



# A SIMPLE MEASURE OF THE GOODNESS OF FIT OF A CAUSAL THEORY TO A TEXT CORPUS

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## Abstract

Suppose an evaluation team has a corpus of interviews and progress reports, plus (at least) two candidate theories of change (ToCs): an original one and a revised one. A practical question is: **which ToC better fits the narrative evidence?**

With almost-automated causal coding as described in (Powell & Cabral 2025; Powell et al. 2025), we can turn that into a simple set of *coverage-style* diagnostics: how much of the coded causal evidence can be expressed in the vocabulary of each ToC.

See also: [Working Papers](#); [Minimalist coding for causal mapping](#); [Magnetisation](#).

**Intended audience:** evaluators and applied researchers comparing candidate ToCs (or other causal frameworks) against narrative evidence, who want a transparent “fit” diagnostic that does not pretend to be causal inference.

**Unique contribution (what this paper adds):**

- A definition of **coverage over causal links** (not just themes): link / citation / source coverage variants.
- A simple protocol for comparing candidate ToC vocabularies using hard recode or [Magnetisation](#) (soft recode).
- A careful positioning of “coverage” relative to mainstream QDA usage (saturation/counting as support for judgement, not a mechanical rule).

## 1. The core idea: “coverage” of evidence by a codebook

In ordinary QDA (thematic coding), researchers often look at how widely a codebook or set of themes is instantiated across a dataset: which codes appear, how frequently, and whether adding more data still yields new codes (saturation). Counting is not the whole of qualitative analysis, but it is a common, explicitly discussed support for judgement and transparency (Saldaña 2015). Critiques of turning saturation into a mechanical rule-of-thumb are also well known (Braun & Clarke 2019).

Our twist is: because we are coding **causal links** (not just themes), we can define coverage over *causal evidence* rather than over text volume.

## 2. Minimal definitions

- A **coded link** is a row of the form `(Source_ID, Quote, Cause_Label, Effect_Label, ...)`.
- A **ToC codebook** is a vocabulary (list) of ToC factor labels you want to recognise in the corpus.
- A **mapping** from raw labels to ToC labels can be done either:
  - strictly (exact match / “hard recode”), or
  - softly via magnetisation (semantic similarity; “soft recode”) — see [Magnetisation](#).

### 3. Coverage measures you can compute

Assume we have a baseline set of coded links  $L$  (from open coding), and a ToC codebook  $C$  (as magnets / targets).

#### 3.1 Link coverage (our main measure)

**Link coverage** = proportion of coded links whose endpoints can be expressed in the ToC vocabulary.

Two variants (pick one and state it explicitly):

- **Both-ends coverage**: count a link as “covered” only if *both* cause and effect are mapped to some ToC label.
- **At-least-one-end coverage**: count a link as “covered” if either endpoint maps (useful when ToC vocabulary is intentionally partial).

#### 3.2 Citation coverage (weighted link coverage)

If your dataset has multiple citations per bundle (or you have `Citation_Count`), compute coverage over **citations**, not just distinct links:

- covered citations / total citations

This answers: “what proportion of the *evidence volume* is expressible in this ToC?”

#### 3.3 Source coverage (breadth)

**Source coverage** = number (or proportion) of sources for which at least (k) links are covered by the ToC vocabulary.

This answers: “does this ToC vocabulary work across many sources, or only a small subset?”

### 4. Protocol (how to use it)

For each candidate ToC:

1. Build a ToC codebook **C** (ideally keep candidate codebooks similar in size and specificity, otherwise you are partly measuring codebook granularity).
2. Map raw labels to **C** (hard recode or soft recode).
3. Compute:
4. link coverage (both-ends and/or one-end),
5. citation coverage (if available),
6. source coverage (with an explicit (k)).
7. Inspect the **leftovers** (uncovered labels/links): what important evidence is the ToC not even able to name?

## 5. How this relates to “coverage” in mainstream qualitative methods

The word “coverage” is used in a few nearby ways in qualitative methodology:

- **Code (or theme) saturation:** whether new data still yields new codes/themes; the distinction between “code saturation” and “meaning saturation” is often emphasised (e.g. Hennink et al. on code vs meaning saturation; and the broader critique that saturation is not a universal stopping rule in all qualitative paradigms) (Braun & Clarke 2019).
- (For orientation, see: Hennink, Kaiser & Marconi (2017) “Code Saturation Versus Meaning Saturation”, *Qualitative Health Research*, DOI: [10.1177/1049732316665344](https://doi.org/10.1177/1049732316665344); Guest, Bunce & Johnson (2006) “How Many Interviews Are Enough?”, *Field Methods*, DOI: [10.1177/1525822X05279903](https://doi.org/10.1177/1525822X05279903).)
- **Counting for transparency:** many QDA approaches use counts (how often codes occur; how widely they occur across cases) as a support for analytic claims, without equating frequency with importance (Saldaña 2015).

What we are doing here is closer to: **how much of the coded evidence can be expressed in the language of a candidate theory**, which is a “fit” diagnostic rather than a claim about truth.

## 6. Caveats

- Coverage is sensitive to **granularity**: broader ToC labels will (almost by definition) cover more.
- High coverage does not imply causal truth; it only implies that the ToC vocabulary is a good *naming scheme* for a large share of the corpus.
- Low coverage can mean either “ToC is missing key mechanisms” or “coding/mapping is too strict” — inspect leftovers before concluding.

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## References

Braun, & Clarke (2019). *To Saturate or Not to Saturate? Questioning Data Saturation as a Useful Concept for Thematic Analysis and Sample-Size Rationales*. <https://doi.org/10.1080/2159676X.2019.1704846>.

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