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The Interpretive Logic of Generalized Analytic Induction

In his study of addiction, Alfred Lindesmith (1968) focused exclusively on conditions that made sense as contributing causes, and searched for invariant connections between the outcome—addiction—and relevant antecedent conditions. He observed an important commonality shared by all opiate addicts: they succumbed to addiction after an explicit and abrupt *recognition* that a long-standing pattern of distress had been a result of repeated opiate withdrawal (Katz 2001) and not of some other ailment. Lindesmith did not treat *recognition* as a variable (i.e., as something that varied systematically across cases) because he was interested only in the consistency of its *presence* as an antecedent condition in instances of opiate addiction (see chapter 1).

Lindesmith's analytic strategy reflects AI's distinctive approach to the assessment of empirical evidence—specifically, how a data set on multiple cases is employed to generate results. In this regard, AI differs from both conventional quantitative analysis and qualitative comparative analysis (QCA; Ragin 1987). Both conventional quantitative analysis and QCA investigate causally relevant conditions that vary by level, degree, or presence/absence.[1] As this chapter demonstrates, generalized AI evaluates the two sides of a binary causal condition *not* as "present versus absent" but as "contributing versus irrelevant." In this approach to evidence, only one side of a binary is considered important; the other side is typically interpreted as "not contributing" and is excluded from consideration (Hammersley and Cooper 2012: 140).

For example, if "state breakdown" is considered a relevant contributing cause of social revolution (as in Skocpol 1979), then the absence of state breakdown can be eliminated from consideration as a possible contributing cause, across all cases included in the analysis. AI typically selects one side of a presence/absence dichotomy as relevant to an outcome, and treats the other side of the dichotomy as irrelevant (Hammersley and Cooper 2012: 155). The evaluation of each condition as contributing versus irrelevant is based on the researcher's substantive and theoretical knowledge, and thus involves interpretive inferences. This aspect of AI follows directly from its roots in qualitative research.

The main contrast addressed in this chapter is between QCA (Ragin 1987) and generalized AI. The contrast with QCA serves to highlight the distinctiveness of generalized AI. The discussion of the chasm separating generalized AI and conventional quantitative analysis is limited, for the simple reason that quantitative techniques require variation in both outcomes and causal conditions. The idea that a causal condition is either contributing or irrelevant is completely foreign to conventional quantitative analysis, which is wedded to the principle of covariation, which in turn requires variation in both antecedent conditions and outcomes. Generalized AI requires neither. For example, if positive instances of social revolution all exhibit state breakdown as an antecedent condition, then neither the antecedent condition nor the outcome varies across relevant cases.

QCA AND POSITIVE CASES

Most QCA applications include both positive and negative instances of the outcome in question. These values, in turn, shape the coding of truth table rows as "true" (causal combinations linked to outcome) or "false" (combinations not linked to outcome). Truth table rows that cannot be coded "true" or "false" on the outcome (typically due to a lack of cases) are called "remainder" rows. Researchers use the remainder rows to craft truth table solutions that are simpler than the "complex" solution (for a discussion of complex, parsimonious, and intermediate solutions, see Ragin 2008: chap. 9). Thus, the typical truth table analysis has three types of rows: true, false, and remainder. The remainder category embraces all truth table rows that cannot be coded true or false.

It is not generally recognized that QCA is capable of analyzing a body of evidence that contains only positive instances of an outcome. When used in this manner, QCA codes truth table rows "true" if they contain instances of the outcome, while rows that are devoid of cases are classified as remainder rows. Thus, in this type of application, there are only two kinds of truth table rows: true (contains instances of the outcome) and remainder (no instances).[2] However, with this setup, the remainder rows cannot be used to craft simpler solutions (i.e., intermediate and parsimonious). Remainder rows are incorporated into truth table solutions if doing so produces a logically simpler solution. However, the results in this setup, with only two kinds of truth table rows, are degenerate because *all* logically possible combinations of conditions (positive and remainder) can be linked to the outcome in question, which is not a meaningful truth table solution. Instead, all remainder rows must be treated as false. The upshot: if an application has only positive cases, the parsimonious and intermediate solutions to the truth table cannot be derived. Only the complex truth table solution is possible.[3]

Nor is it generally recognized that QCA's "complex" solution to truth table analysis uses only truth table rows with coded outcomes equal to 1 (true), even in applications where there are both positive and negative instances of the outcome and thus all three kinds of truth table rows—true, false, and remainder. To generate the complex solution, truth table rows with outcome equal to 1 are paired and compared with each other, in an attempt to eliminate conditions one at a time through a "bottom-up" process known as incremental elimination. Consider, for example, an analysis with four causal conditions (A, B, C, and D) and an outcome (Y). If A•~B•C•D → Y and A•~B•~C•D → Y, it is possible to eliminate condition C/~C when conditions A, ~B, and D are present, yielding A•~B•D → Y (tilde indicates negation or *not*; arrow indicates the superset/subset relationship; multiplication symbol indicates combined conditions; plus sign indicates alternate combinations or alternate conditions). Condition C/~C is eliminated in this particular context (A•~B•D), but not in other contexts (e.g., A•B•D). To eliminate two conditions, four rows, all coded 1 (true) on the outcome, must be matched. For example, if A•B•C•D, A•B•~C•D, A•~B•C•D, and A•~B•~C•D are all coded 1 (true) on the outcome, then both B/~B and C/~C can be eliminated, yielding A•D → Y.[4] To eliminate three conditions, eight rows with the outcome must be matched, and so on. These requirements follow directly from QCA's configurational logic.

For QCA's complex solution to yield useful results, it is important to have a nontrivial proportion of truth table rows coded 1 (true). Consider, for illustration, Olav Stokke's (2004) truth table for successful shaming of violators of international fishing agreements (table 6-1). Please note that only Stokke's positive cases are shown in the truth table, which is all that is required to derive the complex solution. Using the three-letter condition labels, as shown in the table, the four truth table rows with positive cases can be rewritten as follows:

adv•~com•shd•inc•rev + adv•com•shd•inc•rev +
adv•com•shd•~inc•~rev +
adv•~com•~shd•~inc•~rev → success

The truth table rule for combining rows to reduce complexity is that two rows can be combined to create a simpler expression if they agree on the outcome (e.g., they are both coded "true") and differ on only one condition. This rule is clearly satisfied by the first two rows because they differ on only com/~com:

adv•~com•shd•inc•rev + adv•com•shd•inc•rev
= adv•shd•inc•rev •(com + ~com)
= adv•shd•inc•rev

TABLE 6-1 Stokke's truth table for successful shaming of violators (positive cases)

Advice (adv)	Commitment (com)	Shadow (shd)	Inconvenience (inc)	Reverberation (rev)	Success
1	0	1	1	1	1
1	1	1	1	1	1
1	1	1	0	0	1
1	0	0	0	0	1

NOTES:

Advice (adv): Whether the shamers can substantiate their criticism with reference to explicit recommendations of the regime's scientific advisory body.

Commitment (com): Whether the target behavior explicitly violates a conservation measure adopted by the regime's decision-making body.

Shadow of the future (shd): Perceived need of the target of shaming to strike new deals under the regime—such beneficial deals are likely to be jeopardized if criticism is ignored.

Inconvenience (inc): The inconvenience (to the target of shaming) of the behavioral change that the shamers are trying to prompt.

Reverberation (rev): The domestic political costs to the target of shaming for not complying (i.e., for being scandalized as a culprit).

However, this simplification is all that is possible for truth table 6-1, yielding the following complex solution:

$$\text{adv}\bullet\text{shd}\bullet\text{inc}\bullet\text{rev} + \text{adv}\bullet\text{com}\bullet\text{shd}\bullet{\sim}\text{inc}\bullet{\sim}\text{rev} +$$
$$\text{adv}\bullet{\sim}\text{com}\bullet{\sim}\text{shd}\bullet{\sim}\text{inc}\bullet{\sim}\text{rev} \rightarrow \text{success}$$

In other words, because the diversity of positive cases is empirically limited in this example (with only four of the thirty-two logically possible combinations displaying the outcome), very little reduction of complexity can be realized.

In part, QCA's goal of reducing complexity is stymied, in this example, by one of its core strengths: its strict adherence to configurational logic. QCA gives equal analytic weight to the presence of conditions and to the absence of conditions. Consider, for example, the last row of the truth table: adv•~com•~shd•~inc•~rev. Three of the conditions that are combined in this expression (the *absence* of an "explicit commitment," the *absence* of a "shadow of the future," and the *absence* of "domestic reverberations") are thought to undermine the success of shaming when they are coded present, and not when they are coded absent. Yet with QCA the truth table is analytically open to the possibility that these three are required to be absent, and are essential to the success of shaming when combined with adv•~inc. QCA users routinely circumvent this limitation by deriving parsimonious and intermediate solutions. However, as noted previously, these two solution types are not derivable using QCA if there are only positive instances of the outcome. Lacking negative cases, and by implication lacking remainders as well, only the complex solution is derivable.

GENERALIZED AI AND POSITIVE CASES

As discussed above, generalized AI interprets conditions as either "contributing" (to the occurrence of the outcome) or "irrelevant." This view of causal conditions contrasts sharply with QCA's view. Using QCA, a condition becomes irrelevant only if it is linked to the outcome when the condition is present and when it is absent, across matched rows. Again:

$$A \bullet \sim B \bullet C \bullet D + A \bullet \sim B \bullet \sim C \bullet D \rightarrow Y$$
$$A \bullet \sim B \bullet D \bullet (C + \sim C) \rightarrow Y$$
$$A \bullet \sim B \bullet D \rightarrow Y$$

C/~C is demonstrably irrelevant, but only in the context of A•~B•D. C/~C could still be relevant in other contexts. This context-specific elimination of causal conditions follows directly from QCA's grounding in configurational logic.

Generalized AI, by contrast, offers a contrasting view and a different treatment of the same evidence (A•~B•C•D + A•~B•~C•D → Y). The foundation of generalized AI's interpretive logic is the researcher's knowledge and understanding of the connection between the causal conditions and the outcome in question. Essentially, the researcher specifies, for each causal condition, whether it contributes to the outcome when it is present or when it is absent.[5] For example, if condition C contributes to the outcome only when it is present (C), then it is irrelevant when it is absent (~C). If a case (or a truth table row) includes ~C (the absence of C) as a condition, then the condition can be dropped from the combination because it is irrelevant (i.e., non-contributing). Consider generalized AI's approach to the evidence used to illustrate QCA: A•~B•C•D + A•~B•~C•D → Y. Assume that the researcher interprets each of the four conditions as contributing when present, and otherwise as irrelevant. Combination A•~B•C•D becomes A•C•D, and combination A•~B•~C•D becomes A•D. Logically, A•C•D is included in (i.e., is a subset of) A•D, which leaves A•D → Y as the solution of A•~B•C•D + A•~B•~C•D → Y. Thus, the generalized AI solution is far simpler than QCA's solution of the same evidence. The difference follows directly from the application of generalized AI's interpretive logic versus QCA's configurational logic.

This same interpretive logic can be applied to Stokke's data in table 6-1. Assume that the researcher interprets conditions adv (advice), com (commitment), shd (shadow of the future), and rev (domestic reverberations) as contributing to the outcome (successful shaming) when present, and otherwise as irrelevant; and interprets condition inc (inconvenient) as contributing to the outcome when negated (~inc), and otherwise as irrelevant. The four truth table rows from table 6-1 are transformed by this interpretive logic as shown in table 6-2, which uses dashes to indicate irrelevant (i.e., non-contributing) conditions. Thus:

adv•~com•shd•inc•rev becomes adv•shd•rev
adv•com•shd•inc•rev becomes adv•com•shd•rev
adv•com•shd•~inc•~rev becomes adv•com•shd•~inc
adv•~com•~shd•~inc•~rev becomes adv•~inc

TABLE 6-2 Stokke's truth table for positive cases viewed through the lens of generalized AI*

Advice (adv)	Commitment (com)	Shadow (shd)	Inconvenience (inc)	Reverberation (rev)	Success
1	–	1	–	1	1
1	1	1	–	1	1
1	1	1	0	–	1
1	–	–	0	–	1

* Dashes replace non-contributing conditions.

Generalized AI's use of interpretive inferences, just demonstrated, is strongly rooted in the case-oriented logic of qualitative research. For example, consider how a qualitative researcher would assess the first combination listed above (adv•~com•shd•inc•rev) as a single case. Armed with the knowledge that shaming succeeded in this case, the researcher would examine its array of conditions and pinpoint those that contributed to the outcome. In this light, three conditions (adv•shd•rev) make sense as components of a recipe for the outcome; the other two (~com•inc) do not. This same interpretive logic applies, as well, to the other three truth table rows, considered as cases. When explaining each case, a qualitative researcher would construct a case narrative based on *contributing* conditions.

Further simplification of table 6-2 is possible using the inclusion rule, which allows more complex terms (subsets) to be absorbed by less complex terms (supersets):

adv•com•shd•rev is included in adv•shd•rev
adv•com•shd•~inc is included in adv•~inc

Thus, generalized AI's solution of the truth table is straightforward, especially when compared to QCA's complex solution. It is simply

adv•shd•rev + adv•~inc → success

According to generalized AI, there are two causal recipes for successful shaming: (1) supportive scientific advice (adv) in situations where it is not inconvenient for the target of shaming to alter its behavior (~inc), and (2) supportive scientific advice (adv) in situations where there are both domestic reverberations for being shamed (rev) and a need to strike future deals (shd).

GENERALIZED AI AND OUTCOME SUBTYPES

As noted previously, generalized AI focuses on causally relevant conditions shared by positive cases. The only universally shared condition in the example presented above is supportive scientific advice (adv). When viewed from a classic AI perspective, the other conditions (shd, rev, and ~inc) can be seen as disconfirming, because there are instances of the outcome lacking each one of these conditions (e.g., rows 1 and 2 both lack ~inc). However, recall that one of the key strategies discussed in chapter 2 for dealing with disconfirming cases is to differentiate subtypes of the outcome in accordance with the different causal recipes. In this example, the investigator would look for qualitative differences between instances of successful shaming generated by adv•~inc versus those generated by adv•shd•rev, and construct a simple, two-category typology of outcomes based on the key differences identified. The contrast would attend to outcome differences between cases in the first two truth table rows (instances of adv•shd•rev) versus cases in the third and fourth rows (instances of adv•~inc). In this example, the researcher might distinguish between successful shaming where compliance is "pro forma" (adv•~inc) and successful shaming where compliance is "strategic" (adv•shd•rev).

Notice also that there is logical overlap between the two recipes: instances of adv•~inc•shd•rev, if they existed, would conform to both recipes. It is possible to assign this overlap to recipe adv•~inc, and thereby clarify and separate the two causal recipes. The first step is to use De Morgan's theorem to derive the complement (negation) of the recipe selected to receive the overlap. Next, the complement (negation) of that recipe is intersected with the other recipe, which narrows the breadth of the second recipe while awarding the overlap to the first:

adv•~inc + adv•shd•rev	generalized AI solution
adv•~inc	selected to receive overlap
~(adv•~inc) = ~adv + inc	recipe negated
(~adv + inc)•adv•shd•rev	intersected with other recipe
adv•inc•shd•rev	results of intersection
adv•~inc + adv•inc•shd•rev	clarified AI solution

The clarified recipes reveal the importance of whether the behavioral change is inconvenient to the targets of shaming. If it is not inconvenient (~inc), then the conditions for successful shaming are simple, namely, supportive scientific advice (adv). However, if the behavioral change is inconvenient (inc), then two additional conditions for successful shaming require satisfaction, the need to strike future deals (shd) and domestic reverberations (rev).

The contrast between QCA's and AI's approaches to the analysis of positive-only cases, just sketched, is sharp. QCA is stymied by the limited diversity of cases and its strict adherence to configurational logic; generalized AI is liberated from these constraints by its use of interpretive inferences. While QCA can be used to generate simpler truth table solutions when analyzing evidence that embraces both positive and negative cases, from the perspective of generalized AI, "negative cases," per se, don't exist. They are simply cases that exhibit outcomes that are different from the focal outcome.

TABLE 6-3 Stokke's truth table for unsuccessful shaming of violators (negative cases)

Advice (adv)	Commitment (com)	Shadow (shd)	Inconvenience (inc)	Reverberation (rev)	Success
1	0	0	1	0	0
1	0	0	1	1	0
0	0	0	1	0	0
1	1	1	1	0	0

TABLE 6-4 Stokke's truth table for "negative" cases viewed through the lens of generalized AI

Advice (adv)	Commitment (com)	Shadow (shd)	Inconvenience (inc)	Reverberation (rev)	Success
–	0	0	1	0	0
–	0	0	1	–	0
0	0	0	1	0	0
–	–	–	1	0	0

WHAT HAPPENED INSTEAD?

As explained in chapter 4, rather than defining cases that lack the focal outcome as "negative cases," AI considers such cases as instances of different outcomes and therefore as deserving of separate treatment. The researcher first identifies noteworthy outcomes among the nonfocal cases. Next, the researcher ascertains the antecedent conditions relevant to each alternate outcome. The relevant antecedent conditions for the alternate outcomes may differ substantially from the ones linked to the focal outcome.

Stokke's study of shaming as a way to induce violators of international agreements to mend their ways includes "negative" cases (where shaming did not have the desired impact). It would be ideal to know what happened in each case, for there may be several different outcomes among the cases that did not respond positively to shaming. Nevertheless, Stokke's negative cases can be used to illustrate generalized AI's approach to the analysis of a set of cases lacking the focal outcome. This illustration assumes (1) that their outcomes—resistance—are relatively homogeneous and (2) that the relevant causal conditions are the reverse of the conditions linked to the focal outcome. In essence, Stokke's "negative" cases of successful shaming are transformed into positive cases of resistance and subjected to the same analytic procedures applied to Stokke's positive cases.

Table 6-3 presents Stokke's negative cases (shaming failed). There are four truth table rows coded 0 (false) with respect to the success of shaming. As mentioned above, the causal conditions used in this example are the same as those used in the analysis of the positive cases (see table 6-1). However, the interpretive inferences are now the reverse of those implemented in table 6-2. The researcher interprets conditions adv (advice), com (commitment), shd (shadow of the future), and rev (reverberations) as contributing to the outcome (shaming failed) when *absent*, and otherwise as irrelevant; and interprets condition inc (inconvenient) as contributing when *present* (inc), and otherwise as irrelevant. The four truth table rows from table 6-3 are transformed by this interpretive logic, as depicted in table 6-4, which uses dashes to indicate irrelevant (i.e., non-contributing) conditions.

Converting table 6-4 into equation form yields

$$\sim\text{com}\bullet\sim\text{shd}\bullet\text{inc}\bullet\sim\text{rev} + \sim\text{com}\bullet\sim\text{shd}\bullet\text{inc} +$$
$$\sim\text{adv}\bullet\sim\text{com}\bullet\sim\text{shd}\bullet\text{inc}\bullet\sim\text{rev} + \text{inc}\bullet\sim\text{rev} \rightarrow \sim\text{success}$$

Once again, further simplification is possible using the inclusion rule, which allows more complex terms (subsets) to be absorbed by less complex terms (supersets):

~com•~shd•inc•~rev	is included in both	~com•~shd•inc and inc•~rev
~adv•~com•~shd•inc•~rev	is included in both	~com•~shd•inc and inc•~rev

Thus, the generalized AI solution of truth table 6-4 is straightforward:

$$\sim\text{com}\bullet\sim\text{shd}\bullet\text{inc} + \text{inc}\bullet\sim\text{rev} \rightarrow \sim\text{success}$$

In other words, shaming fails when it is inconvenient for the target to conform and there are no domestic reverberations, or when such inconvenience is combined with no explicit violation of a commitment and no need to strike future deals.

It is instructive to clarify the two recipes by assigning their overlap (~com•~shd•inc •~rev) to one of the two recipes:

~com•~shd•inc + inc•~rev	generalized AI solution
inc•~rev	selected to receive overlap
~inc + rev	recipe negated
(~inc + rev)•(~com•~shd•inc)	intersected with other recipe
~com•~shd•inc•rev	results of intersection
~com•~shd•inc•rev + inc•~rev	clarified solution

The clarified solution shows the pivotal impact of domestic reverberations. When domestic reverberations are absent, shaming will fail if it is inconvenient for the target to change its behavior. However, when domestic reverberations are present, the inconvenience of the change must be combined with an absence of an explicit commitment and no need to strike future deals.

CONTINGENT CONDITIONS

This chapter has emphasized generalized AI's use of interpretive inferences to transform "present versus absent" dichotomies to "contributing versus irrelevant" dichotomies. In many situations, however, a researcher will suspect that a condition is "contributing when present" in some contexts, while in other contexts it is "contributing when absent (i.e., negated)"—in short, that the valence of a contributing condition may be *contingent* on the other conditions involved. In these situations, the researcher has the option of treating such conditions as conventional presence/absence dichotomies, in order to ensure that their contrasting contributions are modeled correctly. Also, once the truth table solution is generated, it is possible to clarify the solution in a way that highlights the contrasting impact of the condition in question (see example in appendix C).

LOOKING AHEAD

Generalized AI's use of interpretive inference is one of the cornerstones of the approach. Applications of generalized AI presented in chapters 7–9 all use the binary opposition "contributing versus irrelevant" for most antecedent conditions, in place of configurational logic's "present versus absent." By focusing on outcomes one at a time and applying interpretive inferences, generalized AI is able to generate simplified representations of cross-case patterns in situations where the outcome is the same for all cases. Chapter 7 presents a step-by-step demonstration of generalized AI, focusing on a common qualitative research design—namely, situations where the researcher has a set of cases selected for study precisely because they all exhibit the same outcome. Chapter 8 provides an illustration of a generalized AI investigation of multiple outcomes, based on a reanalysis of data published in 2006 by Jocelyn Viterna on women's mobilization into the Salvadoran guerrilla army. Chapter 9 demonstrates the application of generalized AI to conventional quantitative data, using the Black female sample from the National Longitudinal Survey of Youth.