Research Brief

Network Analysis to Visualize Qualitative Results: Example From a Qualitative Content Analysis of The National Child Abuse Hotline

Laura M. Schwab-Reese, MA, PhD[1]
Nicholas C. Lenfestey, MPH[1]
Amelia W. Hartley, BS[1]
Lynette M. Renner, MSW, PhD[2]
Tyler Prochnow, PhD[3]

Data visualization, such as figures created through network analysis, may be one way to present more complete information from qualitative analysis. Segments of qualitatively coded data can be treated as objects in network analysis, thus creating visual representations of the code frequency (i.e., nodes) and the co-occurrence (i.e., edges). By sharing an example of network analysis applied to qualitative data, and then comparing our process with other applications, our goal is to help other researchers reflect on how this approach may support their interpretation and visualization of qualitative data. A total of 265 de-identified transcripts between help-seekers and National Child Abuse Hotline crisis counselors were included in the network analysis. Post-conversation surveys, including help-seekers' perceptions of the conversations, were also included in the analysis. Qualitative content analysis was conducted, which was quantified as the presence or absence of each code within a transcript. Then, we divided the dataset based on help-seekers' perceptions. Individuals who responded that they "Yes/Maybe" felt more hopeful after the conversation were in the "hopeful" dataset, while those who answered "No" were in the "unhopeful" dataset. This information was imported to UCINET to create co-occurrence matrices. Gephi was used to visualize the network. Overall, code co-occurrence networks in hopeful conversations were denser. Furthermore, the average degree was higher in these hopeful conversations, suggesting more codes were consistently present. Codes in hopeful conversations included information, counselor support, and problem-solving. Conversely, nonhopeful conversations focused on information. Overall, network analysis revealed patterns that were not evident through traditional qualitative analysis.

Keywords: child abuse; network analysis; visualization; qualitative; content analysis

Qualitative research typically yields more detailed information than can be fully reported in a paper, as large amounts of data are indexed into

[1]*Purdue University, West Lafayette, IN, USA*
[2]*University of Minnesota, St Paul, MN, USA*
[3]*Texas A&M University, College Station, TX, USA*

Authors' Note: *This project was supported by the Children's Bureau (CB), Administration for Children and Families (ACF) of the U.S. Department of Health and Human Services (HHS) as part of a financial assistance award in the amount of US$6 million with 100% funded by CB/ACF/HHS. The contents are those of the author(s) and do not necessarily represent the official views of, nor an endorsement by, CB/ACF/HHS, or the U.S. Government. For more information, please visit Administrative and National Policy Requirements.* *Address correspondence to Laura M. Schwab-Reese, Department of Public Health, Purdue University, 812 West State Street, MTHW 214F, West Lafayette, IN 47907, USA; e-mail: lschwabr@purdue.edu.*

Health Promotion Practice
Month XXXX Vol. XX, No. (X) 1–10
DOI: 10.1177/15248399241283144
Article reuse guidelines: sagepub.com/journals-permissions

researcher-defined categories (i.e., codes) and themes (Wertz, 2011). Although illustrative quotes and patterns of these themes' frequency and co-occurrence are often presented, the large number of codes often means only a selection is shared, limiting the transparency of the research process (Pokorny et al., 2018). Recently, there have been efforts to improve the transparency of this process by developing ways to present more complete information. For example, it is possible to present code co-occurrence cluster analysis to identify groupings of codes and to visualize hierarchical clusters (Guest & McLellan, 2003). Data visualization approaches are particularly promising, as they assist in describing and sharing complex data in more easily understood ways. Network analysis visualization is one such approach. Network analysis consists of two elements: nodes that represent individuals, entities, or objects, and edges that depict relationships or connections across nodes (Pokorny et al., 2018). Coded segments of data can be treated as nodes, which allows them to be understood as a complex system of ideas. The relationships between these codes can be treated as edges. Doing so allows for the creation of visual representations of the frequency of codes (i.e., nodes) and their co-occurrence (i.e., edges). See Pokorny et al. (2018) for a detailed description of the methods used to visualize qualitative data as networks.

As network analysis is an emerging approach to analyzing qualitative data, the purpose of this brief is to describe its utility for understanding complex data. By sharing an example of network analysis applied to qualitative data, and then comparing our process with other applications, our goal is to help other researchers reflect on how this approach may support their interpretation and visualization of qualitative data.

METHOD

Study Background

The National Child Abuse Hotline provides child maltreatment-related services (Childhelp, 2023). The hotline is staffed 24/7/365 with counselors trained to have conversations about maltreatment. Beyond discussing the help-seekers' situations, counselors provide support and resources. After offering phone-based services for more than 30 years, Childhelp added text and chat options in 2018. Providing support via written communication was complicated by the lack of visual and non-verbal cues. To address this limitation, Childhelp partnered with the authors to build an evidence-informed practice model. As part of this process, Childhelp shared de-identified transcripts and meta-data (i.e., help-seekers' demographics, help-seekers' post-conversation surveys). The Purdue University Institutional Review Board (IRB) approved this study.

TABLE 1
Description of the Sample (n = 265)

Demographic Characteristic	n *(%)*
Age (years)	
<13	45 (16.98)
14–15	64 (24.15)
16–17	50 (18.87)
18–21	24 (9.06)
>21	54 (20.38)
Missing	28 (10.57)
Gender	
Female	186 (70.19)
Male	48 (18.11)
Gender expansive	18 (6.79)
Missing	13 (4.91)
Race/ethnicity	
White	138 (52.08)
Black	21 (7.92)
Hispanic	29 (10.94)
Asian	18 (6.79)
Other	20 (7.55)
Missing	39 (14.72)

Sample

We purposefully selected 314 conversations from the 1,153 written conversations in July 2020. Conversations were chosen to capture the demographic diversity of help-seekers and the range of perspectives about the conversations. Before conversations began, help-seekers were asked to share their age, gender, and other demographic information. After the conversation, they shared their perceptions of the conversation. The post-conversation survey assessed five outcomes, including *hopefulness* (i.e., does the help-seeker feel more hopeful after the conversation?).

A total of 265 help-seekers were included in the network analysis. Help-seekers who did not complete the post-conversation survey (n = 49) were excluded. The final sample included primarily individuals who self-identified as young, female, and White (Table 1). Most help-seekers were satisfied with the conversations they had with Childhelp counselors (Table 2).

TABLE 2
Help-Seekers' Perceptions of the Conversations (n = 265)

Help-Seeker Perceptions	n *(%)*
More hopeful	
Yes/maybe	226 (85.28)
No	36 (13.58)
Missing	3 (1.13)
More informed	
Yes/maybe	238 (89.81)
No	21 (7.92)
Missing	6 (2.26)
More prepared	
Yes/maybe	205 (77.36)
No	44 (16.60)
Missing	16 (6.04)
Less stressed	
Yes/maybe	180 (67.92)
No	71 (26.79)
Missing	14 (5.28)
Good way	
Yes/maybe	244 (92.08)
No	18 (6.79)
Missing	3 (1.13)

Qualitative Coding

Qualitative content analysis was conducted as described in the work by Schreier (2012). We began by reviewing all conversations. In a second review of the conversations, we took notes on patterns and areas where conversations were similar and where they diverged. We met to discuss and define possible codes as we built the codebook. After completing a first draft, we applied codes to 30 conversations and compared the coding. In the second round of pilot coding, we focused on how well the coding scheme captured the content. Then, two members of the team applied the codebook to the full dataset, including recoding previously piloted conversations.

The final codebook consisted of 109 codes. For this analysis, only the 41 codes focused on conversation content and rapport-building were included. These codes capture the topics, conversational dynamics, and flow of the conversations. Codes that describe the help-seeker (e.g., age, gender) and help-seekers' answers to the post-conversation surveys were excluded because they were used to stratify the network analysis. Dedoose, a qualitative data analysis program, was used to code the transcripts.

Network Analysis and Visualizations

The qualitative analysis was summarized as the presence or absence of each code within a transcript. This study used two-mode co-occurrence networks to understand the presence of codes with conversations. Connections between codes were present if they co-occurred during a conversation. This connection was also given a value based on the number of conversations in which these codes co-occurred.

Then, we divided the dataset based on help-seekers' perceptions. For this analysis, we focused on one outcome, hopefulness, and presented the results for individuals who did and did not feel more hopeful after the conversation. Individuals who responded "Yes" or "Maybe" to the hopefulness question were in the "hopeful" dataset, while those who answered "No" were in the "unhopeful" dataset. This allowed a more detailed review of the methodology, findings, and related codes.

After the data were coded and sorted into the assigned dataset, they were imported to a statistical software package, UCINET, to create co-occurrence matrices (Borgatti et al., 2002). The co-occurrence matrices were imported to a network graphing program, Gephi, to visualize the network (Bastian et al., 2009). The Fruchterman–Reingold layout was selected for the network visuals (Fruchterman & Reingold, 1991). Network statistics for the network analysis were calculated using Gephi. The statistical measures used include degree (i.e., the number of connections a node has with each unique node), weighted degree (i.e., the combined degree and weight of edges used to measure a node's relative importance within a network), betweenness centrality (i.e., the measure of how frequently a given node is located along the shortest path between two nodes within a network), and closeness centrality (i.e., the measure of how close a given node is to all other nodes within a network).

Once these analyses were completed, we compared the network analysis metrics between conversations that increased and did not increase hopefulness. First, we compared the network of co-occurring codes across the levels of the outcome. Theoretically, codes that are more central within these networks would represent important elements within conversations. Then, descriptive differences were reviewed as well as visual representations of each network.

RESULTS

Overall, 85.3% of the sample (n = 226) reported feeling more hopeful after the conversation (hereafter: hopeful conversations), and 13.6% of the sample (n = 36) reported that they did not feel more hopeful (hereafter:

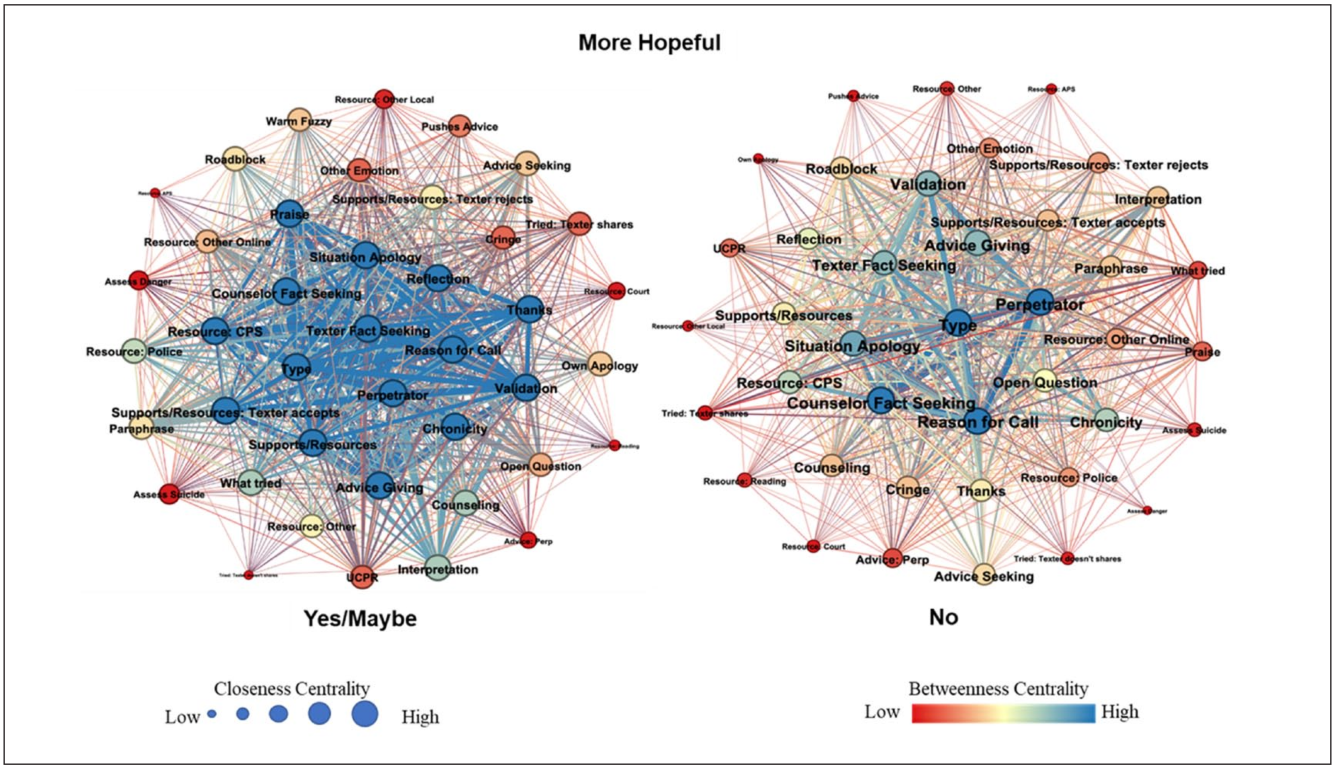

FIGURE 1 Characteristics of Conversations, by Whether the Help-Seeker Reported Feeling More Hopeful Post-Conversation

unhopeful conversations). Overall, code co-occurrence networks in hopeful conversations were denser than in unhopeful conversations (density: 0.92 vs. 0.79; Figure 1). Furthermore, the average degree was higher in these more hopeful conversations (average degree: 36.63 vs. 30.60) which suggests more codes were consistently present. Specifically, the hopeful conversations had 15 codes, (indicated in blue in Figure 1) that occurred frequently and often co-occurred with other codes, compared with only 4 codes in unhelpful conversations. The degree, weighted degree, betweenness centrality, and closeness centrality for each variable are listed in Appendix A.

There was additional nuance among the most common codes. Codes in hopeful conversations included information about the maltreatment (e.g., who is the perpetrator; what type of abuse is being experienced), provision of support by the counselor (e.g., validation; reflecting feelings), and problem-solving with the help-seeker (e.g., advice giving; resources). Conversely, unhopeful conversations tended to focus on information. Overall, these findings suggest that users feel more hopeful after engaging in detailed conversations that balance their need for information, emotional support, and resources. Additional details about the codes, including examples of relevant conversation segments, are available in Appendix B.

DISCUSSION

This research brief outlines how we adapted network analysis to visualize the results of a qualitative content analysis of discussions between help-seekers and counselors. We demonstrate this process through an example contrasting more and less hopeful help-seeker conversations, revealing patterns not evident through traditional analysis. Conversations fostering hope included a variety of content including, discussing maltreatment, providing emotional support, and offering resources.

Our approach was most like the study by Yu et al. (2021) on fashion technology. Yu and colleagues analyzed conversations about fashion technology on Twitter, specifically direct-to-garment (DTG) printing, to understand its impact on the industry. Both studies compare network metrics to deduce crucial insights between groups—Yu and colleagues tracked changes in conversations over time, while we assessed the differences based on help-seekers' hopefulness. Beyond visualizing co-occurrence, network analysis also can be used to map a network of organizations, individuals, or topics in relation to each other with directed graphs. Neither Yu et al. (2021) nor our study used directed graphs. However, this approach has some advantages. In these graphs, nodes are linked by arrows which indicate chronology or the direction of the flow of information, goods, services, etc. This introduces several new metrics to analyze the network, including in-degree, out-degree, and PageRank Centrality. In-degree and out-degree give additional meaning to the graph's connectedness. The in-degree and out-degree (i.e., the number of connections coming into and out of the node, respectively) indicate the node's influence within the network. Those with high in-degrees receive critical information, while those with high out-degrees are critical components of the information flow (i.e., their removal would stop the flow of information).

Network analysis can also map relationships within a network using directed graphs, where nodes and their connections indicate information flow and influence. For instance, Abbassinia and colleague's (2021) study on organizational response to a fire and Liu and colleagues' (2021) research on guideline development meetings employed in-degree and out-degree to gauge influence and information dynamics. Unlike Abbassinia et al. (2021) and Liu and Xiao (2021), our study could only show connectedness and centrality, which still conveyed important information about the networks.

A second type of directed graph maps concepts instead of organizations. Larosa and Mysiak (2020) highlight how this approach can be applied in a qualitative setting to build a conceptual model. Their study included a directed network to understand the key components of business models for climate services. Several manners of analysis were used to understand the complex graph that emerged. First, in-degree and out-degree provide an idea of a node's connectedness to other components of the typical business model and the chronology of their use. Second, color coding was used to distinguish nodes representing different business model portions. This enabled a more comprehensive analysis to visualize how different parts of the business model were related. The size of the nodes was determined by their PageRank Centrality. PageRank Centrality is a measure of importance for directed graphs that integrates in-degree with the importance of the nodes to which it is connected. Thus, a node with highly influential nodes coming into it has a high PageRank Centrality. Combining these statistical tools with the basic characteristics of the graph (e.g., what percentage of edges pointed to a single node, how tightly connected are a given set of nodes), Larosa and Mysiak extrapolated useful information on the business models used for climate services in their sample and the strategies managers used in the climate service industry.

IMPLICATIONS FOR PRACTICE AND RESEARCH

Altogether, there are many ways to approach network analysis of qualitatively coded data. Overall, these approaches allow in-depth information to be extracted from the data and patterns to be identified in the connections between ideas. Undirected graphs provide a rich picture of the similarities and differences in these relationships between different levels of independent variables, while directed graphs allow users to capture the chronology or flow within a network. Both have useful applications in qualitative research, empowering scholars to capture the relationships between concepts at a given time point (single undirected graph), shifts in conceptual frameworks over time (series of undirected graphs), the flow of information through a network (directed graph of organization), the chronological relationship of concepts (directed graph of conceptual framework), and more. Depending on the research question, each variation of the network analysis has its own strengths and weaknesses and can be used to the researcher's advantage to garner an enhanced understanding of their qualitative data.

CONCLUSION

Network analysis is a promising approach to visualize the rich, complex data created through qualitative analysis. In this example, we gained additional insight into the combinations of features associated with help-seekers' feelings more hopeful.

APPENDIX A
Network Metrics for Hopefulness = "Yes" or "Maybe"

Node	*Degree*	*Weighted degree*	*Closeness centrality*	*Betweenness centrality*
Reason for call	40	2,810	1	3.093035
Counselor fact-seeking	40	2,733	1	3.093035
Advice-giving	40	2,572	1	3.093035
Perpetrator	40	2,395	1	3.093035
Type	40	2,392	1	3.093035
Validation	40	2,224	1	3.093035
Texter fact-seeking	40	2,019	1	3.093035
Situation apology	40	1,892	1	3.093035
Resource: CPS	40	1,815	1	3.093035
Thanks	40	1,637	1	3.093035
Supports/resources	40	1,528	1	3.093035
Praise	40	1,506	1	3.093035
Supports/resources: texter accepts	40	1,314	1	3.093035
Chronicity	40	1,262	1	3.093035
Reflection	40	1,222	1	3.093035
Interpretation	39	1,293	0.97561	2.146105
Counseling	39	795	0.97561	2.146105
What tried	39	747	0.97561	2.146105
Resource: police	38	743	0.952381	1.970503
Resource: other	37	180	0.930233	1.470474
Supports/resources: texter rejects	38	616	0.952381	1.428118
Paraphrase	38	1,203	0.952381	1.347416
Roadblock	38	375	0.952381	1.347416
Advice-seeking	38	847	0.952381	1.187918
Own apology	38	471	0.952381	1.187918
Warm fuzzy	37	304	0.930233	1.165889
Resource: other online	37	890	0.930233	1.095711
Open question	37	1,176	0.930233	1.014169
Pushes advice	36	140	0.909091	0.691308
Other emotion	37	982	0.930233	0.525486
Unconditional positive regard	37	824	0.930233	0.525486
Cringe	37	781	0.930233	0.525486
Tried: texter shares	37	509	0.930233	0.525486
Resource: other local	33	135	0.851064	0.096774
Assess suicide	34	175	0.869565	0.030303
Resource: court	31	88	0.816327	0.030303
Assess danger	33	203	0.851064	0
Advice: Perp	30	198	0.8	0
Resource: reading	23	36	0.701754	0
Tried: texter does not share	20	32	0.666667	0
Resource: APS	21	30	0.677966	0

Network Metrics for Hopefulness = "No"

Node	*Degree*	*Weighted degree*	*Closeness centrality*	*Betweenness centrality*
Reason for call	39	454	1	11.232747
Counselor fact-seeking	39	451	1	11.232747
Perpetrator	39	434	1	11.232747
Type	39	421	1	11.232747
Situation apology	38	364	0.975	9.40217
Texter fact-seeking	37	276	0.95122	8.580952
Advice-giving	38	404	0.975	8.57077
Validation	38	374	0.975	8.57077
Chronicity	36	236	0.928571	7.629433
Resource: CPS	36	222	0.928571	7.322138
Reflection	34	184	0.886364	6.243776
Open question	36	241	0.928571	5.611449
Thanks	35	212	0.906977	5.157701
Supports/resources	35	256	0.906977	5.136146
Advice-seeking	34	103	0.886364	4.721932
Roadblock	35	213	0.906977	4.700865
Paraphrase	34	209	0.886364	4.31587
Interpretation	34	211	0.886364	4.296408
Cringe	35	196	0.906977	4.09678
Resource: counseling	35	171	0.906977	4.09678
Supports/resources: texter accepts	34	144	0.886364	4.06641
Resource: other online	33	109	0.866667	3.307137
Supports/resources: texter rejects	33	104	0.866667	3.200623
Resource: police	31	110	0.829787	3.082527
Other emotion	32	143	0.847826	2.88795
Unconditional positive regard	30	98	0.8125	2.184303
Praise	31	135	0.829787	1.866262
Advice: Perp	31	72	0.829787	1.219169
What tried	29	134	0.795918	1.163148
Resource: other	23	42	0.709091	0.631594
Resource: reading	24	33	0.722222	0.496292
Assess suicide	23	35	0.709091	0.329625
Tried: texter does not share	21	31	0.684211	0.18003
Tried: texter shares	24	71	0.722222	0
Own apology	15	29	0.619048	0
Resource: court	21	21	0.684211	0
Pushes advice	18	18	0.65	0
Resource: other local	17	17	0.639344	0
Resource: APS	16	16	0.629032	0
Assess danger	12	12	0.590909	0

APPENDIX B
Qualitative Codebook, including Code Title, Description, and Example Quote

Code	*Description*	*Example*
Reason for call	First indication of why the help-seeker reached out to the hotline	Hello, my friend has told me to call dcf because she believes she is abused. Is it illegal to leave bruises on a child or slap a child in the face?
Counselor fact-seeking	Counselor asks questions about facts	Can you provide a bit more information about this?
Advice-giving	Counselor gives advice to the help-seeker	One more thing that might be helpful is to write down some positive points about yourself and why you deserve not to be hurt.
Perpetrator	Help-seeker identifies the person engaged in abuse or neglect	They were my legal guardian
Type	Help-seeker provides enough information to identify the type of abuse	They are experiencing daily verbal abuse and mild physical abuse.
Validation	Counselor validates the help-seeker experience	I can understand why you are feeling unsafe.
Texter fact-seeking	Texter asks questions about facts	Where I can do the report?
Situation apology	Counselor apologies about an aspect of the help-seeker situation	I'm sorry they dismissed you and your feelings like that.
Resource: CPS	Counselor or help-seeker discusses child protective services	It's CPS' place to assess child welfare. It is important your story gets reported to the correct agency.
Thanks	Counselor thanks the help-seeker	Thank you for sharing that with me.
Supports/resources	Counselor asks about or recommends available supports/resources	How do you usually cope with the abuse when its going on?
Praise	Counselor makes a positive value judgment about the help-seeker	Okay good—it sounds like you're doing all the right things
Supports/resources: texter accepts	Help-seeker is receptive to the supports/resources offered by the counselor	I think I'll look into the trevor project right now,
Chronicity	Help-seeker identifies the length of time since the abuse started	It's been awhile so I guess a month.
Reflection	Counselor re-states the feelings described by the help-seeker	That must have been scary for you.
Interpretation	Counselor provides additional insight beyond what was shared by the help-seeker	It is normal to have some conflict with Mom, but from what you are telling me, its really upsetting you and you would like to change how things are with Mom.
Resource: counseling	Counselor or help-seeker discusses counseling	I have a counselor. . . but my mom refuses to make an appointment or take me to see her
What tried	Counselor asks what the help-seeker has tried to improve the situation	Has your family ever tried counseling?
Resource: police	Counselor or help-seeker discusses law enforcement	Okay, are the police on their way?

(continued)

APPENDIX B (CONTINUED)

Code	*Description*	*Example*
Resource: other	Counselor or help-seeker discusses a resource not otherwise specified	Can you call 911 and ask for the paramedics?
Supports/resources: texter rejects	Help-seeker is not receptive to the supports/resources offered by the counselor	But I absolutely cannot have contact with him. Not even an email like that.
Paraphrase	Counselor provides an overview of the information provided by the help-seeker	You said that you have tried to talk to Dad about it, but that didn't seem to help.
Roadblock	Issues that make it difficult to continue the conversation (e.g., technical difficulties, help-seeker uninterested in suggested options, and brainstorming other possibilities)	It appears we might be having some technical difficulties, so if there are any delays that is why.
Advice-seeking	Help-seeker asks for advice	what should I do next to help my friend
Own apology	Crisis counselor apologizes for issues with the platform or their actions	sorry for the confusion
Warm fuzzy	Individual analyzing the data perceives the moment of strong connection between the help-seeker and crisis counselor	I know it's a difficult situation at home and it is hard to be there but from our chat today, I think you are doing so well.
Resource: other online	Counselor or help-seeker discusses an online resource otherwise not specified	7 Cups—Free 24/7 online chat providing emotional support from volunteers. Community forums/chat rooms available for teens and adults. www.7cups.com/
Open question	Counselor asks a question that requires an extended response	What do you think?
Pushes advice	Counselor persists with the same idea after the help-seeker declines	You need some help and we can help you figure out how to get it. But it starts with telling people.
Other emotion	Rapport-building efforts not otherwise specified	I'm glad you reached out today
Unconditional positive regard (UCPR)	Counselor affirms the help-seeker regardless of their behavior	You deserve to feel safe and be safe.
Cringe	Individual analyzing the data perceives moment of strong disconnect between the help-seeker and crisis counselor	There is nothing it appears you can do.
Tried: texter shares	When asked about what they have tried, the help-seeker shared prior efforts	I tried but no luck.
Resource: other local	Counselor or help-seeker discusses another local resource otherwise not specified	If you would like I could get you the ombudsman's information for the area? They are the office that handles issues related to how CPS handles things.
Assess suicide	Counselor assesses for risk of self-harm	Are you currently having thoughts of suicide?
Resource: court	Counselor or help-seeker discusses the court system	that is something you could confirm with a family law attorney.

(continued)

APPENDIX B (CONTINUED)

Code	*Description*	*Example*
Assess danger	Counselor assesses for risk of immediate harm to the help-seeker	Are you in a safe place right now?
Advice: Perp	Counselor recommends communicating with the abuser	Do you think you might feel comfortable writing your dad a letter explaining how you feel?
Resource: reading	Counselor or help-seeker discusses reading materials	We do have some books as resources if you are interested as additional options I can provide to you?
Tried: texter does not share	When asked about what they have tried, the help-seeker did not share prior efforts	She won't respond to any of my messages.
Resource: APS	Counselor or help-seeker discusses the adult protective system	That's why it's good for you to reach out to the Adult Protective Services, they might have some suggestions.

ORCID iDs

Laura M. Schwab-Reese https://orcid.org/0000-0002-9174-1730
Lynette M. Renner https://orcid.org/0000-0001-8220-4928
Tyler Prochnow https://orcid.org/0000-0001-7886-4456

REFERENCES

Abbassinia, M., Kalatpour, O., Motamedzade, M., Soltanian, A., & Mohammadfam, I. (2021). Application of social network analysis to major petrochemical accident: Interorganizational collaboration perspective. *Disaster Medicine and Public Health Preparedness*, *15*(5), 631–638.

Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: An open source software for exploring and manipulating networks. *Proceedings of the International AAAI Conference on Web and Social Media*, *3*(1), 361–362.

Borgatti, S., Everett, M. G., & Freeman, L. C. (2002). *UCINET for Windows: Software for social network analysis*. Analytic Technologies.

Childhelp. (2023). *National Child Abuse Hotline*. https://www.childhelphotline.org/

Fruchterman, T. M., & Reingold, E. M. (1991). Graph drawing by force-directed placement. *Software: Practice and Experience*, *21*(11), 1129–1164.

Guest, G., & McLellan, E. (2003). Distinguishing the trees from the forest: Applying cluster analysis to thematic qualitative data. *Field Methods*, *15*(2), 186–201.

Larosa, F., & Mysiak, J. (2020). Business models for climate services: An analysis. *Climate Services*, *17*, 100111.

Liu, S., & Xiao, Q. (2021). An empirical analysis on spatial correlation investigation of industrial carbon emissions using SNA-ICE model. *Energy*, *224*, 120183.

Pokorny, J. J., Norman, A., Zanesco, A. P., Bauer-Wu, S., Sahdra, B. K., & Saron, C. D. (2018). Network analysis for the visualization and analysis of qualitative data. *Psychological Methods*, *23*(1), 169–183.

Schreier, M. (2012). *Qualitative content analysis in practice*. Sage.

Wertz, F. J. (2011). *Five ways of doing qualitative analysis: Phenomenological psychology, grounded theory, discourse analysis, narrative research, and intuitive inquiry*. The Guilford Press.

Yu, Y., Moore, M., & Chapman, L. P. (2021). Social network analysis of an emerging innovation: Direct-to-Garment printing technology. *Journal of Fashion Marketing and Management*, *25*(2), 274–289.