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QUALITATIVE COMPARATIVE ANALYSIS: A METHOD OF GROWING INTEREST IN MANAGEMENT RESEARCH

Seweryn KRUPNIK[1*], Johannes MEUER[2]

[1] Jagiellonian University, Poland; seweryn.krupnik@uj.edu.pl, ORCID: 0000-0003-2486-0702
[2] Kuehne Logistics University, Hamburg, Germany, johannes.meuer@klu.org, ORCID: 0000-0003-3443-6761
*Correspondence author

Purpose: Qualitative comparative analysis (QCA) allows a systematic and transparent comparison of cases while investigating explanatory conditions as sufficient or necessary for an outcome to occur. This paper aims to illustrate the usefulness of QCA in management research.
Approach: There are five steps in a standard QCA process: 1) constructing a configurational model and selecting the conditions and outcome of interest, 2) identifying empirical cases and calibrating the data into sets, 3) converting the dataset into a truth table, 4) analysing set relations between the conditions and the outcome and 5) evaluating, interpreting and visualising the findings. We discuss these five steps and illustrate their application with a fictional analysis of configurations of conditions leading to high investment in research and development (R&D). In addition, we review the recent literature on QCA, including its application in management studies.
Findings: We provide information on QCA-related resources and events, including workshops and summer schools. Current challenges in the diffusion and development of QCA involve analysing large data samples and including QCA in mixed-methods and multi-method research designs. Future challenges are related to configurational theorising, including time in the analysis and the foundations and procedures on which causal claims are made in QCA.
Practical implications: QCA is gaining popularity in management research. Its assumptions about social reality and research procedures align well with management research questions and practices. There are many areas for further development. Nevertheless, QCA is a valuable tool for management researchers.
Value: This paper focuses on the use of QCA in management research. It sheds light on the standard procedures involved in QCA and describes the application of QCA in management research based on the current literature.

Keywords: Qualitative comparative analysis, R&D investment, Comparative research.

Category of paper: General Review.

1. Introduction

Qualitative comparative analysis (QCA) is a relatively new research method that is attracting increasing attention in management research. QCA is a formalised comparative method inspired by comparative case study research (Yin, 2004) that uses set analytics and Boolean algebra to explicitly and systematically compare cases. These features of QCA allow it to identify conditions that are sufficient or necessary for an outcome to occur and to handle relations of considerable causal complexity.

There are many reasons for the growing popularity of QCA. These include the ability of QCA to allow researchers to explore complex causal relations structures when, for example, an outcome is explained not only by one condition but by the co-occurrence of many conditions. As such, QCA is suited to studies that aim to build typologies and investigate causal relations. In addition, QCA is systematic and transparent. Thus, all researchers can replicate the analysis and relatively easily engage in a discussion about decisions that were made during the analysis and the obtained results. QCA can be applied to a large number of cases. An additional advantage of QCA is that it can be integrated with other qualitative and quantitative methods.

While there is already an abundance of QCA studies in management research (Kumar et al., 2022; Kraus, Ribeiro-Soriano, Schüssler, 2018; Riog-Tierno, Gonzalez-Cruz, Llopis-Martinez, 2017), including papers published in this journal (e.g. Kwiotkowska, 2022), there is a need to share recent developments and good practices (Rubinson et al., 2019; Thomann, Ege, Paustyan, 2022). In this paper, we address this need by illustrating the use of the five-step QCA process in management research using a hypothetical scenario. The target audience of this paper is management researchers who have some knowledge of QCA and are interested in applying it in their research.

We place QCA within the context of management research and briefly illustrate the use of QCA in five steps. Towards the end of the paper, we discuss current developments and challenges in QCA and offer practical tips for those interested in learning more about QCA. The novel aspects of this paper are the review of the current literature on QCA and the demonstration of the application of QCA using a hypothetical Polish example.

2. QCA in Business and Management Research

2.1. Historical background

QCA emerged in 1987 with the publication of ‘The comparative method. Moving beyond qualitative and quantitative strategies’ by Charles Ragin (1987). QCA originated in comparative sociology and political sciences and was primarily used in these fields until the early 2000s.

Until this point, the application of QCA was limited to crisp sets (i.e. binary indicators), allowing researchers to distinguish only two states. With the publication of 'Fuzzy-set social sciences' (Ragin, 2000), researchers were now able to measure and express nuances—a change that led to the swift expansion of QCA across the social sciences, including the first applications of QCA in management research (Kitchener, Beynon, Harrington, 2002; Takahashi, Nakamura, 2005) and the development of the first software for QCA analyses, such as fs/QCA and Tosmana (Cronqvist, 2017; Drass, Ragin, 1992).

QCA became more widely known in management research by publishing several conceptual, methodological and empirical studies (Bell, Filatotchev, Aguilera, 2014; Crilly, 2011; Fiss, 2007, 2011; Greckhamer et al., 2008). Together, these studies comprehensively introduced the conceptual logic and analytical approach underlying QCA to the management community and triggered the emergence of a community of management researchers with a shared interest in configurational comparative methods. From the mid-2010s, the use of QCA in management research began to rapidly spread from the core field of organisational theory and organisational sociology into related fields, such as strategy and technology management, governance and entrepreneurship and human resource management or managerial cognition research, with many researchers publishing studies on QCA in leading academic journals (Aversa, Furnari, Haefliger, 2015; Crilly, Zollo, Hansen, 2012; Garcia-Castro, Francoeur, 2016; Meuer, Rupietta, Backes-Gellner, 2015; Pajunen, 2008). During this period, the expertise of editorial boards in dealing with QCA papers and of reviewers in constructively developing these papers substantially increased, as did the QCA community. Together, these developments led to tailored QCA-related training, regular events (e.g. the Annual Professional Development Workshop [PDW] at the Academy of Management [AOM] and International QCA Workshops) and the purposeful integration of QCA with other research methods (e.g. Fischer, Maggetti, 2017; Gabriel et al., 2018; Meuer, Rupietta, 2017a). Today, QCA has established itself as arguably the most important and frequently used analytical method for configurational comparative research in the management literature.

2.2. Typical applications

There are several reasons why QCA is increasingly applied in management research. At a foundational level, the conceptual perspective of QCA closely aligns with many dominant theories in management research (Fiss, 2007). Organisations—as the unifying theme of management research—are often conceptualised as configurations of interconnected elements. Thus, management researchers face many phenomena that are configurational by nature, making configurational research both conceptual and methodological.

Another reason why QCA is increasingly applied in management research is that its approach to configurational theorising is closely aligned with many fields in management research. Rather than examining the role and magnitude of individual explanatory factors as a cause of an outcome of interest, QCA's approach to theorising allows researchers to explicitly distinguish necessary from sufficient conditions. In so doing, QCA also closely aligns with typology theorising, an approach to theorising that is often used in management research, as indicated by prominent typologies (e.g. Hall, Soskice, 2001; Miles, Snow, 1978; Van Knippenberg et al., 2004).

Furthermore, QCA's approach to empirical research is attractive to management researchers. On the one hand, QCA is a case-based method, requiring familiarity with entire cases (rather than individual variables). On the other hand, QCA is similar to more quantitative empirical methods in that its analytic approach is transparent, systematic and formalised. In fact, many researchers have drawn on QCA because it offers a means to systematically analyse data sets with only a few observations. For these reasons, QCA is often described as being able to bridge the qualitative and quantitative divide in the social sciences. The applicability of QCA to smaller samples while remaining transparent, systematic and formalised makes it particularly suited to being integrated with other methods.

2.3. Standard QCA process

The choice of research method always needs to be aligned with the research question that an empirical study addresses. Moreover, most methods have certain prerequisites in terms of the nature of the investigated phenomena, volume and type of data. In general, QCA appears to be a valuable method for investigating complex associations between necessary and sufficient conditions or for identifying complex patterns or typologies through a systematic and case-comparative approach. The five steps of a standard QCA process are illustrated in Figure 1.

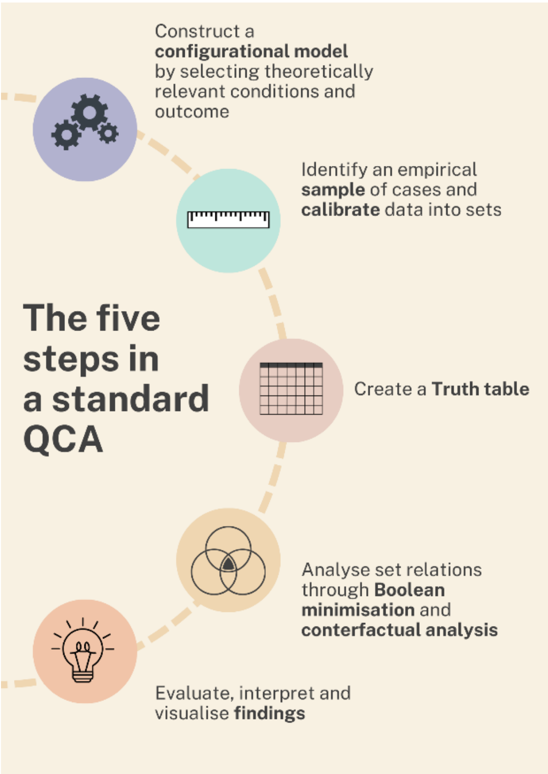

Figure 1. The five steps in a standard QCA.

In the first step, the researcher develops a configurational model. This step includes both selecting the outcome and the explanatory conditions, as well as engaging in ‘configurational theorising’. The selection of the explanatory conditions may be inductive (e.g. based on the researcher’s observations or substantive arguments) or deductive (e.g. based on theoretical considerations). Through configurational theorising, the researcher reveals causally complex associations between the outcome and (among) explanatory conditions, addressing such questions as why would conditions appear in combinations or why would a certain condition be more important in one bundle than in other bundles.

In the second step, the researcher constructs the dataset. This step includes identifying the relevant cases (usually through case selection), defining measures and calibrating data into either crisp or fuzzy-set membership scores. QCA is relatively flexible in terms of data requirements, utilising both quantitative and qualitative data (e.g. archival material, interviews, recordings, surveys and official statistics). Historically, QCA studies have used small sample sizes of between 12 and 50 cases (small-N QCA). However, a few early studies and a growing number of recent studies have used much larger samples (large-N QCA). Two important considerations when constructing the dataset are to ensure sufficient diversity among cases, both in the outcome and in the explanatory conditions, and to have a high enough ratio of cases to conditions[i].

The researcher then calibrates the outcome and conditions by assigning membership scores based on substantive and theoretical knowledge. Calibration is relatively unknown in the social sciences but common in other fields and refers to the process of transforming raw data into meaningful set-membership scores. The researcher calibrates the data by defining three critical, meaningful qualitative anchors (Ragin, 2000, 2008) that determine whether a case is a member of a set (full membership) or not a member of a set (full non-membership) or whether it is unclear whether a case is in or out of a set. Calibration is a critical step in QCA, substantively, because it ensures that the researcher analyses meaningfully measured conditions and mathematically, because it transforms data into set-membership scores, a prerequisite for the Boolean minimisation that QCA uses to analyse datasets. Due to its importance, researchers often spend a significant amount of time on calibration and on discussing and proposing best practices around calibration, such as avoiding symmetric calibration, the full range of Likert scales or central measures of tendencies (Rubinson et al., 2019).

In the third step, the researcher converts the dataset into a so-called truth table. The truth table is a mathematical instrument in logics and Boolean algebra. Each row in the truth table corresponds to one logically possibly combination of present and absent conditions. The truth table captures the entire universe of all logically possible combinations. The size of the truth table (i.e. the number of rows) is determined by the number of conditions included in the model. The number of rows is 2^k, with k referring to the number of conditions, so that the truth table size exponentially increases with the number of conditions in the model. The truth table provides two important pieces of information about each configuration (i.e. truth table row):

the frequency number and the consistency score of a configuration. The first piece of information, the frequency number, indicates how many cases correspond to a configuration. Each case in a dataset corresponds to only one configuration. Thus, some configurations may appear frequently, whereas others may only have one case, and some may not appear at all in a dataset. Configurations for which no empirical evidence (i.e. no cases) is found are called ‘logical remainders’; the observation that one often only finds small (i.e. limited) number of configurations in reality is called ‘limited diversity’.

The second piece of information, the consistency score of a configuration, is a number that shows the proportion of cases with a given cause or combination of causes that also display the outcome. The consistency score ranges from 0 to1, where a score of 1 indicates that all cases with that configuration show the outcome. A lower consistency score indicates that while some cases with this configuration exhibit the outcome, others do not. These two indicators are used to select configurations that appear often (frequency) and are strongly associated (consistency) with the outcome of interest for further analysis.

In the fourth step, the researcher minimises the configurations to synthesise and reduce their complexity[ii]. Here, QCA follows Mill’s methods of agreement and disagreement: two foundations in logic concerned with the systematic matching and comparison of cases or configurations (Ragin, 1987). For example, if two configurations associated with the outcome are similar in all conditions but one, QCA would consider this one differing condition irrelevant for explaining the outcome. Similarly, if all configurations associated with the outcome have only one condition in common, QCA would consider this condition important (or necessary) for explaining the outcome. Through this systematic comparison of configurations, QCA eliminates irrelevant conditions. In doing so, it identifies a more condensed, or parsimonious, number of configurations[iii].

In the fifth step, the researcher analyses the QCA results, usually by illustrating the results graphically, for example, through a configuration chart (Ragin, Fiss, 2008), considering the overall solution coverage and consistency and describing and explaining each configuration that appears in the results. When interpreting the results, it is important to interpret the roles of combinations of conditions, not just the role of an individual condition across multiple configurations. When interpreting the results, ‘return to the cases’ is common in a standard QCA process to identify and explain the mechanisms underlying each configuration. A researcher analysing a small dataset may refer to specific cases, similar to an in-depth case analysis. When analyzing a large sample, additional descriptive statistics of the sub-sample of cases of one configuration may help to provide additional insights into the mechanism of a configuration.

3. Illustrating the Use of QCA

To illustrate the application of QCA, we apply the five-step process outlined in Figure 1 to a hypothetical research scenario[iv].In this hypothetical scenario, a researcher who has already conducted a comparative case study on six companies located in a Kraków Technology Park decides to include all 31 companies registered in the park. The researcher is primarily interested in understanding and explaining why these companies invest heavily in R&D (INV).

3.1. A configurational model explaining high R&D investments

Step 1 involves constructing a configurational model and selecting theoretically relevant conditions and the outcome. Based on the comparative case study already conducted and a literature review, the researcher considers three conditions explaining R&D investments: being a large company (BIG), operating in high-tech industry (HIGH), and receiving public funding for R&D (PUB). This step, known as scoping (Furnari et al., 2021), refers to the identification of conditions that may plausibly explain the outcome of interest (i.e. R&D). In addition, central to all QCA analyses, the researcher theorises and explains why these conditions might be expected to be connected to one another. This explanation is important for developing working hypotheses about the configurational nature of the conditions and their conjunctive relation to the outcome of interest. For example, one hypothesis may be that large firms or firms operating in high-tech industries receive more public funding. Another hypothesis may be that such firms have high R&D expenditures, irrespective of or in the absence of public R&D funding. The process of configurational theorising is important because it clarifies why configurations of conditions and not independent, individual variables can be expected to explain the outcome and because it motivates the choices of configurational methods, such as QCA.

3.2. Identifying cases and calibrating data

Step 2 involves identifying the empirical sample and calibrating the data into set membership scores. Having identified and selected the cases, the next step is to define, measure and calibrate the outcome and conditions. In our example, the researcher draws on a variety of qualitative and quantitative data, including short interviews with each company, information from their annual reports and publicly available databases.

To measure the outcome, high R&D investment, the researcher uses a measure of R&D intensity (i.e. R&D expenditure to sales ratio) each year. The data are collected through a short round of phone interviews. The measure of R&D intensity ranges from 3 to 45%. In the absence of theoretical and substantive arguments to define thresholds, the researcher uses the 10th, 50th and 90th percentiles to calibrate the set of companies with ‘above average R&D investments’. Quantitative anchoring points compromise the quality of QCA. To take account of this issue and ensure that the analysis meets best practices, the researcher performs additional robustness tests (Oana, Schneider, 2021), shifting the anchoring points and then precisely labels the outcome.

For calibrating the set of large firms, the firms are categorised according to employee number: small (< 50 employees), medium (51-250 employees) and large (> 250 employees). Moreover, the researcher uses corporate reports, webpages and newspaper articles to calibrate a crisp (i.e. binary) set of high-tech industry firms. Last, to calibrate the set of firms that receive public R&D support, the researcher analyses a publicly available database set to determine whether the firm received public funding in the three years before the outcome was measured.

Table 1.
Calibration of the outcome and conditions

Condition	Data source	Measure	Calibration	Set label
Above-average R&D investments (INV)	Phone interview data	R&D intensity	Scores from 0 to 1, with 10th, 50th and 90th percentiles having respective scores of 0.05, 0.5 and 0.95	The set of companies with above-average R&D investments
Large firm (BIG)	Annual reports	Number of employees	0: Less than 50 employees 0.4: Between 51 and 250 employees 1: More than 250 employees	The set of large firms
High-tech industry (HIGH)	Corporate documents, webpages	Documented evidence on high-tech industry	0: No high-tech industry 1: High-tech industry	The set of firms in a high-tech industry
Public support (PUB)	Public database	Receiving public support in the 3 years before the outcome was measured	0: no public support 1: public support	The set of firms that received other public support

Note. INV: high investment; BIG: large firm; HIGH: high-tech industry; PUB: public support.

Table 1 provides an overview of the outcome and the conditions in the example. At this point, the researcher has constructed the dataset[v] for the analysis. This dataset is similar to other conventional datasets (cases across rows and conditions across columns) but with one major difference: The outcome and conditions are measured in set-membership scores that indicate whether a case is rather ‘in’ or rather ‘out’ of a set, such as the set of large firms.

3.3. Truth table of configurations of conditions explaining R&D investments

Step 3 in QCA involves constructing and analysing the truth table. The truth table is arguably the most important analytical instrument in QCA. Instead of a conventional data table, the truth table contains one row for each logical possible combination of conditions. One row may, for example, describe a configuration of firms with high membership scores for each attribute (e.g. large high-tech firms with public funding). Another row may capture a configuration of firms with one high and two low membership scores (e.g. large firms with no public funding not operating in a high-tech industry).

Table 2.
Truth table

Row	BIG	HIGH	PUB	INV	Cases
1	0	0	0	0	2, 3, 19, 20, 21, 22, 23
2	0	0	1	1	1, 6, 7, 11, 12, 16, 17, 18
3	0	1	0	0	8, 9, 10, 13, 14, 15
4	0	1	1	1	4, 5, 24
5	1	0	0	1	29, 30, 31
6	1	0	1	1	27
7	1	1	0	1	28
8	1	1	1	1	25, 26

Note. INV: high investment; BIG: large firm; HIGH: high-tech industry; PUB: public support.

In our example using three conditions, the truth table contains eight rows, as indicated in Table 2[vi]. For each configuration (i.e. row), the truth table provides additional information on the outcome and the cases that exhibit one of the configurations. For example, row 1 describes a configuration with low set-membership scores (absent) in all three conditions. The configuration may also be written out in Boolean terminology: big*high*pub. The condition label written in small letters signifies the absence of the condition, "*" indicates conjunction, and "+" disjunction. The seven firms that exhibit this configuration also exhibit low R&D investments. In contrast, row 5 captures a configuration of conditions of large firms not operating in a high-tech industry and not receiving public R&D support (BIG*high*pub). Yet, the three cases matching this configuration all show high membership scores in the set of firms investing in R&D.

An alternative to a truth table is a Venn diagram in which each condition is represented by one circle and the combination of all conditions as overlapping (or intersections) circles. The membership of cases in diverse configurations of conditions is represented by the locations of their numbers (Figure 2). Take again the case of row 1: a configuration of cases where all conditions are absent. This configuration is represented by the field outside the circles, where all such cases are located. The grey shaded area symbolises the occurrence of the outcome. In our example, this is the case in the fields inside the circles BIG and PUB. The non-shaded area symbolises the absence of the outcome. In short, both the truth table and the Venn diagram provide an overview of all logically possible combinations of conditions, information about how each configuration is linked to the outcome of interest and information about the corresponding number of cases.

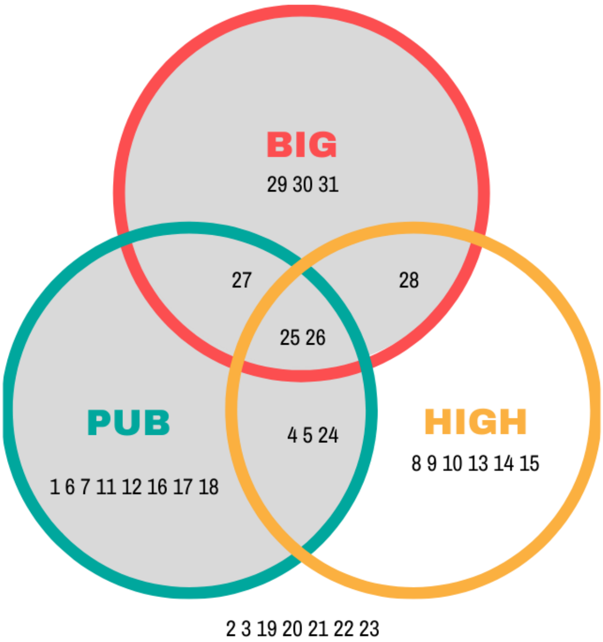

Figure 2. Venn diagram.

3.4. Analysing the truth table and simplifying the configurations

At this point, the truth table primarily describes the configurations leading to high R&D investments. Rows 2, 4, 5, 6, 7 and 8 all show such configurations. However, the configurations may be simplified by systematically comparing each configuration with each other and eliminating those conditions that appear irrelevant for explaining high R&D investment. In our example, a comparison of the configurations in row 2 (big*high*PUB) and row 4 (big*HIGH*PUB) reveals that both configurations share the absence of large firms (big) and the availability of public R&D funding (PUB). Yet, whether firms operate in a high-tech industry seems irrelevant to explain investments in R&D. Thus, smaller firms that receive public R&D funding seem to invest more in R&D (big*PUB). Comparing the other rows reveals analogous observation. Comparing rows 5 (BIG*high*pub) and 6 (BIG*high*PUB) allows the configurations to be minimised into a more simplified solution (BIG* high). Moreover, comparing rows 7 (BIG*HIGH*pub) and 8 (BIG*HIGH*PUB) minimises the configurations into a simplified solution (BIG*HIGH). As these two simplified configurations (BIG*high; BIG*HIGH) are comparable and can be minimised into BIG. In this way, we can observe the outcome for the enterprises that are either smaller and received public support (green circle in Fig. 1 without the area overlapping the red circle) or big (red circle). In Boolean terms, the minimised solution is big*PUB+BIG→ EXP, which means that for an enterprise to have high R&D expenditures, it is sufficient to be either a smaller firm and receive public support or to be a large firm. Thus, to have high R&D expenditures it is sufficient to be either a large firm or to receive public support.

3.5. Evaluating, visualising and interpreting the results

The results of the QCA reveal two configurations, or explanations, for when firms invest heavily in R&D. Smaller firms that receive public funding support (big*PUB) invest heavily in R&D, as do large firms (BIG). These two configurations are sufficient for explaining high investments in R&D. The results highlight some of the unique features and opportunities of QCA related to the notion of complex causality. The results illustrate the ability of QCA to identify results marked by conjunctural causation (i.e. several conditions in conjunction explain an outcome). The results also demonstrate the ability of QCA to reveal equifinality, which refers to the notion that there may be multiple ways to explain the same outcome. In our case, we identify two ways: either being small and receiving public funding or being large. The third notion of complex causality in QCA is the notion of 'causal asymmetry'; that is, the configurations of conditions explaining the presence of the outcome (e.g. high R&D investments) are different than the configurations of conditions explaining the absence of the outcome (i.e., not high R&D investments).

The results of QCA go beyond traditional qualitative or quantitative research by clearly identifying groups of cases and describing them through the lenses of configurations of conditions. Stakeholders may use such results in their design of support for the companies. For example, different types of support may be offered to the identified groups.

The results can be visualised and then used to better evaluate and communicate the findings to stakeholders (Ragin, Fiss, 2008; Rubinson, 2019). Alternatively, the results can be visualised using a Venn diagram (for a model with three conditions) or an adjusted form of Venn diagrams for models with more than four conditions. Having identified the configurations for high R&D investment, the next step is to explain the results. To do so, the researcher may speculate that small firms on their own do not have slack resources to invest in R&D and hence require external funding, which in our case is provided by public support. Once these two conditions appear simultaneously (i.e. in conjunction), they explain high investments in R&D. For large firms, the additional public funding appears irrelevant, possibly because large firms have sufficient slack resources to independently invest in R&D.

The results of QCA do not in themselves provide a causal explanation. Instead, they are primarily descriptive. For unravelling the mechanisms inherent in each configuration, researchers must conduct a formalised post-QCA, for example, in the form of additional in-depth case studies or focused analysis of cases that belong to only one of the configurations.

4. Current Issues in the Diffusion and Development of QCA

QCA is now commonly accepted and utilised among diverse disciplines, and papers describing QCA studies have been published in many high-profile journals. Discussions are ongoing about methodological aspects of QCA and possible applications in other areas, such as in mixed-methods and multi-method research (e.g. De Block, Vis, 2019; Meuer, Rupietta, 2017a; Rihoux, Álamos-Concha, Lobe, 2021). At the same time, QCA is not without limitations and faces several challenges in the future, such as the need for more clarity around best practices (e.g. Greckhamer et al., 2018; Rubinson, et al., 2019) and the need for more configurational theorising (e.g. Furnari et al., 2021).

4.1. Best practices for small-N and large-N QCA studies

Since the late 2010s, scholars have highlighted substantive differences between the application of QCA with a few cases (small-N or case-centred QCA) versus that with a large number of cases (large-N or condition-centred QCA). Small-N QCA is the traditional form of QCA (for typical examples, see: Halme et al., 2018; Vergne, Depeyre, 2016). Researchers applying small-N QCA have in-depth knowledge of the investigated phenomenon and thus high familiarity with the cases. In small N-QCA, models are created via inductive coding and theorising, and their primary purpose is theory development. Calibration in small-N QCA is based on substantive knowledge of the cases, and expectations related to the model's parameter of fit are stricter than for large samples. In contrast, large-N QCA applications are better suited to exploring data, identifying patterns and typologies across cases and theory testing (see for example, Fiss, 2011; Misangyi, Acharya, 2014). Large-N QCA usually involves less familiarity with cases and focuses more on the analytical technique. While conditions in large-N studies resemble variables, mixing QCA with statistical methods is quite popular. With the diffusion of QCA into new fields of research in management and beyond, the distinction between small- and large-N QCA is likely to grow, a development that may require best practices specific for each approach and researchers to develop distinct best practices and distinct skill sets.

4.2. QCA and other research methods

QCA is often described as a comparative method that lies halfway between qualitative and quantitative approaches. As such, it is well suited to be integrated with both approaches. Meuer and Rupietta (2017a) and Rihoux et al. (2021) reviewed strategies for integrating other research methods before, during or after QCA. Using methods before QCA most often helps in identifying conditions worth including in the analysis. Moreover, other methods may simply serve as a way of collecting data. They may also be used during QCA to provide support for important methodological decisions. QCA followed by other types of analysis may provide additional support (or not) for the conclusions of the research. Across all mixed-methods approaches involving QCA, it appears that the more QCA is integrated with other research methods, the stronger the explanatory power of the research design. Future QCA research is likely to rely on mixed-methods QCA.

The distinction between small-N and large-N QCA studies provides opportunities for the integration of QCA with other analytical techniques. Small-N QCA studies draw more comprehensively on the richness and diversity of case study research. They also provide opportunities to learn from process and longitudinal research (e.g. Aversa et al., 2015). In small-N QCA studies, the integration of QCA with process tracing is gaining popularity (e.g. Álamos-Concha et al., 2020). Thus far, large-N QCA has been integrated primarily with statistical methods and with advanced econometric and data science techniques. More recently, researchers have begun experimenting with integrating QCA with advanced modelling approaches, for example, using artificial intelligence during calibration (e.g. Pappas, Woodside, 2021; Schimpf, Barbrook-Johnson, Castellani, 2021; Shrestha et al., 2021).

4.3. Future challenges

Although QCA is constantly developing, some challenges remain to be resolved. Some of the most important of these concerns the relationship between theory and configurational thinking, incorporating the time component into the analysis and the rigour of making causal claims.

4.3.1. Configurational theorising

QCA involves adopting a particular conceptual perspective and a specific analytical technique. QCA always includes a theory or conceptual model and empirical data. Since the early days of QCA, the conceptual perspective underlying the analysis has been grounded in the notion of complex causality, a notion that in essence covers three tenets of causal complexity: conjunctural causation, causal asymmetry and equifinality. Over the past three decades, the conceptual perspective, one that draws on configurational thinking and deterministic causality, has not progressed to the same extent as an analytical technique. Therefore, researchers may find the conceptual part of their study challenging.

There is a consensus within the QCA community that it is time to move beyond the notion of complex causality as the only rationale for applying QCA. Instead, more attention should be paid to configurational theorising. Furnari et al. (2021) proposed a structured approach to ‘configurational theorising’. They argued that configurational theories are well suited to addressing causal complexity, especially considering the challenges of conjunction, equifinality and asymmetry inherent in causal complexity. They proposed a model of the configurational theorising process that includes three stages and corresponding sets of heuristics. The contribution of Furnari et al. (2021) are possibly only the beginning of a new period of research that focuses more explicitly on configurational theorising. There are ample opportunities to contribute to the debate.

4.3.2. Time and QCA

QCA was developed to systematically compare cases at one point in time. One of its most frequently mentioned limitations relates to its inability to incorporate aspects of time and processes in the analysis (e.g. Caren, Panofsky, 2005; Fischer, Maggetti, 2017; Furnari, Meuer, 2016). The question of time component in configurations may be related to both cross-case level (i.e., temporal order of conditions) and within-case level (i.e. a change in the cases themselves). In the past, researchers have attempted to address questions relating to time and processes using models developed based on the logic and analytics of QCA (Caren, Panofsky, 2005; García Castro, Casasola, 2011; Schneider, 2019; Schneider, Rohlfing, 2013). However, only a few of these models have been used in empirical studies. QCA researchers acknowledge these challenges and continue to develop new methods of addressing time in QCA (Pagliarin, Gerrits, 2020; Rupietta, Meuer, 2021). These new methods require validation and applications to the simulated and real-world data to better understand their opportunities and limitations. Hence, much remains to be done to develop QCA methodology and illustrate its usefulness across many academic fields.

4.3.3. Methodological rigor and causal claims

As with many analytical methods, the question of how to unambiguously identify causal mechanisms and allow researchers to claim causality is much debated (Baumgartner, Thiem, 2017; Haesebrouck, Thomann, 2021). In its traditional form, as a small-N in-depth comparative case method, QCA relies heavily on a researcher’s substantive and theoretical knowledge to identify only those conditions that influence the outcome (Greckhamer et al., 2018; Ragin, 1987). With the increasing application of QCA to large samples, several new methodological challenges have emerged, of which two appear particularly important.

First, QCA describes a particular interdependency among causal conditions and their association with a certain outcome. In statistical analysis, this objective is closely related to theorisation around moderating and mediating variables (Baron, Kenny, 1986). In QCA, researchers use terms such as ‘combine’, ‘interdepend’ and ‘interact’ in relation to causal conditions, but how these conditions produce a particular outcome remains vague. Thus, the interrelationship between factors needs to be more accurately conceptualised, and methodologies for empirically studying different forms of interdependencies with QCA need to be developed. The concepts of mediating and moderating mechanisms may be valuable starting points (Du et al., 2022).

Second, the risk of omitted variables (or in QCA terms ‘omitted conditions’) is a general methodological concern (Radaelli, Wagemann, 2019). One possible indicator of omitted variable bias is a QCA model in which all cases are clustered in one or two configurations. Such a cluster may mean that the model includes too few distinguishing conditions The risk of omitted conditions is more likely in large-N studies where researchers lack familiarity with the research setting and context and the individual research case. Thus, the primary instrument safeguarding against an omitted condition in small-N QCA is the researcher’s familiarity with the research case. One option where an important explanatory factor is known but there are no data to include the factor as a condition is to use a proxy condition.

5. Summary and Practical Recommendations

QCA is an exciting research approach that continues to grow in management research. There are many opportunities not only to apply QCA but also to contribute to its development. In this paper, we provided only a brief introduction to QCA in management research, including the background, basic steps and challenges faced by researchers. For researchers curious to learn more about QCA, there are many sources of QCA-related information, including books, events, training and software. In terms of the literature, Charles Ragin's original monographs continue to be an excellent source of information (e.g. Ragin, 1987, 2000, 2006). There are also a number of important QCA textbooks (Schneider & Wagemann, 2013), with more recent ones authored by Mello (2022) and Oana, Schneider and Thomann (2021). In addition, there are regular workshops, trainings and conferences where QCA researchers meet. Table 3 provides information on useful courses, training and regular conferences. For more information about software, training and conferences, interested readers may want to visit the webpage of the Comparative Methods for Systematic Cross-case Analysis (COMPASS) network, which is an academic community of QCA researchers across all disciplines. Or simply get in touch with us directly by writing an e-mail!

Table 3.
QCA-related sources of information, courses and conferences

Sources of Information	**Massive Open Online Courses**
Comparative Methods for Systematic Cross-case Analysis (COMPASS) network https://compasss.org Facebook group: Qualitative Comparative Analysis and Fuzzy Sets	Erasmus University Rotterdam/Coursera https://www.coursera.org/learn/qualitative-comparative-analysis
Summer/winter schools	**Conferences and workshops**
The European Consortium for Political Research (ECPR) https://ecpr.eu/ Erasmus Research Institute of Management https://www.erim.eur.nl/doctoral-programme/courses/summer-school/ Global School in Empirical Research Methods, University of St. Gallen https://www.gserm.ch/stgallen/ Nijmegen School of Management, Radboud University, the Netherlands 2022 Summer School in Social Research Methods - Nijmegen School of Management (ru.nl)	Paper Development Workshop https://compasss.org/intlqca/ QCA Conference of the Americas (AQCA) https://compasss.org/aqca/ Academy of Management https://aom.org/events European Group for Organisational Studies https://egos.org/ European Academy of Management https://euram.academy/

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Appendix

Table 4 presents the membership scores of all the cases included in the analysis. The data were used as inputs in the analytical part of the QCA.

Table 4.
Input data

ID	BIG	HIGH	PUB	EXP
1	0	0	1	1
2	0	0	0	0
3	0	0,3	0	0
4	0	1	1	1
5	0	1	1	1
6	0,1	0	1	1
7	0,1	0	1	1
8	0,1	1	0	0
9	0,1	1	0	0
10	0,1	1	0	0
11	0,1	0	1	1
12	0,1	0	1	1
13	0,1	1	0	0
14	0,1	1	0	0
15	0,1	1	0	0
16	0,1	0,3	1	1
17	0,4	0,3	1	1
18	0,4	0,3	1	1
19	0,4	0,3	0	0
20	0,4	0,3	0	0
21	0,4	0	0	0
22	0,4	0	0	0
23	0,4	0	0	0
24	0,4	0,7	1	1
25	1	0,7	1	1
26	1	1	1	1
27	1	0,3	1	1
28	1	0,7	0	1
29	1	0,3	0	1
30	1	0	0	1
31	1	0	0	1

Footnotes

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[i] There are suggestions in the literature describing the minimal number of cases (N) in relation to the number of conditions (C) as $N = C * 3$ or $N = 2^C$, which for four conditions translates to a minimal number of cases of 12 or 16, respectively (Schneider, Wagemann, 2013).

[ii] For the sake of brevity, in this paper, we do not describe the analysis of necessity (Schneider, Wagemann, 2013), which should be the first step of investigating set relations.

[iii] In a standard QCA process, the researcher conducts a separate analysis of the occurrence of the outcome and non-occurrence of the outcome.

[iv] The scenario is inspired by the actual research (Krupnik et al., 2023).

[v] The dataset that we use in our illustration is available as in the appendix.

[vi] The dataset not only includes crisp (i.e. 0 and 1) but also fuzzy-set membership scores (i.e., between 0 and 1). The truth table in QCA simplifies the input data only on the surface but continues to operate mathematically with fuzzy-set member scores.