Research & Analysis / Data Interpretation

Scan findings for causal claims that aren’t supported by the data design — and suggest appropriate phrasing.
Difficulty: Advanced
Model: GPT-4 / Claude / Gemini
Use Case: Report Review, Academic Writing, Data Communication
Updated: May 2026
Why This Prompt Exists
“Correlation does not imply causation” is the most ignored rule in data analysis.

You get:

- business decisions based on confounded correlations that fail when implemented
- reports that say “X drives Y” when the data only shows they move together
- confidence in findings that reverses when you actually run an experiment
- stakeholders demanding causal actions from correlational evidence
- expensive A/B tests that could have been avoided with honest causal assessment

But causal claims require specific evidence:

- randomization (A/B test, RCT) → strongest
- natural experiment (policy change, discontinuity) → strong with assumptions
- longitudinal with controls (time order, confounders) → suggestive
- cross-sectional correlation (single time point) → not causal
- qualitative mechanism (interviews, process tracing) → supports but doesn’t prove

Without auditing, you’ll accidentally claim causation.

This prompt reviews your findings for causal overreach.

The Prompt

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Assume the role of a causal inference auditor who catches overclaims.

Your task is to review findings and flag inappropriate causal
language.

Generate:

1. CAUSAL CLAIMS FOUND
   - List each claim that implies causation (e.g., "drives,"
"increases," "reduces," "causes," "leads to")
   - Quote the exact wording

2. DATA DESIGN ASSESSMENT
   - Study design (RCT / quasi-experiment / longitudinal / cross-
sectional)
   - Controls included (what confounders are accounted for)
   - Time order established? (Does X precede Y in the data?)

3. APPROPRIATE PHRASING (per claim)
   - Current (too causal) → replace with → Suggested (correlational)
   - Example: "Increasing ad spend drives sales" → "Ad spend is
associated with higher sales"

4. REMAINING THREATS TO CAUSALITY
   - Reverse causation (Y causes X instead)
   - Omitted variable bias (Z causes both X and Y)
   - Selection bias (sample not representative)
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- Measurement error (X or Y measured poorly)

5. RECOMMENDATION
   - Safe to imply causation (with caveats)
   - Suggest correlation-only language
   - Redesign study before making causal claims

INPUTS:

Finding or report excerpt:
[PASTE TEXT WITH CLAIMS]

Study design description:
[E.G., "Survey of 500 customers at one time point"]

Data source:
[E.G., "CRM data, observational"]

Field/discipline norms:
[E.G., "Marketing analytics — causal language is common but often wrong"]

RULES:
- Be conservative — if unsure, flag as correlation-only
- Distinguish between statistical and causal language (many people confuse them)
- Suggest alternative interpretations for every causal claim
- Note when causal language might be defensible with additional assumptions

How To Use It

- Run this on every report before sharing with stakeholders — especially executives.
- Use it on your own writing — we're all blind to our own causal overreach.
- When reviewing others' work, run this to prepare feedback.
- For academic papers, this catches reviewer criticisms before they do.
- Keep a list of safe causal verbs (affects, predicts, is associated with) and dangerous ones (drives, causes, powers).

Example Input

Finding or report excerpt:
"Our analysis shows that companies with higher social media engagement drive 23% more revenue. Therefore, we recommend increasing social media posting to boost revenue."

Study design description:
"Cross-sectional correlation of 200 companies. Revenue and engagement measured in same quarter. No control variables."

Data source:
"Public financial reports and social media API"

Why It Works
Most people know correlation isn't causation — then immediately forget when writing conclusions.

This framework improves outcomes by forcing:

- causal claim identification (catches what you actually wrote)
- design assessment (matches claim strength to evidence strength)
- appropriate phrasing (gives you the right words)
- threat specification (what could still be wrong)

- clear recommendation (safe vs. unsafe)

Great causal auditing doesn’t stop you from making claims — it stops you from making wrong ones.

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