Australasian Marketing Journal 27 (2019) 129–135

Contents lists available at ScienceDirect

Australasian Marketing Journal

journal homepage: www.elsevier.com/locate/ausmj

From dataset to qualitative comparative analysis (QCA)—Challenges and tricky points: A research note on contrarian case analysis and data calibration

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ARTICLE INFO

Article history:
Received 9 November 2018
Accepted 11 November 2018
Available online 3 December 2018

Keywords:
Customer loyalty
Contrarian analysis
Data calibration
Fuzzy set
Qualitative comparative analysis

ABSTRACT

This research note provides technical aspects of qualitative comparative analysis (QCA) for scholars seeking to better understanding the potentiality of the method. The note answers a few frequently asked questions about contrarian case analysis and data calibration and show how to implement these two relevant steps technically and appropriately. This study provides useful details and technical explanations on why and how to turn case data by using contrarian case analysis and how to calibrate data into fuzzy sets.

CHINESE ABSTRACT

本研究说明为寻求更好地了解定性比较分析 (QCA) 方法的潜力的学者提供关于该方法的技术上的支持.该说明回答了一些关于逆向案例分析和数据校准的常见问题, 并展示了如何在技术上合理实施这两个步骤.针对于如何使用逆向案例分析来转换案例数据及其原因, 以及如何将数据校准到模糊集合 (fuzzy sets) , 本研究提供了有用的细节和技术上的解释.

1. Beyond the "All-or-Nothing" association via qualitative case analysis

As marketing and supply chain management scholars, we aim to understand and explore the mechanisms underlying the creation of customer loyalty (Russo and Confente, 2017); in particular, we investigate the key antecedents of this dimension that help in building and increasing it, in both business-to-business (B2B) and business-to-customer (B2C) settings. Various ways are available to classify and distinguish types of customer loyalty; for example, scholars have suggested that loyalty incorporates both attitudinal and behavioural loyalty and that customer satisfaction is usually an antecedent of loyalty. However, the link between customer satisfaction and customer loyalty is often unclear, and this counterintuitive message only became clear to the authors after a very helpful insight from Professor Arch Woodside.

The initial data analysis adopted for this note is a three-way interaction model, which suggested that switching costs does indeed play a role in estimating loyalty, and that returns management capabilities are not sufficient to generate loyalty alone, but do play a role after value and satisfaction are established. However, the authors now recognise, "the hypotheses in the paper are overly simplistic and do not offer sufficient new and unique findings. However, such findings are highly likely to be in your data" (Woodside, 2014). This key advice prompted us to go beyond the analysis of the main effects of particular antecedents that are commonly provided with regression analysis, but may lead to confusion and reduced accuracy (Armstrong, 2012). These apparently confounding results are difficult to explain by traditional methods; however, with the application of qualitative comparative analysis (QCA) under the lens of complexity theory (Urry, 2005; Wu et al., 2014) our findings offer a noteworthy contribution with an intriguing configuration because a very different perspective is obtained on the sources of customer loyalty, compared with existing loyalty research and our expectations (Russo et al., 2016). On the basis of that enlightenment, we embraced QCA for other research projects, which has allowed us to gain a richer and deeper perspective on data samples, going beyond the 'all-or-nothing' association pre-

Abbreviations: B2B, business-to-business; B2C, business-to-customer; QCA, qualitative comparative analysis; fsQCA, fuzzy-set QCA.

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https://doi.org/10.1016/j.ausmj.2018.11.001
1441-3582/

sumed by traditional statistical models such as multiple regression analysis and structural equation modelling (Schneider, 2018). With this research note, we seek to contribute with technical aspects of QCA for scholars who are interested in applying and better understanding the potential of the method to test propositions and create and test theory. It is not always possible to show every detail in a paper; therefore, we frequently receive open questions from colleagues around the world about specific aspects of this method. Consequently, this study provides useful details on why and how to calibrate data, and a technical explanation on how to use contrarian case details and case analysis; and how to calibrate case data into fuzzy sets by providing a step-by-step guide. The need to provide a more transparent explanation of the QCA process is also justified by the fact that some articles apply this approach, may not articulate much about the calibration technique and other specific steps.

The remainder of this research note is organised as follows. First, Section 2.1 briefly describe the context of the sample and the antecedents of customer loyalty. Section 2.2 discusses complexity theory and QCA to drive our sample data. Section 2.3 and 2.4 presents contrarian case analysis and calibration of data as common problems of this method. Section 3 and 4 concludes by presenting the solutions of our study and provide some implications along with opportunities for further research.

2. Research method

The aim of this article is not to describe the QCA method in a detailed step-by-step manner, but rather to highlight the key elements or "warning" aspects of QCA that researchers need to carefully take into account.

2.1. Data collection and sample

We asked participants to complete an online survey based on their experience regarding online shopping quality and the performance of e-tailers[1] in a B2C context. Respondents were asked to provide their evaluation according to a list of key antecedent conditions selected from existing literature that may contribute to increased "e-satisfaction" and "e-loyalty". For our analysis demonstration, we only refer to those constructs that are related to e-loyalty. Questions were related to dimensions such as customer satisfaction, trust and repurchase intention, and participants attributed to each a score evaluated via a 7-point Likert scale (from 1 = highly disagree to 7 = highly agree).

In addition, the second part of the survey covered demographic characteristics (e.g., age, gender and education), previous online purchases (e.g., category of good/service, amount/number of purchases and average spending), return experience (returners v. non-returners using a dichotomous scale) and information about e-tailers chosen by participants.

A total of 352 completed surveys were available for our analysis.

2.2. Appropriateness of qualitative comparative analysis: the case of e-loyalty

To address the need to understand better a phenomenon and its relationship with other dimensions within a complex scenario, recent research has attempted to adopt and apply other methods to analyse data and information. As in an ecommerce context, unique situations are potentially without limit, particularly with the advent of new channels, because consumers can easily switch from one 'e-marketplace' to another. Moreover, consumers increase their expectations in relation to after-sales services and, in particular, the leniency of returns policies. Assuring a wider and safer alternative allows companies to better respond to market demand and to increase the level of satisfaction and loyalty. Digital transformation should help companies to be more integrated with consumers, but the level of complexity involved in following consumer changing behaviour is dramatically higher than in the past. Therefore, for example, several questions need to be investigated: Is loyalty generated by the same attributes for every consumer? Can companies provide different service levels to reach the same outcome?

The traditional focus on net-effects methods (e.g., regression analysis) can be misleading in understanding the real meaning of consumer behaviour. Thus, 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). This infers that, for instance, the relationships between loyalty and other variables might not always be linear.

In particular, the use of statistical analysis to represent reality might not be suitable in certain cases. Symmetric tests, in fact, rarely match reality well, except when testing the association of two or more items to measure the same construct (e.g., coefficient alpha is a symmetric test) (Woodside, 2015). Conversely, asymmetric tests reflect realities well because the causes of high Y scores usually differ substantially from the causes of low Y scores (i.e., the principle of causal asymmetry; see Fiss, 2011).

In addition, realities can include more than one combination to explain a phenomenon (outcome variable). The outcome depends on how the Xs are combined rather than on the levels of individual attributes per se (de Villiers, 2017; Greckhamer et al., 2013; Ordanini et al., 2014; Russo and Confente, 2017; Schneider and Wagemann, 2010).

Under these circumstances, a useful tool that can help researchers to screen and identify the right combinations of variables is fuzzy-set QCA (fsQCA) software, which we adopted for this study, following the four-step procedure suggested by Fiss (2011). For further information about the usage and guidelines of fsQCA, visit the website: http://www.u.arizona.edu/~cragin/fsQCA/ or http://www.compasss.org/.

QCA is a set-theoretic method that empirically investigates the relationships between the outcome of interest (customer loyalty in this study) and all possible combinations of binary states (i.e., presence or absence) of its conditions. In our study, we have satisfaction, trust, repurchase intention, amount of products purchased and whether the consumer is a returner or not (Fiss, 2007; Ragin, 2000). Such relationships may not be symmetric, but the same outcome can be achieved via different combinations of variables or via the presence or the absence of the same variable. This is supported by complexity theory (Schmitt et al., 2017; Urry, 2005; Wu et al., 2014), which indicates the occurrence of such cases (e.g., X decreases if Y increases, even though the main relationship is that X increases if Y increases). Complexity theory argues that multiple paths or different combinations of elements (e.g., trust, satisfaction and repurchase intention) can lead to the same outcome (e.g., customer loyalty). 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' (Gabriel et al., 2018; Woodside, 2016a). In essence, different 'recipes' can exist for consumer loyalty.

Given that in real life, exceptions almost always occur to a statistically significant main effect, modelling the causes leading to the contrarian directional outcomes may likely provide important findings (Woodside, 2016b). Such contrarian cases are easily verifiable by creating quintiles for both X and Y variables and cross-tabulating the quintiles (Russo and Confente, 2017). In our case,

[1] Online retailers either via web-based online shops or mobile-based applications for online purchases.

Table 1
Examples of frequent questions received by the authors about contrarian analysis.

No.	Question
1	How to judge contrarian cases? That is, how to find contrarian cases?
2	With reference to Table XX, as variable x1 and variables x2 are made of three items each. If we take the average or composite of x1 and x2, then how to do analysis in Table XX, as there are 5 columns and rows respectively. I would be thankful if you could guide me the step-by-step approach how to make this table in SPSS, please.

contrarian case analysis helps to better illustrate the complexity of customer loyalty. However, we frequently receive questions from scholars about the usefulness and interpretation of contrarian analysis (see Table 1).

2.3. Contrarian analysis

Here, we provide an example of cross-tabulation between our outcome variable (customer loyalty) and one of its antecedents (customer satisfaction). These two variables are multi-item constructs constituted by three items each. Respondents evaluated them according to a 7-point Likert scale.

The first step is to obtain the average mean of the items belonging to the construct and then create quintiles. The software SPSS provides this calculation via the following steps:

- TRANSFORM → RANK CASES → RANK TYPES → Ntiles: 5

After the quintiles of the variables of interest are obtained, the second step is to create a cross-tabulation among these variables to relate and investigate the relationships. A 5 × 5 table is created using the same software via the following steps:

- ANALYSE → DESCRIPTIVE STATISTICS → CROSS-TABS

We discovered the existence of contrarian cases by building a contingency table—in some cases a low degree of satisfaction leads to high customer loyalty, while in others a high degree of satisfaction leads to a low degree of customer loyalty (see Table 2).

After this analysis, the first step of the QCA procedure, *defining the property space*, defines the property space where all possible configurations of attributes of an outcome are identified. Decisions about the number of variables and their inclusion or exclusion are not random but should be employed with reference to the theoretical background of previous literature. A useful way to illustrate the usefulness of property spaces is to design a graph as suggested by Dusa (2007). More recently, Woodside (2014) presented Venn diagrams as well as a way of illustrating the possibilities of the presence and absence of ingredients in complex antecedent conditions (i.e., recipes) indicating high scores in an outcome condition.

Defining the property space involves providing information about the combinations of attributes, which comprises all combinations of binary states (presence or absence) of the X attributes that could influence the outcome variable (ours is customer loyalty). These combinations are displayed in Fig. 1, which is defined as a “truth table”. The table shows the potential configuration of attributes in their combination of presence (high scores of X are assigned 1) or absence (low scores of X are assigned 0) in determining the outcome variable (high values of loyalty are assigned 1). Following the first step, as suggested by Fiss (2007), we used these set measures to construct a data matrix (truth table) with 2^k rows, where k is the number of causal conditions (variables) used in the analysis. Each row of this table is associated with a specific combination of attributes, and the full table thus lists all possible combinations (for our study, we have $2^5 = 32$ combinations). Some rows may contain more cases, some very few and some zero cases if there is no empirical evidence of specific combinations of attributes.

2.4. Calibration assessment and issues

Set-membership measures is the second phase of the analysis and consists of setting membership measures for the attributes. The conventional set (labelled the “crisp” set) is dichotomous; that is, a case can be “in” (present = 1) or ‘out’ (absent = 0), while the fuzzy-set membership scores specify membership in intervals between 0 and 1. Ragin (2008) reworked QCA for the use of fuzzy sets that significantly help social science research in all disciplines, such as organisation studies, management, marketing and recently supply chain management, to become more realistic and thus more fit for a business context that is not considered a mere agglomeration of dichotomies (Ma et al., 2018; Misangyi et al., 2017; Rihoux and Marx, 2013; Russo et al., 2018; Schneider and Wagemann, 2006; Wagemann et al., 2016; de Villiers and Tipgomut, 2018).

In our case, we calibrated measures specifying three qualitative anchors: the threshold for full membership, the threshold for full non-membership and a crossover point for each of the variables included in the analysis (Ragin, 2008). One of the most challenging parts of the QCA procedure is calibration. This has been confirmed by previous studies (Crilly et al., 2012; Greckhamer et al., 2018; Kraus et al., 2018; Misangyi et al., 2017) and from the questions we have received from scholars asking for our help. By the application of calibration, the process is moving clearly from quantitative to qualitative research because the membership values are attributed as degrees of the phenomenon under investigation (Goertz and Mahoney, 2012). Correct calibration is a core activity of every QCA because mistakes may change the consistency and robustness of the findings. This is one of the advantages of fuzzy sets, because they are based on calibration rather than measurement.

To provide an answer to the question in Table 3, we support the statement of Greckhamer et al. (2018, p. 7) that “for both crisp and fuzzy sets, effective calibration is a *half-conceptual, half-empirical* process of identifying thresholds that meaningfully represent differences in kind and differences in degree among cases.” In addition, to assess the validity and robustness of this process and related results, it is fundamental to clearly report and justify the threshold so that the reader can have access to such information (e.g., Misangyi et al., 2017).

Particularly when considering the crossover point, some attention has to be placed on its calibration as some cases may be shifted from one row to another row of the truth table and may change some patterns of the configurations (Greckhamer et al., 2018; Thomann and Maggetti, 2017). Considering a Likert scale, as in our case, the endpoints of the 7-point Likert scales serve as the two qualitative anchors for calibration of full membership (value 7) and full non-membership (value 1), while the crossover point is a calculated attribute by observing the distribution and median score of each attribute. Although sample-based calibration should be avoided whenever possible (Greckhamer et al., 2018; Wagemann et al., 2016), and this practice has been discussed by highlighting its weaknesses, in the case of survey-based data coming from individuals’ self-reported perceptions, this choice can be justified as a ‘median’ cross-point, which is better than simply attributing the midpoint of the scale. Otherwise, for all 7-point Likert scale–based variables, the midpoint would always be 4 and would not take into account the type of reality and variable of interest. Conversely, we totally agree that sample-based calibration should be avoided where a crossover point already exists from the existing literature or has been determined from secondary data that show a membership or non-membership for a specific dimension/situation above or below this threshold. Scholars in other disciplines (e.g.,

Table 2
Cross-tabulation of quintiles of cases for customer loyalty (LOY) and customer satisfaction (SAT).

	SAT		LOY					Total
			1	2	3	4	5	
SAT	1	Count	46	14	9	1	0	70
		% within SAT	65.7	20.0	12.9	1.4	0.0	100.0
	2	Count	13	32	17	29	5	96
		% within SAT	13.5	33.3	17.7	30.2	5.2	100.0
	3	Count	4	8	13	12	5	42
		% within SAT	9.5	19.0	31.0	28.6	11.9	100.0
	4	Count	8	8	13	17	25	71
		% within SAT	11.3	11.3	18.3	23.9	35.2	100.0
	5	Count	2	11	9	18	33	73
		% within SAT	2.7	15.1	12.3	24.7	45.2	100.0
Total		Count	73	73	61	77	68	352
		% within SAT	20.7	20.7	17.3	21.9	19.3	100.0

Note.

= the numbers in the box indicate support for the positive main effect.

= the numbers in the box represent cases that are contrary to the highly significant, statistically positive linear relationship indicated by phi = 0.72; the contrarian cases have very low or low SAT but very high or high LOY scores, or have high or very high SAT but low or very low LOY scores.

phi = 0.72, $p < .001$.

Table 3
Example of a question received frequently by the authors regarding calibration.

If a study uses ***7-point Likert scale****. 1 = Completely disagree; 7 = Completely agree. The endpoints and the midpoint of the 7-point Likert scales serve as the three qualitative anchors for calibration of full membership (value 7), full non-membership (value 1) and the crossover point (value 4).*

Calibration process is as follows, is it right?

Scale	1	2	3	4	5	6	7
	↓	↓	↓	↓	↓	↓	↓
fsQCA value	0	0	0	0.5	0.5	1	1

political science and social science) where the method has become prominent adopt well-known criteria external to the study sample to calibrate the dataset (e.g., expert panel and independent report). For example, Stockermen (2013) used a combination of external data and contextual knowledge, such as consolidation/longevity of democracy and UNDP Education Index, to calibrate the variables of cases. A similar approach has been adopted by Berg-Schlosser (2018) when considering the "Human Development Index" and the quality of democracy while Downey and Stanyer (2010) used secondary sources to determine their membership of democracies with personalised mediated political communication. In disciplines such as marketing, organisational science and supply chain management, comprehensive contextual studies to support an effectiveness calibration are rare, particularly when scholars have to deal with a unit of analysis constituted by the consumer's or supplier's perception and qualitative data (de Block and Vis, 2017). However, as a general rule we recommend following the principle of transparency so that readers can assess the validity and robustness of the calibration process and the resulting sets, as we explain later. Second, the resulting fuzzy-set scores have to reflect both substantive knowledge and the existing research literature.

Consequently, to be more consistent, instead of establishing a fixed number for the crossover point, we evaluated the median of each attribute, as did other studies. Such calibration was applied to the 7-point Likert dimensions considered in our study. For example, considering our outcome variable, customer loyalty, the endpoints of the 7-point Likert scale served as the two qualitative anchors for calibration of full membership (value 7) and full non-membership (value 1), while the crossover point was calculated as 4.5, the median value.

Edit Truth Table

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rep	trust	sat	return	quantity	number	loy	raw consist.	PRI consist.	SYM consist
0	0	0	0	0	25 (14%)	0	0.716252	0.053552	0.054475
1	1	1	0	1	20 (26%)	1	0.949612	0.860548	0.876568
1	1	1	1	1	18 (37%)	1	0.965665	0.932504	0.942549
1	1	1	0	0	16 (46%)	1	0.935041	0.759091	0.800959
0	0	0	0	1	12 (53%)	0	0.785398	0.186924	0.188663
0	1	1	0	0	11 (60%)	1	0.885878	0.310876	0.315738
0	0	0	1	1	10 (65%)	0	0.780979	0.367881	0.368721
0	0	0	1	0	8 (70%)	0	0.738547	0.194647	0.199253
1	1	1	1	0	7 (74%)	1	0.908742	0.725089	0.756732
0	1	0	0	0	7 (78%)	1	0.870770	0.171319	0.173968
1	1	0	0	1	4 (81%)	1	0.953199	0.703429	0.707647
1	0	1	0	1	4 (83%)	1	0.954159	0.740383	0.741276
1	0	1	1	1	3 (85%)	1	0.952762	0.817337	0.817338
1	0	0	0	1	3 (87%)	1	0.935859	0.563237	0.567062
1	0	0	0	0	3 (88%)	1	0.910842	0.333827	0.333828
0	1	0	1	1	3 (90%)	1	0.904104	0.594340	0.594340
0	1	0	0	1	3 (92%)	1	0.914682	0.394051	0.394051
1	1	0	0	0	2 (93%)	1	0.934261	0.470405	0.473355
1	0	1	0	0	2 (94%)	1	0.939710	0.494815	0.495549
0	1	0	1	0	2 (95%)	1	0.869448	0.364628	0.364628
1	0	0	1	1	1 (96%)	1	0.940407	0.713044	0.713044
0	1	1	1	1	1 (97%)	1	0.926829	0.696398	0.698795
0	1	1	1	0	1 (97%)	1	0.895559	0.451405	0.451404
0	1	1	0	1	1 (98%)	1	0.938075	0.611814	0.611814
0	0	1	1	1	1 (98%)	1	0.927427	0.645976	0.645977
0	0	1	0	1	1 (99%)	1	0.897993	0.379310	0.383164
0	0	1	0	0	1 (100%)	1	0.887340	0.164139	0.165049
1	1	0	1	1	0 (100%)				
1	1	0	1	0	0 (100%)				
1	0	1	1	0	0 (100%)				
1	0	0	1	0	0 (100%)				
0	0	1	1	0	0 (100%)				

Specify Analysis Cancel Standard Analyse

Fig. 1. Truth table of potential combinations.

Considering the non-Likert dimensions, the study includes two variables, the amount of purchases and whether the respondent was a returner of products or not in the online context. Regarding the first variable, because in this case there is no accepted threshold determining whether there is a fixed number of purchases and individual needs to consider a consumer a 'heavy online purchaser', we considered the distribution of the number of purchases as 50% by finding that the crossover point was set at 2, while the endpoints were 4 (full membership) and 1 (full non-membership).

Regarding the second variable, this was a dichotomous variables (yes = returner and no = non-returner) and we attributed 1 to returners and 0 to non-returners. This is in line with previous research where the presence of returns frequently leads to repurchase and implies that the customer is highly likely to be loyal (Mollenkopf et al., 2007). This is the reasoning behind including this input as an 'ingredient' in our loyalty recipe—the fact that a consumer not only buys from the same e-tailer but also returns product.

Overall, to allow replication, researchers should specify procedures for assigning fuzzy membership scores to cases, and these procedures must be both open and explicit so that they can be evaluated by other scholars.

Going back to the truth table, after showing all the numbers of rows and combinations, the table needs to be reduced, adopting two conditions: (1) the minimum number of cases required for a solution to be considered and (2) the minimum consistency level of a solution (Ragin, 2008). 'Consistency' here refers to the degree to which cases correspond to the set-theoretic relationships expressed in a solution. This represents the third step: *consistency in set relations.*

Considering the first condition, the threshold 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). Therefore, we considered only configurations that had at least four best-fit cases. The column "number" of Fig. 1 shows the distribution of best-fit cases (respondents) across the configurations in our sample. We set the cases that led to high levels of online customer loyalty by setting the variable customer loyalty

Table 4
Main configurations for customer loyalty.

Configurations	Solutions			
	1	2	3	4
Satisfaction	●	●		
Trust	●		●	●
Repurchase intention	●	●	●	⊗
Amount of online purchases		●	●	⊗
Product returner		⊗	⊗	⊗
Consistency	0.92	0.94	0.94	0.85
Raw coverage	0.81	0.37	0.36	0.30
Unique coverage	0.36	0.01	0.01	0.01
Solution coverage	0.85			
Solution consistency	0.88			

as equal to 1, which represents that an outcome of high loyalty is present. In both cases, 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 satisfy the requirement of consistency. A configuration is accepted when its consistency measure exceeds a threshold, in line with QCA literature, of 0.80 (Ragin, 2008).

The last step is the *logical reduction and analysis of configuration*, which aims at identifying only those configurations that, beyond being consistent, also have an adequate level of coverage. Coverage explains the relevance of the combinations; it measures that share of consistent memberships as a proportion of the total membership in the outcome set. It can be interpreted as a type of *R*-square value extracted from correlational methods (Woodside and Baxter, 2013). The accepted threshold for coverage is fixed at 0.010 (Ragin, 2008). Such an indicator provides researchers with support to assess the empirical relevance of configural statements. QCA calculates both raw and unique coverage scores; compared with raw, unique coverage controls for overlapping explanations by partitioning the raw coverage.

3. Main results from the qualitative comparative analysis

Table 4 shows the coverage and consistency of the four combinations that the software selected to be ‘sufficient’ with the four steps following the above-described procedure. We adopted this useful table to present our results as suggested by Ragin and Fiss (2008), where black circles (●) indicate the presence of a condition, and circles with a cross (⊗) indicate its absence. Further, a blank cell indicates the ‘do not care’ condition, which means a specific condition is not considered in a solution.

Solution 1 reflects the combination with the highest coverage, which encompasses the presence of satisfaction, trust and repurchase intention as the ‘recipe’ that builds customer loyalty in the online context. This means that it can be seen as the best solution in representing high customer loyalty.

Solution 2 provides a recipe for gaining customer loyalty by combining satisfaction, repurchase intention, a high amount of online purchases and individuals who do not return their products.

Solution 3 replaces satisfaction with trust, compared with Solution 2. These two solutions have the same consistency and coverage, representing a ‘substitute’ for each other to reach the same outcome.

Solution 4 reflects the combination with the lowest coverage but still a sufficient recipe consisting of trust as a present condition and the absence of repurchase intention, low amount of online purchases and individuals who are not returners.

Noticeably, the existence of multiple sufficient configurations for customer loyalty indicates equifinality (Fiss, 2011). Considering the coverage, the findings indicate an overall solution coverage of 0.85 and an overall consistency of 0.88, which indicates that a substantial proportion of the outcome is covered by the four configurations.

4. Conclusion

Embracing the QCA method is challenging and such method has expanded significantly during the past 5 years in several disciplines such as organisational studies, marketing. With this research note, we primarily contribute by providing evidence of the need to adopt contrarian analysis, highlighting the presence of contrarian cases by cross-tabulation, which goes beyond the ‘all-or-nothing’ association presumed by traditional statistical models such as multiple regression analysis and structural equation modelling. We highlight how the strength of the method for marketing scholars relies on the calibration of measures, which are transformed into concepts by assigning a membership value in the interval of 0 to 1. However, a possible problem is determining the membership criteria because different findings and implications can emerge from different crossover points.

Another contribution of our research note is the presentation of a specific technical example to demonstrate how to execute each step, as well as details about the activities. We also contribute to the customer loyalty literature by going beyond the ‘all-or-nothing’ effect computed by other methods. Interestingly, our third solution indicates that when trust is high, customers indicate high customer loyalty even in the absence of other variables. This is an important finding as it highlights the complexity of the factors that affect customer loyalty within the context of ecommerce.

Finally, we encourage scholars to apply QCA, as it opens up a large number of avenues for further research in B2B and B2C research. We promote its application to other business contexts as well, primarily when examining complex phenomena such as satisfaction, brand loyalty, trust, purchase intention and engagement in a social media context. In particular, we promote further research on the issues related to data calibration to shed more light on this procedure, particularly when dealing with perceptions and qualitative data in general. In this vein future research should attempt to identify via QCA which configurations (or single conditions) are more regularly associated with an outcome over time (Furnari, 2018).

Another venue to extend its application is to consider to apply QCA not just in case of success, such as in our case to determine those recipes that determine high level of customer loyalty but also in case of not success, that is exploring those combinations and those situations that leads a brand or a company to fail. Consider for instance, the case of losing customer loyalty, or increasing the number of unsatisfied customers. Further research employing QCA is required in order to better investigate the underlying mechanisms that are responsible to such company failures.

Acknowledgements

The authors would like to thank the Guest Editors Rouxelle De Villiers and Arch Woodside for their invitation to participate in the debate on a relevant technical aspect of QCA.

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