

Avoiding Common Errors in QCA: A Short Guide for New Practitioners

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QCA is increasingly being adopted by researchers from a variety of disciplines and industries. As is only natural when learning a new methodological approach, not all of these applications are free of errors. In this paper, we provide a list of common errors that we have seen when reviewing QCA projects. We provide this list as a “cheat sheet” in the hopes of helping researchers improve their projects and avoid some of the most common mistakes encountered in the wild.

For each item we briefly explain what the error is and why it is considered a problem. We also describe possible remedies whenever applicable. The order of items follows the logic of the research cycle. These discussions are by no means comprehensive and we strongly recommend that the reader review the following texts for more information:

- Ragin, C.C. (1987). *The Comparative Method*
- Ragin, C.C. (2008). *Redesigning Social Inquiry*
- Oana, I., C.Q. Schneider and E. Thomann (2021). *Qualitative Comparative Analysis with R: A Beginner’s Guide*
- Mello, P.A. (2022). *Qualitative Comparative Analysis: An Introduction to Research Design and Application*
- Rutten, R. (2024). *Qualitative Comparative Analysis: Learning from Cases*

Also, for discussions of recommendations for standards of good practice in QCA research, readers are referred to the following articles:

- Schneider, C. Q., and Wagemann, C. (2010). Standards of good practice in qualitative comparative analysis (QCA) and fuzzy-sets. *Comparative Sociology*, 9, 397–418.
- Greckhamer, T., Furnari, S., Fiss, P., and Aguilera, R. (2018). Studying configurations with qualitative comparative analysis: Best practices in strategy and organization research. *Strategic Organization*, 16, 482–495.
- Rubinson, C. (2019). Presenting qualitative comparative analysis: Notation, tabular layout, and visualization. *Methodological Innovations*, May–August, 1–22, DOI:10.1177/2059799119862110.

A List of Common Errors in QCA

Approaching QCA

1. Substituting QCA for small-N statistical analysis

An important advantage of QCA is that it can be used to analyze small- and medium-N data (as well as large-N). However, this does not mean that it is always appropriate for small- and medium-N analysis. Keep in mind that conventional statistical analysis and QCA are designed to answer different types of research questions.

2. Using variable-oriented language

Causality in QCA is expressed as conditions being sufficient or necessary for the outcome, not in terms of independent variables having an effect on a dependent variable. That is, QCA focuses on the causes of effects, rather than the effects of causes. This is particularly important when verbalizing the sufficiency of a conjunction of multiple conditions. For example, from a configurational perspective, it is not that having friends and having a job have independent, positive effects on happiness. Rather, it is the combination of having both friends and a job that is sufficient for being happy. (Note also, that singular tense is used here because there is a single combination, comprised of multiple conditions.)

Whereas a variable reports the magnitude of an empirical phenomenon, a condition is a constitutive component of the case(s) under consideration. Conditions do not report magnitudes but qualitative states. In QCA, cases have (degrees of) membership in conditions—both explanatory conditions and the outcome condition.

3. Asserting causation without identifying mechanisms

QCA is a descriptive, not inferential, technique. If you wish to establish causation, you need to identify the underlying mechanism(s) at work, drawing upon substantive and/or theoretical knowledge. (This is why QCA is frequently applied in conjunction with in-depth case studies.)

Setting up research

4. Including only cases for which the outcome is present

QCA is a method for studying diversity. This means that your data set must include observations where the outcome is absent. It also means that your truth table must include rows where the outcome is False (i.e., consistency is less than your specified threshold). If all of your (non-remainder) truth table rows are consistent with the presence of the outcome, reconsider your calibration strategy. It may be that you have miscalibrated one or more conditions, or that you need to recalibrate to a more specific target set (e.g., from “moderate civic engagement” to “strong civic engagement”).

If your data set only includes observations where the outcome is present, you may instead employ analytic induction (AI), as described in Ragin (2023) *Analytic Induction for Social Research*, which is closely related to QCA and available open access.

5. Using nouns to name conditions instead of adjective phrases

Nouns refer to variables; a condition must have an adjective attached. For example, “GDP” is a variable while “Developed country” is a condition. “Income” is a variable; “Very rich individual” is a condition. “Years of education” is a variable; “Highly educated person” is a condition. In each of these examples, only the adjective phrase refers to a set in which observations may have membership. Clarifying the adjective phrase for each of your conditions will help with calibration.

Calibration

6. Using symmetric calibrations

It is important to remember that calibration is asymmetric. That is: the negation of “rich” is not “poor” but, rather, “not rich.” When calibrating your conditions, you need to carefully consider what is meant by “fully in” (fuzzy score=1.0) and “fully out” (fuzzy score=0.0). “Fully out” is only the opposite of “fully in” in the case of true dichotomies, which is rare (e.g., “biologically male” is equal to “not biologically female” if and only if we ignore intersex conditions).

Other examples:

- (a) the negation of “developed country” is not “under-developed country” but, rather, “not-developed country”
- (b) the negation of “large company” is not “small company” but, rather, “not-large company”
- (c) the negation of “happy family” is not “sad family” but, rather, “not-happy family”

7. Calibrating to 0.5

When an observation is assigned a fuzzy-set score of 0.5 for a given condition, that observation will have equal membership in all truth table rows but will not have maximum membership in any truth table row. It is unclear what this score means substantively because the crossover point is the point of maximum ambiguity, where the observation is neither in nor out of the target set. The case will appear to drop out of the truth table analysis, as it doesn't belong to any corner of the vector space. If you have many observations scoring at (or close to) 0.5, it often means that there is something wrong with your calibration strategy. (This may be a consequence of using symmetric calibrations or conceiving of your conditions as variables rather than sets, discussed above).

8. Failing to explain calibrations

It is crucial that you explain what your calibrations mean substantively. It is not sufficient to simply report the values that correspond to, e.g., 0.0, 0.5, and 1.0. You also need to explain why, e.g., 14+ years of education corresponds to “fully in the set of educated people.” Especially when space is limited, we recommend providing a table that describes each condition, the calibration rules and this justification.

9. Mechanistic calibration

Successful calibration requires one to carefully reflect upon the nature of one's measures and their meaning. Automated and statistical clustering/rescaling techniques rarely produce useful calibrations. Also avoid simply adopting another researcher's calibrations without first considering how they may need to be adjusted for your particular project.

10. Using a measure of central tendency and/or the variable's distribution to calibrate

In general, you should avoid using the variable's distribution as the basis for your calibration. Having a higher-than-average income does not mean that one is rich. Instead, you need to rely upon substantive and theoretical knowledge of your domain in order to develop meaningful calibrations. If substantive and theoretical knowledge does not exist, you need to get to know your cases better. If you nevertheless use the variable's distribution as a basis for your calibration, make this clear when naming the condition: “Above-average family size” or “Below-average family size.”

11. Using the full range of a Likert-type scale or index to calibrate

This is not always an error but often is. When calibrating a Likert-type scale or index, you should not automatically assign the bottom value to 0.0, the middle value to 0.5, and the maximum value to 1.0. Instead, you should carefully consider the meaning of the scale. In particular, consider whether some values may need to be collapsed together. For example, with a 7-point scale, it may be the case that scores 1-3 are “fully out” of the target set, 4 is “more out than in,” 5 is “more in than out” and 6-7 are “fully in.” The precise calibration depends upon the what the scale means.

You also should not automatically use the same calibration strategy for all conditions. Just because you have multiple 7-point measures does not mean that you should calibrate them all in the same way. Instead, think about what each item means substantively.

Analysis and interpretation

12. Using a sufficiency consistency threshold < 0.80

In *Redesigning Social Inquiry*, Ragin states that the consistency threshold for sufficiency testing should not be less than 0.75 and recommends a threshold of at least 0.85, especially for macro-level data. Most QCA reviewers today anticipate a sufficiency consistency threshold of at least 0.8, but this is only a rule of thumb. Lower thresholds may be acceptable when accompanied by a substantive and/or theoretical justification.

13. Ignoring very low unique coverage scores

Very low unique coverage scores indicate substantial overlap among your sufficiency recipes. This often indicates that you really have a single recipe with slight variants due to substitutable conditions. To understand the nature of the overlap, begin by identifying the observations that belong to the overlapping recipes.

14. Not running a separate QCA for the negation of the outcome

If you wish to explain both the presence and the absence of the outcome, as is common in QCA, you need to conduct a separate analysis for each. Recall that QCA is asymmetric and the combination of conditions that explains the presence of the outcome may be different from the one that explains its absence.

Do not be surprised, however, if analyzing the absence of the outcome yields indeterminant results and/or low consistency scores. Cases lacking the outcome are often quite heterogenous. In such instances, it is appropriate to focus on explaining the presence of the outcome and simply acknowledge that understanding the absence of the outcome will require further research.

15. Neglecting to conduct a necessity test

QCA is not only about sufficiency. It is important to also test for necessity, unless you have a theoretical or methodological justification for not doing so.

16. Analyzing conditions that are always present

If a condition is always present, for all observations in your data set, it has no explanatory power because it is necessary for the presence of the outcome and also for the absence of the outcome. There are two ways of thinking about such a condition. It may be a “trivial necessary condition” (e.g., oxygen is necessary for both war and peace) or it may be a scope condition that describes your sample. Alternatively, it could simply indicate that you have miscalibrated and need to revise your calibration of that condition.

17. Ignoring low solution coverage scores

A low solution coverage indicates that there are many instances of the outcome that are not explained by your model. Whether that is problematic needs to be discussed. It may be that there are good theoretical reasons for this, that your model is poor or that your model simply does not explain everything and that further research is needed. A low coverage score is not necessarily an indication of poor research design but should not be ignored and needs to be explained.

18. Ignoring equifinality because coverage is low

One of QCA’s strengths is that it can identify when there are multiple pathways to the same outcome (equifinality). However, researchers sometimes ignore pathways with low coverage. Just because a pathway only explains a relatively small number of cases doesn’t mean that it is unimportant. For example, just because most instances of lung cancer are due to smoking does not mean that we should not study other causes.

19. Failing to interpret the results

Do not simply conclude your project by presenting your Boolean solution(s) and their consistency/coverage scores. Rather, you must explain what your results mean. A statement of necessity or sufficiency verbalizes a cross-case regularity that must then be interpreted into a causal mechanism. For example, if having both friends and a job is sufficient for being happy, this indicates that having a social network to satisfy your emotional needs and having an income to satisfy your material needs produces happiness. Return to your cases to assess the substantive meaning of your empirically observed cross-case regularity. Remember that in QCA causation is established through substantive knowledge, not empirical metrics.

Author biographies

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