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A Step-by-Step Guide of (Fuzzy Set) Qualitative Comparative Analysis:

From Theory to Practice via an Implementation in a B2B Context

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Abstract

One of the challenges researchers face in using an analytic method is to fully understand its underlying logic and find ways to successfully incorporate it into the research process. Qualitative Comparative Analysis (QCA) is an example in case, where such a challenge has been partly addressed so far, despite the increasing popularity of the method. Although QCA user guides are widely available, researchers may face difficulties in implementing the method to address real-world, complex social phenomena. To address this issue, the present methodological paper provides a step-by-step guide of QCA and links the background theory of the method to its practical implementation, via an example in the business-to business (B2B) context of open and closed innovation. The paper provides practitioners and researchers alike with a clear roadmap on how to exploit the full potential of the method in order to derive insightful explanations in applied data analysis.

Keywords: Qualitative comparative analysis, FsQCA, Fuzzy set, Crisp set, Causal complexity, Configurations

1. Introduction

Qualitative Comparative Analysis (QCA)—a method originally introduced by Ragin (2000) — capitalizes on the merits of both qualitative and quantitative research methods, while addressing some of their inherent limitations. Specifically, in contrast to qualitative methods that focus on the in-depth analysis of a limited number of cases, QCA allows researchers to conduct cross-case comparisons in medium sample-sized case studies (Finn, 2022). At the same time, contrary to quantitative approaches that are variable-orientated, QCA handles each case as a holistic unit and therefore, enables researchers to generate complex explanations of the examined phenomena (Fainshmidt et al., 2020).

Embracing causal complexity is considered as one of the main advantages of QCA, supplementing in this way both variable- and case-oriented approaches. Specifically, QCA has reinvigorated configurational theory that allows for the detection of causal complexity (Misangyi et al., 2017). Configurational theory emphasizes that causality is complex in that it is characterized by the three mutually connected features of causal asymmetry, conjunctural causation, and equifinality. Causal asymmetry suggests that although the presence of certain conditions may lead to a certain outcome, their absence does not necessarily imply outcome absence (Fiss, 2011). Conjunctural causation suggests that a condition can influence the outcome, only if it is combined with other conditions. In other words, there are combinations of conditions (configurations) that lead to any given outcome and therefore, QCA allows the examination of combinatorial effects, rather than net effects, as is the case with conventional correlational methods (Ragin & Fiss, 2008). Equifinality suggests that multiple alternative combinations of conditions may lead to the same outcome (Schneider and Wagemann, 2010; Wagemann et al., 2016). Although these three features of the configurational perspective that characterize causal complexity have been recognized in past literature (see Short, Payne, & Ketchen, 2008 for a review), empirical work on configurations is generally limited. In fact, until recently, there was a lack of relevant tools, such as QCA, capable of fully capturing causal complexity, in the form of these three features (Fiss et al., 2013). Conventional correlation-based approaches, such as regression analysis, are not designed to address conjunctural causation, equifinality, and asymmetry (Ragin, 2000), as these approaches mostly rely on a “general linear reality” (Abbott, 1988) or “net effects thinking” (see also Ragin, 2008; Skarmeas et al., 2014).

By combining the virtues of within-case analysis and cross-case comparisons, QCA is becoming increasingly popular across different scientific fields of study. For example, QCA contributions can be found in the fields of political science (e.g., Blake & Adolino, 2001; Gordin, 2001), sociology (e.g., Nomiya, 2001), law and criminology (e.g., Tarohmaru, 2001), linguistics (e.g., Mendel & Korjani, 2012), and education (Nistor, Stanciu, Lerche, & Kiel, 2019). In the field of business and management, the first contribution was published in 2005, by Raymond Kent, and since then, the number of QCA applications has been growing steadily. Specifically, the field of business and management has been the fastest growing field of published QCA studies (see Rihoux et al., 2013), with several applications in the areas of international business (e.g., Verbeke et al., 2018; Ciravegna et al., 2018), innovation management (e.g., Huang & Huarng, 2015; Kaya et al., 2020), organizational behaviour and strategic management (e.g., Fiss, 2011; Oyemomi et al., 2019), inter-organizational alliances (e.g., Leischnig & Geigenmuller, 2018), socially responsible practices and corporate social responsibility (e.g., Crilly, Zollo, & Hansen, 2012; Saridakis et al., 2020), and consumer research (e.g., Saridakis & Angelidou, 2018), among others.

A growing number of QCA applications in recent years can also be found in the sub-field of business-to business (B2B) and industrial marketing. The majority of QCA applications within the particular context have been published in the academic outlets of *Industrial Marketing Management*, *Journal of Business Research*, and *Journal of Business* *and Industrial Marketing* (see Gligor et al., 2021), with *Industrial Marketing Management* being the leading outlet with approximately 21 published studies that implement QCA. The high number of QCA contributions in *Industrial Marketing Management* can also be attributed to the journal's editorial policy that encourages methodological advancements within industrial marketing. These publications focus on research topics, such as big data analytics (e.g., Sun et al., 2020), buyer-supplier relationships (e.g., Zaefarian et al., 2017; Habib et al., 2020), value co-creation and trust in B2B relationships (e.g., Franklin & Marshall, 2019; Santos, 2021), social entrepreneurship (e.g., Halberstadt et al., 2021), and servitization (e.g., Ambroise et al., 2018), among others.

One of the challenges that comes with the increasing popularity and applicability of the method is to fully understand its underlying logic and the way in which it can be incorporated into the research process. Given that this challenge has been partly addressed so far in the existing literature, the purpose of this paper is to provide an overview of how to incorporate QCA's analytic tools in actual data analysis and develop a roadmap for its successful implementation. We offer all the details on how to perform the analysis that are not usually included in a typical research article to make the method easy-to-apply by the scholarly community. The present step-by-step guide builds on existing studies, by thoroughly discussing the various phases of QCA implementation, while it also presents main analyses that need to be conducted, via an applied example in the B2B context of open and closed innovation.

The remainder of the paper is organised as follows: First, we discuss the background theory of QCA as a research approach and explain the advantages it offers for conducting comparative research over symmetric-based analysis. Also, we introduce the main concepts underlying QCA with which users need to be familiar in order to use the method in a meaningful way. Second, we provide suggestions on how to employ the tools QCA offers for research and how to interpret their outputs. The various phases of QCA are also discussed via an application in the B2B context of open and closed innovation. Further, we explain how a researcher can incorporate QCA results in the data analysis and describe how to explore cases, causal recipes, and single conditions based on QCA results. Last, we present our empirical results and summarize some concluding remarks and implications for research.

2. Main concepts and background theory of QCA

In this section we introduce the main concepts and theory underlying QCA. Specifically, the notion of *sets* and the relations of *necessity* and *sufficiency* will be covered. This will be followed by an overview of the parameters used for assessing fit, namely *consistency* and *coverage*. Then, the *truth table* as a central tool for data analysis will be explained, as well as the process of *minimization* and the different *solution* terms offered by QCA. Understanding these concepts is crucial for using QCA in a meaningful way, as they provide the basis for running the analysis and interpreting the results.

2.1. (Fuzzy) sets and Boolean operations

QCA examines set relations. A set can be seen as a group of values that represents the degree of membership in a specific category (e.g., degree of a firm's membership in the category of *"radical innovation"*), or else, the degree of membership in a specific (causal or outcome) condition (Woodside & Zhang, 2013). The researcher transforms variables either into *crisp* or *fuzzy* sets. If membership in a specific condition is binary (i.e., cases are either members or non-members in the condition), the respective set is called crisp set (Ragin, 2008). Crisp sets record a value of 1 to cases that are members in a given condition and 0 to non-members. Fuzzy sets, in contrast, allow the recording of varying degrees of membership in conditions and therefore, each case can take on any value from the continuous range of 0 to 1. The value of 1 signifies full membership in a specific condition, the value of 0 signifies complete non-membership, while the value of 0.5 signifies neither membership, nor non-membership—the crossover point of maximum ambiguity (Fiss, 2011; Woodside, 2013). For example, a fuzzy set score of 0.85 suggests that the respective case (firm, individual, etc.) is mostly a member in the given condition.

To analyze data on the basis of the assigned set membership scores, QCA draws on Boolean algebra. Boolean algebra uses three basic operations that can be applied to fuzzy and crisp sets, namely intersection, union, and negation. Figure 1 provides an overview of these operations and their relevance to QCA. Dashed areas highlight the result of the respective operations.

INSERT FIGURE 1 ABOUT HERE

In using QCA, researchers are usually interested in estimating a case's membership score in complex conditions, called recipes or pathways (i.e., combinations of two or more conditions). In essence, such scores equal to the degree of membership in the intersection of the fuzzy-set scores of the simple conditions that comprise the full recipe (Woodside & Zhang, 2013). For example, as shown in figure 1, if the following membership scores in parentheses are the fuzzy-set scores for the two conditions of the first case in the dataset: A (0.42), B (0.98), the case's membership score in the complex condition of A*B equals to 0.42. The asterisk (*) represents the logical *"AND"* in fuzzy sets terminology and the intersection value equals to the minimum score across the two simple conditions that comprise the recipe of the complex condition.

Set union (the logical *"OR"*, symbolized by the operator "+") is used to refer to alternative causal recipes identified by QCA (connected via logical *OR*) that lead to a given outcome. As mentioned earlier, QCA tackles the issue of *equifinality*, meaning that multiple alternative pathways may lead to the same outcome.

Finally, the logical *"NOT"* is symbolized by the operator "~". In QCA, researchers are also interested in estimating negated sets, which represent the absence of (or degree of non-membership in) a given condition (see e.g., Woodside & Zhang, 2013). If a set is denoted by *A*, the respective negated set is usually denoted by *"~A"*. Membership of a case in a negated set equals to one minus the membership score in the non-negated set.

2.2. Set relations and the concepts of necessity and sufficiency

QCA uses Boolean methods to assess whether (single or combinations of) causal conditions are necessary and/or sufficient for the outcome of interest to occur. A cause is necessary (but not sufficient) if it must be present for a certain outcome to occur, but this cause alone is not enough for the outcome to occur (Ragin, 1987). In other words, when a causal condition is necessary for an outcome, then all occurrences of the outcome will certainly exhibit presence of the given causal condition. In set relations terminology, the outcome set Y is a subset of the necessary causal condition set A; that is, in each case of the dataset, the degree of membership in set Y is less than or equal to the degree of membership in set A ($Y \leq A$). As shown in figure 2, necessity can be visualized in two ways, by using Venn diagrams or XY plots. Using a Venn diagram, the circle representing the outcome set Y is completely engulfed by the circle representing the causal condition set A (set Y is a subset of set A). This Venn diagram shows that there are cases included in set A that are not in set Y (meaning that condition A is not sufficient by itself), but all cases in set Y are also in set A. By plotting causal condition A against outcome Y, if all cases fall on or below the main diagonal (dashed area), this indicates necessity ($Y \leq A$). Cases falling above the main diagonal contradict necessity.

INSERT FIGURE 2 ABOUT HERE

In contrast, a cause condition is defined as sufficient (but not necessary), if by itself it can produce a certain outcome, even though there are other causal conditions, besides this one, which may also produce the same outcome without the presence of this cause (Ragin, 1987). When a causal condition is sufficient for an outcome, then all occurrences of the causal condition are followed by the outcome of interest. In set relations terminology, the sufficient causal condition set A is a subset of the outcome set Y (Ragin, 2008); that is, across all cases, the degree of membership in condition A is consistently less than or equal to the degree of membership in outcome Y ($A \leq Y$). As shown in figure 3, visualized in a Venn diagram, the circle representing condition set A is completely engulfed by the circle representing outcome set Y (set A is a subset of set Y). Similarly, when A is plotted against Y, all cases on or above the main diagonal indicate sufficiency.

INSERT FIGURE 3 ABOUT HERE

2.3. Assessing fit: Parameters of consistency and coverage

In reality, causal conditions or combinations of causal conditions that always conform to a relation of necessity or sufficiency are rare. At least a few cases in the population will usually deviate from the general patterns. Therefore, it is important to be able to assess how well the cases in a dataset fit a relation of necessity or sufficiency. In QCA, two measures provide evidence of fit, namely consistency and coverage (Ragin, 2006).

Consistency ranges from 0 to 1 (with 0 indicating no consistency and 1 indicating perfect consistency) and represents the degree to which a causal condition (or combination of conditions) leads to an outcome (Ragin, 2008), or else, the degree to which a relation of necessity or sufficiency between a causal condition (or combination of conditions) and an outcome is met within a given data set (Ragin, 2006). In statistical terms, it resembles the notion of significance. Usually, conditions or combinations of conditions are “quasi-necessary” or “quasi-sufficient” in that the causal relation holds in a great majority of cases, but some cases deviate from this pattern.

In contrast, coverage provides a measure of empirical relevance. Coverage represents how many cases in the dataset that have high membership in the outcome condition are represented by a particular causal condition (or combination of conditions). In other words, it gives an indication of how much of the outcome is covered (explained) by a causal condition (or combination of conditions) (Ragin, 2008). In statistical terms, the measure of coverage is analogous to the coefficient of determination (i.e., r2), that is the amount of variance of the dependent variable that is explained by the independent variables examined (Woodside, 2013). Such an indicator, with values again ranging between "0" and "1", provides researchers with support to further assess the empirical relevance of configural statements.

2.4. Cases as configurations of conditions: Truth tables

QCA constructs a data matrix, called truth table, and analyses it to identify combinations of causal conditions (causal recipes) that are sufficient to produce the outcome of interest. The truth table consists of 2^k rows that enumerate all possible combinations of binary states (presence or absence) of the *k* causal conditions examined in a study. Each row of the table is associated with a unique complex combination of causal conditions. Table 1 shows a hypothetical truth table with four causal conditions (A, B, C, D) that may or may not lead to the outcome of interest Y. The truth table consists of $2^4=16$ rows (all possible combinations/configurations, based on the four causal condition). Additional columns show the number of empirical cases in the dataset that show the particular combination with the outcome present (or absent), and what a configuration's level of consistency with sufficiency is (i.e., how consistent a given configuration is in displaying the outcome Y).

By looking at whether the case(s) assigned to a truth table row agree in displaying the outcome (indicated by the consistency column), the researcher can assess whether a given configuration of conditions can be regarded as sufficient for the outcome. For example, row 6 represents a configuration that is perfectly consistent in displaying the outcome (highly sufficient), as it is shown by 4 cases in the dataset, all of which display the outcome (consistency = 1.0). In contrast, row 4 represents a configuration that is not very consistent in displaying the outcome, as it is shown by 1+5=6 cases in the dataset, only one of which is displaying the outcome (consistency = 1/6 = 0.167). Rows like this one that have empirical cases in the dataset with the outcome both presence and absence are also called contradictory rows. Evidently, perfectly consistent rows (e.g., row 6) have no contradictions in the dataset.

INSERT TABLE 1 ABOUT HERE

Also, most empirical phenomena are usually characterized by "limited diversity" (Ragin, 1987). In QCA, limited diversity manifests itself in that some truth table rows will usually remain empty, suggesting that there are no empirical cases contained in the dataset that belong to these rows (e.g., Rows 1, 2, 5, 7, 12 in Table 1). These empty rows are also called “logical remainders”. Being able to identify contradictions and logical remainders is a distinct strength of QCA.

2.5. Boolean minimization and simplifying assumptions

QCA identifies the configurations of conditions that are perfectly consistent with being sufficient to display the outcome. These are also called “primitive expressions.” In Table 1, using Boolean notation, the primitive expressions are: ~A*B*~C*D (row 6), ~A*B*C*D (row 8), A*B*~C*D (row 14), and A*B*C*D (row 16). Such terms are precise descriptions of conjunctions of conditions that are sufficient for the outcome (Grofman & Schneider, 2009). Often, however, they are quite complex because models include more than just four causal conditions. QCA uses *“Boolean minimization”* to reduce the primitive expressions and arrive at intelligible solutions.

Using the primitive expressions that were identified as sufficient in the truth table, Boolean minimization serves to identify more and more general combinations of conditions sufficient for the outcome that remain logically true (Thiem and Duşa, 2013). One way this process works is by focusing on pairs of configurations that differ in only one condition but agree in displaying the outcome. Take the primitive expressions from Table 1: both ~A*B*~C*D (row 6) and A*B*~C*D (row 14) consistently show the outcome. In such a case, the presence or absence of condition A does not influence the occurrence of the outcome Y. This reduces primitive expressions to simpler combinations of conditions. Specifically, ~A*B*~C*D ≤ Y and A*B*~C*D ≤ Y can be simplified to B*~C*D ≤ Y. As the end product of this minimization process, QCA identifies “causal recipes”, which are combinations of conditions that are generalizations of the patterns that exist in the data set and are minimized in their complexity (Duşa, 2007).

Due to limited diversity, it is often hard to find pairs of configurations that differ on only one condition and agree in displaying the outcome. Therefore, simplifying assumptions can be used to continue the minimization process (Ragin, 2008). Simplifying assumptions are theory-driven assumptions of how a given causal condition might be causally linked to the outcome. Simplifying assumptions for which there is strong empirical or theoretical evidence on how a condition contributes to an outcome (i.e., when present or absent) are called *"easy counterfactuals"* (Ragin and Sonnett, 2005). In such cases, the researcher can formulate a directional expectation of how the condition could be related to the outcome, which serves as a simplifying assumption. If, however, there is no empirical or theoretical evidence on how the presence or absence of a condition contributes to an outcome, one should refrain from using simplifying assumptions.

2.6. Complex, parsimonious, and intermediate solutions

Depending on how the researcher approaches the simplifying assumptions, the analysis of the truth table analysis may produce three alternative solutions, namely complex, parsimonious, and intermediate solution (Ragin, 2008). The causal recipes/pathways contained in each of these solutions may slightly differ with each other, but they are equal in terms of logical truth and never contain contradictory information (Schneider & Wagemann, 2007). The complex solution does not allow for any simplifying assumptions to be included in the analysis. As a result, the solution is often hardly reduced. The parsimonious solution reduces the causal recipes to the smallest number of conditions possible. The conditions included in this type of solution are only the *"prime implicants"* (i.e., the conditions which are needed to describe the causality of outcomes of cases), while the decisions on logical remainders are made automatically, without any theoretical or substantive arguments on whether a simplifying assumption makes sense (Schneider & Wagemann, 2007). Finally, the intermediate solution includes selected simplifying assumptions to reduce complexity, but only those assumptions that are consistent with theoretical and/or empirical knowledge (Schneider & Wagemann, 2007).

3. An applied example in the context of open and closed innovation

3.1. Overview of the problem domain

Although researchers have long emphasized the importance of finding the right balance between different innovation approaches (Deschamps, 2005; Mendell & Ennis, 1985), as open innovation co-evolves with closed innovation, it is crucial to examine how different levels of openness, in the form of external knowledge sourcing, can be either complemented or substituted by different levels of internal resources, in the form of human capital and internal R&D. In this direction, we illustrate the use of QCA via an applied example to identify alternative causal configurations of external knowledge sourcing and internal resources that lead to high levels of firm radical innovative performance.

Our contention is that firms who adopt a highly open innovation approach might need to mobilize individual elements rather than a broad range of internal resources to enhance their absorptive capacity and thus, their ability to combine heterogeneous knowledge accessed through external sourcing. Moreover, we argue that firms who adopt a less open innovation approach need to substitute these knowledge sources with significantly higher mobilization of internal resources. To get these relationships right, we further claim that we need to recognize the role of firm age. In fact, younger firms may be more likely to adopt a more closed innovation approach, despite their limited resource base. In the following sections we illustrate the usefulness of QCA within the given B2B research domain.

3.2. Phases of QCA implementation

In implementing QCA we follow several phases, which are outlined in Figure 4. These phases include the construction/collection of data, the conversion of the raw data into sets (a process called data calibration), the definition and analysis of the property space, as well as the production of the solution and the interpretation and presentation of results. Optional phases may also include testing for specific necessary and/or sufficient conditions, plotting relevant findings, and validating the solution generated. In the following, we describe in detail each one of these implementation phases via our applied example.

INSERT FIGURE 4 ABOUT HERE

3.3. Data and Variables

The data for our applied example come from the Spanish Technological Innovation Panel (PITEC), covering the period from 2013 to 2016. PITEC compiles the Spanish surveys of the Community Innovation Survey (CIS), which is one of the most used secondary datasets for studying innovation (Laursen & Salter, 2006). The survey is carried out by the Spanish National Statistics Institute (INE), the Spanish Foundation for Science and Technology (FECYT), and the Foundation for Technical Innovation (COTEC). PITEC data contains detailed information on the innovation activities of Spanish firms.

Survey questions regarding external knowledge sourcing and internal resources refer to the average of the three-year period (from 2013 to 2015). To measure our outcome variable (i.e., innovative performance), however, we use data from the year 2016. We, therefore, account for the time lag that exists between innovation activities and innovation outcomes (Hess & Rothaermel, 2011).

We use a range of proxies from the Spanish surveys of the CIS secondary database to operationalize the variables in this study. *Suppliers, customers, competitors,* and *universities*, reflect the extent to which the focal firm involves these actors in its knowledge sourcing activity. Each of these variables was coded as 1 for high usage of the respective knowledge source, 2 for medium knowledge source usage, 3 for low knowledge source usage, and 4 for not relevant/no usage. To measure *human capital*, we used the number of employees with higher education as a percentage of total number of employees. *Internal R&D* was measured as the internal expenditure on R&D per employee. *Age* was measured as the number of years since the firm's founding. Finally, *innovative performance* was measured by using the percentage of turnover due to innovations on goods and services that were an innovation for the market in which the business operates. This measure reflects the success of the firm's radical innovation. Examples of innovations on goods and services introduced by the firms of our dataset include, but are not limited to, changes in the materials of the goods, introduction of software that improves accessibility, new functions in existing goods or services, introduction of ecological goods and services, services related to the internet and electronic commerce, etc. Table 2 presents relevant descriptive statistics of our final sample, which consists of 176 firms operating across various industries. .In the following section we provide a thorough illustration of how QCA can be implemented in the particular problem domain.

INSERT TABLE 2 ABOUT HERE

3.4. Calibration

One of the most challenging phases of QCA is the conversion of raw variables into set membership scores—a process called data calibration. Both crisp and fuzzy set calibration is half-conceptual and half-empirical (Greckhamer et al., 2018). Considering our four categorical scales with four states that were used in our study to capture different levels of external knowledge source usage (i.e., 1=High; 2=Medium; 3=Low; 4=Not relevant/not used), the left endpoint of the scale (value 1) conceptually serves as the qualitative anchor for calibration of full membership (i.e., high usage level of the respective external knowledge source). In contrast, the *"low"* category (value 3) conceptually serves as the qualitative threshold for calibration of full non-membership (i.e., low usage level of the respective external knowledge source), while the midpoint of the scale (value 2) serves as the crossover point of maximum ambiguity (i.e., medium usage level of the respective external knowledge source). Given the above three conceptual qualitative thresholds of full membership (value 1), neither membership nor non-membership—point of maximum ambiguity (value 2), and full non-membership (value 3), it can be inferred that the *"not relevant/not used"* category (value 4) conceptually signifies complete non-membership in the given condition (i.e., no usage of the respective external knowledge source), and therefore it was converted into a zero value set membership score during the calibration.

For all other variables considered in our study, namely human capital, internal R&D, age, and radical innovation, the crossover points, as well as the thresholds of full non-membership and full membership were empirically calculated, given the lack of relevant substantive knowledge to theoretically identify sensible thresholds that determine which cases can be meaningfully considered to be, for example, fully in versus fully out the set of firms with high levels of internal R&D in our given study setting. Therefore, we set specific criteria for the three breakpoints of these variables, based on the observed distribution and percentile scores. These breakpoints include the 0.05 percentile for the threshold of full non-membership, the 0.50 percentile (i.e., median) for the crossover point of maximum membership ambiguity, and the 0.95 percentile for the threshold of full membership (see Ragin, 2008). Although literature has documented some weaknesses of sample-based calibration, when there is no theoretical evidence about specific membership thresholds, the choice of the "median" as a crossover point is justified and is better than arbitrarily assigning the midpoint of a scale (Greckhamer et al., 2018; Wagemann et al., 2016).

In total, our sample consists of 176 cases (firms). Figure 5 illustrates relevant data for the first 38 cases of the dataset. Raw and respective calibrated (fuzzy set) data are presented in separate columns. Specifically, the first eight columns of the dataset include "supp" that represents raw data for the external knowledge source usage of "suppliers", "custom" for "customers", "comp" for "competitors", "univ" for "universities", "age" for "firm age", "hc" for "human capital", "rndint" for "internal R&D", and "rad_sal" for our outcome variable—"innovative performance". The last eight columns of Figure 5, with the "f_" prefix, present the respective calibrated fuzzy set membership scores, based on the calibration process discussed earlier.

INSERT FIGURE 5 ABOUT HERE

3.5. Test for necessity

The analysis of necessary conditions in QCA is a separate (optional) procedure that looks at which individual factors may be necessary or mostly necessary for the outcome to occur. The most commonly used method to identify single necessary conditions is to plot the cases with their causal (X) and outcome (Y) condition membership scores in an XY scatterplot and identify to which extent the cases are on or below the diagonal (see Figure 2). As noted earlier, an individual factor may be necessary or mostly necessary for the outcome to occur if the membership score on the outcome is consistently lower than the membership score of the causal factor under consideration. In the XY plot, X can be considered necessary for Y if most cases are on or below the diagonal, although some cases are allowed to be above the line, as long as the total distance of these cases to the diagonal (the consistency quantity) is not too large. The recommended threshold for necessity consistency is 0.9. If the necessary condition is above this threshold, the presence of X is considered necessary for the presence of Y.

In our example, we analyse which single causal conditions (if any) are necessary for the presence of innovative performance ("f_rad_sal"). The same analysis can be conducted for combinations of causal conditions. Specifically, we consider our six single causal conditions, namely the presence of the external knowledge source of suppliers (f_supp), customers (f_custom), competitors (f_comp), and universities (f_univ), as well as the presence of internal capabilities in the form of human capital (f_hc) and internal R&D (f_rndint). Table 3 shows the necessity consistency scores for evaluating whether each one of the six conditions is necessary for the presence of the outcome. Based on the common necessity consistency threshold of 0.9, we find that none of the conditions is necessary by its own.

INSERT TABLE 3 ABOUT HERE

Figure 6 shows relevant XY plots indicating that cases are almost equally scattered above and below the diagonals. These scatterplots confirm that none of the individual factors is necessary or mostly necessary for the outcome to occur.

INSERT FIGURE 6 ABOUT HERE

3.6. Definition of the property space

As noted earlier, in this phase the researcher defines the property space and identifies all possible combinations of binary states (presence or absence) of the *k* causal conditions examined in the study. In our case, we defined the property space by using the calibrated fuzzy set scores to construct a data matrix—called truth table, with 2^k rows $(k=7)$. Each row of this table is associated with a unique complex combination of causal conditions. Our full truth table consists of $2^7=128$ rows, which enumerate all possible combinations/configurations, based on our seven causal conditions (i.e., the four external knowledge sources, firm age, and the two internal capabilities, namely human capital and internal R&D) that potentially explain our desired outcome (i.e., innovative performance). Some of these combinations are displayed in Figure 7.

INSERT FIGURE 7 ABOUT HERE

Our full truth table displays all potential configurations of causal conditions in their combination of presence (coded as 1) or absence (coded as 0). Some rows may contain zero cases (see column *"number"*), if there is no adequate empirical evidence in the dataset that the respective complex combination co-occurs with high membership score in the desired outcome condition (logical reminders). To put it differently, rows with zero cases in the column *"number"* signify that in our sample there is not a single case/observation/firm in which the presence of the respective complex combination co-exists with the presence (high membership score) of the outcome. Specifically, the column *"number"* shows the distribution of "*best-fit"* cases (i.e., firms with high levels of innovative performance) across the configurations in our sample. In the following phase, we explain in more detail the way in which *"best-fit"* cases were assessed and how exactly our truth table was analysed, by referring to the measures of consistency and coverage.

3.7. Analysis of the property space

After defining the property space, the researcher needs to reduce the length of the truth table by conducting two types of analyses. The first analysis is descriptive in nature and assesses the distribution of cases across the property space to identify "areas" that are inhabited by "*best-fit"* cases (i.e., cases in the sample that exhibit high levels of the desired outcome) and areas that are not. As noted earlier, the column "number" of Figure 7 shows the distribution of "best-fit" cases across the configurations in our sample. Consistent with previous studies using medium-sized samples of up to 200 cases (see e.g., Ragin, 2008), we considered only configurations that contained at least one "best-fit" case, while all other configurations were dropped from further analysis, reducing in this way the length of our truth table. By considering only configurations that contained at least one "best-fit" case, while dropping all other configurations that contained zero "best-fit" cases, we reduced the length of the truth table, making in this way the analysis of the property space more manageable. This decision did not result in any loss of data, given that the configurations that were dropped were not exhibiting high levels of the desired outcome in our dataset, and therefore they were inadequate in explaining the outcome in question.

The second and most important analysis to further reduce the length of the truth table involves an investigation of the causal configurations that are *"sufficient"* to attain the outcome of interest. Although both necessity and sufficiency should generally be investigated, QCA is mostly used to allow for the detection of causal complexity, by focusing on the sufficiency of combinations of causal conditions presented in the truth table to produce an outcome (Ragin, 2000). Causal complexity implies that two or more combinations of conditions can be sufficient for the same outcome and that a specific causal condition may have different effects depending on the additional conditions that occur in a given combination. QCA mainly focuses on examining the sufficiency of causal configurations by ensuring that only combinations that satisfy the criterion of "consistency" will be considered.

Consistency ranges from 0 to 1 and represents the degree to which (or else how frequently) a causal configuration leads to an outcome (Ragin, 2008). The “raw consistency” column in our truth table (Figure 7) can therefore be interpreted as a test for sufficiency (Woodside, 2013). We calculated consistency scores for all possible causal combinations of the truth table, and then, we decided which of all possible configurations will be considered in the final solution. Combinations with high consistency scores indicate pathways that almost always lead to the given outcome condition (Elliott, 2013).

In assessing causal sufficiency, QCA employs the probabilistic concept of quasi sufficiency wherein sufficiency is assessed based on certain consistency benchmarks: A causal condition can be almost always sufficient (significantly passing a benchmark of 0.8), usually sufficient (significantly passing a benchmark of 0.65), or sufficient more often than not (significantly passing a benchmark of 0.50) in causing the outcome (Ragin, 2000). We considered configurations with consistency score of 0.77 or above. The two criteria we used to reduce the length of our truth table are presented in Figure 8.

INSERT FIGURE 8 ABOUT HERE

After conducting these two analyses, we were able to identify in our truth table only those configurations for which there is strong empirical evidence suggesting that they lead to high levels of radical innovation. These configurations in the reduced truth table were identified by setting the variable “f_rad_sal” as equal to 1, which represents that an outcome of high innovative performance is present, and equal to 0, otherwise (see Figure 9 of the final reduced truth table after implementing the two criteria).

INSERT FIGURE 9 ABOUT HERE

Once the researcher has chosen the combinations with high consistency scores that will be included in the final solutions, the next step is the logical reduction of the remaining configurations, by identifying only those configurations that, beyond being consistent, also have an adequate level of "coverage". As noted earlier, coverage represents how many cases in the dataset that have high membership in the outcome condition are represented by a particular causal configuration. Coverage gives an indication of how much of the outcome is covered (explained) by each configuration or the solution as a whole (Ragin, 2008; Woodside, 2013). Such an indicator provides researchers with support to further 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 (Ragin, 2006).

The higher the consistency cut-off point the researcher sets for selecting the best combinations, the higher the final solution consistency will be, but the lower the respective solution coverage (Elliott, 2013; Ragin, 2006). Literature suggests that a solution is informative when consistency is above 0.70 and coverage is between 0.25 and 0.65 (see e.g., Ragin, 2008; Woodside, 2013).

3.8. Solution generation

The output produced after the implementation of the above analyses provides three types of solutions, namely complex, parsimonious, and intermediate solution. Each of the three solutions consists of a set of pathways (i.e., recipes or statements of combinations of causal conditions) that are predictive of high membership score in the outcome condition (Ragin, 2008). A complex solution makes no simplifying assumptions. As a result, if the researcher considers a large number of causal antecedent conditions, the derived solution will be fairly complicated. The parsimonious solution uses the remainders (i.e., combinations of the antecedent conditions that are not observed in the dataset) to simplify the solution. This is a strong assumption, and hence, the parsimonious solution should only be used if the assumptions made are fully justified. Finally, the intermediate solution distinguishes between "easy" and "strong" assumptions, and takes into consideration only the "easy" remainders when simplifying the solution. Evidently, the complex solution is the most appropriate, as it makes no assumptions, and is highly recommended especially when the number of causal conditions is not very large (Ragin & Sonnett, 2005; Elliott, 2013).

Table 4 presents our estimated complex solution by utilizing fundamental notations of Boolean algebra and main Boolean operators. Our findings indicate an overall solution coverage of 0.41 and an overall solution consistency of 0.71, meaning that a substantial proportion of the innovative performance outcome is covered by the five derived configurations.

INSERT TABLE 4 ABOUT HERE

3.9. Test for proposed sufficient pathways

After obtaining the solution with the alternative pathways that explain the outcome of interest (potential sufficient complex conditions), we can optionally test for sufficiency of the derived pathways and examine for how many cases in the sample these pathways hold strong (Pappas, 2018; Pappas et al., 2020). This is performed by computing the specific configuration we want to test and plotting it against the outcome of interest. For example, as is shown in Table 4, a proposed sufficient pathway leading to high levels of innovative performance can be the following: mature firms, with low levels of internal R&D, and presence of supplier, customer, competitor, and university external knowledge sources (see pathway "Suff1": *f_age*~f_rdin*f_supp*f_custom*f_comp*f_univ*). To test for sufficiency of the given pathway, we first compute a new fuzzy set variable, as the set intersection (Logical *AND*) of the above six single conditions that comprise the given pathway. Subsequently, the new variable is plotted against the outcome of interest (i.e., innovative performance).

We performed this test for all five pathways of our solution, presented in Table 4. Relevant XY plots are presented in Figure 10. As noted earlier, a (single or complex) causal statement may be sufficient for the outcome to occur if the membership score on the outcome is consistently higher than the membership score of the causal condition under consideration. In the XY plot, X can be considered sufficient for Y if most cases are on or above the diagonal, although some cases are allowed to be below the line, as long as the total distance of these cases to the diagonal is not too large. The plots show that our five pathways are adequately supported as sufficient conditions. Evidently, there is no single pathway that predicts all cases with high scores on the outcome, as other pathways also exist that predict high scores of the same outcome. This is an indication of equifinality, in that multiple alternative pathways may lead to the same outcome of interest (Woodside, 2017).

INSERT FIGURE 10 ABOUT HERE

3.10. Validation

In order to validate the solution generated, the researcher can optionally implement the following two-step validation method. First, the sample can be randomly divided into a subsample and a holdout sample. Second, the researcher must run the same analysis described above for the subsample, and then the findings obtained should be tested against the holdout sample. Specifically, from the findings of the subsample, each pathway of the solution generated, needs to be modelled as a new fuzzy set variable—i.e., the set intersection of the single conditions that comprise the given pathway—following a similar procedure as the one described earlier. Each one of the new fuzzy set variables computed must then be plotted against the outcome of interest using the holdout sample (Pappas, 2018; Pappas et al., 2020). The results we were able to produce after implementing this validation method were qualitatively similar.

3.11. Interpretation and presentation of results

Table 5 shows the configurations/pathways that the analyses showed to be *"sufficient"*, based on the above described procedures. We adopt this useful table to present our results, as suggested by Ragin and Fiss (2008), where black circles (●) indicate the presence of a condition, and white circles (○) indicate its absence. Further, a blank cell indicates the "do not care" condition, which means a specific condition is not considered in a solution.

INSERT TABLE 5 ABOUT HERE

The results suggest compellingly that mature firms tend to adopt a more open innovation approach than younger firms, by combining a higher number of external knowledge sources. Noticeably, the existence of multiple sufficient configurations for innovative performance is indicative of equifinality (Fiss, 2011).

For mature firms, three pathways that lead to high innovative performance have been identified. The solution suggests that mature firms, which adopt a more open innovation approach—by combining all four knowledge sources—need to exhibit low levels of internal R&D (pathway 1) or high levels of internal capabilities in the form of human capital (pathway 2). Alternatively, mature firms, which adopt a moderate open innovation approach—by combining high levels of customer and competitor knowledge sources with low levels of supplier and university knowledge sources—also possess low levels of internal capabilities in the form of human capital and high levels of internal capabilities in the form of internal R&D (pathway 3).

For younger firms, two pathways that lead to high innovative performance have been produced. The solution suggests that in order to innovate, younger firms adopt moderate levels of open innovation, by combining two knowledge sources. To innovate they need to possess either high levels of both types of internal capabilities—if they rely on supplier and customer sources (pathway 2) — or low levels of both capabilities—if they rely on competitor and university sources (pathway 1).

4. Discussion and implications for research

The aim of this methodological paper is to help researchers understand the underlying logic of QCA and develop a step-by-step guide that outlines the various implementation phases of the method for less familiar users. Given the increasing complexity of the business and marketing phenomena, the popularity of methodological tools that allow researchers to embrace and detect causal complexity is also expected to increase (Woodside, 2018). QCA is an example in case, as it can benefit practitioners and academics in several important ways. First, QCA can be used to identify how different antecedent conditions combined into a causal recipe (configuration) may explain an outcome of interest—a feature also known as conjunctural causation (Ragin and Fiss, 2008). In conventional correlational approaches, such as regression analysis, interdependencies among independent variables are tested as interactions. Specifically, correlation-based studies use two- and three-way interactions to examine configurations. Although, empirically, three-way interactions represent the boundaries of interpretable regression analysis, from a theoretical perspective, a configuration may well exceed the limit of three variables (Dess et al., 1997). QCA is particularly designed to identify configurations consisting of multiple causal conditions that are sufficient to lead to an outcome.

Second, QCA can identify configurations where high and low values of the same causal condition may exert the same influence on the outcome of interest—a feature known as asymmetry. For example, some of the mature firms in the dataset used for our demonstration, can achieve high levels of innovative performance through configurations that require high levels of internal capabilities in the form of human capital (pathway 2), while other mature firms can achieve this through configurations that involve low levels of human capital (pathway 3). Correlation-based methods treat relationships as symmetric and estimate the net effect of an independent variable on a dependent variable (Gligor et al., 2019; Fiss, 2011; Woodside, 2015). In contrast, QCA allows researchers to identify different ways through which a given causal condition can lead to a certain outcome, as explained above.

Third, QCA allows for the identification of alternative causal recipes (configurations of conditions) that lead to the same outcome of interest—a feature known as equifinality (Schneider & Wagemann, 2010; Wagemann et al., 2016). QCA revealed in our dataset the existence of multiple sufficient configurations for high levels of innovative performance. Regression-based logic does not take equifinality into account. Although interaction effects can test a nonlinear relationship, it is assumed that this relationship is relevant for all cases in the dataset. In contrast, researchers can employ QCA to identify alternative solutions, and thus provide a more nuanced coverage of the factors explaining the desired outcome.

Fourth, QCA bridges the gap between qualitative and quantitative methods and proposes a third—complementary—way that provides thorough insights into the phenomena of interest (Wagemann et al., 2016; De Villiers & Tipgomut, 2018). Our illustration in the B2B context of open and closed innovation provided a more holistic and accurate picture of the examined complex interrelationships. We estimated alternative causal configurations that are sufficient for high levels of innovative performance and described combinatorial complexities assuming asymmetric relationships, rather than symmetrical net effects. In this way, relevant results can advance the extant open innovation literature on the external knowledge sources and internal capabilities determinants of radical innovation, by shedding new light on several important issues, such as the interdependence among factors, the fact that both types of (internal and external) factors collectively (and not in isolation) are important in understanding radical innovation, and that there is a high degree of complexity underlying the determination of radical innovation. For instance, regarding interdependency, the application of QCA enhances our understanding regarding what types of external knowledge sources firms need to access to enhance their innovative performance, depending on the type and level of internal resources they possess. It can also enhance our understanding about the type and level of internal resources firms have to possess, to be able to successfully assimilate knowledge sourced from external sources (absorptive capacity), depending on the configuration, extent, and intensity of the open innovation approach. The analysis therefore provides further insights in relation to previous studies that explored the overall breadth of knowledge sources (Laursen and Salter, 2006; Tsinopoulos et al., 2019), or those that explored the effect of different dimensions of absorptive capacity through a regression model (Kafouros et al., 2020).

However, there are also limitations in the use of QCA that need to be taken into account. First, formally testing causal complexity implies that the researcher develops specific hypotheses about how multiple causal conditions will combine (conjunctural causality), what different combinations will comprise multiple pathways to the outcome (equifinality), and/or how both the presence and absence of particular causal conditions may lead to the outcome (causal asymmetry). Evidently, developing such configurational hypotheses can be much more challenging than developing linear predictions. Second, because QCA considers all possible combinations of causal conditions, the number of combinations increases exponentially with the addition of conditions. Therefore, researchers should be focusing on theoretically relevant conditions to limit the complexity of their analyses and findings. Although even in conventional regression analyses there have been calls for developing more parsimonious models (Spector & Brannick, 2011), QCA's logic contrast with the custom logic of correlation-based methods that often consider an extended number of variables as "controls". Last, researchers using QCA should be cautious when they develop theoretical insights beyond their study's cases (Cress & Snow, 2000; Greckhamer et al., 2013). Generalization in QCA studies has been criticized for being "modest" (Rihoux & Ragin, 2009) and that studies using QCA should build or elaborate on theories of specific phenomena within a bounded scope (e.g., Campbell et al., 2016; Crilly, 2011; Fiss, 2011). However, some scholars do not agree with this limitation. Since its advent, it has become obvious that, in addition to small sample sizes, QCA can handle a medium, as well as a large number of cases (Befani, 2013). Indeed, several studies have compared QCA and regression analysis by applying them to the same datasets (e.g., Lisboa et al., 2016; Skarmeas et al., 2014, 2018; Vis, 2012). These studies conclude that, while QCA can adequately handle the same number of cases as regression, and is, thus, as strong on external validity, it leads to a fuller understanding of the conditions under which the outcome occurs, providing richer information on the complexity of causal relations. While QCA's limited, mid-range generalizability to other samples, and inherently focused model specification are critical issues, researchers need to account for them in their research designs and theoretical claims.

In spite of its potential limitations, the use of QCA could be equally revealing in other areas of B2B and industrial marketing, such as branding mechanisms, big data analytics, entrepreneurial marketing, customer-related behaviors, social and environmental sustainability (Gligor et al., 2021). Applying QCA in those areas of study may uncover new patterns that had been overlooked by correlational research approaches. Given the increasing complexity of contemporary business environments, what it seemed to be an outlier case, may actually exert unexpected influence, and QCA may reveal alternative pathways to equifinal outcomes. We hope that the ideas presented here can be particularly useful for scholars who want to apply QCA in their research and motivate further utilization of this evolving technique.

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Table 1. Hypothetical truth table

Row#	A	B	C	D	Cases with Outcome Y Present	Cases with Outcome Y Absent	Consistency	Type of configuration
1	0 (no)	0 (no)	0 (no)	0 (no)	0	0	??	logical remainder
2	0 (no)	0 (no)	0 (no)	1 (yes)	0	0	??	logical remainder
3	0 (no)	0 (no)	1 (yes)	0 (no)	0	4	0.0	Non-contradictory row
4	0 (no)	0 (no)	1 (yes)	1 (yes)	1	5	0.167	Contradictory row
5	0 (no)	1 (yes)	0 (no)	0 (no)	0	0	??	logical remainder
6	0 (no)	1 (yes)	0 (no)	1 (yes)	4	0	1.0	Non-contradictory row
7	0 (no)	1 (yes)	1 (yes)	0 (no)	0	0	??	logical remainder
8	0 (no)	1 (yes)	1 (yes)	1 (yes)	5	0	1.0	Non-contradictory row
9	1 (yes)	0 (no)	0 (no)	0 (no)	0	3	0.0	Non-contradictory row
10	1 (yes)	0 (no)	0 (no)	1 (yes)	1	7	0.125	Contradictory row
11	1 (yes)	0 (no)	1 (yes)	0 (no)	0	10	0.0	Non-contradictory row
12	1 (yes)	0 (no)	1 (yes)	1 (yes)	0	0	??	logical remainder
13	1 (yes)	1 (yes)	0 (no)	0 (no)	1	5	0.167	Contradictory row
14	1 (yes)	1 (yes)	0 (no)	1 (yes)	6	0	1.0	Non-contradictory row
15	1 (yes)	1 (yes)	1 (yes)	0 (no)	6	2	0.75	Contradictory row
16	1 (yes)	1 (yes)	1 (yes)	1 (yes)	8	0	1.0	Non-contradictory row

Table 2. Descriptive statistics of our sample

Characteristics of the firms in our sample	Mean	Std. Dev.	Type of measure
Age	32.756	21.01	count
Size (number of employees)	537.813	3118.065	count
Human capital	36.67216	31.3199	percentage
Internal R&D	1619778	3414769	count
Innovative performance (radical innovation)	41.174	45.018	percentage
Industry classification of the firms in our sample (branch of activity)	**Percentage of firms (%)**		
Administrative Activities and Auxiliary Services	1.13		
Aircraft and Spacecraft Manufacturing	0.56		
Card and Paper	0.56		
Chemicals	10.2		
Computing, Electronic, and Optical Products	1.70		
Construction	2.27		
Electrical Materials and Equipment	1.70		
Energy and Water	0.56		
Extractive Industries	1.13		
Financial and Insurance Activities	0.56		
Food, Drink, and Tobacco	7.95		
Furniture	0.56		
Graphic Arts and Reproduction	0.56		
Leather and Footwear	1.13		
Manufactured Metallic Goods	5.68		
Metallurgy	1.70		
Motor Vehicles	6.81		
Other Computing and Communications Services	1.13		
Other Machinery and Equipment	4.54		
Other Manufacturing Activities	2.27		
Other Transport Equipment	0.56		
Pharmaceuticals	3.97		
Programming, Consulting, and Other Computing Activities	3.97		
R&D Services	11.3		
Repair and Installation Of Machinery And Equipment	1.70		
Rubber and Plastics	3.97		
Sanitation, Waste Management, and Decontamination	0.56		
Shipbuilding	0.56		
Textiles	2.27		
Trade	3.97		
Transport and Storage	1.70		
Various Non-Metallic Mineral Products	1.70		
Wood and Cork	0.56		
Wood and Cork	1.70		
Other Activities	8.81		

Table 3. Necessary condition analysis of single causal conditions for the presence of innovative performance

Single causal condition	Necessity consistency score
suppliers (f_supp)	0.710299
customers (f_custom)	0.696167
competitors (f_comp)	0.596538
universities (f_univ)	0.553790
human capital (f_hc)	0.696167
internal R&D (f_rndint)	0.671260

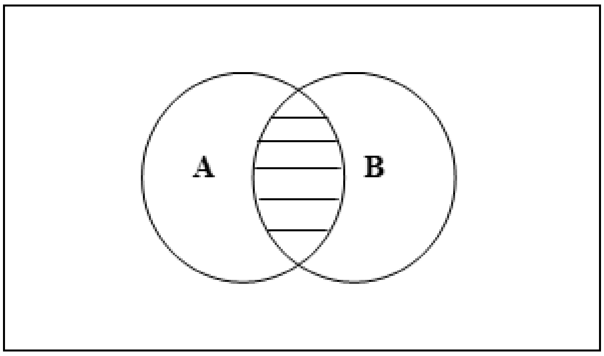
Table 4. Complex solution for the outcome condition of innovative performance

COMPLEX SOLUTION	Raw coverage	Unique coverage	Consistency
Radical innovation			
Model: f_rad_sal = f(f_age, f_hc, f_rdin, f_supp, f_custom, f_comp, f_univ)			
Mature firms			
Suff1: f_age*~f_rdin*f_supp*f_custom*f_comp*f_univ	0.172231	0.023494	0.758755
Suff2: f_age*f_hc*f_supp*f_custom*f_comp*f_univ	0.157393	0.004946	0.803427
Suff3: f_age*~f_hc*f_rdin*~f_supp*f_custom*f_comp*~f_univ	0.192193	0.050874	0.785560
Young firms			
Suff4: ~f_age*~f_hc*~f_rdin*~f_supp*~f_custom*f_comp*f_univ	0.130896	0.031090	0.775916
Suff5: ~f_age*f_hc*f_rdin*f_supp*f_custom*~f_comp*~f_univ	0.243950	0.104045	0.780226
solution coverage: 0.405582; solution consistency: 0.708423			

Table 5. Configurations for achieving high levels of innovative performance

	Pathways for high membership score in the outcome condition of innovative performance*				
Causal condition	*Mature firms*			*Young firms*	
	1st	**2nd**	**3rd**	**1st**	**2nd**
Human capital		●	○	○	●
Internal R&D	○		●	○	●
Suppliers	●	●	○	○	●
Customers	●	●	●	○	●
Competitors	●	●	●	●	○
Universities	●	●	○	●	○

**Black circles indicate very high presence of a condition, and white circles indicate very low presence (i.e., absence) of a condition. Blank spaces in a pathway indicate "don't care".*



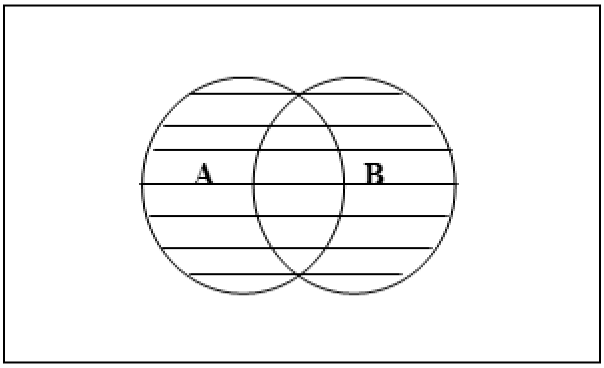
Meaning: The shared parts of sets A and B

Denoted as: A*B

Computed as: A*B = min(A, B); i.e., if A=0.42 and B=0.98, A*B=min(0.42, 0.98)=0.42.

QCA relevance: Combination of conditions that form a recipe/pathway (i.e., A and B together)

Set Intersection (Logical *AND*)



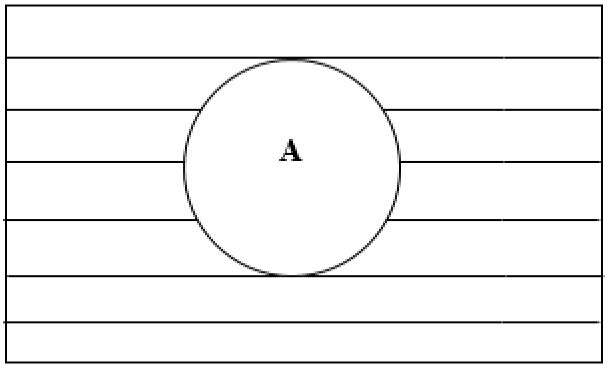
Meaning: The parts of set A, set B, or both

Denoted as: A+B

Computed as: A+B = max(A, B); i.e., if A=0.42 and B=0.98, A+B=max(0.42, 0.98)=0.98.

QCA relevance: Alternative causal recipes/pathways (i.e., combinations of conditions) that lead to an outcome

Set Union (Logical *OR*)



Meaning: The portion excluded from set A

Denoted: ~A

Computed: ~A = 1-A; i.e., if A=0.42, ~A = 1-0.42=0.58.

QCA relevance: The absence or very low presence of a condition

Set Negation (Logical *NOT*)

Figure 1. Boolean operations and their relevance to QCA

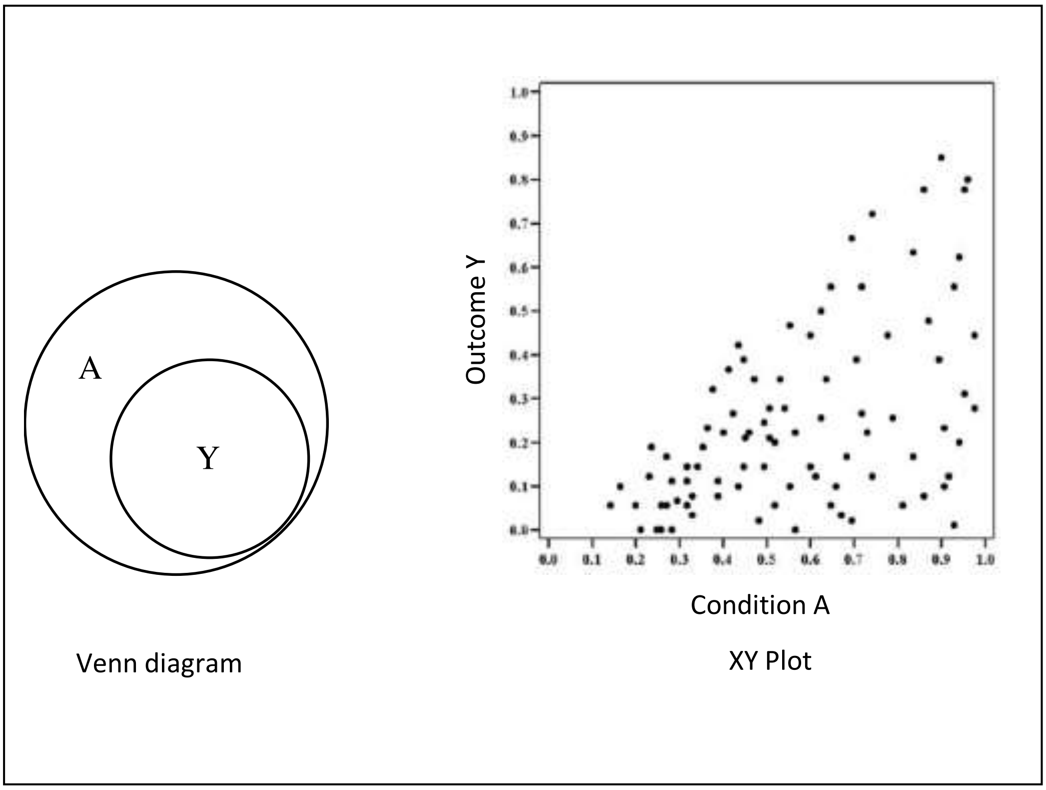


Figure 2. Visualising necessity (Y ≤ A)

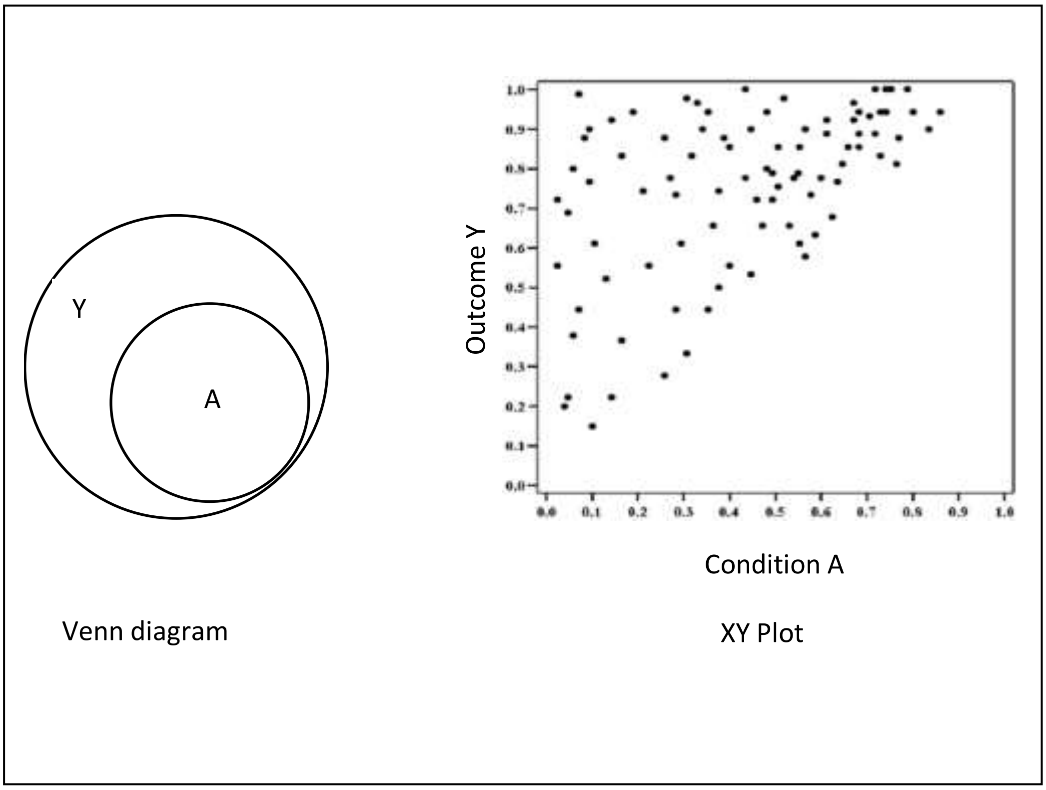


Figure 3. Visualising sufficiency (A ≤ Y)

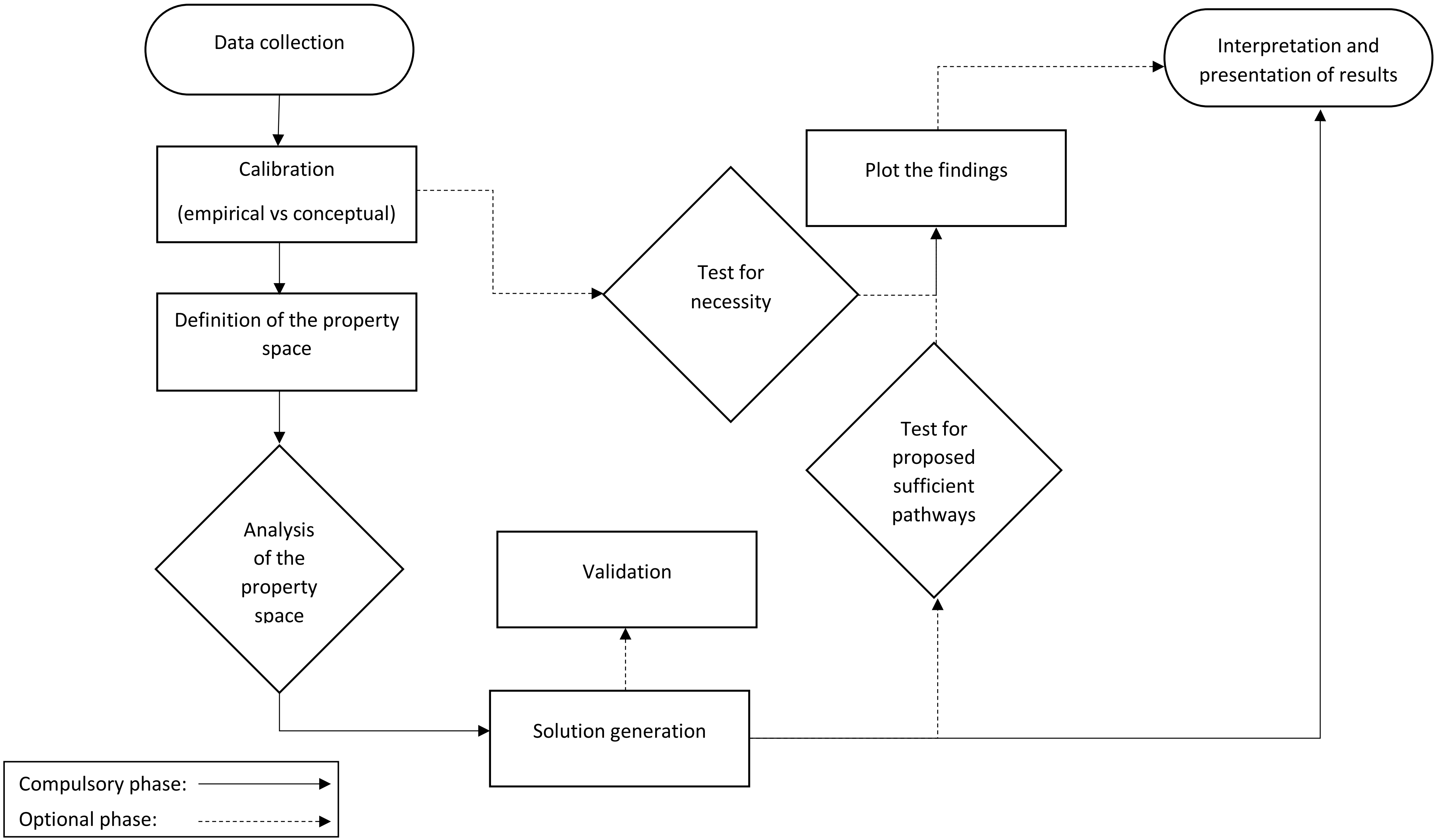


Figure 4. Phases of QCA implementation

FS/QCA Data Sheet

File Variables Cases Analyze Graphs

Case	supp	custom	comp	univ	age	hc	rndint	rad_cal	f_supp	f_custom	f_comp	f_univ	f_age	f_hc	f_rndint	f_rad_cal
1	2	3	3	3	19	55.6	2513128	0	0.5	0.05	0.05	0.05	0.16	0.77	0.73	0.05
2	2	2	3	2	68	5.3	230496.4	0	0.5	0.5	0.05	0.5	0.94	0.09	0.3	0.05
3	2	1	4	3	70	10.9	348430.9	8746.1384	0.5	0.95	0	0.05	0.95	0.16	0.5	0.68
4	4	4	4	4	69	5.2	0	0	0	0	0	0	0.95	0.09	0.05	0.05
5	1	2	4	4	62	100	21426.53	0	0.95	0.5	0	0	0.92	0.95	0.06	0.05
6	4	4	3	2	46	36.6	292986.7	104000	0	0	0.05	0.5	0.78	0.62	0.44	1
7	1	2	2	1	47	41.2	196252.5	1902.1778	0.95	0.5	0.5	0.95	0.79	0.66	0.24	0.54
8	2	3	3	3	46	9.4	20556.02	0	0.5	0.05	0.05	0.05	0.78	0.14	0.06	0.05
9	2	1	2	2	34	35	316569.4	1126.7904	0.5	0.95	0.5	0.5	0.6	0.6	0.49	0.52
10	4	4	4	1	43	5.2	0	0	0	0	0	0.95	0.74	0.09	0.05	0.05
11	2	2	2	2	42	39.1	0	6265	0.5	0.5	0.5	0.5	0.73	0.64	0.05	0.63
12	2	1	2	3	26	34.5	1085541	0	0.5	0.95	0.5	0.05	0.41	0.6	0.58	0.05
13	1	1	1	1	35	27	121735.3	0	0.95	0.95	0.95	0.95	0.62	0.52	0.13	0.05
14	2	2	2	1	87	8.3	509803.2	1008.0452	0.5	0.5	0.5	0.95	0.98	0.12	0.52	0.52
15	3	2	4	4	32	20.3	0	0	0.05	0.5	0	0	0.57	0.37	0.05	0.05
16	3	3	3	3	26	14	255556	0	0.05	0.05	0.05	0.05	0.41	0.21	0.35	0.05
17	1	1	1	1	19	55	104601.8	0	0.95	0.95	0.95	0.95	0.16	0.77	0.12	0.05
18	2	1	3	2	180	11.1	639740.3	5445	0.5	0.95	0.05	0.5	1	0.16	0.54	0.61
19	1	2	1	2	20	63.6	106844.2	0	0.95	0.5	0.95	0.5	0.18	0.83	0.12	0.05
20	1	1	3	2	42	0	201113.2	17020	0.95	0.95	0.05	0.5	0.73	0.05	0.25	0.81
21	3	2	2	2	26	6.6	206465.1	481.05681	0.05	0.5	0.5	0.5	0.41	0.1	0.26	0.51
22	4	1	1	4	83	19.2	220093	0	0	0.95	0.95	0	0.98	0.34	0.28	0.05
23	2	1	2	4	45	16.7	76818.01	0	0.5	0.95	0.5	0	0.77	0.28	0.09	0.05
24	1	1	2	4	42	74.1	322365.6	1520.9074	0.95	0.95	0.5	0	0.73	0.88	0.5	0.53
25	1	1	2	4	32	24.4	915984.6	0	0.95	0.95	0.5	0	0.57	0.49	0.57	0.05
26	4	2	2	4	31	18.5	1401672	684.4986	0	0.5	0.5	0	0.55	0.32	0.62	0.51
27	2	1	3	3	27	12.8	494171	892.14672	0.5	0.95	0.05	0.05	0.45	0.19	0.52	0.52
28	2	1	2	4	23	10.8	46535.04	0	0.5	0.95	0.5	0	0.28	0.16	0.07	0.05
29	2	2	2	3	22	11.5	637354.8	0	0.5	0.5	0.5	0.05	0.25	0.17	0.54	0.05
30	2	2	2	4	35	15.6	824561.3	747.0848	0.5	0.5	0.5	0	0.62	0.25	0.56	0.51
31	3	3	3	1	28	31	696316.2	0	0.05	0.05	0.05	0.95	0.5	0.56	0.54	0.05
32	4	2	3	3	53	9.6	1446581	109000	0	0.5	0.05	0.05	0.85	0.14	0.62	1
33	1	1	1	1	52	100	668068.4	6457.4087	0.95	0.95	0.95	0.95	0.85	0.95	0.54	0.63
34	2	2	3	2	49	56.3	138923	8535	0.5	0.5	0.05	0.5	0.82	0.78	0.15	0.67
35	1	1	1	4	48	17	425156.3	0	0.95	0.95	0.95	0	0.81	0.28	0.51	0.05
36	2	2	3	2	58	38	79987.16	0	0.5	0.5	0.05	0.5	0.89	0.63	0.1	0.05
37	2	2	3	3	41	25.3	226747.9	0	0.5	0.5	0.05	0.05	0.72	0.51	0.29	0.05
38	3	3	2	3	34	14.7	177656.9	1895.3995	0.05	0.05	0.5	0.05	0.6	0.23	0.21	0.54

Figure 5. Illustrative data for the first 38 cases of our dataset

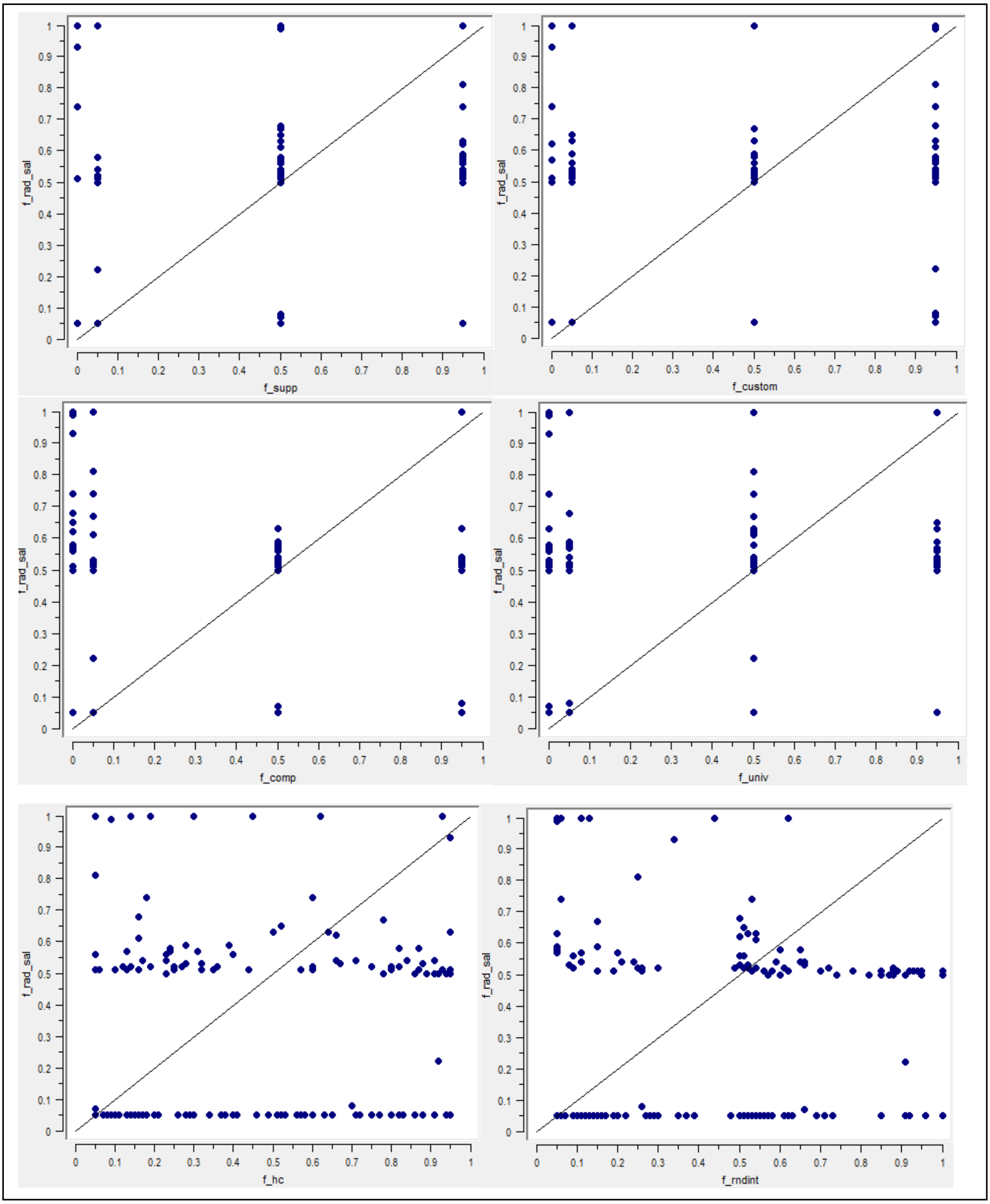


Figure 6. Scatterplots of cases with their membership scores in the six single causal conditions and the outcome condition of innovative performance.

Edit Truth Table

File Edit Sort

f_supp	f_custom	f_comp	f_univ	f_age	f_hc	f_mdint	number	f_rad_sal	raw consist.	PRI consist.	SYM consist
1	1	1	1	0	1	1	4 (11%)		0.747331	0.094388	0.126280
0	0	0	0	1	0	0	4 (22%)		0.517657	0.133988	0.134692
1	1	1	1	1	0	0	2 (28%)		0.777673	0.105660	0.107692
1	0	0	1	1	0	0	2 (34%)		0.695685	0.092551	0.095571
0	0	0	0	1	1	0	2 (40%)		0.611761	0.191449	0.191449
1	1	1	1	1	1	1	1 (42%)		0.903686	0.336065	0.336065
1	1	1	1	1	1	0	1 (45%)		0.811958	0.223108	0.223108
1	1	1	1	0	1	0	1 (48%)		0.754782	0.177842	0.177842
1	1	1	0	1	0	1	1 (51%)		0.727077	0.045113	0.045113
1	1	1	0	0	1	1	1 (54%)		0.755319	0.075650	0.075650
1	1	0	0	1	1	0	1 (57%)		0.636216	0.082305	0.082305
1	1	0	0	0	1	1	1 (60%)		0.780226	0.158009	0.160439
1	1	0	0	0	0	0	1 (62%)		0.597350	0.057754	0.057754
1	0	0	1	1	1	0	1 (65%)		0.728550	0.169684	0.169684
1	0	0	0	1	0	0	1 (68%)		0.592053	0.112692	0.112692
0	1	1	0	1	0	1	1 (71%)		0.785560	0.086154	0.086154
0	1	1	0	1	0	0	1 (74%)		0.669930	0.053042	0.053042
0	1	0	0	0	1	1	1 (77%)		0.760089	0.103306	0.103306
0	1	0	0	0	0	1	1 (80%)		0.682622	0.073211	0.073825
0	1	0	0	0	0	0	1 (82%)		0.579880	0.041446	0.041446
0	0	1	1	0	0	0	1 (85%)		0.775916	0.267123	0.267123
0	0	0	1	1	0	0	1 (88%)		0.595932	0.168759	0.168759
0	0	0	1	0	0	1	1 (91%)		0.694215	0.125296	0.125891
0	0	0	0	0	1	1	1 (94%)		0.732410	0.163334	0.168385
0	0	0	0	0	1	0	1 (97%)		0.630555	0.105200	0.105200
0	0	0	0	0	0	0	1 (100%)		0.540034	0.066335	0.066335
1	1	1	1	1	0	1	0 (100%)				
1	1	1	1	0	0	1	0 (100%)				
1	1	1	1	0	0	0	0 (100%)				
1	1	1	0	1	1	1	0 (100%)				
1	1	1	0	1	1	0	0 (100%)				
1	1	1	0	1	0	0	0 (100%)				
1	1	1	0	0	1	0	0 (100%)				
1	1	1	0	0	0	1	0 (100%)				
1	1	1	0	0	0	0	0 (100%)				
1	1	0	1	1	1	1	0 (100%)				

Figure 7. Initial truth table presenting illustrative full combinations

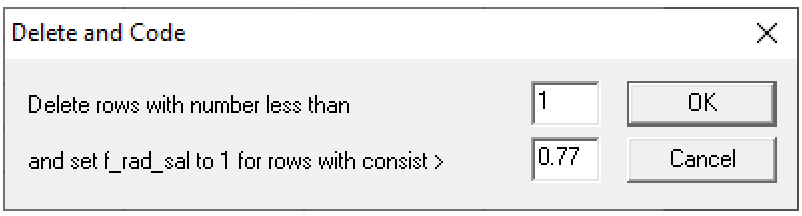


Figure 8. Criteria used to reduce the length of the truth table

Edit Truth Table

File Edit Sort

f_supp	f_custom	f_comp	f_univ	f_age	f_hc	f_mdint	number	f_rad_sal	raw consist.	PRI consist.	SYM consist
1	1	1	1	1	1	1	1	1	0.903686	0.336065	0.336065
1	1	1	1	1	1	0	1	1	0.811958	0.223108	0.223108
0	1	1	0	1	0	1	1	1	0.785560	0.086154	0.086154
1	1	0	0	0	1	1	1	1	0.780226	0.158009	0.160439
1	1	1	1	1	0	0	2	1	0.777673	0.105660	0.107692
0	0	1	1	0	0	0	1	1	0.775916	0.267123	0.267123
0	1	0	0	0	1	1	1	0	0.760089	0.103306	0.103306
1	1	1	0	0	1	1	1	0	0.755319	0.075650	0.075650
1	1	1	1	0	1	0	1	0	0.754782	0.177842	0.177842
1	1	1	1	0	1	1	4	0	0.747331	0.094388	0.126280
0	0	0	0	0	1	1	1	0	0.732410	0.163334	0.168385
1	0	0	1	1	1	0	1	0	0.728550	0.169684	0.169684
1	1	1	0	1	0	1	1	0	0.727077	0.045113	0.045113
1	0	0	1	1	0	0	2	0	0.695685	0.092551	0.095571
0	0	0	1	0	0	1	1	0	0.694215	0.125296	0.125891
0	1	0	0	0	0	1	1	0	0.682622	0.073211	0.073825
0	1	1	0	1	0	0	1	0	0.669930	0.053042	0.053042
1	1	0	0	1	1	0	1	0	0.636216	0.082305	0.082305
0	0	0	0	0	1	0	1	0	0.630555	0.105200	0.105200
0	0	0	0	1	1	0	2	0	0.611761	0.191449	0.191449
1	1	0	0	0	0	0	1	0	0.597350	0.057754	0.057754
0	0	0	1	1	0	0	1	0	0.595932	0.168759	0.168759
1	0	0	0	1	0	0	1	0	0.592053	0.112692	0.112692
0	1	0	0	0	0	0	1	0	0.579880	0.041446	0.041446
0	0	0	0	0	0	0	1	0	0.540034	0.066335	0.066335
0	0	0	0	1	0	0	4	0	0.517657	0.133988	0.134692

Figure 9. Final reduced truth table

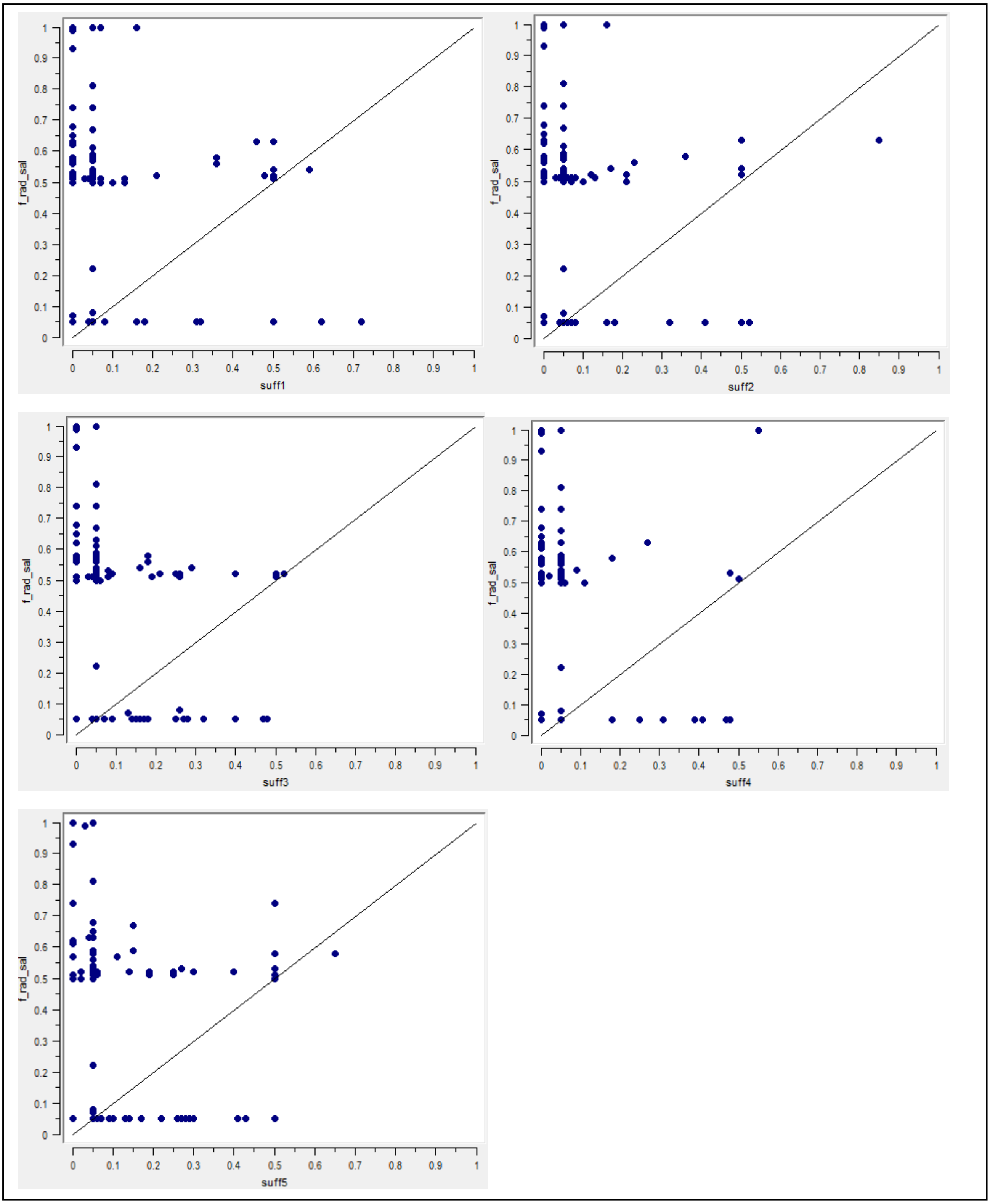


Figure 10. Testing for sufficiency of specific complex conditions