6-14-2024

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Citation Details

Kenzie, E. S., Wakeland, W., Jetter, A., Lich, K. H., Seater, M., & Davis, M. M. (2024). Mapping mental models through an improved method for identifying causal structures in qualitative data. Systems Research and Behavioral Science. Portico.

Received: 26 May 2023 | Revised: 13 March 2024 | Accepted: 23 May 2024

DOI: 10.1002/sres.3030

RESEARCH PAPER

SYSTEMS and BEHAVIORAL RESEARCH SCIENCE

WILEY

Mapping mental models through an improved method for identifying causal structures in qualitative data

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Funding information
Agency for Healthcare Research and Quality

Abstract

Qualitative data are commonly used in the development of system dynamics models, but methods for systematically identifying causal structures in qualitative data have not been widely established. This article presents a modified process for identifying causal structures (e.g., feedback loops) that are communicated implicitly or explicitly and utilizes software to make coding, tracking, and model rendering more efficient. This approach draws from existing methods, system dynamics best practice, and qualitative data analysis techniques. Steps of this method are presented along with a description of causal structures for an audience new to system dynamics. The method is applied to a set of interviews describing mental models of clinical practice transformation from an implementation study of screening and treatment for unhealthy alcohol use in primary care. This approach has the potential to increase rigour and transparency in the use of qualitative data for model building and to broaden the user base for causal-loop diagramming.

KEYWORDS

causal structures, causal-loop diagramming, mental models, model development, qualitative data analysis, system dynamics

1 | INTRODUCTION

Qualitative research, particularly interviewing, has long been used in the development of system dynamics models, although the exact methods for gleaning model structure from qualitative data have not always been specified (Eker & Zimmermann, 2016; Luna-Reyes & Andersen, 2003; Newberry & Carhart, 2023). Recently, more attention has been paid within the system dynamics field to adding methodological rigour to the process of building diagrams and models from qualitative data (Newberry & Carhart, 2023; Tomoaia-Cotisel et al., 2022). Such rigour enhances the credibility of system dynamics models and opens the door to broader uses in applications such as system dynamics, qualitative research, implementation science, and program evaluation.

Existing approaches for systematically analysing qualitative data for causal-loop diagram development "shift power from modeler to data" (Kim & Andersen, 2012) by employing rigourous processes for coding and tracking data (Baugh Littlejohns et al., 2018; Biroscak et al., 2014; Chen et al., 2019; Kim & Andersen, 2012; Tomoaia-Cotisel et al., 2022; Turner, Gates, et al., 2013; Yearworth & White, 2013). However, these approaches can be time consuming (Valcourt et al., 2020) and do not adequately describe the identification of larger causal structures (e.g., feedback loops) and structures communicated implicitly. Because verbal communication involves a fair amount of implied information (Grice, 1975), these approaches may miss causal structures (e.g., feedback loops and archetypes) that were implied but not explicitly outlined by the participant. Methods are needed that efficiently enable the identification of larger causal structures (i.e., feedback loops and archetypes) and structures that are communicated implicitly, while documenting modeller input and other sources to ensure transparency (Jalali & Beaulieu, 2023). In this study, we developed an improved method for identifying causal structures in qualitative data drawing from prior approaches in system dynamics and qualitative research. We pilot this method to describe mental models of clinical practice transformation using data from an implementation study about screening and treatment of unhealthy alcohol use in primary care.

2 | METHODS

2.1 | Study setting: ANTECEDENT case

Qualitative interview data from an ongoing implementation science study were used to pilot the analytic approach. The study, titled Partnerships to Enhance Alcohol Screening, Treatment and Intervention (ANTECEDENT) (Singh et al., 2022), is being conducted by the Oregon Rural Practice-based Research Network (ORPRN), housed at Oregon Health & Science University (Davis et al., 2021). ANTECEDENT utilizes practice facilitators to support primary care clinics in implementing screening, brief intervention, and referral to treatment (SBIRT) and medication-assisted treatment for alcohol use disorder (MAUD) in primary care clinics in Oregon. Practice facilitators are skilled individuals who provide support for the adoption of evidence-based practices within primary care (Baskerville et al., 2012; Nguyen et al., 2020). The data set included semistructured qualitative interviews with six ANTECEDENT practice facilitators collected at study baseline. The aim of these interviews was to better understand how novice practice facilitators conceptualize strategies to tailor implementation support based on clinic differences, personal expertise, and characteristics of the evidence-based clinical intervention (Riordan et al., 2022). To address the question of tailoring, practice facilitators' mental models of clinical practice change were examined (Haque et al., 2023; Holtrop et al., 2021). An analyst who participated in interview data collection and analysis (EK) subsequently conducted the causal-loop diagram mapping analysis. Diagrams produced in this analysis will be compared with those produced in future rounds of data collection as part of the longitudinal study.

2.2 | Causal structure concepts

The identification of causal structures in qualitative data depends on analysts' familiarity with how causal structures are conceptualized and differentiated in system dynamics. This section describes the minimum knowledge base that analysts should have to use this method. Causal-loop diagrams contain a variety of causal structures at different scales, including individual variables, causal links, feedback loops, and archetypes. As seen in Figure 1, these structures are hierarchically related, with increasing causal information contained in structures with increasing complexity.

In system dynamics, anything that has the capacity to increase or decrease over time can be considered a variable (Anderson & Johnson, 1997; Sterman, 2000). This categorization includes tangible quantities of things that exist in

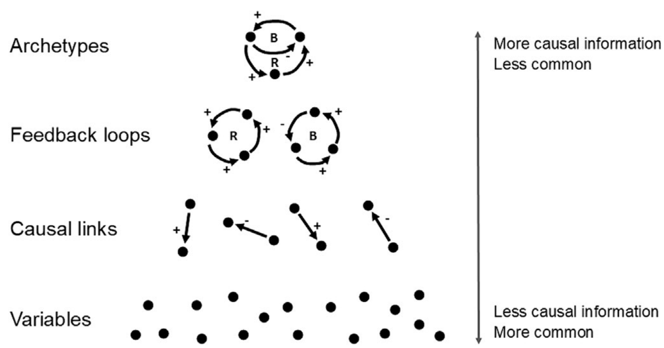


FIGURE 1 Hierarchical relationships between variables, causal links, feedback loops, and archetypes. Variables are elements in a system that can be isolated or connected and that show a pattern of behaviour over time. Causal links are unidirectional relationships describing hypothesized cause and effect. Feedback loops can be reinforcing or balancing and consist of circular causal connections. Archetypes are certain configurations of loops and variables describing common system structures that produce predictable behaviour. Model components contain more causal information and become less common higher in the hierarchy. See Sterman (2000) for further description of basic causal structures and Senge (2010) for further description of archetypes.

the world, such as water (as in the well-known bathtub examples for system dynamics), people, and resources; internal mental states, such as happiness or confidence; or other abstract quantities, such as the likelihood of an event. The choice of variables to include in a model is determined by the problem or system behaviour the modeller is trying to better understand (Sterman, 2000). The "story" of a problem in a system dynamics model is told by describing how key system variables change over time.

Variables in system dynamics are considered to be endogenous to the system if they are determined by other variables within the system boundary (i.e., in the model; Sterman, 2000). Exogenous variables—also called *drivers*—influence endogenous variables but are not themselves affected by any other variables in the model (Ford, 2010). Because exogenous variables are assumed to be largely outside the influence of endogenous factors, they serve as a type of model boundary. Figure 2 illustrates the distinction between endogenous, exogenous, and excluded variables.

Feedback loops are a defining characteristic of causal-loop diagrams (Anderson & Johnson, 1997; Baugh

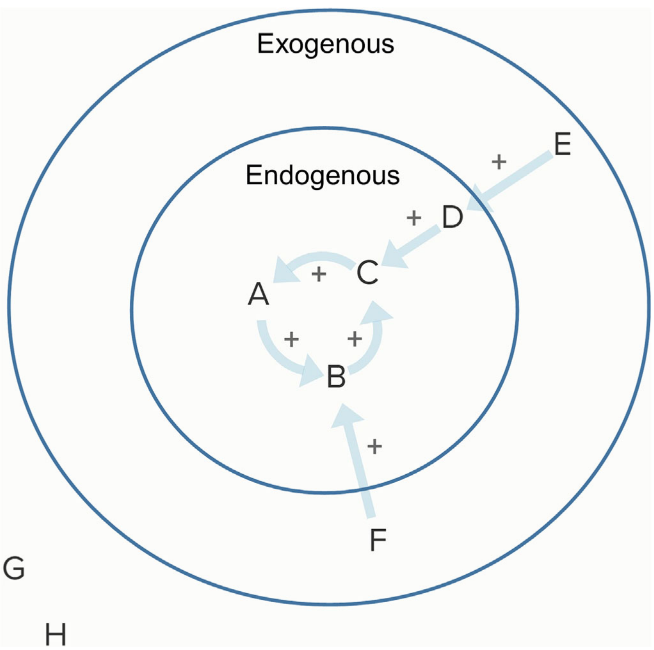


FIGURE 2 Types of system boundaries for causal-loop diagramming. In the centre of the diagram, variables A, B, and C exist in a reinforcing feedback loop. Variables A, B, C, and D can be considered endogenous because their behaviour is determined by other variables in the model. Variables E and F are exogenous drivers to the system because they affect it but are not themselves determined by variables in the model. Variables G and H are excluded; their existence is acknowledged but they are not connected with other variables in the model. Distinguishing endogenous, exogenous, and excluded variables constitutes boundary selection in system dynamics modelling. Adapted from Ford (2010). [Colour figure can be viewed at wileyonlinelibrary.com]

Littlejohns et al., 2021; Kenzie et al., 2023; Meadows, 2008; Sterman, 2000). In system dynamics models and in the complex systems they represent, feedback relationships are the source of nonlinear behaviour. Feedback loops reflect commonly understood dynamics but can themselves be difficult to recognize. Reinforcing feedback loops—in which effects are compounded and growth or decline is exponential—are often described as 'vicious' or "virtuous" cycles (Meadows, 2008). Reinforcing behaviour is dominant when a system is being pulled out of balance or getting "out of control." A balancing feedback loop, in which change in one direction is countered by change in the opposite direction, brings a system towards an implicit or explicit goal or set point (Sterman, 2000).

In natural language, a person's description of how they pursued a goal can contain a significant amount of implicit information. For example, it is reasonable to assume that the mental model of somebody who says they are *trying to lose weight* or *learning to play the piano* likely includes the variables outlined in Figure 3—desired and actual states, a gap describing the difference between them, and actions taken for improvement. However, speakers do not necessarily identify each of these distinct variables and the causal relationships between them, presumably because a shorthand phrase is sufficient for communicating the basic idea of goal-directed behaviour. The phrase *vicious cycle* mentioned above similarly conveys information about causal structure without explicitly outlining the variables in a reinforcing loop.

Archetypes are certain configurations of variables and loops that have been recognized by the systems science field as describing a particular system behaviour common across multiple settings (Kim, 1994; Kim & Anderson, 2007; Meadows, 2008; Senge, 2010). A common example is the tragedy of the commons, in which a shared resource is exploited and ultimately eliminated due to a short-sighted incentive structure that motivates individuals to take from the commons even when it hurts the collective. The phrase *arms race* communicates the escalation archetype, in which competing actors devote increasing amounts of resources to best one another. As with feedback loops, phrases such as *tragedy of the commons* or *arms race* convey a significant amount of implicit information about causal structure. If analysed using methods that detect only explicit causal links, information about these larger causal structures would be missed.

2.3 | Analysis process

The process outlined here has been designed to improve upon prior methods of purposive text analysis to increase time efficiency, tracking of contributions, and orientation towards larger causal structures. Analysis steps are

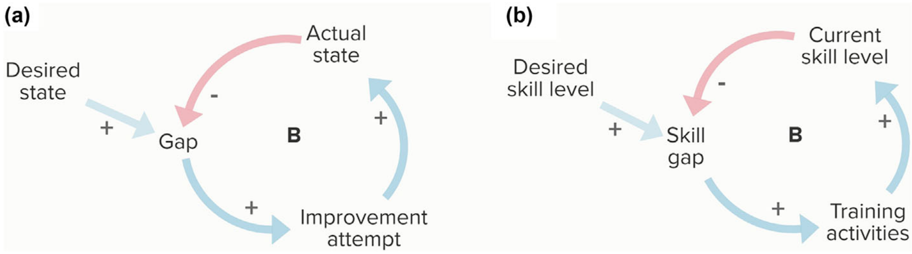


FIGURE 3 Generic structure and example of goal-directed balancing feedback loops. Causal-loop diagrams of a generic structure (a) and an example (b) show the structure of goal-directed feedback loops. In Figure 3a, a gap variable describes the difference between the actual state or level and the desired state. The larger this gap, the larger the improvement attempt that is made to try to bring the actual in line with the desired. As improvement attempts increase, the actual state is improved and the gap is decreased. Over time, the actual state trends towards the desired state, all else being equal. Figure 3b describes the same structure using an example of pursuing training in order to improve skills to a desired level. Plus signs in causal-loop diagrams indicate a causal relationship in the same direction, while negative signs indicate opposite causal effects. The letter "B" is included inside the feedback loops to indicate a balancing feedback loop. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Analysis process for generating causal maps from qualitative data.

Analysis step	Approach	Source of approach	Input	Output
1. Get familiar with data	Read transcript, listen to audio recording	Qualitative analysis (e.g., Braun & Clarke, 2006)	Interview transcripts and audio recordings	Big-picture understanding of data
2. Review research questions/focus	Identify whose mental model(s) to depict and associated boundaries	Qualitative analysis, systems dynamics	Research questions, research proposal	Orientation towards needed information
3. Identify, code, and make note of casual structures	Code causal structures and summarize in causal-loop diagram notation	Qualitative analysis; Kim and Andersen (2012); system dynamics	Qualitatively coded quotations	Causal structures identified with codes unique to specific claim; unique IDs attached
4. Generate query report with coded data	Use CAQDAS to generate report	Qualitative analysis	Coded documents	Query report including quotations, codes, comments with causal structures, and quotation numbers
5. Sketch causal-loop diagrams of loops and archetypes; sketch modeller hypothesis diagram if applicable	Sketch using causal-loop diagram notation	System dynamics	Query reports	Sketches of loops and archetypes, with quotation numbers attached
6. Create & clean up causal mapping table	Aggregation of causal links into table	Kim and Andersen (2012); requirements of visualization platform	Query reports, causal-loop diagram sketches	Table detailing variables, links, direction, valence, tags, descriptions, and quotation numbers
7. Render causal-loop diagrams using visualization software	Upload table; rearrange according to causal-loop diagram norms	System dynamics; procedures of visualization software	Causal mapping table; visualization software	Causal-loop diagrams rendered in digital visualization platform
8. Refine causal-loop diagrams	Edit model to reduce repetition & for logical clarity	Criteria described in current paper informed by system dynamics	Rendered causal-loop diagrams in visualization software	Revised causal-loop diagrams in visualization software

Abbreviation: CAQDAS, computer-assisted qualitative data analysis software.

informed by a blend of qualitative research methods, prior mapping analysis methods, and standards and norms for creating causal-loop diagrams from system dynamics (Braun & Clarke, 2006; Kim & Andersen, 2012; Sterman, 2000). The eight steps in the analysis process are outlined in Table 1.

To streamline the coding and model generation process, two types of software are used. ATLAS.ti (Version 8.0, Scientific Software Development GmbH), a computer-assisted qualitative data analysis software (CAQDAS) program, is used to keep track of causal structures associated with source text. Other CAQDAS software (e.g., Nvivo and MAXQDA) would also be suitable for this analysis. Kumu, a web-based data visualization platform created initially for network modelling,[1] is used to render the causal-loop diagram from data about those structures. We are not aware of other programs that have the data upload and mapping capabilities of Kumu, but this procedure could be adapted to suit other mapping tools. The use of these software tools is intended to facilitate easier and more robust tracking of source material and modeller input and to allow greater modeller engagement with qualitative source material when identifying key model dynamics.

In line with qualitative methods of thematic analysis, the first step (step 1 in Table 1) was to get familiar with the data through listening to audio recordings and reviewing transcripts (Braun & Clarke, 2006). This informal phase oriented the analyst to the data and allowed a "big picture" understanding to start to develop. Research questions were reviewed to orient the analyst towards needed information (step 2). Transcripts were entered into ATLAS.ti, coded for causal information (step 3), and then query reports were generated, compiling coded interview segments (step 4). Query reports were reviewed and larger causal structures (feedback loops and archetypes) were sketched after close reading of the source text (step 5). A table compiling causal and attribution data was produced (step 6) and uploaded for visualization (step 7). The causal-loop diagrams were then refined (step 8). Because the research question for the ANTECEDENT case involved comparing practice facilitator mental models, separate causal-loop diagrams were created for each participant. The following sections provide further detail about steps 3–9.

2.3.1 | Coding for causal structures (step 3)

Because this causal mapping was done as a secondary analysis, the data used for this study were already uploaded to a common file in ATLAS.ti and coded and analysed using an immersion crystallization approach (Borkan, 2022). Therefore, the data had been segmented into quotations with associated codes and automatically numbered by the software according to the document number and the order of the quotation. For example, the second quotation in document 4 was numbered 4:2. Each quotation contained a portion of the interview in which a single idea or set of ideas were described. Had the data not been previously coded, segmentation could have been done during this step. Codes corresponding to the components of causal maps outlined in the previous section, which are outlined in Table 2, were applied to the existing quotations in ATLAS.ti.

Data were coded using structures that were as large as possible, in order to preserve the key dynamics of the data. For example, when a feedback loop was observed, it was coded as such, even though it could have been coded as a series of individual causal links.

During the coding process, variables and causal structures were described in quotation comments using a combination of causal-loop diagram notation and narrative text (see Table 3 for examples).

Individual variables are ubiquitous in qualitative data. In system dynamics modelling, variables are nouns that could increase or decrease in some way (e.g., quantity) and are phrased in a way that indicates presence (Sterman, 2000). Capturing variables that fit these criteria in source text required a degree of translation between interviewees' natural language and causal-loop diagram notation (see Table 3 for coding examples).

When coding for causal links, multiple types of statements were identified, such as if/then statements, hypotheticals, and counterfactuals. Implied variables were noted in parentheses. Causal segments were not created

TABLE 2 Codes indicating model components used during analysis.

Code	Definition
Causal_archetypes	Explicit or implied references to system archetypes or common structures
Causal_behavior	Descriptions of how system or variable behaviour change over time, particularly pertaining to problem definition
Causal_boundaries	References to what is included vs. excluded, important vs. less important, inside vs. outside scope, etc., to understanding the problem behaviour
Causal_feedback loops	Explicit or implicit references to reinforcing or balancing feedback loops
Causal_link	Explicit or implicit references to causal relationships between variables
Causal_variable	References to variables or factors relevant to understanding the problem behaviour. This code is used for isolated variables that are not mentioned in the context of a causal link, feedback loop, or archetype.

[1]www.kumu.io.

for every statement in the interview. Choices for what to code were guided by the research questions and what informants focused on in their interview.

Code descriptions for feedback loops contained a combination of casual links and narrative description (see Table 3). Reinforcing feedback loops were indicated by descriptions of mutually amplifying variables, exponential behaviour, or terms such as "vicious" or "virtuous" cycle. Balancing feedback loops were often indicated by mention of implicit or explicit goals and actions made to achieve them. Enough description was provided in the coding notes to enable later sketching of those causal structures, but the notes for larger causal structures did not necessarily include every variable and relationship. These variables were later captured by revisiting the source quotations and aligning variable wording with other identified structures. Positive [→] or negative [→(−)] valence of causal connections was indicated.

Descriptions of behaviour over time or instances in which effect variables caused further change to their causes were indications of a feedback relationship. The "causal_behavior" code was used in two ways: when a participant identified a variable as being an indicator of system performance, or when they described the behaviour of that variable over time.

Many quotations included multiple types of causal structures. For these quotations, the appropriate causal codes from Table 3 were applied and the corresponding comments were divided according to code. For example, loops and links were listed separately within one comment. The quotation numbers tied to sections of text generated by ATLAS.ti were used as identification tags to trace variables and causal links to places in the text. The notation describing causal structures used in the quotation comments illustrated in Table 3 adhered to standard norms for causal-loop diagramming (Anderson & Johnson, 1997; Sterman, 2000), which are summarized in Table 4.

2.3.2 | Generation of query reports and sketching causal structures (steps 4 and 5)

After all relevant quotations were coded for causal information, query reports were generated for each transcript. The reports contained quotations, associated codes, and the quotation comments containing causal structures in causal-loop diagram notation.

Based on the notes in the query report, freehand sketches were created for each coded feedback loop.

TABLE 3 Coding examples from ANTECEDENT case.

Quotation	Code	Comment
I think with a little bit of empowerment you can kind of build a champion, even if somebody doesn't come forward as "I am the champion", then it's still possible to maybe through some motivational interviewing, like elicit some motivation and kind of collaboratively design a champion. (Participant 3)	Causal_links	Motivational interviewing → empowerment → champion
I think that training that I've received since I've started at ORPRN is going to be really valuable also .... I'm really ... a doer. I learn by doing things and without context for the things that I'm learning, I can sometimes struggle to apply that knowledge. I'm both eager and nervous to get out there and start applying the knowledge that I've gained ... because that's really how I think I'm going to get the most out of what I've had the opportunity to learn and hope to learn that a bit better. (Participant 5)	Causal_loops	PERC training → PERC knowledge and skill → PERC application of knowledge with clinics → PERC knowledge and skill (reinforcing)
[The clinic] had a very specific E[H]R-related request [the fulfillment of which] would make [their] reporting way easier ... They were already planning to report for that metric and hoping to meet, they call it the cutoff, the baseline, the benchmark. ... Their concerns had to do with IT constraints but they ... had a sense for what their numbers were and felt that what they were doing met the criteria as far as screening and the intervention. (Participant 4)	Causal_links	EHR/IT constraints → (−) clinic ability to report on SBIRT

Abbreviations: →, causal link with positive valence; → (−), causal link with negative valence; C/S, clinic/staff; EHR, electronic health record; IT, information technology; PERC, practice enhancement research coordinator (a practice facilitator role at ORPRN).

These sketches were drawn using a tablet and stylus so they could be easily edited and digitally archived, although pen and paper would have also been sufficient. This analysis also allowed for identification and recording of modeller hypothesis structures—feedback loops or archetypes that were compatible with the source data, but were not directly generated from it. These hypothesis structures are akin to memoing in qualitative analysis (Birks et al., 2008; Strauss, 1987) and are a way for researchers to document their evolving understanding of the data. Modeller hypothesis diagrams are tracked separately from diagrams generated directly from source data.

2.3.3 | Creation of causal mapping tables (step 6)

After the loops were identified, the causal links from the freehand sketches and query report were transferred to a causal mapping table. Separate tables were created for each interview using Excel. The table followed the format prescribed by Kumu for uploading data for visualization, which includes variable names, connection valence, and descriptive text and tags for both individual variables and links (see Supporting Information S1). Quotation numbers were included in descriptions of each variable and link. ATLAS.ti attaches quotation numbers to coded segments of text that appear in every form of data output, including the coding window and query reports, which aided the navigation of source data.

Several tags were created in the causal mapping tables in Excel to enable easier navigation of data after maps were generated. Tags were created corresponding to the type of code used in generating that causal link (e.g., link and loop). Tags corresponding to a multilevel theoretical framework relevant to the subject matter of the interviews were also applied. Finally, tags were also included indicating whether a variable or connection were implied and whether the link involved a delay.

Each causal link and variable identified in the loop sketching phase was recorded in the causal mapping table according to the procedure outlined above. Causal links identified in the coding phase were then transposed from the query report generated by ATLAS.ti to the table in Excel. During this process, variable names were refined for clarity and consistency, often deferring to names identified during the loop sketching phase. After all variables and connections were added, a final review was made to combine synonyms and check for typographical errors. The existence of separate query reports with coding notes and tables created a paper trail documenting the modeller's choices (e.g., combining variables).

2.3.4 | Generation of causal-loop diagram from causal mapping table (steps 7 and 8)

The causal mapping table was then uploaded to Kumu for visualization of the causal-loop diagram using their causal-loop design template. An initial layout of the model was automatically generated by the software and pinned to enable custom changes to the position of variables and connections within the diagram. A single Kumu map was created for each interviewee's data. If not using Kumu for visualization, the map could also be generated manually with other software by using the causal mapping table as source data.

The positioning of variables and connections within the diagrams was changed by the analyst to align with the norms outlined in Table 4. Loop variables were arranged in circles with curved arrows and exogenous variables were placed at the periphery, connected to loops with straight arrows when possible. Isolated variables were clustered and placed at the periphery. Variables covering similar themes were clustered into regions of the diagram. Delay symbols were added to connections tagged with "delay."

After positioning variables and connections, the diagram was reviewed for several types of necessary edits. If any remaining synonyms were identified, model sections were combined. In some models, certain causal links were rendered moot by other causal structures that conveyed the same idea in more detail. In other instances, new connections were made between model segments

TABLE 4 Design features of causal-loop diagrams.

Diagram feature	Description
Variable names	Indicates presence of a noun (e.g., *Trust between facilitator and staff*; *Clinic knowledge of quality improvement*; *Motivation to provide better care*)
Arrow directionality	Unidirectional
Arrow valence	Positive or negative valence. The form of the link must equate to *an increase in A results in an increase or decrease in B.*
Visual layout	Minimize overlap; make loops explicit; cluster variables with similar themes when possible
Endogenous vs. exogenous vs. excluded variables	Endogenous variables connected towards centre of diagram; exogenous at periphery with straight arrows; isolated variables at periphery; excluded clustered & labelled

reflecting logical necessities or implied statements. This was done at the discretion of the modeller, with the goal of aligning the diagram to the mental model of the interviewee. For any variables or connections added in the mapping phase, a tag of "added" was included in the diagram in Kumu. Effort was made to minimize the amount of added variables and connections, in order to maintain fidelity to interviewees' mental models. Versions of the map prior to and following editing were preserved for future reference.

3 | APPLICATION TO ANTECEDENT CASE

The procedure outlined above and summarized in Table 1 was used to identify causal structures in data from six practice facilitator interviews at the start of ANTECEDENT study. The interviews focused on facilitator mental models of how clinics implemented changes to SBIRT, including feedback dynamics driving practice change. The six facilitators identified many similar variables when describing their mental models of how clinics successfully change, but the causal structures in which those variables were configured varied considerably. The resulting diagrams exhibited varying degrees of complexity. Results included in this article showcase the application of the modelling process outlined above; full results of this longitudinal study will be presented in a future article.

Participant mental models included many of the same variables, such as *Clinician and staff (C/S) motivation and buy-in*, *PERC communication skills*, and *Health system affiliation*. Due to differences in wording by participants, an attempt was made to harmonize variable names representing the same constructs during table compilation. If necessary, the paper trail for these judgements could be traced due to the use of quotation numbers and query notes.

The number of variables included in the diagrams ranged from 73 to 122, with three diagrams containing remarkably similar numbers of variables and links (see Supporting Information S2). It should be noted, however, that the number of variables present does not necessarily indicate a more complex mental model.

Causal links were by far the most frequent causal structure identified in the diagrams. While many of the variables were consistent across participants, the configuration of causal links connecting those variables varied considerably. Figure 4 illustrates how four participants conceptualized the variable *Clinician and staff motivation and buy-in*. The differences in number of causal links and feedback loops across Figure 4a–d indicate differences in the participants' mental models as expressed in the interviews.

The diagrams also varied in the number of feedback loops identified. One diagram contained zero feedback loops, while the highest number was 7. It is worth noting that the number of feedback loops does not necessarily reflect the complexity of the participant's mental model; variation in speaking style, for example, could be a factor. Most feedback loops identified were reinforcing loops. To illustrate how data were coded and diagrammed, Table 5 shows each step in the process for a specific loop. In the quotation, one facilitator describes how seeing ways in which SBIRT activities can make positive impacts in patients' lives is important for maintaining long-term change.

Coding for implied information also enabled the identification of causal structures that would have been ignored using link-based methods. A key topic of the ANTECEDENT interviews was ways in which practice facilitators provide assistance to clinics so they can improve their SBIRT reporting and activities to meet benchmarks set by coordinated care organizations (CCOs), Oregon's Medicaid health plans (McConnell et al., 2017, 2014). The causal structure of this topic is a simple goal-directed balancing feedback loop: Current clinic SBIRT performance is compared with the CCO benchmark and activities such as changes in workflows or training are used to improve performance and reporting capabilities if needed (see Figure 5). In the setting of the interview, participants were able to correctly assume that the interviewer possessed this basic knowledge about SBIRT quality improvement based on how the interview was framed and the questions that were asked. While all of the participants referred to components of this causal structure and their responses were consistent with it, none of them explicitly identified each variable and causal link. Therefore, a causal structure that is arguably central to the participants' mental models would have been ignored using methods focused exclusively on causal links (e.g., Kim & Andersen, 2012).

No archetypes were directly identified in the source data, but one was identified as a modeller hypothesis based on a combination of observations across participant diagrams. Many of the practice facilitator interviews discussed clinic bandwidth as a factor limiting a clinic's ability to participate in quality improvement projects. Due to the similarity between that idea and the carrying capacity of a resource, we explored applying the carrying capacity archetype to the subject of the interviews. Figure 6 shows the generic carrying capacity archetype provided by Sterman (2000) compared with a causal-loop diagram created based on a modeller's synthesis of the source material.

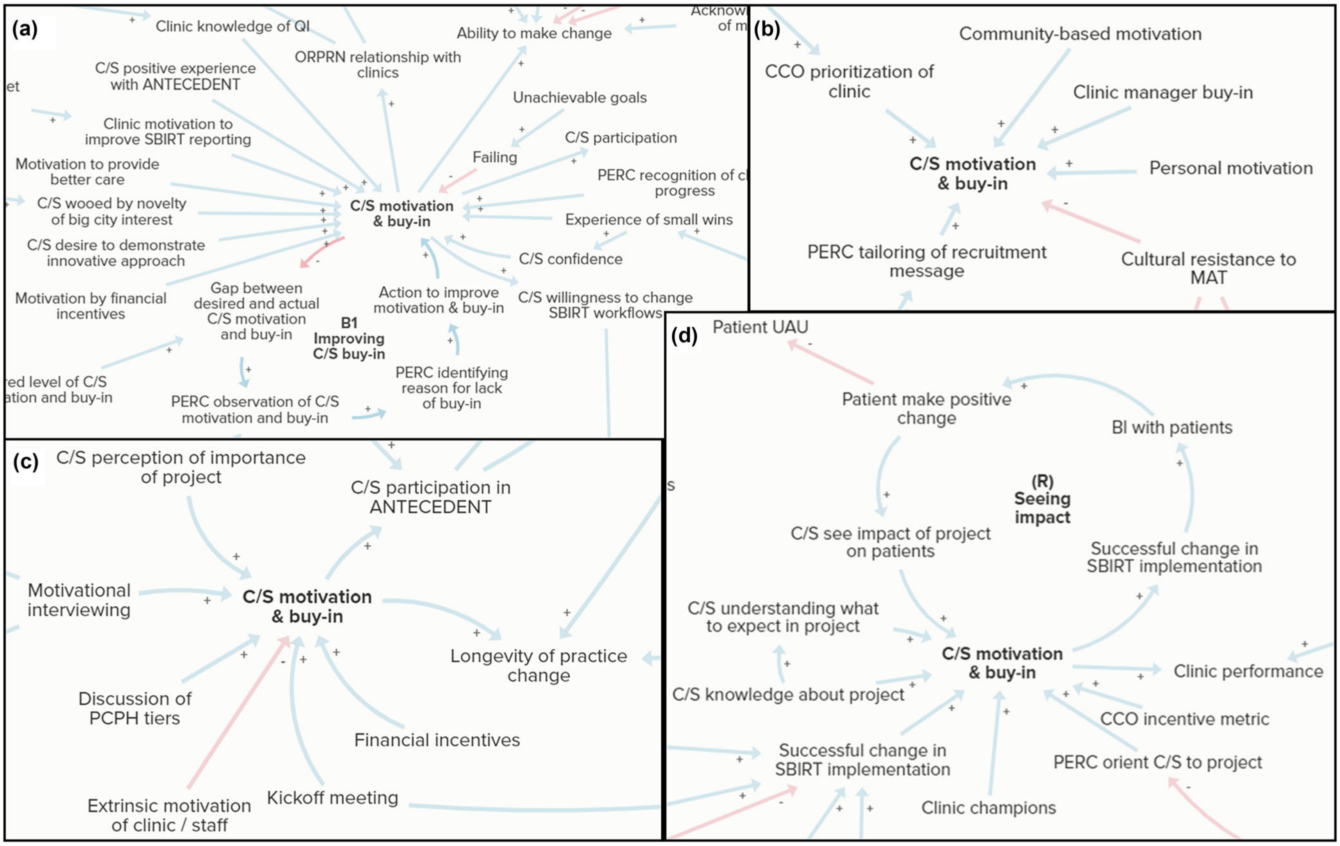


FIGURE 4 Causal structures surrounding clinician and staff motivation and buy-in (*C/S motivation & buy-in*) across four participants. The number of causal links and type of causal structures vary across diagrams. These diagrams were excerpted from larger diagrams summarizing participant mental models. [Colour figure can be viewed at wileyonlinelibrary.com]

4 | DISCUSSION

In this research, an improved method for identifying causal structures in qualitative data was illustrated using a sample case. Drawing from prior approaches and qualitative research methods, this approach specifies a process for identifying larger causal structures in qualitative data, including structures communicated implicitly. The use of coding and visualization software improved efficiency and tracking of source data. The method successfully produced diagrams representing practice facilitators' mental models of clinical practice change.

4.1 | Comparison to prior approaches

The frequency, manner, and timing of modeller input in the process of diagram development represent a key difference between the approach outlined here and prior approaches. In methods presented by Kim and Andersen (2012) and subsequent researchers (Biroscak et al., 2014; Clarke et al., 2021; Turner, Kim, & Andersen, 2013), the modeller assembled coherent causal-loop diagrams from causal links that had been identified and entered into a table. Larger causal structures, then, are created by the modeller without consulting directly with the source text. In the modified procedure outlined in this article, causal structures are identified during coding and query review, which encouraged greater focus on these elements and enabled much of the model design decisions to take place during a close reading of the source text. This centring of analysis around the data is in line with principles of qualitative analysis (Braun & Clarke, 2006; Ezzy, 2013; Ritchie & Lewis, 2003; Strauss, 1987) and builds credibility in modelling. A figure contrasting Kim and Andersen's approach with ours can be found in Supporting Information S3. While valuable to the resulting model, coding for multiple types of causal structures and model components is more complicated than coding for only causal links and requires training in causal-loop diagram modelling. However, fluency in system dynamics is also required for other methods for generating models from qualitative data.

The rigourously interpreted quotation (RIQ) method recently presented by Tomoaia-Cotisel et al. (2022), which was developed in parallel to this research, bears

TABLE 5 Data associated with steps in diagramming a feedback loop.

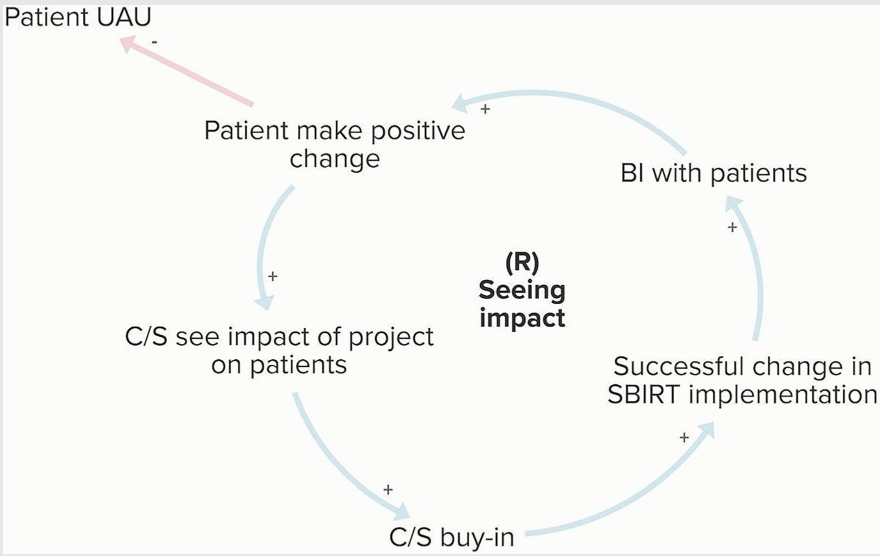
Quotation:	**Interviewer:** I'm wondering about change in the long-term. Not just signing up or making some changes initially, but what helps clinics be successful in the long-term and really make that sustainable? **Interviewee 5:** Well, not to sound like a broken record, but I think that having that buy-in is obviously really important and I think for the clinics to be able to see how this impacts their patients positively is really important. So, seeing some results, seeing the benefits of a patient that's been offered a brief intervention and takes that to heart and does decide to make some changes or do whatever is a good next step for them. I think that those are the aspects that might sustain that change and encourage the clinics. So, I think seeing those results is going to be a strong or a big motivator for the clinics in implementing the work and being motivated to sustain that.
Code:	Causal_feedback loops
Comment:	C/S buy-in building over time C/S see impact of project on patients → C/S buy-in → successful change in long term SBIRT performance → BI with patients → patients make positive change → C/S see impact ... (reinforcing loop)
Diagram:	

FIGURE 5 Goal-directed balancing feedback loops describing practice SBIRT quality improvement process. In the "activities" balancing feedback loop, the gap between the adequacy of current clinic SBIRT activities (enabled by reporting) and the CCO performance metric constitutes an improvement need. PERCs (ORPRN practice facilitators) use implementation strategies to help the clinic with improvement activities (such as workflow changes) and to improve SBIRT activities (e.g., through clinician training). SBIRT reporting is dependent on certain technical and staffing capacities and can result in CCO financial incentive payments. Distinct 'reporting' and 'activities' feedback loops illustrate that both are necessary to recognize and address improvement needs. [Colour figure can be viewed at wileyonlinelibrary.com]

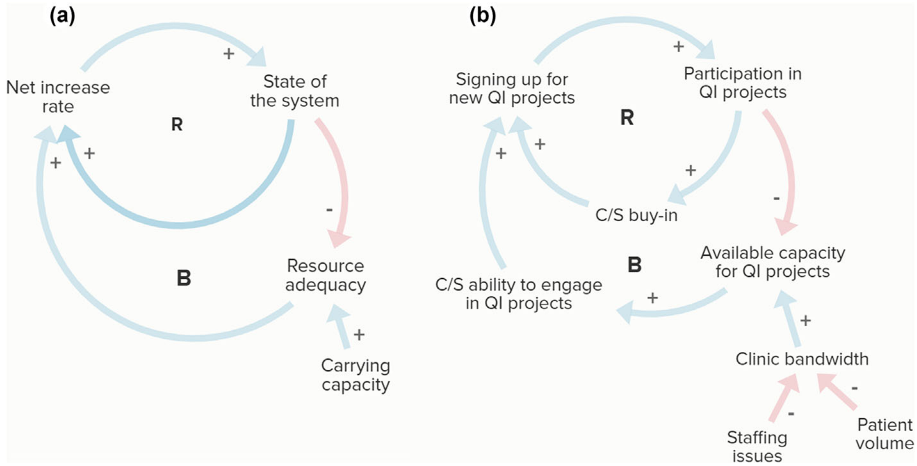


FIGURE 6 Modeller hypothesis diagram showing carrying capacity archetype applied to ANTECEDENT case. Figure 6a describes the carrying capacity archetype adapted from Sterman (2000). A net increase rate improves the state of the system, which in turn further increases the net increase rate, forming a reinforcing feedback loop. An improved state of the system compromises resource adequacy, which decreases the net increase rate, forming a balancing feedback loop. Resource adequacy is limited by carrying capacity. The behaviour for the archetype is an s-shaped curve, in which exponential growth turns to slow progression towards an upper limit (the carrying capacity). Figure 6b describes the same dynamics. Signing up for new quality improvement (QI) projects results in more participation in QI projects and more clinician and staff buy-in, leading to more project signups—a reinforcing loop. More participation in QI projects leads to less capacity and ability to engage in them, which leads to less sign-ups. The carrying capacity variable in this scenario is clinic bandwidth, which is influenced by staffing issues and patient volume in this model. [Colour figure can be viewed at wileyonlinelibrary.com]

the most similarity to our work. Both approaches involve rigourous analysis at the quotation level to identify causal structures, track modeller influence, and acknowledge the importance of implicit communication in qualitative data. Because the focus of RIQ is on using qualitative data to confirm or disconfirm causal structures in an existing model, Tomoaia-Cotisel and colleagues outline processes for comparing individual structures and documenting alignment and discordance. Our approach, however, was designed to systematically produce diagrams reflecting the mental models of interview participants. Due to this focus on early stage model conceptualization, we present a process for integrating causal structures across multiple quotations into a single diagram reflecting a participant's mental model.

In prior work, Kim and Andersen (2012) used identification numbers for specific claims in the source text as well as separate identification numbers for specific connections in the model, resulting in a large quantity of identification numbers to keep track of. Identification tags were also tracked manually. Our use of CAQDAS software to automate the generation of quotation numbers and data visualization software to automate the attachment of information to model components made tracking less time consuming. The use of quotation numbers also means that multiple components can get tied to the same quotation, creating a grouping of components associated with a certain part of the participant narrative. This grouping allows for the tracking of implicit components and enables selective display of grouped components using the data visualization software, allowing for greater contextualization during analysis. Coding by quotation allowed for navigating the text at a level of comprehension defined by the interviewee and enabled mapping to build on existing qualitative analysis. The use of visualization software for mapping the causal-loop diagrams eased the process of model construction and enabled selective display of certain variables for analysis. Reliance on CAQDAS and visualization software, however, may present financial barriers to researchers and require some expertise in those platforms.

Sketching of feedback loops based on source text provided an opportunity for identifying key implicit variables and precisely naming variables based on their function within the loops. This use of freehand sketching to identify loops during analysis is in line with standard methods of creating qualitative system dynamics models (Anderson & Johnson, 1997; Hovmand, 2014; Sterman, 2000; Turner & Goodman, 2023) and provided an opportunity to name explicit and implicit variables in the feedback loops. By putting this loop sketching phase early in the model creation process, the modeller could base the causal structures on a close reading of the source text. Early loop sketching also allowed precise variable names to be created that could be used in later phases of causal mapping table generation. Incorporating variables and links that are not explicitly referenced in the text gives a degree of influence to the modeller that can be understood to be similar to the role of interpretation held by a qualitative analyst.

Attention to implied variables allowed for the identification of many feedback loops that would have been missed using a method that only coded for causal links, such as those used by Kim and Andersen (2012), Turner, Gates, et al. (2013), Turner, Kim, and Andersen (2013), Turner et al. (2014), and Biroscak et al. (2014). Nearly all of the feedback loops identified using the improved method contained implied variables. This illustrates a potentially important advantage of the new approach.

The identification of modeller hypothesis structures can help the researcher understand their own mental model and guide subsequent rounds of data collection. Sketching of modeller hypothesis structures provides a way to document modellers' understanding of the target system. For example, the carrying capacity model that was identified in this research (see Figure 6) was used to inform a follow-up round of interviews.

4.2 | Data-driven versus modeller-led approaches

The diagrams produced in this analysis consisted of multiple causal structures present in participants' mental models. These diagrams contained more disconnected causal structures and isolated variables than are commonly found in causal-loop diagrams generated through modeller-driven processes. These top-down processes typically aim to describe a simple feedback structure associated with a certain system behaviour (Cassidy et al., 2022; Sterman, 2000). The bottom-up, data-driven process used in our research, in contrast, captures the "messiness" of participant mental models as found in qualitative data, which includes a large number of variables and single causal links. This approach may be most appropriate when adherence to source data is important, when comparing individuals' mental models, or in combination with modeller-driven approaches. Larger feedback structures could also be obtained through iterative data collection and modelling. Further research should identify best practices for matching approach to purpose and for combining processes.

The data analysed for this study was produced in semistructured interviews that focused in part on practice facilitators' mental models of clinical practice change and therefore contained information relevant for mapping mental models. Greater clarification and probing designed to elicit information about causal structures, however, might have produced even richer data for causal-loop diagramming. The large number of causal structures found in our research may also indicate a need for follow-up interviews to clarify and streamline the causal models. Different numbers of variables, causal links, and feedback loops observed in the diagrams across participants could be understood to reflect differences in participant mental models (e.g., between novices and experts), speaking styles, or inconsistent application of the analysis method. Follow-up interviews or triangulation with other data collection methods (e.g., participant review of the diagram) may control for variations in speaking style (i.e., how explicitly a participant describes their mental model). The use of multiple analysts in the identification of loops during query review and during diagram editing may improve reliability. Further research should examine iterative processes of data collection tailored to identification of mental models. Guidelines for creating interview guides designed to elicit causal structures would also be useful. Based on our experience with this study, our research team has developed a protocol for collecting data suitable for this type of analysis by drawing from best practices in qualitative interviewing and system dynamics modelling, described in a separate article (Kenzie et al., 2024). Research could also explore ways to further enhance the reliability of this method, for example through incorporating other approaches from qualitative research (e.g., triangulation and member checking). Further research could also address how to aggregate (Ryan et al., 2021) or analyse (Pluchinotta et al., 2022) the models developed using this approach.

4.3 | Potential applications

Because it provides a way to systematically identify causal structures in qualitative data while tracking the modeller's contribution, the method outlined here has the potential of adding rigour to the use of interviews for system dynamics model building. This method could be used to augment group model building processes. Models gleaned from preliminary individual interviews could form the basis of a participatory modelling session (Hovmand, 2014; Vennix et al., 1996), or interviews could be used when synchronous participation is impractical or impossible (Luna-Reyes & Andersen, 2003). This method could also be used as part of an alternative to group model building. As mentioned earlier, semistructured interviews are a broadly accessible mode of data collection, both for the interviewee and interviewer, while group model building can present logistical and accessibility barriers to participation (Valcourt et al. 2020). Moreover, a process of analysing, comparing, and synthesizing individual mental models may be preferable to a group modelling process, depending on the goals of the modelling project.

This approach to identifying causal structures in qualitative data has possible uses in qualitative and mixed methods research. The production of causal-loop diagrams from qualitative data can be seen as a kind of translation or conversion of information from one form to another and could therefore be used as an alternative way to identify themes or otherwise gain insights from qualitative data (Kenzie et al., 2022). Navigating qualitative data in this way could be useful for identifying patterns in mental models in the context of community engagement, program evaluation, or collaborative partnerships. It could also augment standard qualitative research in a variety of settings.

When considering applications of this method, it should be understood that this approach is designed to identify causal structures in mental models illustrated in causal-loop diagram notation, which may differ from complete, parsimonious causal-loop diagrams designed to communicate specific structures. The purpose of the diagramming effort should guide choices about final diagram contents and integration with other modelling efforts.

Developing systematic approaches for identifying causal structures in qualitative data is a step towards making individuals' perspectives and insights computationally "legible," which would enable integration with other forms of data. Integration or comparison between various kinds of data could support more robust monitoring and evaluation in complex systems. Researchers studying learning health systems call for such approaches to data synthesis (Friedman & Flynn, 2019; Guise et al., 2018; Guo et al., 2022).

4.4 | Ramifications for automated model generation

Automatic methods of extracting causal information from text are being developed using natural language processing, but they are currently far from reliable (Doan et al., 2019; Jung, 2017; Nazaruka, 2020, 2023; Pattison et al., 2023; Pechsiri et al., 2019; Sakahira & Hiroi, 2021). The idea of using these automated methods for generating causal-loop diagrams from text data has been explored (Newberry & Carhart, 2023; Owen et al., 2018; Pechsiri et al., 2019) and would indeed be transformative if successful. Possible applications include analysis of qualitative data for research and synthesis of scientific literature for review. This type of machine learning-based analysis, however, would likely rely on identification of individual causal links rather than causal structures. As illustrated in this research, exclusive reliance on causal links obscures implicit causal structures in natural language. The prospect of automatically generating causal-loop diagrams from text data, therefore, may be further in the future than previously thought.

5 | CONCLUSION

Qualitative data contains a wealth of information about individuals' mental models of complex systems. Establishing processes for systematically identifying causal structures in this data has the potential to improve the transparency and rigour, and therefore credibility, of our modelling. In this paper, we have presented a method that draws from existing approaches, system dynamics best practice, and qualitative research methods to identify causal structures in qualitative data. This approach focuses on the identification of larger causal structures communicated implicitly or explicitly and utilizes software to improve efficiency. We successfully applied this approach to interview data describing mental models of clinical practice transformation. Aside from supporting the development of system dynamics models, this approach could be used to communicate qualitative findings in a variety of research and evaluation settings. Future research should identify strategies for data collection tailored to this approach and processes for integrating data-driven identification of causal structures with top-down modelling approaches. Opportunities for further streamlining data extraction and synthesis, potentially through rapid or automated methods, should also be explored.

ACKNOWLEDGEMENTS

We would like to thank the practice facilitators who participated in interviews for this research as well as our research funders. This study was supported by the Agency for Healthcare Research and Quality, Grant Award Number 1R18HS027080-01. The content provided is solely the responsibility of the authors and does not necessarily represent the official views of the funders.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The datasets supporting the conclusions of this article are included within the article and its supporting files.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Kenzie, E. S., Wakeland, W., Jetter, A., Lich, K. H., Seater, M., & Davis, M. M. (2024). Mapping mental models through an improved method for identifying causal structures in qualitative data. *Systems Research and Behavioral Science*, 1–16. https://doi.org/10.1002/sres.3030