32. Qualitative comparative analysis (QCA)

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INTRODUCTION

In what has perhaps become the most-cited general textbook on social science research methods, King et al. (1994: 87) once wrote that the ideas of United States (US) sociologist Charles Ragin, who had proposed the method of qualitative comparative analysis (QCA) a few years earlier (Ragin 1987), "contain no new features." In contradistinction, US political scientist John Gerring held in another well-received textbook that "QCA is a significant addition to our arsenal of social science methods" (Gerring 2001: 209). This range of positions on QCA has not narrowed over the last 20 years. Instead, it has widened, and often quite considerably so: "a wholly ineffective research method" and "fatal distraction" for some (Lucas and Szatrowski 2014: 3), a "promising and genuinely new tool to our methodological tool kit" for others (Markoff 1990: 178).

The first goal of this chapter is to convince you that QCA and closely related methods of configurational data analysis can add significantly to our accumulation of knowledge about cause–effect relations, when applied correctly. A second goal is to demonstrate the functionality and workings of QCA in order to give applied researchers concrete technical guidance on how to employ the method, and on how to avoid technical and interpretative pitfalls along the way. A third and last goal is to introduce two more recent configurational methods that have solved many of the methodological and technical problems that QCA still remains affected by. Researchers interested in advanced applications should thus have a look at these two alternatives. Needless to say, a single chapter cannot cover all aspects of QCA and related methods in sufficient detail, yet it should provide a good starting point to become acquainted with the foundations of these methods and explore their potential.

More specifically, the chapter will take readers from the theoretical foundations to the concrete procedural protocol of QCA. You will learn that the theory of causation and the methods of inference which QCA is built on have been around for about 200 years, but also that, at the same time, QCA was the first method to operationalize this theory in an analytically standardized way. In this sense, King et al. (1994) as well as Gerring (2001) both have some claim to the truth: QCA was the first method to operationalize the so-called INUS theory of causation with the Boolean-algebraic tools of switching circuit design—an innovation, indeed—yet neither the INUS theory of causation nor Boolean algebra are recent innovations. How QCA works on the ground will be explained subsequently by drawing on a relatively recent publication from the area of international politics. After reading the chapter, you should thus be able not only to make informed analytical decisions in your own empirical project, but also to justify these decisions to supervisors, reviewers, or colleagues based on solid theoretical knowledge.

The chapter proceeds as follows. It first traces the origins of QCA as a distinct method of causal inquiry, its proliferation and current use across different disciplines. The next section explains what QCA searches for, and how it goes about pursuing that search target. This rather theoretical section is fundamentally important for understanding what QCA wants to achieve and how its output must be interpreted. The chapter then proceeds to the "art" of implementing QCA by reviewing a QCA study on burden sharing in multinational military operations. The following section clarifies three misunderstandings about QCA that have considerably influenced the method's broader perception. Lastly, I point readers to two alternatives to QCA, namely coincidence analysis (CNA) and combinational regularity analysis (CORA). These two methods are not affected by many of the conceptual and analytical problems that continue to plague QCA, and may thus provide an attractive option for applied researchers. The final section draws conclusions.

THE ORIGINS AND PROLIFERATION OF QCA

If you read a chapter on QCA, you may have asked yourself already where to situate the method in relation to other methods you know. The first question may have been whether QCA is a quantitative or a qualitative method. What can be said for sure is that QCA is a member of the family of configurational comparative methods (CCMs), or simply, configurational methods.[1] CCMs can be distinguished most clearly from other methods of empirical data analysis by their explicit reliance on Boolean-algebraic principles, in both their inferential foundations as well as their mathematical operations (Thiem et al. 2016).

In this connection, the timing of QCA's introduction has played a role in its strategic positioning. The method was first presented in the mid-1980s by US sociologists Kriss Drass and Charles Ragin at a time when the "paradigm wars" between advocates of qualitative and those of quantitative methods were reaching another peak in many fields of the social sciences (Drass and Spencer 1987; Ragin 1987; Ragin et al. 1984). Not surprisingly, the subtitle to Ragin's (1987) pioneering book *The Comparative Method* was *Moving beyond Qualitative and Quantitative Strategies*. Most contemporary proponents of QCA have kept this distance and remain hesitant to clearly identify themselves with one or the other tradition. Today, this is still reflected in the tendency to separate QCA into a "technique" or "method" on the one hand—suggesting a position closer to the quantitative side—and an "approach" that requires intimate case knowledge on the other hand (Ragin 2014).[2] Thus, QCA is not easy to assign to either group, but as we will see later, the method has, at heart, considerably more in common with quantitative than with qualitative methods.

As a relatively recent addition to the methodological toolkit of empirical data analysis, has QCA become a success? Here, the answer must be a definite "Yes," with some qualifications. Figure 32.1 shows the number of QCA applications in peer-reviewed journal articles per year between 1984, the year of the method's first appearance in Ragin et al. (1984), and 2017.[3] In total, there have been 1153 applications in 1146 journal articles across 483 scientific journals (some articles include several different applications). Articles are divided into three categories: applied, agenda, and methodological. Applied articles use QCA as a method, but put empirical substance at their center; agenda articles serve as introductions of QCA to a particular scientific community; and methodological articles address concrete technical or broader epistemological issues in relation to QCA. Applied articles are further divided by the variant of QCA that they have used. Currently, there exist three variants: crisp-set QCA (csQCA), multi-value QCA (mvQCA) and fuzzy-set QCA (fsQCA) (the main difference between these three variants will be explained later).[4] Landmark events such as the publication of an important textbook or the release of major software have been added to provide further orientation and contextualize developments.

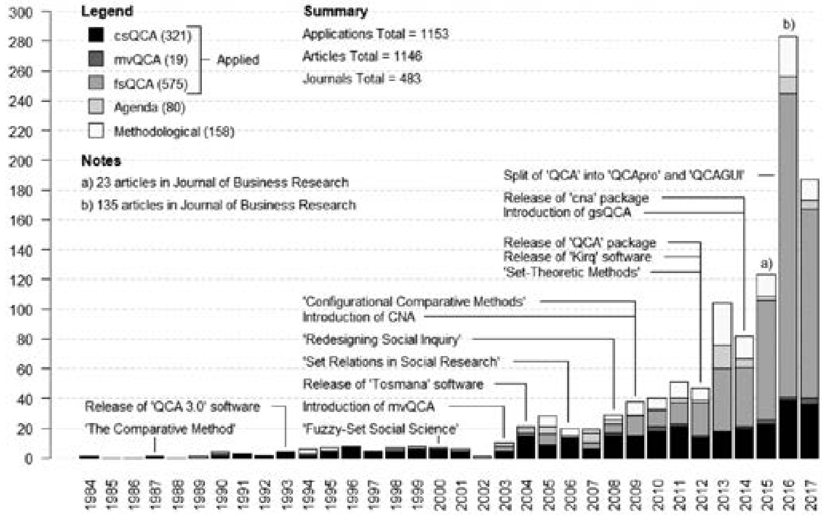

Figure 32.1 *Number of QCA applications per year between 1984 and 2017*

Allowing for a publication lag of two years, only about four applied articles per year were published on average throughout the first decade following the introduction of csQCA in Ragin (1987). After a subsequent downward trend in publication numbers over the 1990s, at whose end it almost looked as if QCA could disappear again, Ragin's sequel *Fuzzy-Set Social Science* (Ragin 2000), which responded to one of the major criticisms against QCA, namely that the method was confined to binary data, eventually got the "Ragin Revolution" (Vaisey 2009) off the ground. In the years from 2003 to 2017, the average number of applied articles rose to 57, and the absolute number has multiplied more than twentyfold from eight articles in 2003 to 167 in 2017. The year 2016 was exceptional because the *Journal of Business Research* alone published no fewer than 135 QCA articles.[5] As can also be seen, the three variants of QCA have been employed very unevenly. Although it was the first variant to have appeared, csQCA has still been used in about 40 articles in 2016 and 2017, but fsQCA has clearly dominated publication figures from 2012 onwards. In contrast, mvQCA has led a niche existence since its introduction in 2006, the reasons for which are explained in more detail in Thiem (2013, 2015a). These figures may create the impression that there exists an implicit ranking of QCA variants in relation to their sophistication, with fsQCA being the most powerful technique, followed by csQCA, and lastly mvQCA. Yet, as we will see later, this impression is delusive.

Agenda articles have been an important driver in this rapid proliferation at the turn of the millennium insofar as they have introduced the method and its possibilities to specific academic communities that would otherwise not have noticed, or at least noticed much later, the method's use elsewhere. The vast majority of these articles did not appear in the early stages of QCA's history, but only after 2003. In 2013 alone, 16 such articles were published. A similar trend can be observed with respect to methodological works, 133 of which have appeared between 2009 and 2017, suggesting an increasing interest in the more technical and procedural aspects of QCA in particular, and CCMs in general. Thus, even if the broader increase in the number of publications and journals across all scientific disciplines is taken into account, the positive trend in QCA's diffusion remains considerable.

Which scientific fields have published most QCA studies? At this point, the success story of QCA has to be qualified. Figure 32.2 shows the shares of applied QCA articles across the eight top-ranking disciplines. Business, political science, and sociology have so far dominated, with about 52 percent of the total, but, applied QCA research has also appeared in many other disciplines by now, including management (4.3 percent), environmental studies (4 percent), and international relations (3.9 percent). What is not visible from these figures, however, is a deep communal influence, even within scientific disciplines. For example, not a single QCA study has appeared so far in the top two general-interest journals in US political science, namely the *American Political Science Review* and the *American Journal of Political Science*. In contrast, most top European political science journals have published several, even dozens, of QCA studies already. Two journals at the forefront are the *European Journal of Political Research* and the *Journal of European Public Policy*. In US sociology, it is the other way around. Here, the *American Sociological Review* and the *American Journal of Sociology* have both published several QCA studies, whereas the *European Journal of Sociology* has remained very hesitant. In the field of international relations, the *Journal of Peace Research*, *Foreign Policy Analysis*, and the *Journal of Conflict Resolution* count among the top publishers of QCA-based research. Being aware of these patterns in the distribution of publications may help you to find an outlet for your own work that has got some review and publication experience with QCA-based research.

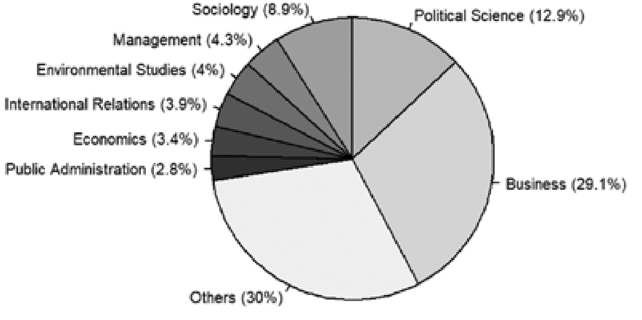

Figure 32.2 Shares of applied QCA articles across different disciplines

THE SEARCH TARGET OF QCA

As I have already alluded to above, QCA's most important theoretical components had actually been around for quite a long time—almost about 200 years—when the method was first proposed in Ragin (1987). Nonetheless, as a method of empirical data analysis, QCA is undoubtedly a real innovation. This innovativeness lies in the fact that it was the first method to operationalize a certain theory of causation by levering the mathematical tools of Boolean algebra, and more specifically, those tools that electrical engineers have developed for designing switching circuits to their needs. In other words, if there is a modern empirical research method that truly deserves the label "interdisciplinary," it is QCA. But, first things first.

To put it succinctly, QCA is an empirical research method for identifying causal relations in terms of INUS conditions (Ragin and Strand 2008: 431–432; Thiem and Baumgartner 2016a: 803; Thiem and Baumgartner 2016b: 347–348). This inferential goal is achieved by means of the algorithmic optimization of Boolean-algebraic functions. We have two central concepts here: INUS causation and Boolean optimization. For understanding what it actually is that QCA searches for and what it outputs as a result, and for understanding how this output must be interpreted, it is fundamentally important to introduce these concepts in more detail.

The idea of INUS causation is one of the oldest about the scientific notion of causation in general. Its roots can be traced back to, at least, British philosopher–politician–economist John Stuart Mill. Mill had already argued in his voluminous masterpiece *A System of Logic* that: "It is usually between a consequent and the sum of several antecedents; the concurrence of all of them being requisite to produce, that is, to be certain of being followed by, the consequent" (Mill 2006, 1843, Book III: 327). Here, Mill straightforwardly anticipated what is known today in QCA as conjunctural causation: the idea that any given effect is never produced by one isolated cause alone, but a co-occurrence of several distinct, sometimes very disparate, causes. Yet, Mill entertained an even more nuanced conception of causation. In a later chapter, he writes:

> It is not true, then, that one effect must be connected with only one cause, or assemblage of conditions; that each phenomenon can be produced only in one way. There are often several independent modes in which the same phenomenon could have originated. One fact may be the consequent in several invariable sequences; it may follow, with equal uniformity, any one of several antecedents, or collections of antecedents. (Mill 2006, 1843: Book III, 435)

Here, Mill described exactly what is known today as "equifinality" in QCA, that is, the idea that alternative co-occurrences of conditions may lead to the same effect.[6]

Conjunctural causation and equifinality represent the two central pillars of QCA's underlying theory of causation. Since the mid-1960s, this theory is called the INUS theory of causation, a theory that belongs to the larger group of regularity theories of causation (see Psillos 2009).[7] Regularity theories were long relegated to the margins of research on causation and causal inference, but numerous areas of the natural as well as the social sciences, from economics over neurology to psychology, continued to invoke the notion of INUS conditionality for building causal arguments (e.g., Hoover 2001; Meehl 1993; Sawcer et al. 2014).

The most modern account of INUS causation is that of John Mackie, who popularized this concept most successfully (Mackie 1980). In particular, Mackie's article "Causes and Conditions" (Mackie 1965) is an eye-opening must-read for every prospective user of QCA (in fact, for everyone generally interested in causation). A purposefully modified example from the area of neurology shall illustrate how QCA connects Boolean-algebraic techniques with the INUS theory of causation. An example from international relations was not chosen in order to emphasize how the INUS theory of causation is a general theory of causation that is potentially applicable in every scientific discipline. From this example, you can simply extract all concepts and procedures, and transfer them to your own specific research area.

Suppose that you read an article about the development of multiple sclerosis in the science part of your favorite Sunday newspaper. Further suppose that this article mentions the genetic risk allele HLA-DRB1*15:01—"15:01" for short—as a potential cause of this disease. On the surface, it may be clear what this statement says: a cause is a difference-maker of some sort (as Mill 2006, 1843, Book III: 352 put it: "change can only be produced by change"), and so the presence of 15:01 should influence a person's development of multiple sclerosis. However, readers may have quite divergent ideas about the exact nature of this influence. One possibility is an interpretation in terms of INUS causation.

In the United Kingdom, for instance, about 15 million people carry 15:01, but only about 40,000 among those affected actually develop multiple sclerosis, and a further 20,000 of the 50 million people who do not carry 15:01 also develop it. In other words, 15:01 is not a necessary cause of multiple sclerosis; many people develop the disease without carrying the allele. Yet, nor is 15:01 a sufficient cause; only a tiny fraction of those who carry it actually develop multiple sclerosis. It is only in combination with heavy smoking and significant deficiency in vitamin D that 15:01 is regularly observed to occur together with multiple sclerosis. Put differently, 15:01 and smoking and lack of vitamin D (and possibly other, as yet unknown, conditions) may cause the development of multiple sclerosis (Mill's "assemblage of conditions").

If other conditions must join 15:01 for the latter to acquire its status as a cause, then 15:01 by itself is insufficient for developing multiple sclerosis, but inside the above-mentioned "and-combination" it is non-redundant. Without 15:01, the combination of heavy smoking and significant deficiency in vitamin D would lose its status as being sufficient for the disease (the same argument applies to heavy smoking and significant deficiency in vitamin D). These three aspects are denoted by three letters in "INUS": "I" (15:01 being insufficient by itself to cause multiple sclerosis), "N" (15:01 being a non-redundant part of an and-combination) and "S" (this and-combination being sufficient for multiple sclerosis). What, then, does "U" denote?

Among those who do not carry 15:01 but still develop multiple sclerosis, it may be the combination of late encounter in life with certain microbes and hormone imbalances that leads to the disease's outbreak, or possibly even other and-combinations of conditions of a very different kind that are currently unknown to neurologists (Mill's "several independent modes"). To be structurally complete, any account of the development of multiple sclerosis should thus acknowledge that 15:01 and heavy smoking (HS) and significant deficiency in vitamin D (SDVD) and possibly other, as yet unknown conditions (X_1) or late encounter in life with certain microbes (LEM) and hormone imbalance (HI) and possibly other, as yet unknown conditions (X_2) or possibly other, as yet unknown and-combinations of conditions (Y), lead to multiple sclerosis. The specific and-combination of 15:01, heavy smoking, and significant deficiency in vitamin D is, therefore, unnecessary for developing it. Other and-combinations, some of them of possibly a very different constitution, may trigger the disease as well.

We now have all the pieces in place: 15:01 is an <u>i</u>nsufficient, but <u>n</u>on-redundant part of a combination of conditions that is itself <u>u</u>nnecessary but <u>s</u>ufficient for the development of multiple sclerosis. In short: 15:01 is an INUS condition of multiple sclerosis. In the Boolean-algebraic branch of propositional logic, which operationalizes the concepts of "sufficiency" and "necessity" functionally, the current state of knowledge about the causes of multiple sclerosis (MS) schematically described above would then be syntactically codified as shown in equation (32.1):

$$(15{:}01 \wedge \mathrm{HS} \wedge \mathrm{SDVD} \wedge \mathrm{X}_1) \vee (\mathrm{LEM} \wedge \mathrm{HI} \wedge \mathrm{X}_2) \vee \mathrm{Y} \leftrightarrow \mathrm{MS}, \tag{32.1}$$

where "$\wedge$" stands for the logical concept "and," also called conjunction; "$\vee$" for the logical concept "or," also called disjunction; and "$\leftrightarrow$" for the logical concept "is necessary and sufficient for," also called equivalence. If it was the case that not all instances of multiple sclerosis could be explained by a given set of data, then the equivalence operator would be replaced with the less strong implication operator, "→," indicating that the disjunction of conjunctions is not necessary for the disease.[8]

The computational challenge for tools of configurational data analysis such as QCA is to identify INUS conditions and their exact interplay, represented by a functional statement corresponding to that of expression (32.1), among the usually large sets of multitudinous assemblages of conditions that regularly occur together with the effect to be explained. It is a challenge because any conjunction that is sufficient for an outcome of interest remains sufficient irrespective of how many further conditions are added to this conjunction. This fact simply follows algebraically because the expression $(A \rightarrow Z) \rightarrow (A \wedge B \rightarrow Z)$ is a tautology, that is, a proposition that can never be false. For instance, if 15:01 and heavy smoking and significant deficiency in vitamin D were sufficient for developing multiple sclerosis, then 15:01 and smoking and lack of vitamin D and being allergic to birch pollen would also form a conjunction that was sufficient for this disease, even though being allergic to birch pollen may not be causally relevant to the development of multiple sclerosis at all. Similarly, any disjunction that is necessary for an effect remains necessary irrespective of how many further conjunctions are added. Again, this follows algebraically because $(A \leftarrow Z) \rightarrow (A \vee B \leftarrow Z)$ is also a tautology.

Usually, you read in methodological and applied QCA work that the method searches for conditions that are necessary and/or sufficient for an outcome, but this description is inadequate, as you now know. It is important that both conjunctions as well as disjunctions are free of redundancies. For example, if being allergic to birch pollen was not causally relevant to the development of multiple sclerosis, then such an allergy is a redundancy from the functional perspective of Boolean optimization.[9] In other words, what matters for the causal interpretability of QCA's output is that conjunctions are minimally sufficient and that disjunctions are minimally necessary. It is by employing Boolean optimization algorithms that QCA generates a set of models in the syntactic form of minimally necessary disjunctions of minimally sufficient conjunctions (Thiem and Baumgartner 2016a, 2016b). Such models are causally interpretable because they are free of redundancies, whereas mere relations of sufficiency and/or necessity are not (Graβhoff and May 2001: 94–97).

HOW DOES QCA WORK IN PRACTICE?

Every standardized method of data analysis has a procedural protocol. That of QCA can be divided into three main phases: (1a) the calibration of the raw data into calibrated data; (1b) the transformation of the calibrated data into a truth table; (2) the algorithmic optimization of the function described by this truth table to a prime implicant (PI) chart; and (3) the decomposition of the PI chart into a set of models, collectively referred to as the solution. The flow chart to this protocol is visualized in Figure 32.3. For illustrating each of these three phases, I replicate some parts of the QCA study of Haesebrouck and Thiem (2018), which addresses the question of why member states of the European Union (EU) contribute more, less, or as much as expected to military missions launched under the EU's Common Security and Defence Policy (CSDP). Analyzing such questions is important for understanding the problems that arise in military burden sharing, which has been a subject of repeated debates in the North Atlantic Treaty Organization as well as the United Nations. The main problem these organizations face is that countries usually undercontribute to joint interventions. However, in the context of the EU's CSDP, several countries have indeed carried disproportionately high burdens on multiple occasions. In trying to understand these phenomena, Haesebrouck and Thiem (2018) combine insights from collective action theory with those from integrated theories of military burden sharing. The results of their study are not of central interest here. More important is the way that the authors proceeded through the different phases of QCA.[10]

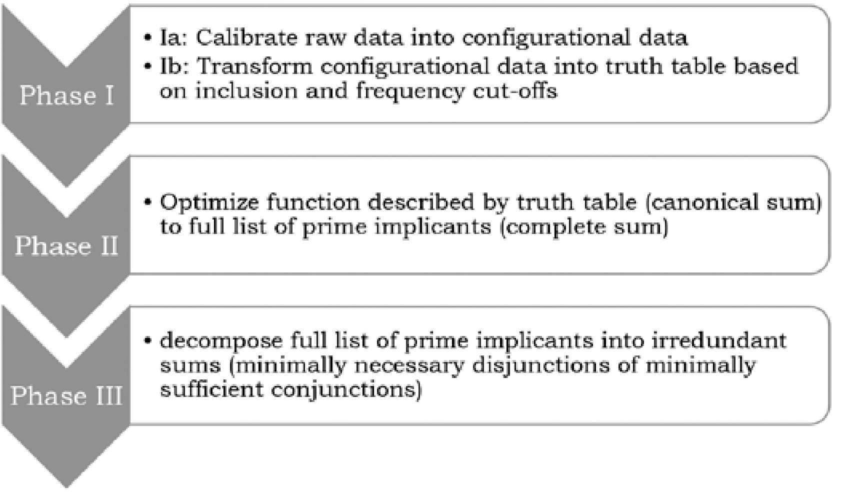

Figure 32.3 Procedural protocol of QCA

Phase Ia: Calibration

Similar to the requirements of other standardized methods of quantitative data analysis, the main input to QCA is a dataset of dimension *n* times *k*, with *n* being the number of cases (rows) and *k* the number of variables (columns). Thus, just as any other quantitative method, QCA requires a structured set of continuous or categorical variables. A requirement specific to QCA is that these data first have to be calibrated, whereby variables and cases are collectively mapped into sets of interest; for instance, the set of highly democratic countries, the set of industrialized economies, or the set of authoritarian governments. This step is fundamental insofar as QCA, and all related configurational methods, always process and infer about specific values of variables, and not variables per se (Thiem et al. 2016). Variables that are to be calibrated are called base variables, and data that are calibrated are referred to as configurational data. Sometimes, the set to be created from the base variable is called the target set. Everything else in the procedural protocol that follows after the phase of calibration is exactly the same across all three variants of QCA.[11]

If the configurational data consist of bivalent variables only, that determines csQCA to be used. For example, whether a person has voted or whether a country is a member of the European Union are naturally bivalent variables and thus need not be calibrated; but one could also dichotomize continuous or multinomial base variables. For instance, whether a country has experienced civil war is usually operationalized via the number of battle deaths. Some authors use 1000 as a threshold, others 25 (see, e.g., Buhaug 2010).

If base variables are multinomial, or if they are continuous but should be transformed into multinomial variables, then mvQCA is used.[12] For example, the World Bank assigns the world's countries to four income groups based on gross national income per capita: low, lower-middle, upper-middle, and high-income economies. The base variable would therefore be given by the continuous variable "gross national income per capita in US$," which, after the informed selection of calibration thresholds (currently US$1035, US$4045, and US$12 535), could be transformed into a four-level multivalent factor.

If at least one base variable in the raw data should be mapped into the unit interval U = [0,1], then the variant to be used is fsQCA. This mapping process can be carried out in numerous different ways, among them the direct assignment of values via expert judgements or some mathematical transformation. Essentially, the possibilities for the creation of fuzzy sets are almost endless, which does not necessarily simplify the process of calibration. Most researchers standardly apply the logistic function because that is the only function implemented in Ragin and Davey's fs/QCA software (Ragin and Davey 2019), but other functions with other parameters may yield very different results (Thiem 2014b). Since fuzzy-set calibration is a huge topic in itself, readers may want to consult Thiem and Duşa (2013a: 51–62) for an overview.

At this point, let us briefly come back to Figure 32.1. You saw that, in contrast to fsQCA and csQCA, the application numbers for mvQCA are minuscule. This status is not due to the analytical inferiority of mvQCA to csQCA or fsQCA. In fact, the analytical capabilities of mvQCA far outreach those of the other two variants because neither csQCA nor fsQCA are able to process factors with more than two levels. Despite all sorts of sophisticated calibration procedures in fsQCA, the analytical depth of its solutions is not distinguishable from that of csQCA: every factor can appear in only two possible states in a solution, either its presence or its absence. With mvQCA, it is possible to produce inferences that are significantly more fine-grained because every factor can, at least theoretically, assume as many states as the data allow, or as the researcher sees fit.[13] Yet, as is the case for every other method of empirical data analysis, the more nuanced and fine-grained the inferences should be, the more data are required.

In summary, configurational data are special in that every data point has a clear substantive meaning relative to some fixed point of reference, which is not the case for raw base variables. For example, the values that the variable "GDP per capita" takes on in a specific set of raw data have no meaning beyond the mere absolute quantity that they express. However, if the value "20'000 US$ GDP per capita" is made the reference point of "a rich country," then every other country value assumes a substantive meaning beyond its mere quantity: US$2000 implies "very poor," US$40,000 implies "very rich."

How have Haesebrouck and Thiem (2018) addressed the issue of calibration in their study? Burden sharing in military missions has generally been analyzed in terms of "what is and what ought to be" (Hartley and Sandler 1999: 668). More specifically, the ratio between a country's actual contribution of resources to a common effort and its ability to contribute has been widely considered the most appropriate index of equity measurement. For determining whether a country is an underprovider, an overprovider, or an equiprovider to a military mission, Haesebrouck and Thiem (2018) construct as a base variable the burden share ratio between a country's expected burden share, as given by its capabilities, and its observed burden share, as given by its contributions, in relation to all contributors. A ratio below unity signals underprovision, one above unity overprovision, and unity indicates equiprovision.

Since exact unity is very rare, the authors apply two thresholds for calibrating their endogenous factor. A country is categorized as an underprovider if it contributes at least a third less than expected. Taking the reciprocal value as the second threshold, a country is categorized as an overprovider if it contributes at least 50 percent above expectations; and if a country contributes roughly in accordance with expectations as demarcated by these two values, it is classified as an equiprovider. Based on this calibration scheme, Germany, for example, has been an underprovider to the mission EUFOR Chad, but an equiprovider to the military mission EUFOR Congo.

Phase Ib: Construction of Truth Table

Before the truth table is constructed, the analyst has to decide which factors to declare as exogenous (independent/explanatory) and as endogenous (dependent/explained). In Haesebrouck and Thiem (2018), there is one endogenous factor—contributor status—and nine exogenous factors, although the authors eventually decide to include only five of them.

Generally speaking, a truth table is a matrix of all "minterms" derivable from the exogenous factors.[14] Minterms are unique conjunctions of as many factor levels, also called "conditions" in QCA, as there are exogenous factors, with each condition representing one level of one exogenous factor such that no exogenous factor occurs twice. For example, two exogenous factors *A* and *B*, each of which has two levels, say 0 and 1, yield four minterms; three exogenous factors *A*, *B* and *C*, the first two of which have three levels each, say 0, 1, and 2, and the third of which has two levels, say 0 and 1, yield 18 minterms. More specifically, the number of minterms is given by the product of the number of levels across all exogenous factors (that is, 2 x 2 = 4 in the first case of A = {0,1} and B = {0,1}; 3 x 3 x 2 = 18 in the second case of A = {0,1,2}, B = {0,1,2} and C = {0,1}).

A matrix of minterms is not enough to constitute a proper QCA truth table. Still missing is a column of output function values, or "output values" for short, which provides information necessary for the process of algorithmic optimization in Phase II. Output values are derived based on two parameters, namely the inclusion cut-off, also called consistency cut-off, and the frequency cut-off. For computing an inclusion cut-off, the analyst has to decide which level of the endogenous factor should act as the outcome (also called the "consequent") of interest. That outcome is the concrete effect to be explained. Recall that this is a fundamental difference to other standardized methods, such as regression analysis, that operate directly on variables. In contrast, CCMs always operate on values of variables (Thiem et al. 2016).

The inclusion cut-off specifies the lower bound for the share of cases that show the outcome in relation to all cases that exhibit the same minterm. The frequency cut-off sets a lower limit for the absolute number of cases within a minterm, for this minterm not to be classified as a remainder. Remainders are minterms without any empirical observations; they receive a question mark, ?, as an output value.[15] If a minterm meets the frequency cut-off but not the inclusion cut-off, it is classified as negative and receives an output value of 0. If a minterm meets the frequency cut-off as well as the inclusion cut-off, it is classified as positive and receives an output value of 1. Essentially, output values are truth values, 1 meaning "true" and 0 meaning "false", of the proposition that the respective minterm is sufficient for the outcome.[16]

A part of the truth table for the analysis of underprovision as the outcome is presented below in Table 32.1. Here, PTS (peacekeeping tradition), CDS (competing deployments), TVL (large

Table 32.1 Excerpt of truth table from Haesebrouck and Thiem (2018)

Minterm	PTS	CDS	TVL	PSH	LPR	*n*	Incl	OUT
1	0	0	0	0	0	2	1.00	1
2	0	0	0	0	1	0	-	?
3	0	0	0	1	0	5	0.60	0
4	0	0	0	1	1	5	0.80	1
5	0	0	1	0	0	0	-	?
6	0	0	1	0	1	0	-	?
7	0	0	1	1	0	3	0.00	0
8	0	0	1	1	1	4	0.25	0
9	0	1	0	0	0	0	-	?
10	0	1	0	0	1	1	1.00	1
…	…	…	…	…	…	…	…	…
27	1	1	0	1	0	4	0.75	1
28	1	1	0	1	1	2	1.00	1
…								
32	1	1	1	1	1	1	0.00	0

trade volumes), PSH (high public support) and LPR (right legislative partisanship) are the exogenous factors, "*n*" gives the number of cases falling into the respective minterm, "Incl" lists the inclusion score of the respective minterm, and "OUT" lists the corresponding output function value at an inclusion cut-off of 0.75.[17]

How should this table be read? First of all, there are 32 possible minterms because $2^5 = 32$. Those minterms that do not occur in the data are marked by "?" under the column "OUT." For instance, minterm 2—the conjunction of no peacekeeping tradition ($PTS^{\{0\}}$), no competing deployments ($CDS^{\{0\}}$), no large trade volumes ($TVL^{\{0\}}$), no high public support ($PSH^{\{0\}}$) and the presence of right legislative partisanship ($LPR^{\{1\}}$)—is not instantiated by any country in Haesebrouck and Thiem's data.

In contrast, minterm 32 is instantiated once in the data and has an output value of 0. As Haesebrouck and Thiem have determined the frequency cut-off to be a single case, that single case is enough not to classify this conjunction as a remainder. Had the authors set this cut-off to 2, the minterm would have been categorized as a remainder. The output value of minterm 32 is 0 because the only case instantiating it does not show the outcome of interest—underprovision—but one of the other two levels of the endogenous factor. The proposition that the conjunction represented in minterm 32 is sufficient for the outcome is, thus, false.

Lastly, there are several minterms, such as 1, 4, or 10, that have received an output value of 1. For these minterms, the proposition that their corresponding conjunction is sufficient for the outcome is true because their inclusion score exceeds the inclusion cut-off of 0.75. The inclusion score of 0.8 for minterm 4, for example, simply means that 80 percent of cases instantiating this minterm show underprovision, whereas 20 percent of cases instantiating this minterm show either over- or equiprovision. Once the construction of the truth table has been completed, then all information necessary to proceed to phase II is present.

Phase II: Finding Minimally Sufficient Conjunctions

For finding all minimally sufficient conditions, an algorithm needs to process the information in the truth table. For this purpose, several different algorithms exist. Some use the information on positive minterms and remainders, others the information on positive and negative minterms. Some start from the most complex scenario and minimize away factors, others start from the least complex scenario and add factors. Essentially, it does not matter which approach an algorithm takes as long as the search target is always the same. For example, the well-known Quine–McCluskey algorithm (QMC), which the vast majority of researchers still consider to be QCA's analytical heart, draws on positive minterms and remainders in a process of minimization (McCluskey 1956). More specifically, QMC uses the following intuitive principle: if two minterms are exactly alike apart from the levels of a single factor, that factor should make no difference to the outcome because the latter does not change. In Boolean algebra, the law associated with this intuition is called the law of distribution (Thiem et al. 2016). It has an analogue in John Stuart Mill's "method of agreement," which allows causal inference to proceed based on the assumption that some condition cannot be a cause of an effect if the effect shows no change while the condition changes and everything else remains the same (Mill 2006, 1843, Book III: 390).

Let us proceed through an example. In Table 32.1, minterms 27 and 28 both show an output value of 1. In other words, the proposition that the minterm is sufficient for the outcome is (in 75 percent of cases of minterm 27 and in all cases of minterm 28) true. However, if the output value remains constant across these two conjunctions of conditions, which are identical apart from their levels with respect to the factor LPR, then LPR cannot be causally relevant in the context of the other conditions. QMC continues to thus minimize away conditions, also incorporating the remainders, until no more combinable terms remain. The end products of this process are all minimally sufficient conditions, that is, all conjunctions of INUS conditions. In QMC, these conjunctions are called "prime implicants." The disjunction of these minimally sufficient conditions, called the "complete sum" in QMC's parlance, is, however, not yet minimal itself.

Phase III: Finding Minimally Necessary Disjunctions

For finding minimally necessary disjunctions of prime implicants, which are called "irredundant sums," QMC builds a prime implicant chart, in which the prime implicants are listed along the rows, and the positive minterms (but excluding remainders that have been used along the way) in the columns. The prime implicant chart for the analysis of underprovision is presented in Table 32.2.

Table 32.2 Prime implicant chart for truth table in Table 32.1

Minterm prime implicant	1	4	10	14	15	27	28	30	31
a: PTS$^{\{0\}}$PSH$^{\{0\}}$	×	–	×	×	–	–	–	–	–
b: CDS$^{\{1\}}$PSH$^{\{1\}}$LPR$^{\{0\}}$	–	–	–	–	×	×	–	–	×
c: CDS$^{\{1\}}$TVL$^{\{0\}}$LPR$^{\{0\}}$	–	–	–	–	–	×	–	–	–
d: PTS$^{\{0\}}$CDS$^{\{1\}}$LPR$^{\{0\}}$	–	–	–	–	×	–	–	–	–
e: TVL$^{\{1\}}$PSH$^{\{0\}}$LPR$^{\{1\}}$	–	–	–	×	–	–	–	×	–
f: PTS$^{\{0\}}$CDS$^{\{0\}}$TVL$^{\{0\}}$LPR$^{\{1\}}$	–	×	–	–	–	–	–	–	–
g: PTS$^{\{1\}}$CDS$^{\{1\}}$TVL$^{\{0\}}$PSH$^{\{1\}}$	–	–	–	–	–	×	×	–	–
h: PTS$^{\{1\}}$TVL$^{\{0\}}$PSH$^{\{1\}}$LPR$^{\{0\}}$	–	–	–	–	–	×	–	–	–

This chart is read as follows. A cross, ×, means that a prime implicant covers the respective minterm, or put in causal language, that the prime implicant represents a potential complex cause of the effect in all cases that corresponded to this minterm. A dash, –, simply means that the minterm is not covered by the respective prime implicant. The algorithmic challenge in this third phase of QCA is to find all combinations of prime implicants that cover all minterms, without including any prime implicants not strictly necessary to do so. How this can be done in a systematic way via, for instance, Petrick's method is explained in Thiem et al. (2020: 9).

For example, you can see that minterms 1, 4, 10, 28, 30, and 31 are covered by a single prime implicant only, namely *a*, *b*, *e*, *f*, and *g*, respectively. These prime implicants are thus essential, and need to be part of every possible explanation of underprovision. Prime implicants that can be substituted with other prime implicants or combinations of prime implicants are inessential. In this particular prime implicant chart, all essential prime implicants already cover all minterms. However, often it turns out that there exist several, and sometimes very disparate, combinations of prime implicants forming a minimally necessary disjunction. The presence of such a phenomenon is called model ambiguity (Baumgartner and Thiem 2017; Thiem 2014c; Thiem et al. 2020). Model ambiguity simply means that there are several alternative causal explanations with respect to the analyzed outcome. The more of these models there are, the higher the degree of model ambiguity and the weaker the conclusions that can be drawn.[18] Whenever you face model ambiguity, it is important to be transparent about it.[19]

Interpretation

As mentioned above, there is one disjunction of prime implicants that is minimally necessary, namely the disjunction consisting of prime implicants *a*, *b*, *e*, *f*, and *g*. As a proper QCA solution, it is written in logic syntax as follows if $\mathrm{CS}^{\{0\}}$ refers to a contributor status of underprovider:

$$\mathrm{PTS}^{\{0\}}\mathrm{PSH}^{\{0\}} \vee \mathrm{CDS}^{\{1\}}\mathrm{PSH}^{\{1\}}\mathrm{LPR}^{\{0\}} \vee \mathrm{TVL}^{\{1\}}\mathrm{PSH}^{\{0\}}\mathrm{LPR}^{\{1\}} \vee \mathrm{PTS}^{\{0\}}\mathrm{CDS}^{\{0\}}\mathrm{TVL}^{\{0\}}\mathrm{LPR}^{\{1\}} \vee \mathrm{PTS}^{\{1\}}\mathrm{CDS}^{\{1\}}\mathrm{TVL}^{\{0\}}\mathrm{PSH}^{\{1\}} \rightarrow \mathrm{CS}^{\{0\}}$$

There are five causal paths to underprovision that could be identified from the data, namely, first, the absence of a strong peacekeeping tradition and the absence of high public support ($\mathrm{PTS}^{\{0\}}\mathrm{PSH}^{\{0\}}$); second, the presence of strong competing deployments, high public support, and the absence of right legislative partisanship ($\mathrm{CDS}^{\{1\}}\mathrm{PSH}^{\{1\}}\mathrm{LPR}^{\{0\}}$); and so on. Remember that this solution neither says that all relevant causes acting in conjunction have been identified, nor that all causal paths to underprovision have been identified. By extension, it cannot be concluded that a factor which was minimized away during phase II has been shown to be irrelevant to an explanation of underprovision within the respective causal path. Instead, it can only be claimed that evidence in favor of the causal relevance of the identified conditions has been found. This nuanced interpretation is very important, and it works similarly to the interpretation of the results of hypothesis tests in regression analysis. Thus, if you would like to set up your QCA research design with appropriate hypotheses, you should phrase them the following way:

H_0: *Exogenous factor X contains no INUS condition for endogenous factor Y.*

H_A: *Exogenous factor X contains an INUS condition for endogenous factor Y.*

Or, even more specifically,

H_0: *Condition* $X^{\{\cdot\}}$ *is not an INUS condition for outcome* $Y^{\{\cdot\}}$.

H_A: *Condition* $X^{\{\cdot\}}$ *is an INUS condition for outcome* $Y^{\{\cdot\}}$.

If X then appears in the solution, you can reject H_0 in favor of the alternative hypothesis. However, if X does not appear, this does not mean that you should accept H_0. Instead, it merely means that we fail to reject H_0. Whether X turns out to contain an INUS condition at some point in the future when we may have obtained the necessary data that would produce such evidence remains open.

WHAT QCA IS NOT

This short section is concerned with three things that QCA is not, but which are often thought to apply to QCA, and which have also often been used to defend or criticize the method. First, it has been argued that QCA is a method for small to moderate numbers of cases (e.g., Gerring 2001: 209; Rihoux 2003: 353; Wagemann and Schneider 2010: 377), that the method works differently when applied to small numbers of cases than when applied to large numbers of cases (e.g., Greckhamer et al. 2013), and that the number of cases determines the variant of QCA to be used (e.g., Herrmann and Cronqvist 2009; Rihoux 2006: 686). These claims do not hold up to scrutiny. QCA proper works with any number of cases larger than one as long as there is at least one situation of difference-making across any two cases (a parallel requirement—at least two cases and variation on covariates—exists for regression analysis). Similarly, there is no change in procedures anywhere in QCA's protocol based on the number of cases. Whether a researcher uses only four cases, or 4000, is irrelevant because the number of cases nowhere influences the process of calibration, truth table construction, Boolean optimization, or the interpretation of the solution. Lastly, the number of cases is irrelevant for the variant of QCA. As we have seen, the variant is determined by the nature of the calibration process only. In sum, the number of cases is an ill-suited criterion for judging the appropriateness of QCA vis-à-vis other methods of causal inference, it does not divide QCA into a small-*n* and a large-*n* version, and it does not influence which variant of QCA researchers should choose.

Second, QCA has traditionally either been positioned between the group of qualitative methods and that of quantitative methods, or has been associated much more with qualitative methods. However, QCA has, in fact, much more in common with quantitative methods: QCA requires a systematically organized dataset, its analytical heart consists of an algorithm that was imported from electrical engineering, and the functional language of the theory of causation QCA operationalizes is squarely rooted in the mathematics of Boolean algebra. Everything that has usually been associated with QCA's qualitative aspects as an approach, such as intimate case knowledge, is neither unique to this method nor necessary for its use (see also Vaisey 2014: 110).

Lastly, but perhaps most importantly, a vast body of literature on logical remainders and counterfactuals has emerged within QCA: the method's conservative and intermediate solution type only exist because of fears of problematic counterfactuals (Ragin and Sonnett 2005; Schneider 2018), and several auxiliary procedures and strategies have been proposed for filtering out such counterfactuals, such as the theory-guided enhanced standard analysis (T/

ESA) (Schneider and Wagemann 2013)[20] or the practice of searching for so-called “contradictory simplifying assumptions” when analyzing some outcome and its negation (Yamasaki and Rihoux 2009: 136–137). If there is a topic in QCA that has widely and continuously dominated the method’s agenda, it is counterfactuals.

The fear of introducing problematic counterfactuals has a single source: QMC, which Ragin imported in the 1980s from electrical engineering for operationalizing QCA. As already mentioned above, QMC utilizes positive minterms and so-called “don’t cares”—the term electrical engineers use for what QCA researchers refer to as logical remainders or counterfactuals—in identifying prime implicants. That explicit usage of “don’t cares,” even though of no inferential importance whatsoever, has deeply worried the QCA community, and out of these worries different QCA-specific ad hoc procedures such as intermediate solutions or T/ESA, which restrict QMC analytical reach in one way or another, were created.

One does not even need to take an introductory course in electrical engineering to discover that all these QCA-specific procedures revolve around a huge phantom menace. The simplest proof: dozens of other algorithms produce exactly the same solutions as QMC proper, but do not rely at all on “don’t cares.” In fact, McCluskey himself proposed one of these algorithms (McCluskey 1962). The entire literature on counterfactuals in QCA is, therefore, a mere artifact of Ragin’s uncommented import of an algorithm that just happens to use “don’t cares.” When applying QCA, you should thus not fall into the trap of fiddling around with remainders to produce conservative or intermediate solutions, the effects of which are a recipe for inferential disaster (Baumgartner and Thiem 2020; Thiem 2019).

ALTERNATIVES TO QCA

As a method of data analysis, QCA has partly become very politicized (see, for example, the special issue in volume 44 of *Sociological Methodology*), which has made it difficult to use and publish with this method in some areas. In addition, QCA continues to occupy a rather ill-defined position vis-à-vis other methods of empirical data analysis (see the section above). Lastly, yet most importantly, QCA remains plagued by many theoretical, methodological, and analytical problems at the most fundamental level to which neither a solution has been found nor about which a consensus has been reached. Fortunately, there exist, at the time of writing, two alternative configurational methods that address almost all of QCA’s currently debated problems. The first is called coincidence analysis (CNA), the second is combinational regularity analysis (CORA).[21]

Coincidence Analysis (CNA)

As the second “modern” configurational method, CNA was developed in philosophy about 20 years later than QCA, and initially in complete isolation from the latter (Baumgartner 2008, 2009). However, close similarities were soon discovered, following which CNA has sought to establish itself with QCA as its reference competitor (Baumgartner 2015; Baumgartner and Epple 2014; Baumgartner and Ambühl 2020).

Although both methods subscribe to a regularity view of causation, the first marked difference between QCA and CNA lies in the latter’s ability to infer causal structures with more than one outcome. Unlike QCA, in which the focus of an analysis is on a single outcome *ab initio*, CNA allows users to let the method test what could be an outcome in the data. Subsequently, it combines the solutions for each identified outcome (called an "atomic solution formula") into a complex conjunction of atomic solution formulas (called a "complex solution formula").[22] In this process, it may happen that an outcome of one atomic solution is a part of the antecedent of another atomic solution, in which case a causal chain is found.[23] In fact, the possibility to identify causal chains has been the main selling point for CNA (Baumgartner 2013; Baumgartner and Epple 2014).

CNA is currently gaining ground in the area of public health (Whitaker et al. 2020), but the only empirical application in international relations so far is Haesebrouck (2019), who analyzes the pattern of European Union member state participation in two recent military operations: the 2011 intervention in Libya, and the operation against the self-proclaimed Islamic State. For applied researchers interested in configurational data analysis, CNA offers many functional advantages over QCA. In addition, the method is considerably less affected by methodological debates and internal inconsistencies. To carry out CNA, an eponymous R package exists (Ambuehl and Baumgartner 2020).

Combinational Regularity Analysis (CORA)

Combinational regularity analysis (CORA) (Sebechlebská et al. 2021) is the youngest configurational method. In contrast to QCA and CNA, CORA explicitly takes all of its algorithmic and technical inspirations from electrical engineering in general, and switching circuit design in particular. Essentially, there are three distinct features of CORA.

First and most importantly, with CORA it becomes possible to analyze multiple outcomes as well as the conjunctions of these outcomes simultaneously (Thiem et al. 2021). To this end, CORA generalizes the requirement of redundancy-freeness from the level of single outcomes, as in QCA and CNA, to entire systems of outcomes. In this way, not only can the causes of individual effects be found, but also the causes of all possible combinations of these effects, some of which may be shared. The most obvious area of application of these procedures is the medical concept of multi-morbidity, which describes the simultaneous presence of multiple diseases in a patient, such as diabetes and depression, for example (Suls and Green 2019).

A second difference to QCA and CNA is that CORA can explicitly address the problem of model ambiguity by a data-mining approach that progresses through tuple-selections of exogenous factors. The idea behind this approach is that any explanatory model that is found with any number of exogenous factors will, *ceteris paribus*, also always be found in an analysis with only those factors involved in this model. More precisely, if CORA cannot identify a fitting model with some set of combinations of factors, it adds one more factor to this set. From this perspective, the approach represents a type of Occam's Razor, which says that explanations that involve fewer variables are, *ceteris paribus*, to be preferred over explanations that are more complex.[24]

Third, CORA is the only configurational method to date that offers a consistent way of visualizing solutions. To do so, it draws on logic diagrams. Logic diagrams are well-established tools in electrical engineering for representing switching circuits, and for many prominent researchers in causal inference, they also "capture … the very essence of causation" (Pearl 2009: 415). Figure 32.4 shows two examples of such diagrams: a multi-output structure in panel (a), and a structure with multivalent inputs in panel (b).

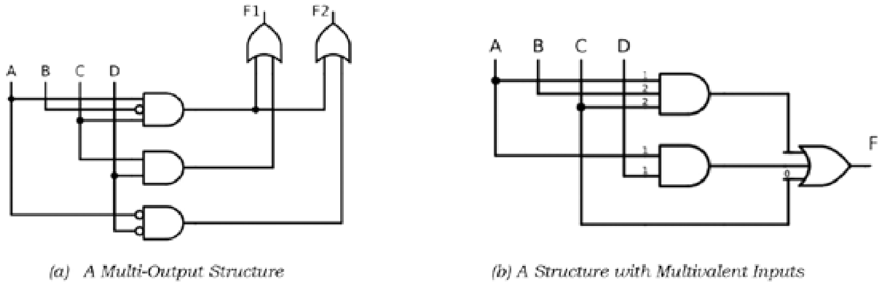

Figure 32.4 The logic diagrams produced with CORA

CONCLUSIONS

There can be no doubt that QCA is a real innovation in the field of empirical research methods. Although its two central pillars—the INUS theory of causation and Boolean optimization—had each been around for quite some time before QCA appeared on the scene, the major achievement of Ragin was to bring the two together. In this sense, QCA represents a prime example of how interdisciplinarity pushes the boundaries of science.

However, interdisciplinarity also requires a significant amount of care. And here, QCA has been plagued for the last 30 years with revelations of problems even in its most fundamental workings. For example, the conservative and the intermediate solution type, both of which have been introduced in response to fears of unwarranted counterfactual assumptions, have been proven to produce high rates of incorrect inferences, even when the data are ideal. What is more, even after 30 years, no consistent way of implementing QCA has been agreed upon, in consequence of which different software packages for QCA may still produce very different solutions even with the same set of data (Thiem and Dușa 2013b).

Fortunately, alternatives have become available that are not only unaffected by these fundamental problems, but also offer many possibilities to carry out more advanced configurational data analysis. With coincidence analysis, researchers can let the method try to identify which factors are exogenous, and which are endogenous. With combinational regularity analysis (CORA), they can analyze even more complex cause–effect relations, in which complexity is not only allowed on the side of causes, but also on the side of effects. In addition, CORA offers a widely accepted and highly effective means of visualization.

NOTES

1. Some scholars prefer the term "set-theoretic methods" (Schneider and Wagemann 2012). However, Clarke (2020) has rightly criticized the use of this term as uninformative because set theory, in one way or another, also forms the mathematical basis of many other methods.
2. In response to continuing criticism, some proponents of QCA have now started to differentiate between various approaches to QCA's approach (e.g., Schneider 2018; Thomann and Maggetti 2020). In addition, others reject methodological evaluations of QCA based on simulations because they argue that these would violate the method's qualitative spirit (e.g., Olsen 2014; Ragin 2014).
3. Based on a dataset of QCA studies that has been maintained by the author since 2011.

4. A fourth variant, which subsumes all other three variants under a generalizing framework, is generalized-set QCA (gsQCA) (Thiem 2014a). However, gsQCA has so far not been implemented in software, and has thus not yet been used.
5. An article published in *Science* found the *Journal of Business Research* (*JBR*) to be the most radical coercer of citations among business and management journals (Wilhite and Fong 2012, Supplementary material: 40). Around that time, *JBR*'s editor was an outspoken advocate and multiple author of several QCA articles that had appeared in *JBR* and elsewhere, which may explain these unusually high figures.
6. The term "equifinality" was originally introduced by von Bertalanffy (1950) for describing differences between inanimate and living systems; in contrast to most physical systems, "the final state may be reached from different initial conditions and in different ways" in open biological systems (von Bertalanffy 1950: 25).
7. In jurisprudence, many core elements of the INUS theory have been very influential (Hart and Honoré 1985). For example, the NESS (necessary element of a sufficient set) theory of causation is a close cousin of the INUS theory (Wright 2013).
8. Both the equivalence and the implication operator are so-called "non-fundamental operators" because they can always be replaced by a combination of "and," "or," and "not," which are fundamental operators (Thiem et al. 2016: 749–751). In other words, "→" and "↔" have no attached causal meaning whatsoever. They just represent functional relations.
9. However, the reverse conclusion does not hold. Not everything that is a redundancy is causally irrelevant. It may simply be that the researcher does not have enough data to show that some condition is non-redundant.
10. Complete replication material for tracing the authors' analytical steps from the calibration of all variables to the generation of the final QCA results is available on the article's website at http://dx.doi.org/10.1080/10242694.2017.1320183.
11. This has not always been the case. In particular, fsQCA has transitioned from an initial inclusion algorithm (Ragin 2000) to the same truth table algorithm that csQCA has always used (Ragin 2008).
12. Strictly speaking, mvQCA requires at least one exogenous factor to be multivalent.
13. Moreover, mvQCA dovetails with QCA's underlying theory of causation, unlike fsQCA, which can create several paradoxical situations (see Thiem and Dușa 2013a: 63–64).
14. In QCA, minterms are sometimes also called "primitive expressions." In electrical engineering, they are also often called "fundamental products." The "min" in "minterms" refers to the fact that these expressions are inputs to a minimization algorithm.
15. In electrical engineering, from which QCA has imported all its algorithmic procedures, truth tables are called "function tables" and remainders are called "don't cares."
16. Any proposition whose main operation is an implication is true whenever the antecedent is false or whenever the antecedent is true and the consequent is true. Expressed functionally, the proposition "A is sufficient for B" ($A \rightarrow B$) is true if, and only if, A is false ($A = 0$), or A is true ($A = 1$) and B is true ($B = 1$). In other words, an output value of 0 implies that the minterm is true but the outcome is false.
17. Theoretically speaking, any value above 0.5 represents more evidence in favor of the truth of the implication, but 0.75 has become a standard starting value. Note that the lower the inclusion cut-off, the less complex solutions in QCA tend to become, and the fewer causal claims QCA tends to make in consequence. The analogue applies vice versa.
18. Thiem et al. (2020) have conducted a meta-analysis of the problem of model ambiguity in applied QCA research. The authors found that model ambiguity is rarely reported, although it affects about a third of all empirical QCA studies.
19. Note in this connection that the QCApro package is currently the only software for QCA that standardly reports all models (Thiem 2018a). In some programs, like the popular fs/QCA package (Ragin and Davey 2019), it is not even possible to find all data-fitting models (Thiem et al. 2020).
20. See Cooper and Glaesser (2016) and Thiem (2016) for a critical discussion of T/ESA.
21. Necessary condition analysis (NCA) is also categorized as an alternative configurational method by some researchers (Dul 2016). However, as Thiem (2018b) has shown, there exists a serious mismatch between the method's purported search target and its actual output, which leads to similar problems to those that QCA suffers from.

22. Differences in results only stem from CNA's approach to optimization: unlike QCA, which minimizes away literals, CNA adds them until a suitable model is found. However, in current versions of the QCA software package (Dusa 2021), for example, these boundaries get blurred because that package also uses a very similar approach. Note also that CNA's complex solution formula is conceptually very different from QCA's complex/conservative solution type.
23. Before CNA switched from a top-down to a bottom-up algorithm, it was possible to mimic the generation of causal chains with QCA (Thiem 2015b).
24. For QCA, this approach has also been tested in Haesebrouck and Thiem (2018) and Lankoski and Thiem (2020). Note also that it is not tantamount to generating by Boolean optimization what is called the minimal sum. The minimal sum is that irredundant sum which has the smallest number of prime implicants, not necessarily the smallest number of variables.

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