remanufactures components from returned, defective, or damaged products Company dismantles unusable returned products to recover renewable and reusable materials	Huang *et al.* (2016)
Product returns recovery responsiveness (RECRESP) (7-point scale: 1 = strongly disagree to 7 = strongly agree)	Our supplier(s) provides me with convenient options for returning items Our supplier(s) handles product returns well Our supplier(s) offers a meaningful guarantee Our suppliers take care of problems promptly	Parasuraman *et al.* (2005) and Russo *et al.* (2017)
Commitment of resources to managing product returns (COMMRES) (7-point scale: 1 = not at all to 7 = extensive implementation)	Company offers technological resources to implement returns management Company offers managerial resources to implement returns management (included the training, skills, experience and knowledge of the employees about product return/recovery) Company offers financial resources to implement returns management	Adapted from Huang *et al.* (2016)
Returns Satisfaction (RETSAT) (7-point scale: 1 = very dissatisfied to 7 = very satisfied)	General return instructions The convenience of making the return The overall process of making your return The overall process of receiving credit for the returned merchandise	Mollenkopf *et al.* (2007)
Customer Satisfaction (SAT) (7-point scale: 1 = strongly disagree to 7 = strongly agree)	We gladly work with this supplier We are very satisfied with the services provided by this supplier Overall, we are very satisfied with this supplier We are very satisfied with the products and services from this supplier We are very pleased with what this supplier does for us Our firm is completely happy with this supplier	Cannon and Perreault (1999), Homburg *et al.* (2014)

Table AI.
Measurement items included in the study

Appendix 2

Model	B	SE	β	t	Sign
(Constant)	−0.104	0.200		−0.519	0.604
PRP	0.126	0.024	0.114	5.261	0.000
PRECP	0.215	0.018	0.284	12.035	0.000
COMMRES	0.192	0.023	0.171	8.335	0.000
RECRESP	0.327	0.022	0.347	14.647	0.000
RETSAT	0.111	0.023	0.111	4.940	0.000
LENGTHPARTNER	0.048	0.021	0.054	2.307	0.021
RETURNRATE	0.015	0.015	0.022	1.043	0.297
Note: Dependent variable: SAT					

Table AII.
Results of the
regression analysis

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