CAUSAL MAP GARDEN

Causal mapping – overview

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Causal mapping has three tasks – gathering, coding and analysing data

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Strong evidence for a link is not evidence of a strong link

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🌻 Intro

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What is causal mapping? What are its strengths and weaknesses? How does a causal map differ from a systems diagram? This chapter has some answers.

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🌻 Why causal mapping ?

What do you think is important in social research?

Here's what we believe, do you agree?

1. 🟦 Social research works best when the **concepts come from people** closest to the subject, not from experts. Quantitative tools can't do that.
2. 🟦 **People's worlds differ**. Not just in details but also in main features too. One size doesn't fit all, especially in a changing world.
3. 🟦 **Social research must welcome data and narratives that don't fit**: messy structure and messy contents.

We also believe social research needs a **causal** lens, do you?

1. 🟦 **Many of the most important questions in research and evaluation** are causal: What drives X? What does Y lead to?
2. 🟦 Asking "**how does your world work?**" can be a really useful question — for interviews and for analysis.
3. 🟦 **Beliefs matter**. What do people *think* drives what? That is critical to know when we're dealing with people, even when they're wrong.
4. 🟦 **People are causation experts**. Mostly, people are right about causation. We make mostly successful causal judgements thousands of times a day. We're the best causation detectors there are.

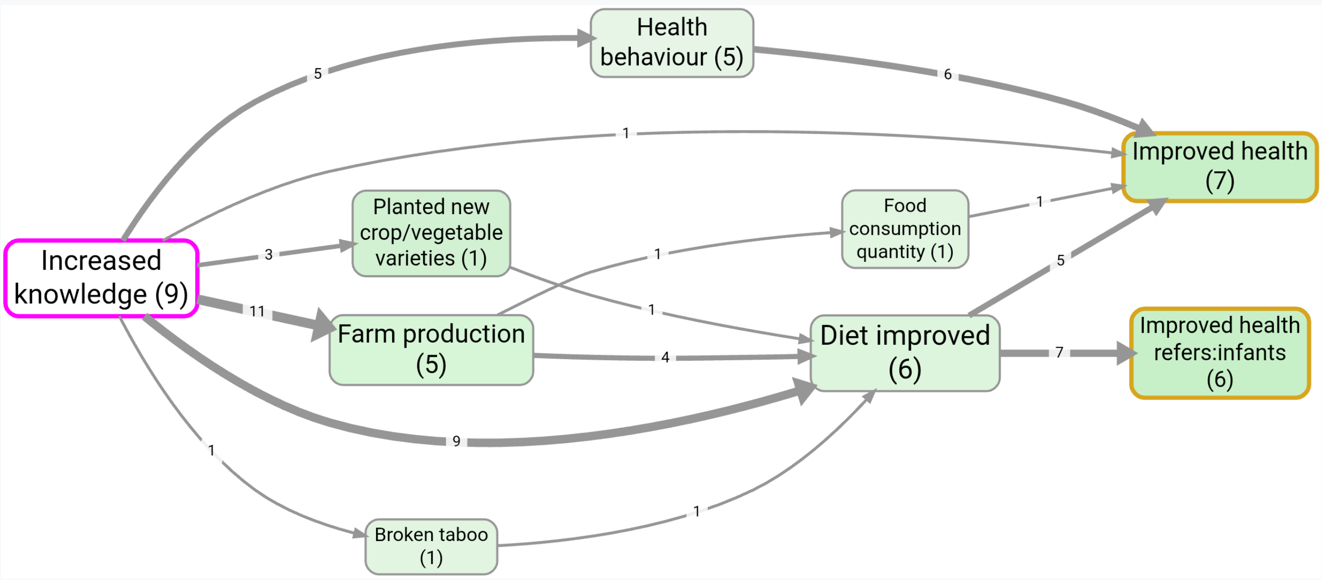
☑️ Causal mapping ticks all of the above boxes.

How can it help in social research, concretely?

☑️ Causal mapping is not an "evaluation method" but an "evidence broker" for evaluation methods like QuIP, Outcome Harvesting and Process Tracing. It finds masses of causal information, organises it, visualises it and feeds it in to other methods for evaluative judgement.

🤖 Causal mapping is a perfect fit to make use of the power of AI, not by using it as a black box but as a low-level coding assistant. We can apply a relatively generic causal coding template to hundreds of interviews documents and be ready to ask and answer causal questions about them very quickly.

🗺️ Stories in, stories out. People tell stories. Causal mapping takes them and outputs stories and maps.



Relevant page: Causal Mapping — the evaluation evidence broker ▸

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🌻 Causal mapping for outsiders

📅 17 Nov 2025

🗺️ What is Causal Mapping?

Causal mapping is a technique to **visualise what people believe causes what** within a complex system. It creates a "mental map" of the cause-and-effect relationships perceived by an individual or a group.

The process starts with **narratives**—such as interview transcripts, reports, or open-ended survey responses. Causal claims within these texts are systematically identified and structured into a network diagram:

- **Nodes (Boxes)** represent the *factors* or *concepts* (e.g., "Better Training").
- **Links (Arrows)** show the *direction of influence* between them.

🧭 Why Use It and Who is it For?

Causal mapping is a powerful tool for analysing **qualitative data** at scale, helping to understand complex, real-world situations.

Who Uses Causal Mapping?

This technique is primarily used by professionals who need to understand complex social systems and justify their decisions:

- **Evaluators:** To empirically verify whether a planned programme works as intended (Theory of Change) and trace its actual influence pathways.
- **Policymakers & Strategists:** To gain a clearer picture of stakeholder perceptions, anticipate risks, and identify effective intervention points (leverage points).
- **Researchers:** To systematically process large volumes of interview data, often across different groups (e.g., comparing views by location), while keeping data transparent.

Why is it useful

The key benefit is turning massive amounts of qualitative input into a structured visual database which is query-able: you can ask it questions.

- **Understand Stakeholder Views:** It reveals how different people believe a system or problem works.
- **Manage Complexity:** It structures messy, interconnected information into a query-able map.
- **Validate Arguments:** It allows quantifying the robustness of evidence for any causal path reported by stakeholders.

🛠️ The Causal Map App

The specialised **Causal Map app** provides a convenient way to do causal mapping. Users can import interviews or reports and "code" them: highlighting causal claims and adding them to the database. Much of this process can optionally be automated using AI, enabling rigorous analysis of larger datasets.

- **Transparency:** Every link in the map is transparently tied back to the **original source quote**. This ensures that outputs are verifiable and avoids acting as a "black box," maintaining the rigour essential for qualitative work.
- **Querying the Map:** The final map is a dynamic model of **causal evidence** that can be actively explored to answer sophisticated questions, such as tracing all direct and indirect links from a single input to a defined outcome.
- **AI as an Assistant:** Generative AI is optionally used as a **tireless, low-level coding assistant** to quickly extract explicit causal claims from text.

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🌻 Mind mapping and causal mapping

📅 12 Feb 2026

🗺️ Mind Mapping and Causal Mapping: Two Sides of the Same Coin?

I recently had a great chat with Liam Hughes from Biggerplate, the global home of mind mapping. It got me thinking about how mind mapping and causal mapping are both about **making connections visible** — but they do it in quite different ways, for different purposes.

If you're a mind mapper, you already know the power of visualising relationships. So what's this "causal mapping" thing all about, and how does it compare?

🤝 What They Have in Common

Both approaches are about taking complex, interconnected information and making it visible:

- **Visualising connections:** Both turn abstract relationships into concrete diagrams with boxes and lines.
- **Managing complexity:** Both help you see the big picture.
- **Externalising thinking:** Both get ideas out of your head (or others' heads) and onto a surface where you can work with them.

In essence, if you're comfortable with mind mapping, you already understand the core intuition behind causal mapping.

🔍 Where They Differ

Mind mapping is also about thinking while you map. That is a creative element which isn't present so much in causal mapping, though you *could* use it like that if you wanted. In causal mapping, especially when you are doing it manually, the creative part of the task is more about creating a causal theory: what are the main factors, how can they best be named, what additional systemisation (if any) like tags should I apply. It's a kind of creative theory-building. But it is not as free as mind mapping as it primarily depends on pre-existing evidence.

Mind Mapping: Creative and Flexible

Mind maps are brilliant for:

- **Brainstorming:** Capturing ideas as they flow, radiating out from a central concept.
- **Personal organisation:** Planning projects, taking notes, structuring your thoughts.
- **Learning and creativity:** Making connections that spark new insights.

Mind maps are wonderfully flexible. You can structure them however makes sense to you. They're personal thinking tools.

Causal Mapping: Evidence-Based and Systematic

Causal maps are mostly specialised for:

- **Analysing narratives:** Systematically extracting what people believe causes or influences what, from interview transcripts, reports, or survey responses. So you usually don't just create a map "in empty space": **you load up a text** such as an interview, highlight any causal claims, and that creates links in your map.
- **Working with multiple sources:** Combining views from dozens or hundreds of different people or documents.
- **Tracing influence paths:** Every arrow represents a claimed directional influence ("X influences Y"), not just "these things are related."
- **Maintaining evidence trails:** Every link traces back to the exact quote that justified it — crucial for rigorous research.

Causal maps are less flexible but more disciplined. They're mostly designed to turn large volumes of qualitative data into a queryable database of causal beliefs. Of course, you can use it just to make a map of just one page of text if you want, but that is not what most people use it for.

Causal mapping isn't new, there were articles on in in 1976 and since then it has been used in disciplines from biology to marketing.

🎯 Overlapping Use Cases

There are definitely spots where both approaches shine:

- **Project planning:** Mind maps help brainstorm what might happen; causal maps can systematically capture stakeholder views about what will cause what, or did cause what.
- **Problem analysis:** Mind maps explore possible factors; causal maps analyse what people or reports actually say about causes and effects.
- **Knowledge management:** Both help structure and retain complex information.

You might even use both: mind map to explore, then causal map to rigorously analyse stakeholder input.

👥 Different (But Overlapping) Audiences

Mind Mappers

Mind mappers are often:

- Students and educators
- Business professionals
- Creative thinkers
- Anyone wanting to organise their thinking

Mind mapping is universal—anyone can benefit from visualising their ideas.

Causal Mappers

Causal mapping serves a more specialised niche:

- **Students:** Using causal mapping as part of a seminar paper or thesis, to create or test a causal theory based on texts.
- **Evaluators:** Verifying whether programmes work as intended (Theory of Change evaluation).
- **Researchers:** Analysing large volumes of interview data systematically.
- **Policymakers:** Understanding stakeholder perceptions to identify intervention points.

These users need rigorous, transparent, evidence-based analysis of what people believe causes what in complex social systems.

Interested in exploring causal mapping further? Check out the Causal Map app or dive into the theory in the causal mapping Garden of Ideas.

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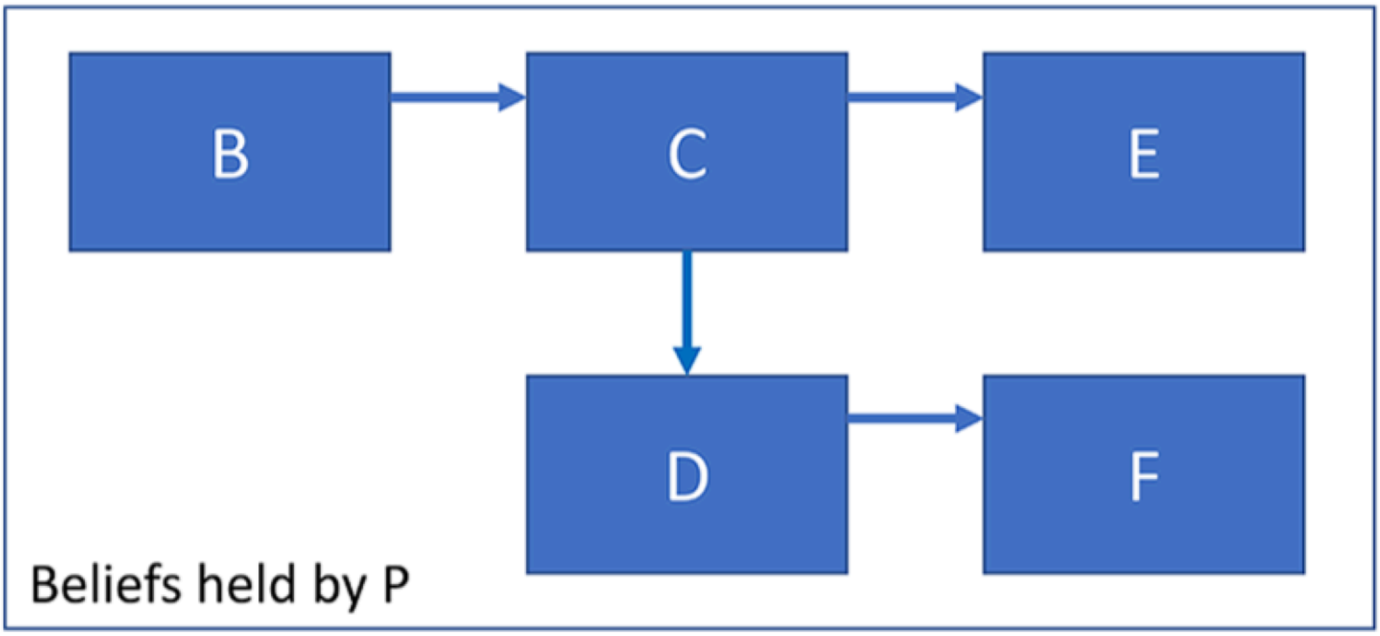
🌻 A causal map consists of multiple links where a link from X to Y means someone believes X influences Y

A **causal map** can be defined as a network consisting of links or arcs between nodes or factors, such that a link from factor C to factor E means that someone (P) believes that C in some sense causally influences E. Every link represents one causal claim.

Alternatively we can say that such a link means that there is some *evidence* (P) that C in some sense causally influences E (seeWe can reason about causal maps using a logic of evidence).



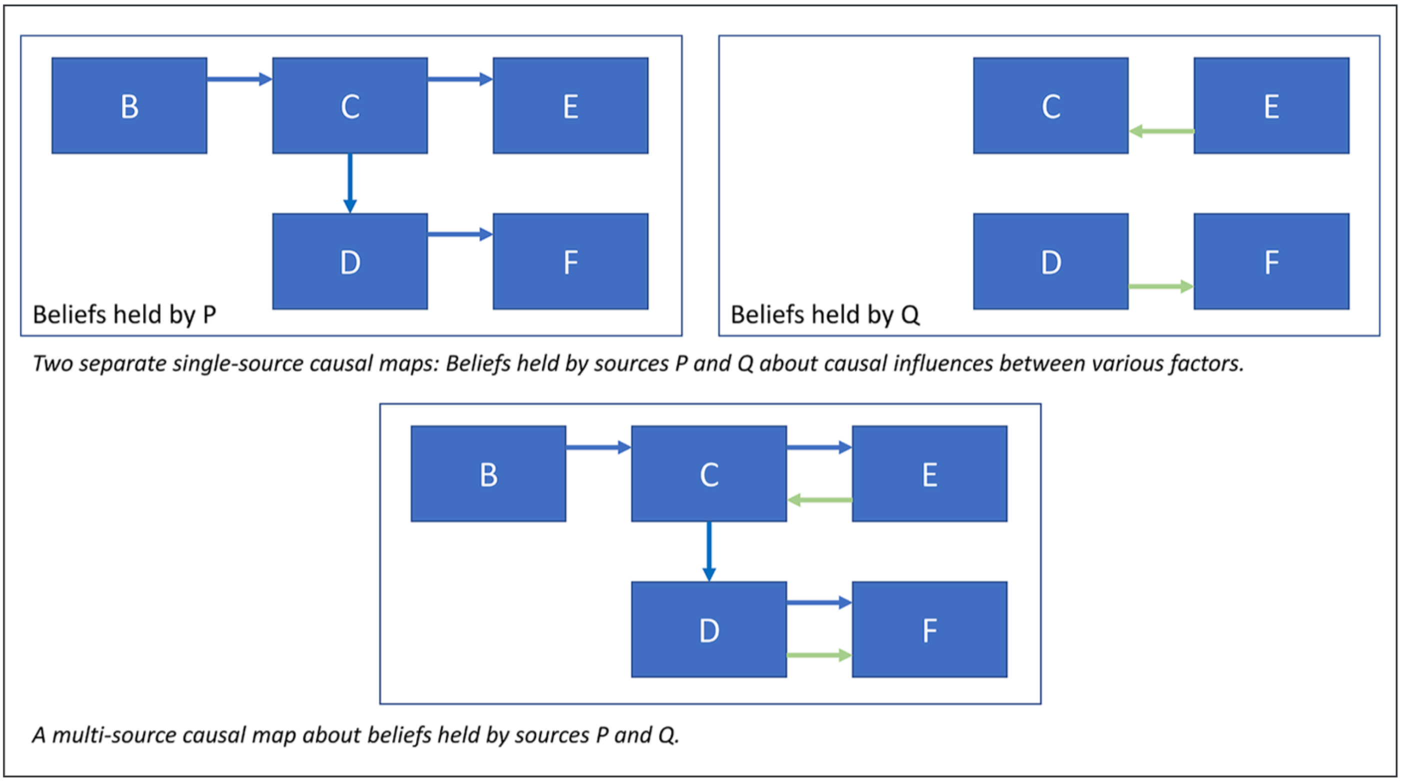
- Causal maps encode a belief about a *usually partial* causal *influence* of C on E, and only in special cases encode *total or exclusive* causation such that C entirely determines E or is *the* cause of E.
- Encoding a claim (like 'the heavy rains were one reason the harvest was worse than usual') in causal mapping does not require us to make any judgement about the quality of the evidence or the ability of the source to correctly judge that this link was causal (although we can add this information if we want).

🌻 Causal mapping helps make sense of many causal claims from many sources

22 Sep 2025

> From Better Evaluation

Causal mapping helps make sense of the causal claims (about "what causes what") that people make in interviews, conversations, and documents. This data is coded, combined, and displayed in the form of maps. These maps show individuals' and groups' mental models and can support further investigation of causal connections.



Top: two separate single-source causal maps: Beliefs held by sources P and Q about causal influences between various factors. Bottom: A combined, multi-source causal map about beliefs held by sources P and Q about causal influences between various factors

Causal mapping is designed for the analysis and visualisation of qualitative data about causal links. It can be used to test an existing theory of change or create collective empirical theories of change about how a program works based on stakeholders' experiences.

People's narratives and reflections about their experiences provide qualitative data that can be coded and displayed as maps to present the cognitive structures (mental models) of individuals and groups and to support further exploration to understand actual causal connections.

These causal maps can help to answer questions about what people think happened and what they think caused this by building links between different factors, such as different kinds of outcomes and inputs. Mapping the chains of results and their linkages builds pictures of causal pathways showing the intermediate steps and connections between them.

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🌻 Causal mapping starts from what people actually say

📅 20 Sep 2025

Causal mapping aims to directly understand and collate the causal claims which people make in narrative (and other) data rather than trying deduce causal connections using statistics or other methods. It starts with what people actually say in real-world contexts and does not rely on heavily pre-structured question formats. Urgent, unexpected, and unwelcome information is treated at face value.

The analyst does not need to have any preconceived conceptual framework; types of causal claims are identified in the data inductively and iteratively. This is a partly creative process, however the decisions made by the analyst are transparent as the underlying text is always available.

At least some of the boundaries of causal mapping research are set by the respondents, not the researchers; what are we going to talk about? What are we not going to talk about?

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🌻 Causal mapping has been used for over 50 years in many disciplines

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> From (Powell et al. 2024)

Causal mapping – diagramming beliefs about what causes what – has been used since the 1970s across a range of disciplines from management science to ecology.

The idea of wanting to understand the behaviour of actors in terms of their internal maps of the world can be traced back further to field theory (Tolman 1948) which influenced Kelly's 'personal construct theory' (Kelly 1955). A seminal contribution was made by Robert Axelrod in political science, with the book The Structure of Decision (Axelrod 1976). Causal mapping is largely based on 'concept mapping' and 'cognitive mapping', and sometimes the three terms are used interchangeably, although 'causal mapping' strictly involves maps that only include explicit causal links, rather than, for example, relationships like 'membership'.3 Axelrod's book presents a comprehensive idiographic approach to how individuals make decisions which he himself mostly refers to as 'cognitive mapping' (although his definition makes it clear that all links are causal). An appendix to the book (Wrightson 1976) gives details about how to code causal links. Bougon et al. (1977) applied a similar approach to a study of the Utrecht Jazz Orchestra as an organisational unit, eliciting 'cause maps' from several individual members and amalgamating them. One strand of literature about causal mapping can be located within the wider literature on sensemaking in organisations pioneered by Weick (1995), and applications within organisations were present almost from the start.

By 1990, there were many different applications of similar ideas, including an edited book (Huff 1990) that offered a unitary approach to 'concept mapping' in the United States. Most authors (Ackermann & Alexander 2016, p. 892; Clarkson & Hodgkinson 2005, p. 319; Fiol & Huff 1992, p. 268; Laukkanen 2012, p. 2; Narayanan 2005, p. 2) use a broadly similar definition of a causal map: A causal map is a diagram, or graphical structure, in which nodes (which we call factors) are joined by directed edges or arrows (which we call links), so that a link from factor C to factor E means that someone (P) believes that C in some sense causally influences E. There is a constructive ambiguity (Eden 1992) about what a collective map is a map of: While maps constructed as a consensus within a group can plausibly be claimed to map 'what the group thinks', this is more problematic for maps constructed post hoc by synthesising individual maps.

We found no significant deviations from this basic definition of a causal map across all the variants of causal mapping reviewed in the following sections, with the caveat that there is variation in how explicit different authors are in describing causal links as representing bare causation as opposed to beliefs about causation.

In the following decades, Eden et al. (1992) applied the approach to understanding and supporting decision-making in organisations, increasingly using the phrase ‘causal mapping’ rather than ‘cognitive mapping’, and they subsequently extended the application of causal maps to fields as varied as risk elicitation and information systems development (Ackermann & Eden 2011; Ackermann et al. 2014), also developing a series of software packages beginning with Decision Explorer (Ackermann et al. 1996). There is now a wealth of literature on using causal mapping for decision support in organisations (including sophisticated approaches to formalise decision support (Montibeller et al. 2008) and even to rank options (Rodrigues et al. 2017)).

Laukkanen (1994, 2012; Laukkanen and Eriksson, 2013) also wrote extensively on causal mapping and developed a software programme called CMAP3 for processing both idiographic and comparative causal maps by importing, combining and analysing factors and links attributed to one or more sources. A broadly similar approach was taken by Clarkson and Hodgkinson (2005) with their Cognizer approach and software.

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🌻 Do use causal mapping when you have large numbers of claims from multiple sources, and more open research questions

> From Better Evaluation.

When to use causal mapping

Causal mapping is useful when seeking to understand the causal pathways influencing the outcomes of programs operating in complex settings. It helps make sense of a program and its context in stakeholders' own words. This includes providing ways to make sense of and organise the different, but sometimes overlapping, labels that different groups use to describe the causal factors that are important to them.

Causal mapping can be used to help make sense of large amounts of qualitative data.

Using this method requires expertise in coding and analysis of qualitative data.

✅ So, use causal mapping if you...

- have a relatively large amount of narrative data
- need help to synthesise a large number of links
- have information from more than one source (for example respondents, documents)
- are interested in differences between the sources and groups of sources
- you don't know the contents or boundaries of the map
- want to capture what your sources actually say, systematically and transparently

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🌻 Do not use causal mapping if you have limited data or want precise models or specific causal links

> From Better Evaluation.

Causal mapping is less frequently used to analyse quantitative data or to do precise mathematical modelling, e.g. of future states of a system under certain conditions.

❌ Do not use causal mapping if you ...

- don’t place high value on the views of the sources
- only have a relatively small map which you can manage with traditional tools for drawing network diagrams (e.g. PowerPoint, kumu.io etc.)
- need to analyse quantitative data and/or need to do precise mathematical modelling, e.g. of future states of a system under certain conditions
- would like to just sketch out a plan (e.g. Theory of Change or similar) without much reference to the different sources underpinning each link

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🌻 Causal mapping approaches differ in application, construction, analysis and how they deal with multiple sources

Reference	Main application of causal mapping	Mode of construction	Dealing with multiple sources	Analysis procedures
(Axelrod 1976)	Understand and critique decision making	Coding documents	Mainly idiographic	Compute polarity of indirect effects in some cases.
(Bougon et al. 1977)	Understand how organisations are constructed and can be influenced.	Semi-structured interview to identify a fixed list of factors aka 'variables'; respondents then say which are linked and give the polarity.	Compare individual maps and combine into global 'average' map.	Identify variables X with high outdegree and Y with high indegree and construct an 'etiograph' to show all the multiple paths from one point to another; discuss how respondents might have influence over some variables.
(Ackermann et al. 2004; Ackermann & Eden 2011; Eden 1992; Eden et al. 1979; Eden et al. 1992)	Decision support and problem solving in organisations. Maps are seen primarily as useful tools rather than research about reality.	Open interviewing of several respondents based on Kelly's Personal Construct Theory. Also map construction directly with groups (1988).	Comparing maps between individuals and analysing group maps directly.	Various structural measures, presence of isolated clusters, hierarchical trees, loops. Simplify individual maps by collapsing X->Y->Z into X->Z.
(Laukkanen 1994; Laukkanen 2012; Laukkanen & Eriksson 2013; Laukkanen & Wang 2016)	Explicitly cognitive, to improve knowledge and understanding in management	Systematic comparative method with semi-structured interviewing: respondents are given anchor topic(s) then asked for causes,	Comparative study of different individual maps, combining data into a database.	Display combined maps for subgroups, e.g. all local managers.

Reference	Main application of causal mapping	Mode of construction	Dealing with multiple sources	Analysis procedures
		effects, causes of causes, effects of effects. Compress the data by standardising factor names. Comprehensive coverage of different map construction possibilities.		

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🌻 Causal mappers believe that humans are good at thinking in terms of causal nuggets

See also Causal mapping has been used for over 50 years in many disciplines

> From Powell, Copestake, et al. (2023

Renewed interest in causal mapping may also be reinforced by the ‘causal revolution’ in quantitative data science initiated by Judea Pearl (Pearl 2000; Pearl & Mackenzie 2018), which has fundamentally challenged the almost total taboo placed on making or assessing explicit causal claims, which was dominant in statistics for much of the twentieth century (Powell, 2018), and this has in turn helped rekindle interest in explicitly addressing causation using qualitative methods.

Causal mapping and most related approaches share the basic idea that causal knowledge – whether generalised or about a specific case or context – can be at least partially captured in small, relatively portable ‘nuggets’ of information (Powell, 2018: 52). These can be assembled into larger models of how things worked, or might work, in some cases. More ambitiously, they may contribute to constructing ‘middle-level theory’ theory, useful for understanding causal processes in other contexts, without necessarily reaching the level of overarching scientific laws (Cartwright, 2020). Causal nuggets are also related to the mechanisms that help to explain how people behave in different contexts (Pawson & Tilley 1997; Schmitt 2020). These can be thought of as causal schema and linked to the hypothesis that human knowledge is stored in chunks that are activated and combined with others in relevant circumstances. This would suggest that we humans do not have a comprehensive set of causal maps in our heads at any one time, but we do have a set of more basic components and the ability to assemble them when the situation calls for it, including when prompted by a researcher.

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🌻 Causal mappers believe that humans are the best detectors of causation

📅 23 Aug 2025

See also Causal mapping has been used for over 50 years in many disciplines

Causal mappers believe that humans are good at thinking in terms of causal nuggets

> From Powell, Copestake, et al. (2023

We claim: our everyday causal understanding is as primary as our perception of, say, colour and arises from more than empirical observations of associations between objects or events; our ability to infer causation goes beyond and is not primarily based on noting correlations. And for all its complexity and intuitive brilliance, it is also just as fallible as our perception of colour or size.

This reaffirms our practice as evaluators of taking the causal claims and opinions of humans (experts and non-experts) seriously (Maxwell 2004; Maxwell 2004); indeed, this kind of information is the bread and butter of most evaluations.

We can thank Judea Pearl for promoting the insight that if you want to thrive in this world, you have to understand causality natively. We humans make causal connections from an early age. We wouldn't survive long if we didn't.

GPT-3.5 just about understood causation. GPT-4 and more recent models understand causal connections within text very well.

Our understanding of the world is drenched with causal understanding: information and hypotheses about how things work (mostly accurate enough, sometimes not). It's really hard for us to *not* think causally: the concept of correlation is much harder to understand than the concept of causation.

Causal Inference?

Causal inference is the process of determining whether and how one event or variable brings about another.

Some writers mistakenly assume that only a controlled experiment can "really" provide a route to causal inference.

We would go so far as to say that we don't usually in any conscious cognitive sense *infer* causation — we just see it, all the time, everywhere. We don't have to teach children to infer causation: we have to teach them to question their perceptions of causation and to distinguish causation from correlation.

Why are humans the best detectors of causation?

1. **Evolutionary Adaptation:**
   Human brains have evolved specifically to detect and act on causal relationships. Survival depends on recognizing which actions lead to which outcomes—e.g., which plants are safe to eat, which animals are dangerous, and how to use tools. This evolutionary pressure has made causal reasoning a core part of human cognition.

2. **Intuitive Causal Models:**
   From infancy, humans build mental models of the world that are fundamentally causal. Children naturally ask "why" questions and seek explanations, not just associations.

3. **Generalization and Flexibility:**
   Humans can generalize causal knowledge across domains. For example, understanding that pushing causes movement can be applied to objects, social situations, and abstract concepts. This flexibility allows humans to detect causation even in novel or ambiguous situations.

4. **Counterfactual Reasoning:**
   Humans often engage in counterfactual thinking—imagining what would happen if things were different. This is a hallmark of causal reasoning and is essential for planning, learning from mistakes, and scientific discovery.

5. **Distinguishing Correlation from Causation:**
   While humans sometimes make errors (e.g., seeing causation where there is only correlation), we are still very good at using context, background knowledge, and intervention to distinguish true causal relationships from coincidence.

6. **Social and Cultural Transmission:**
   Human societies accumulate and transmit causal knowledge across generations through language, stories, and education. This collective causal understanding is a foundation of science, technology, and culture.

7. **Observation and Pattern Recognition:**
   Humans are adept at noticing regularities and anomalies in their environment. We naturally look for patterns—such as temporal precedence (A happens before B), co-occurrence, and changes following interventions—that suggest causal relationships. Even without formal training, people intuitively apply principles like "no effect without a cause" and "causes precede effects."

8. **Intervention and Experimentation:**
   Humans frequently test their causal hypotheses by intervening in the world—changing variables and observing outcomes. This hands-on experimentation, whether in childhood play or scientific research, is a powerful tool for distinguishing causation from mere correlation.

9. **Use of Multiple Sources of Evidence:**
   Humans combine different types of evidence—temporal order, statistical regularities, mechanistic explanations, and observed interventions—to make robust causal inferences. We can weigh conflicting evidence, consider alternative explanations, and update our beliefs as new information arises.

In sum, humans are not just passive recipients of causal information; we are active causal detectives, constantly inferring, testing, and refining our understanding of how the world works. This multifaceted approach to causal inference is what makes us the best detectors of causation.

Conclusion

Causal reasoning is not just a feature of human cognition—it is its backbone. Our ability to detect, infer, and act on causal relationships is what allows us to navigate, survive, and thrive in a complex world. While formalised, controlled experiments are an incredible tool for causal inference in very particular contexts such as some areas of education and economics where multiple very similar causes are regularly followed by multiple very similar effects, if we had to stick to that kind of knowledge and that kind of context we would never be able to get out of bed in the morning, let alone get the kids to school.

Humans remain the best detectors of causation, both individually and collectively.

See also: 400 realist causation

References

Maxwell (2004). *Using Qualitative Methods for Causal Explanation*. SAGE Publications Inc. https://doi.org/10.1177/1525822X04266831.

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🌻 Causal mapping is part of the qualitative branch of the new causal revolution

📅 22 Aug 2025

See also Causal mapping has been used for over 50 years in many disciplines

> From Powell, Copestake, et al. (2023
>
> Renewed interest in causal mapping may also be reinforced by the 'causal revolution' in quantitative data science initiated by Judea Pearl (Pearl 2000; Pearl & Mackenzie 2018), which has fundamentally challenged the almost total taboo placed on making or assessing explicit causal claims, which was dominant in statistics for much of the twentieth century (Powell, 2018), and this has in turn helped rekindle interest in explicitly addressing causation using qualitative methods.

Related

- chapter intro

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🌻 Wise as folk

23 Aug 2025

See also Causal mapping has been used for over 50 years in many disciplines

Causal mappers believe that humans are the best detectors of causation

Causal mappers believe that humans are good at thinking in terms of causal nuggets

Where "folk" comes from

Somewhere in the last century social science picked up a tic. It started putting the word *folk* in front of anything ordinary people do with their minds. Folk psychology. Folk biology. Folk physics. Folk taxonomy. Folk theories of disease, of weather, of justice.

The word travels from the German *Volk* through folklore and anthropology: folk tales, folk songs, folk medicine, folkways. William Graham Sumner published *Folkways* in 1906 to name the customs a people inherit without examining them. That is the freight the word still carries. *Folk* means handed down, untutored, quaint, and above all not yet corrected by science.

In most of these usages *folk* just labels the intuitive everyday theory ordinary people hold: folk psychology is the framework we all use to predict each other, folk biology our common-sense sorting of living kinds, folk physics our feel for how objects move. Even there the word is doing quiet work, marking the everyday version as the naive cousin of the proper science.

Philosophy of mind then took the *folk psychology* case and pushed it much further into a technical doctrine. Here folk psychology is not just our ordinary talk of beliefs and desires; it is recast as an implicit *theory*, and a bad one. The eliminativists, Paul and Patricia Churchland chief among them, treated that theory as a primitive proto-science, a stopgap that a mature neuroscience would one day throw out, the way chemistry threw out phlogiston. That is a special, contested usage rather than what the word usually means. But it shows the freight the marker always carried. Call something *folk* and you have already decided it is wrong, or at best a charming first draft awaiting the grown-ups.

Turning it on its head

Now apply that same marker to causal reasoning and listen to how absurd it sounds. *Folk causation*. The everyday, untutored, pre-scientific way that ordinary people work out what causes what, pending replacement by proper method.

Replacement by what, exactly?

Humans are the best causation detectors on the planet. Not approximately, not as a courtesy. We read cause and effect faster, across more domains, and from less data than any instrument, any animal, and until very recently any machine we have built. A toddler works out that pushing the cup tips the juice. You work out from a half-sentence and a tone of voice why a colleague went quiet in a meeting. We do this constantly, mostly accurately, and we could not survive a single morning without it. As Judea Pearl keeps insisting, if you want to thrive in this world you have to understand causality natively, and we do so from infancy.

To stamp *folk* on that achievement is to get the relationship backwards. The controlled experiment is the latecomer, the special case, the narrow tool that works beautifully when you have many near-identical causes followed by many near-identical effects, and not otherwise. Everyday causal reasoning is the foundation that experiment is built on top of, not a rough sketch that experiment improves. You cannot design a trial, read its result, or decide it matters without the very faculty the word *folk* sneers at.

So the condescension runs the wrong way round. The right comparison is not naive opinion against rigorous science. It is a general-purpose causal engine of staggering reach against a precision instrument with a tiny field of view. Both are valuable. Only one of them gets breakfast made and the kids to school.

What we actually claim

Our everyday causal understanding is as primary as our perception of colour. It does not come mainly from logging correlations between events; it is fundamentally prior to that, and it is of course just as fallible as our sense of colour or size. This is why we take the causal claims of people, expert and non-expert, seriously (Maxwell 2004; Maxwell 2004). That kind of evidence is the bread and butter of evaluation.

It is also why we resist the idea that we *infer* causation through some conscious cognitive step. Mostly we just see it, everywhere, all the time. We do not teach children to infer causes. We teach them the opposite discipline: to question what they already see, and to separate a real cause from a mere co-occurrence.

What humans bring to this is not folklore. It is evolved machinery sharpened by survival, intuitive causal models built from infancy, the ability to carry a cause learned in one domain into a completely different one, counterfactual imagination, the habit of intervening to test a hunch, and a culture that accumulates and passes on hard-won causal knowledge through language and stories. Errors happen. We sometimes see a cause where there is only a coincidence. But the system that occasionally or even often misfires is the same system that underwrites every experiment ever run.

Conclusion

Causal reasoning is not a quaint feature of human cognition awaiting correction. It is the backbone of it. The word *folk* was always a way of holding ordinary minds at arm's length, of marking them as pre-scientific so that the real scientists could get on. Used for causation it is not just wrong, it is upside down, because the faculty being patronised is the one doing the patronising.

So we will keep the verb and drop the slur. Humans remain the best detectors of causation, individually and collectively. Don't call us folk.

See also: 400 realist causation

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🌻 Causal mapping differs from related approaches - epistemic, less predictive, unsophisticated, many links, many sources, unclear boundaries

Distinguishing features / Approach	Axelrod	Fuzzy Cognitive Maps (FCM)	Luke Craven / System Effects	Participatory Stakeholder Mapping (PSM)	Classic QuIP	Causal Map default style
How is the causal map assembled?						
Focus on how the world works		Y	Y	Y	?	Y
Focus on how people think			Y	?	?	Y
Focus on how different (groups of) people think			Y	-	Y[1]	Y
Make deductions from how people think to how the world works			Y		Y?	Y?
Maps are a summary of qualitative data analysis of textual causal claims for each link	Y?		?	N	Y	Y
What is the nature of the links and the factors?						
Include negative/minus as well as positive/plus links		Y	Y[2]	Y	-	Y
Links can have different strengths		Y	-		-	Y
Attempt to calculate resultant strength of multiple links influencing a factor		Y	-		-	-
Attempt to model dynamic changes over time		Y	-		-	-
Going beyond linear/additive combinations		-	-	-	-	-
Historical versus theoretical						
Focus on (evaluation of) past events			-		Y	Y
Focus on general understanding		Y	Y		-	Y

Approach Distinguishing features	Axelrod	Fuzzy Cognitive Maps (FCM)	Luke Craven / System Effects	Participatory Stakeholder Mapping (PSM)	Classic QuIP	Causal Map default style
How is the causal map assembled?						
Focus on how the world works		Y	Y	Y	?	Y
Focus on how people think			Y	?	?	Y
Focus on how different (groups of) people think			Y	-	Y(#_ftn1)	Y
Make deductions from how people think to how the world works			Y		Y?	Y?
Maps are a summary of qualitative data analysis of textual causal claims for each link	Y?		?	N	Y	Y
What is the nature of the links and the factors?						
Include negative/minus as well as positive/plus links		Y	Y(#_ftn2)	Y	-	Y
Links can have different strengths		Y	-		-	Y

Approach Distinguishing features	Axelrod	Fuzzy Cognitive Maps (FCM)	Luke Craven / System Effects	Participatory Stakeholder Mapping (PSM)	Classic QuIP	Causal Map default style
Attempt to calculate resultant strength of multiple links influencing a factor		Y	-		-	-
Attempt to model dynamic changes over time		Y	-		-	-
Going beyond linear/additive combinations		-	-	-	-	-
Historical versus theoretical						
Focus on (evaluation of) past events			-		Y	Y
Focus on general understanding		Y	Y		-	Y

(#_ftnref1) Individuals, not groups

(#_ftnref2) Separate maps for enablers and for barriers

> From (Powell et al. 2024)

Most evaluators are probably more familiar with related approaches under the term 'systems mapping', recently covered by Barbrook-Johnson and Penn (2022). They provide an overview table of relevant methods on pp. 169 ff. – fuzzy cognitive maps (FCM), participatory systems mapping (PSM), Bayesian belief networks (BBN), causal loop diagramming (CLD), systems dynamics (SD) and theory of change (ToC) – which will be briefly mentioned here.

SD, CLDs, FCMs and BBNs are all ways to encode information about networks of interconnected causal links and follow formal inference rules to make deductions based on them, for example, to calculate the strength of indirect effects or to predict behaviour over time. The oldest of the three methods, SD (Forrester 1971), models flows of a substance (for example, of energy or money) within a network over time, whereas the other three methods model 'bare' causal connections between network elements. SD uses general mathematical functions to model the connections and explicitly models non-linear relationships. CLDs are related but mathematically simpler, modelling causal effects in a semi-quantitative way. FCMs might seem to be of more interest for causal mapping; Kosko's original article on FCM (Kosko 1986) takes Axelrod's work as its starting point. This tradition (Chaib-Draa & Desharnais 1998; Khan & Quaddus 2004; Taber 1991) was originally introduced to model causal reasoning (Kosko 1986, p. 65): If person or group P believes the set of causal propositions making up a map M, the model attempts to predict the strength with which they could or should also believe some other propositions, for example, about indirect effects and how they might change over time. In practice, however, FCM is less interested in cognition than in making predictions about the world. The difference between FCM and the other three methods is more about the fuzzy logic used to make the predictions rather than about the cognitive nature of the data.

BBNs are also designed to make causal inferences by doing calculations with data about causal connections. While FCMs make essentially qualitative predictions such as 'increasing' and 'decreasing', BBNs use directed acyclic graphs (networks without loops) to make quantitative predictions about the probability of events, particularly about the probability that one event was the cause of another.

All four approaches are primarily ways to make predictions about causal effects within a network of factors, and (despite the words 'cognitive' and 'belief' in the names of two of the four) the relative lack of interest in who is doing the reasoning sets FCM, BBNs and SD apart from causal mapping as outlined earlier.

In the last few years, PSM has featured in several publications in evaluation journals and guides (Barbrook-Johnson & Penn 2021; Hayward et al. 2020; Sedlacko et al. 2014; Wilkinson et al. 2021), alongside mapping of 'systems effects' (Craven 2020). Indeed, Craven's work (see also Craven 2017) can be considered causal mapping with a particular emphasis on systems aspects. Barbrook-Johnson & Penn (2022) explicitly exclude causal maps from their overview of systems mapping because they are arguably included via FCM and because they 'sometimes emphasise developing representations of individual mental models rather than representations of systems' (p. 11). Nevertheless, PSM is closer to the tradition of causal mapping (and of more direct interest to evaluators) than the previous four approaches because it is a more concrete and pragmatic intervention to construct a map with specific group of stakeholders to support decisions. A devotee of causal mapping could claim that approaches like PSM are just variants of what they have been doing for the last 50 years, just as a devotee of systems mapping might consider causal mapping as a form of PSM.

Finally, logic models and ToC can be considered causal maps in which they make assertions about past or future causal links that one or more stakeholders believe to be important. They are also political artefacts that aim to justify and inform action by establishing an agreed synthesis of multiple perceptions of change and may also gain legitimacy by being the product of an agreed process of participatory planning and co-design. They do not, however, normally retain information about which stakeholder(s) believe which claim. Reflecting on logic models and theories of change provides one entry point for thinking more carefully both about who actually makes these claims and about the symbols and rules employed to construct them (Davies 2018).

We think it is useful to distinguish this tradition of causal mapping from related activities in six ways, as set out in the following section. None of these distinctions are definitive, and many are shared with other approaches. To systems people who want to say that causal mapping is just systems mapping and to causal mappers who want to say that systems mapping is just causal mapping (and we have heard both arguments many times), we can only say, perhaps we should all just get to know each other first.

First, the raw material for causal maps comprises claims about, perceptions of or evidence for causal links. Causal maps are primarily epistemic, meaning that their constituent parts are about beliefs or evidence, not facts; yet their logic tends to be parallel to, and based upon, the logic of non-epistemic systems maps and similar diagrams that are broadly used across a range of sciences. Some systems mapping techniques are also sometimes concerned with stakeholder beliefs; causal mapping does this more systematically.

Second, causal maps tend to be unsophisticated about the types of causal connection they encode. To explain this, we should note that causal claims in ordinary language are expressed in an endless variety of ways: ‘C made E happen’, ‘C influenced E’, ‘C may have been necessary for E’, ‘C was one factor blocking E’, ‘C had a detrimental effect on E’, ‘C had a surprisingly small effect on E’ and so on. With a few exceptions, causal mapping analysts do not even try to formally encode this rich and unsystematic range of causal nuance, relying instead simply on the lowest common denominator: A link from X to Y means simply that someone claims that X somehow causally influences or influenced Y.

There is one exception: Many causal mapping approaches do accommodate information about the polarity of links, marking each link as either positive or negative, for example, the claim ‘the recession led to unemployment’ could be coded as a negative link from ‘the recession’ to ‘employment’.

In general, causal maps usually encode a belief about partial causal influences of C on E and only in special cases do they encode total or exclusive causation such that C entirely determines E. This also means that encoding a claim does not require us to make any judgement about the quality of the evidence or the ability of the source to judge that this link was causal (although it may be very useful to do so).

Third, causal mapping often handles **large numbers** of causal claims, sometimes many thousands. Handling large numbers of claims en masse in this way is made much easier because of the relatively unsophisticated nature of the way claims are coded (as discussed earlier).

Related approaches in evaluation tend to bring more sophisticated tools to bear on a much smaller number of causal links. In process tracing, for example, researchers may produce diagrams depicting claims about causal links but tend to focus on testing the strength of a relatively small number of specific 'high-stakes' causal links, whether through verbal reasoning, application of Boolean logic or Bayesian updating (Befani & Stedman-Bryce 2017).

Fourth, causal maps may originate from one or many sources, each reporting on one or many cases. In a causal map, the links all originate from one person or document a 'single-source' or 'individual' or 'idiographic' causal map, as in Axelrod's original work (Axelrod 1976). But we can also draw causal maps that incorporate information from a variety of different sources, as illustrated in Figure 1.

The simplest causal maps refer to only one context and contain information from only one source (which may be the consensus view of several people, treated as speaking with a single voice). Various forms of systems mapping such as PSM could be understood as a special case of causal mapping in this sense.

There are many other variants. One source might give differentiated information about different cases or contexts, or many sources might give information about just one context, as when different water systems experts each give their (possibly differing) opinion about the same water catchment area, for example.

Another frequent type of causal map is drawn from many sources, each reporting on their own situation or context, such as their perception of drivers of change in their own lives. In coding and analysis of this sort of data, one source equals one case and one context; these can subsequently be aggregated across many sources who, for example, all share a similar context.

Fifth, causal maps do not necessarily specify a clear system boundary. The boundaries of a causal map are usually defined more loosely, partly by data collection but also by the sources themselves. Indeed, some systems proponents would say that the term 'systems diagram' simply signals a readiness to use systems approaches (Williams 2022).

Finally, causal mapping, especially in management sciences and operations research, has nearly always been at least as interested in process as in the result. There is often a focus on the process of reaching consensus as part of the task of solving a business problem, rather than on the universal accuracy or validity of the final map.

Related

- chapter intro

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🌻 Causal mapping has three tasks – gathering, coding and analysing data

📅 9 Oct 2025

Different approaches to these three tasks are discussed in turn in the following sections.

- Task 1 — Gathering narrative data
- Task 2 — Coding causal claims as causal qualitative data analysis
- Task 3 — Analysing data, Answering questions

🌻 Task 1 – Gathering narrative data

📅 21 Sep 2025

> From (Powell et al. 2024)

How to collect causal claims from which to draw causal maps?

(There is also a whole chapter about this task: Task 1 — Introduction)

There are a wide variety of options, including in-depth individual interviews (Ackermann et al. 2004), reuse of open-ended questions in structured surveys (Jackson & Trochim 2002), literature reviews (in which 'sources' can be documents rather than individuals) and archival or secondary material within which pre-existing causal claims are already made (Copestake, 2020). Other approaches aim to build consensus by using structured collaborative processes, including Delphi studies and PSM (Penn & Barbrook-Johnson 2019). Guidelines for causal mapping may include procedures for collecting primary data, with forms of elicitation including back-chaining ('what influenced what?') and forward-chaining (what resulted, or could result, from this?)

With primary data collection, we can distinguish between relatively closed and open approaches and whether respondents are forced to choose between pre-selected optional answers or can formulate their own (see Table 2). Interviewers may also be guided by a chaining algorithm; for example, they may be instructed to iteratively ask questions like 'You mentioned X, please could you tell me what were the main factors that influenced X or led to it happening.'

Table 2. Different approaches within primary data collection for causal mapping, with example questions.

Admissible answers / Scope of questions	Explicit: factors are explicitly identified	Implicit: factors are not explicitly named
Closed: questions with a predetermined focus	Which factors in this list influenced this particular event?	What influenced this particular event?
Open: a freer discussion	Identify the biggest change you experienced in relation to X, and list three factors that influenced it	Tell me what has changed for you in the last x years

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🌻 Task 2 – Coding causal claims as causal qualitative data analysis

📅 21 Sep 2025

> From (Powell et al. 2024)

Some approaches such as that suggested by Markiczy and Goldberg (1995) directly elicit causal links from their sources, perhaps by asking respondents to suggest causal links between a predetermined list of causal factors, and thus, after finishing Task 1, are already in a position to create causal maps.

(See also the dedicated chapters on coding...)

- Task 2 — Introduction
- Tasks 2 & 3 — Extensions — Introduction

More explicitly, qualitative approaches are faced with Task 2: encoding causal claims in the form of explicit causal links and factors. This task is similar to ordinary qualitative data analysis (QDA), whether done manually or using tools like NVivo, Dedoose and AtlasTI. However, these tools are designed to capture general concepts, rather than claimed causal links between concepts, which is what we need for causal mapping. QDA for causal mapping also starts with a corpus of narrative data, but it does not create causal links between independent concepts that might already have been coded using ordinary non-causal thematic analyses. Rather, in causal QDA, the primary act of coding is to highlight a specific quote from within a statement and identify the causal claim made by simultaneously identifying a pair of causal factors: an 'influence factor' and a 'consequence factor'.

The causal factors only exist as one or other end of a causal link and have no meaning on their own. Each claim forms a link in the visual representation of the causal map. The Axelrod school had its own coding manual describing how to highlight areas of text expressing causal connections and code them as links between causal factors, originally inspired by evaluative assertion analysis (Osgood et al., 1956).

Manual causal coding of text data, like ordinary thematic coding, requires a considerable investment of time and expertise to do well. We now use natural language processing to at least partially automate this; however, the process is essentially the same, and discussion of this is beyond the scope of the present article.

Where do the labels for the causal factors come from? As with ordinary QDA and thematic analysis (Braun and Clarke, 2006), approaches vary in the extent to which they are purely exploratory or seek to confirm prior theory (Copestake 2014). Exploratory coding entails trying to identify different causal claims embedded in what people say, creating factor labels inductively and iteratively from the narrative data. Different respondents will not, of course, always use precisely the same phrases, and it is a creative challenge to create and curate this list of causal factors. For example, if Alice says ‘Feeling good about the future is one thing that increases your wellbeing’, is this element ‘Feeling good about the future’ the same as ‘Being confident about tomorrow’ which Bob mentioned earlier? Should we encode them both as the same thing, and if so, what shall we call it? We might choose ‘Positive view of future’, but how well does this cover both cases? Laukkanen (1994) discusses strategies for finding common vocabularies. As in ordinary QDA, analysts will usually find themselves generating an ever-growing list of factors and will need to continually consider how to consolidate it – sometimes using strategies such as hierarchical coding or ‘nesting’ factors (as discussed in the following section).

The alternative to exploratory coding is confirmatory coding, which employs an agreed code book, derived from a ToC and/or from prior studies. QuIP studies mostly use exploratory coding but sometimes supplement labels with additional codes derived from a project’s ToC, for example, ‘attribution coding’ helps to signify which factors explicitly refer to a specific intervention being evaluated (Copestake et al. 2019, p. 257). However, careful sequencing matters here because pre-set codes may frame or bias how the coder sees the data (Copestake et al. 2019). Again, the positionality of the coder matters just as much when doing causal coding as it does for any other form of qualitative data coding.

Combining Tasks 1 and 2

Tasks 1 and 2 result in a coded data set of causal claims, each of which consists of (at the very least) the labels for a pair of causal factors. Those using a more explicit elicitation approach have been able to skip Task 1.

See also

- Manually code your first project for the practical first step.

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🌻 Task 3 – Analysing data, Answering questions

📅 21 Sep 2025

> From (Powell et al. 2024)

The extensive causal mapping literature provides many examples of its use to answer evaluation questions (see Powell, Copestake, et al., 2023, p. 110), for example:

- Getting an overview of respondents' "causal landscape". This can be useful for orientation or for particular tasks like triaging masses of information to identify key outcomes and possible causal pathways when planning an Outcome Harvesting (Wilson-Grau & Britt 2012) or Process Tracing (Befani & Stedman-Bryce 2017) project.
- Weighing up evidence about contribution: in particular, tracing back and comparing the possibly multiple contributory causes of an important outcome or consequence (Goertz & Mahoney 2006), or examining effects of causes.
- Reporting key metrics of the causal network, for example, to reveal which factors are most central in the whole network or to identify feedback loops.
- Asking whether the empirical ToC matches the plan (Powell et al. 2023, p. 7).
- Making comparisons between groups or across timepoints.

One way to simplify is to derive from the global map several smaller maps that focus on different features of the data. For example, maps may selectively forward-chain the multiple consequences of a single cause – including those activities being evaluated: effects of causes (Goertz & Mahoney 2006) – or trace back to the multiple contributory causes of an anticipated or highly valued outcome or consequence: causes of effects. A series of simpler causal maps, each selected transparently to address a specific question, generally adds more value to an evaluation than a complicated, if comprehensive, single map that is hard to interpret. The downside of this is that selectivity in what is mapped and is not mapped from a single database opens up the possibility of deliberate bias in selection, including omitting to show negative stories.

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Sets of individual links with the same influence and consequence factor (co-terminal links) are usually represented bundled together as a single line, often with thickness of the line indicating the number of citations, and/or with a label showing the number of links in the bundle. The map has not fundamentally changed, but the visualisation is much simpler.

Relevant page: Simplification - factor and link frequency ▸

Another way to simplify a global causal map is to produce an overview map showing only the most frequently mentioned factors and/or links. Care should be taken if this leads to omitting potentially important but infrequently mentioned evidence about, for example, an unintended consequence of an intervention.

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Another common way to simplify is to combine sets of very similar factors into one. For example, if hierarchical coding has been used, it is possible (with caveats) to ‘roll up’ lower-level factors (such as health behaviour; hand washing and health behaviour; boiling water) into their higher-level parents (health behaviour), rerouting links to and from the lower-level factors to the parent (Bana e Costa et al., 1999).

Relevant page: Reporting global network statistics ▸

Large causal maps can also be analysed quantitatively, including by tabulating which factors are mentioned most often, identifying which are most centrally connected or calculating indicators of overall map density, such as the ratio of links to factors (Klintwall et al., 2023; Nadkarni and Narayanan, 2005). We are wary of the value of summarising maps in this way, not least because results are highly sensitive to the granularity of coding. For example, although a specific factor such as ‘improved health’ might have been mentioned most often, if two subsidiary factors had been used instead (such as ‘improved child health’ and ‘improved adult health’), these two separate factors would not have scored so highly.

Tasks 2 & 3 — Extensions — Introduction

References

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🌻 Strong evidence for a link is not evidence of a strong link

📅 23 Sep 2025

Never confuse the two.

TODO

Our approach clearly distinguishes evidence from facts and does not automatically warrant causal inferences

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🌻 Causal mapping is easier if we are realist about causation

22 Aug 2025

Causal mapping is easier if we are realist about causation. We can say that narrative accounts are full of claims about causal powers, that X had the power to affect Y, and X did exercise that power and Y was affected (perhaps in this particular case in spite of or with the assistance of other things).

Causal realism invites us to say that things **have the causal power** to affect other things.

The weird thing is that most physical and natural scientists think about causation in a realist way, but in the social sciences we tell ourselves not to because it isn't scientific (!).

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🌻 Causal mapping is good at coping with messiness and complexity

21 Sep 2025

> From (Powell et al. 2024)

... recognising head-on the ambiguity of much narrative causal data, particularly when confronted with large bodies of data collected in disparate ways. Evaluators must contend with messiness: imprecise system boundaries, differing specification of claimed causal influences and lack of clear or consistent information about what case or group of cases claims refer to. Causal mapping can contend with all this ambiguity rather than shying away from it. It can make use of messy operational data, treating urgent, unexpected and unstructured information at face value. This is made possible by distinguishing clearly between two analytical steps in evaluation: The first is to gather, understand and assemble causal evidence from different sources (those in a position to have useful evidence about relevant causal links and chains) to construct, compare and contrast the evidence for and against different possible causal pathways. By focusing on this task, causal mapping lays a more reliable foundation for the second, often critical, task of using the assembled data to make judgements about what is in fact really happening. This avoids the confusion and ambiguity that often arises when evaluators seek to address both steps simultaneously by constraining what data are collected to fit a prior view of reality which other stakeholders may or may not share.

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References

Powell, Copestake, & Remnant (2024). *Causal Mapping for Evaluators*. https://doi.org/10.1177/13563890231196601.

🌻 Granularity, generalisability and chunking are coding problems for causal mapping too

> From (Powell et al. 2024)

An illustrative example

!

A positive feature of causal maps, illustrated by the Figure, is that they capture a lot of information in a way that is quick and easy to understand. This example reveals that Source S provided a narrative that connects the intervention to improved feeling of wellbeing as a direct consequence of taking more exercise and via the effect of this on their health. This source also suggests a positive feedback loop, with more exercise making them more physically fit and encouraging even more exercise. The information from Source T is more fragmented; there are two causal statements claiming that improved feeling of wellbeing can result from more exercise and improved health, although T does not link the two causally, nor make any causal link back to the intervention. In addition, T suggests that an additional factor, 'more confidence in the future', also contributes to improved feeling of wellbeing. The two sources of evidence do agree on certain points; there is scope for generalisation beyond either individual source (and can be scaled up from here), both in assessing the multiple outcomes of the intervention and in understanding what explains improved feeling of wellbeing. Generalisability is strengthened when a link is reported by different sources in different contexts. We believe that within causal mapping, we should never make the mistake of thinking that stronger evidence for a causal link is evidence that the causal link is strong; only that there is more evidence for it.

Relevant page: Strong evidence for a link is not evidence of a strong link ▸

. The example also reveals some potential weaknesses of causal maps. First, there is ambiguity about the precise meaning of the labels and the extent to which their use is conceptually equivalent between the two sources. There is also ambiguity about whether they are referring to their own personal experience (and if so, over what period) or speaking in more general terms. Furthermore, the diagram sacrifices details, including how the statements shown relate to the wider context within which each source is situated. To mitigate this, an important feature of any causal mapping procedure is how easily it permits the user to trace back from the diagram to the underlying transcripts and key information about the source (e.g. gender, age, location etc.). Where this is possible, the diagram can be regarded in part as an index or contents page – an efficient route to searching the full database to pull out all the data relating to a specific factor or causal link, in order to validate any conclusions we draw. In particular, we recommend as a technique to mitigate this danger.

Relevant page: The transitivity trap ▸

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Powell, Copestake, & Remnant (2024). *Causal Mapping for Evaluators*. https://doi.org/10.1177/13563890231196601.