

Causal Structure: Confounders, Colliders, Mediators and What Intervention Adds

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Abstract

Causal inference depends on the structure that connects variables, not on a generic rule to “adjust for more covariates”. A variable can be a confounder, mediator, collider or effect modifier only relative to a specified causal question and structure. Adjustment for a genuine confounder can close a non-causal path; adjustment for a mediator can remove part of the total effect of interest; conditioning on a collider or its descendant can create an association that was not present before conditioning. Measurement error can further distort causal effect estimates even when the qualitative causal graph is correctly specified. This article defines the causal-role vocabulary used by INF, distinguishes observation from intervention, and explains why variable selection for adjustment must follow the target causal contrast rather than statistical association alone. It does not attempt to provide a complete causal-inference course. Its purpose is to establish the structural discipline required before later INF articles discuss selection bias, evidential strength, generalisation and robustness.

Keywords: causal inference; confounding; collider; mediator; intervention; causal diagram; identification; measurement error; effect modification

1. Causal questions require a structure

A causal claim asks what would happen under a change, intervention or contrast, not merely whether two variables are associated. Pearl's structural framework and the potential-outcome approach developed in modern epidemiology provide complementary formal languages for this distinction [1,2]. Both make clear that causal identification requires assumptions that are not contained in the observed joint distribution alone.

2. Confounder, mediator and collider are roles, not intrinsic labels

The same measured variable can play different causal roles in different questions. A confounder is, under a specified causal structure, a common cause of exposure or intervention and outcome, or otherwise a variable on an open non-causal path between them that must be blocked for the target contrast. A mediator lies on a causal path from exposure to outcome. A collider is a common effect of two or more variables on a specified path. Effect modification is different again: it concerns variation in the magnitude or form of a defined effect across levels of another variable.

Role	Structural meaning	Typical inferential consequence
Confounder	Common cause or other source of an open non-causal path	Failure to address it can bias a target causal contrast.
Mediator	Variable on a causal path from exposure to outcome	Conditioning can remove part of the total effect; mediation requires a separately defined estimand.
Collider	Common effect of two or more variables on a path	Conditioning on it or a descendant can open a non-causal association.
Effect modifier	Variable across whose levels a defined effect differs	Signals heterogeneity of the target effect; not a synonym for confounding.

3. Why “adjust for everything” fails

Covariate adjustment is not automatically protective. Conditioning on a common cause can be necessary for exchangeability in an observational analysis, while conditioning on a collider can induce bias [3,4]. Conditioning on a mediator changes the causal question when the intended estimand is the total effect. Therefore variable inclusion should be justified by the causal structure and estimand, not by significance, correlation with the outcome, stepwise selection or the fact that adjustment changes an estimate.

4. What intervention adds

Intervention separates the manipulation of a variable from passive observation. In a randomised experiment, assignment can create exchangeability for the intervention contrast within the study population, subject to adherence, loss to follow-up, measurement and other design conditions. In observational studies, causal interpretation requires additional identification assumptions. Graphical criteria and potential-outcome assumptions provide ways to state those conditions explicitly [1,2].

Intervention does not automatically identify mechanism. A treatment may change an outcome through several pathways; the total effect can be identified without establishing which pathway carries it. Direct and indirect effects require additional definitions and assumptions [5,6].

5. Measurement error belongs inside causal reasoning

Causal diagrams often represent variables as if measured without error, yet the recorded proxy can differ materially from the intended construct. Measurement error in exposure, confounders, mediators or outcomes can attenuate, amplify or otherwise distort effect estimates depending on structure and error process. General measurement-error theory shows that the direction and magnitude of distortion are not captured by a universal correction rule [7]. INF therefore treats measurement error as a possible distortion of causal estimation, while HEB retains ownership of measurement-system failure as a diagnostic topic.

6. The collider boundary with INF-003

INF-002 owns the collider as a causal role and the structural rule that conditioning on a collider or its descendant can open a path. INF-003 owns the selection mechanisms by which observations reach the analysed dataset, including selection on a collider, survivorship and missingness. This separation prevents “collider bias” from becoming an undifferentiated label for every form of selection.

7. Causal identification is not causal truth

Identification means that the target causal quantity is uniquely determined under the stated model and assumptions by the observable distribution or experimental design. It does not prove that the assumptions are true. This is why sensitivity analysis, negative controls, triangulation and external information can matter even when the mathematical identification criterion is satisfied. INF-004 and INF-009 later address rival structures and robustness.

8. Minimum reporting discipline

- State the causal estimand or intervention contrast.
- Draw or otherwise state the assumed causal structure relevant to adjustment.
- Justify each adjusted variable by causal role rather than association alone.
- Distinguish total, direct and indirect effects when mediation is discussed.
- State whether selection occurs before or after exposure/intervention and outcome measurement.
- Identify material measurement error in causal variables and the direction in which it could affect inference.
- Separate identification under assumptions from empirical validation of those assumptions.

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Data and materials statement

No new experimental dataset was generated for this article. The article is a methodological analysis based on the cited literature and the frozen ownership architecture of the INF series.