10

Core Features of Generalized Analytic Induction

This chapter summarizes core features of generalized AI and concludes with a discussion of potential applications. The core features discussed range from its general orientation as a research strategy to practical procedures involved in applying the method. Considered together, these features define a strategy of social inquiry that differs fundamentally from that of conventional quantitative research.

- AI is applied to outcomes that are more or less the same across a range of cases. AI focuses analytic attention on one outcome at a time, and avoids pooling different outcomes in a single analysis. Rather than analyzing a dichotomized outcome as present versus absent, AI emphasizes the separate treatment of each outcome—the focal outcome and substantively important alternate outcomes.
- AI prioritizes the identification of antecedent conditions shared by instances of an outcome. Shared antecedent conditions, in turn, provide a basis for the specification of causal recipes, which in turn serve as guides to causal interpretation at the case level. AI is not an inferential technique; rather, it is largely descriptive and interpretive.
- AI eschews the concept of negative cases, especially when the set of negative cases is defined simply by their failure to display the focal outcome. Negative cases are more appropriately viewed as positive instances of alternate outcomes.
- AI is especially well suited for research questions addressing qualitative outcomes. The guiding question in most such applications of AI is "How did the outcome happen?" "How" questions prioritize positive cases and focus the investigation on combinations of shared antecedent conditions (i.e., "modal configurations").

- AI is dynamic and iterative. The conceptualization of the outcome is open to revision as the investigation proceeds, and the specification of antecedent conditions may be revised as case knowledge deepens. The research process is iterative, as positive/disconfirming cases motivate revisions to the conceptualization of the outcome or to the specification of the working hypothesis.
- AI, especially generalized AI, evaluates the consistency of the set-analytic connection between antecedent conditions and outcomes using enumerative criteria. Generalized AI assesses the degree to which the "inclusion" relation between antecedent conditions and an outcome is satisfied. Classic AI seeks perfect inclusion, with no positive/disconfirming cases remaining at the conclusion of the investigation.
- AI relies heavily on interpretive inferences when assessing antecedent conditions. An interpretive inference recasts a presence-versus-absence dichotomy as a contributing-versus-irrelevant dichotomy, which in turn simplifies the assessment of antecedent conditions. As shown in the applications presented in chapters 6–9, AI's interpretive logic mimics the case-oriented researcher's goal of developing case narratives based on contributing conditions.
- AI's truth table solutions are normally presented in "sum-of-products" form. Converting them into "product-of-sums" form, as demonstrated in chapter 7, can uncover conditions that constitute substitutable ways of satisfying a more general causal requirement. Identifying substitutable conditions can greatly simplify a causal formula. Appendix D describes a procedure for converting a sum-of-products expression into a product-of-sums expression.
- The interpretation of a truth table solution with two (or more) causal recipes can be enhanced by "clarifying" the recipes—assigning the overlap exclusively to one of the recipes and removing it from the other(s). The first step is to determine which recipe is to be awarded the overlap. The second step is to derive the complement (negation) of the selected recipe using De Morgan's theorem. Third, the negation of the recipe is intersected with the alternate recipe, which narrows the breadth of the second recipe while awarding the overlap to the first:

A•B + C•D	two overlapping recipes (overlap: A•B•C•D)
A•B	recipe selected to receive overlap
~(A•B) = ~A + ~B	the complement of the selected recipe
(~A + ~B) • C•D	complement intersected with the second recipe
A•B + C•D•(~A + ~B)	clarified recipes
A•B + C•D•~A + C•D•~B	clarified recipes in sum-of-products form

- When antecedent conditions vary by level or degree, they can be calibrated as fuzzy sets. Once converted into fuzzy sets, they can be utilized as antecedent conditions in truth tables, which sort cases according to their combinations of conditions. The calibration of an interval or ratio-scale variable as a fuzzy set must be grounded in theoretical and substantive knowledge, especially with respect to the crossover point separating cases that are more "in" versus more "out of" the target set (appendix B; see Ragin 2008: chaps. 4 and 5).

POTENTIAL APPLICATIONS

Generalized AI is a flexible tool with many potential applications. This book emphasizes its relevance to "how" questions, where the goal is to identify the antecedent conditions shared by a set of cases with the same outcome. However, generalized AI can be used to address any research question regarding the decisive features or elements shared by the members of a category or set. Consider, for example, the wide array of outcomes, both hypothetical and empirical, mentioned in this work:

becoming a marijuana user
succumbing to opiate addiction
resorting to embezzlement
the rise of modern tyrants
successful local management of common pool resources
the emergence of bureaucratic authoritarian states
the breakdown of democratic regimes
the successful shaming of violators of international agreements
long-term commitment to being an Olympic-caliber athlete
movement organizations that secured advantages for their constituents
being "in" versus "well-out-of" poverty
participation of women in El Salvador's guerrilla army
protesting IMF-mandated austerity measures
engaging in electoral fraud

These outcomes vary on a number of important dimensions. For example, they range in scale from outcomes specific to individuals to outcomes relevant to countries. They also vary in terms of the degree to which they invoke immediate, proximate conditions versus conditions that are more long-term, structural, or contextual in nature. Finally, they vary in terms of their potential for offering findings or conclusions that are transferable to other settings. Some are strongly anchored in specific times and places, while others have wide implications.

As demonstrated in chapter 9, generalized AI can be used in conjunction with variable-oriented methods. Most conventional variable-oriented methods focus on the separate impact of "independent" variables on outcomes. The usual goal is either to gauge the relative importance of competing variables or to demonstrate that a theoretically decisive variable has an independent impact. In either case, the key task is to isolate each independent variable's separate contribution to the outcome. Generalized AI, by contrast, focuses on combinations of contributing conditions—modal configurations. This feature counterbalances the emphasis of the variable-oriented approach on assessing each condition's net contribution to an outcome. Furthermore, by highlighting combinations of conditions, generalized AI provides a bridge to causal interpretation. Combinations of conditions are often suggestive of causal mechanisms, which, in turn, can be explored and assessed at the case level (Goertz 2017).

Generalized AI also can be used in conjunction with case-oriented methods, especially those that examine multiple instances of a qualitative outcome. Many applications of case-oriented methods culminate in a "composite portrait" of such instances. The researcher constructs a representation of the category based on common features. For example, a researcher might construct a composite portrait of committed environmental activists based on interviews with a sample of activists. Very often, the composite portrait that results is an amalgamation of noteworthy features of selected instances, chosen because of their salience to the researcher. Generalized AI makes the process of constructing representations of cross-case evidence both systematic and transparent. By applying the same analytic frame to each case (via truth tables) and directly assessing the degree to which combinations of features are shared across cases, generalized AI brings rigor to a research approach that is often seen as ad hoc.

Generalized AI also aids process tracing, an important case-oriented research tool. One of the central goals of process tracing is to gather case-level evidence relevant to causal mechanisms (Goertz 2017; Schneider and Rohlfing 2016). Often, researchers posit mechanisms based on cross-case analysis and then process trace at the case level as a way to assess the inferred mechanism (Goertz and Haggard 2022). As noted previously, generalized AI focuses on *combinations* of causally relevant antecedent conditions, which in turn are suggestive of causal mechanisms. In addition to offering greater guidance to the effort to identify mechanisms, generalized AI also can be used to aid the selection of cases for in-depth, process-oriented examination. Thus, generalized AI formalizes and systematizes basic analytic strategies commonly practiced by qualitative researchers.