The Qualitative Report

Volume 27 | Number 11

How To Article 13

11-26-2022

A Conversation in Time: A New Concept for Creating Stream Graphs for Qualitative Data Visualization

Emily S. Nelson
Kent State University - Kent Campus, emilynelson515@gmail.com

Sheryl Chatfield
Kent State University - Kent Campus, schatfi1@kent.edu

Recommended APA Citation

Nelson, E. S., & Chatfield, S. (2022). A Conversation in Time: A New Concept for Creating Stream Graphs for Qualitative Data Visualization. *The Qualitative Report*, *27*(11), 2605-2622. https://doi.org/10.46743/2160-3715/2022.5713

A Conversation in Time: A New Concept for Creating Stream Graphs for Qualitative Data Visualization

Abstract

Despite the affinity between qualitative research and non-text visual information, the range and application of creative visualizations used to give depth and dimension to qualitative research reports is limited. Thoughtfully designed visualizations, including those which emphasize color, have myriad advantages, including the ability to compress information into an easily understood summary. The purpose of this paper is to describe a new method, developed by the first author, suitable for capturing temporal aspects of conversations and word volume for presentation in an engaging visual way. This method uses the widely available software program Microsoft Excel, in conjunction with R, an open source/open access software environment for statistical computing and graphics, to transform typed transcripts from individual interview research into a specific type of volume graph known as a stream graph. This "how to" paper describes the process and illustrates results from interview research with eight U.S. public school teachers conducted to discuss mental health resources for students. The stream graph approach provides qualitative researchers another tool for visualizing the rich contextual data collected during interviews.

Keywords

qualitative research, data visualization, interview visualization, stream graph, interview research

The Qualitative Report 2022 Volume 27, Number 11, 2605-2622
https://doi.org/10.46743/2160-3715/2022.5713

A Conversation in Time: A New Concept for Creating Stream Graphs for Qualitative Data Visualization

Emily S. Nelson and Sheryl L. Chatfield
Kent State University, Ohio, USA

Despite the affinity between qualitative research and non-text visual information, the range and application of creative visualizations used to give depth and dimension to qualitative research reports is limited. Thoughtfully designed visualizations, including those which emphasize color, have myriad advantages, including the ability to compress information into an easily understood summary. The purpose of this paper is to describe a new method, developed by the first author, suitable for capturing temporal aspects of conversations and word volume for presentation in an engaging visual way. This method uses the widely available software program Microsoft Excel, in conjunction with R, an open source/open access software environment for statistical computing and graphics, to transform typed transcripts from individual interview research into a specific type of volume graph known as a stream graph. This "how to" paper describes the process and illustrates results from interview research with eight U.S. public school teachers conducted to discuss mental health resources for students. The stream graph approach provides qualitative researchers another tool for visualizing the rich contextual data collected during interviews.

Keywords: qualitative research, data visualization, interview visualization, stream graph, interview research

Introduction

Simple visualizations for quantitative data such as bar charts, tables, and line charts improve comprehension and help readers make decisions (Peters, Dieckmann, et al., 2007; Peters, Hibbard, et al., 2007). However, in a systematic review of qualitative data display in articles published between 2007 and 2009 in three qualitative methods journals, Verdinelli and Scagnoli (2013) and found just 215, or 27%, of published qualitative manuscripts included a visual display or diagram. These authors later described visualization use in published qualitative research as "under-utilized and under-developed" (Scagnoli & Verdinelli, 2017, p. 1). To further explore this deficiency, Scagnoli and Verdinelli solicited detail from a panel of seven qualitative journal editors. The editor panelists suggested lack of training and few available exemplars might inhibit use of visualizations in qualitative research reports. Panelists also recommended visualizations in qualitative research should be focused on improving communications by emphasizing aspects such as structure, aesthetics, and simplicity of design. Visual depictions of data are not new; the practice of presenting data in a visual format has gone on for centuries. Examples from the past include maps of celestial bodies in the sky over ancient Egypt, 17th century graphs of distances between cities, and a map of a cholera outbreak in the 19th century. These historical efforts inspired innovation that eventually led to the current day availability of digital graph, chart, and illustration-making software (Friendly, 2008). Rose (2014) described tremendous growth in use of visual research methods during the 21st century and suggested this growth parallels changes in contemporary society: as society itself has become more reliant on visual information, the need for and interest in visual research methods has also expanded. Healthcare professionals and educators have found use of infographics, a specific type of visual representation, to be particularly effective for enhancing the understanding of data. Patel et al. (2020) documented the results of using infographics to help healthcare professionals make clinical decisions and found 85% of participants described infographics as useful for answering their questions. Visual representations of information are additionally beneficial for students learning new concepts (Lamb et al., 2014; Yarbrough, 2019). Dunlap and Lowenthal (2016) suggested the combination of text and visuals enhance learning and memory when compared to text on its own.

In their seminal text on qualitative data analysis, Miles and Huberman (1994) encouraged readers to: "Think display. Adapt and invent formats that will serve you best" (p. 114). This emphasis is continued in an updated version of this work where the authors stated: "the idea of display is central to this book" (Miles et al., 2015, p. 108). With this paper, we aim to present an additional example of a visualization method and to provide detailed guidance to enable researchers to apply and expand on our method. The remainder of this paper is organized as follows: first, we describe a range of published qualitative research studies which incorporate visual elements in the results or findings, concluding this research review section with observations on the important role of conversation in interview research. Following, we describe and demonstrate the stream graph method as applied to conversation data. We conclude this "how to" paper with reflections and recommendations for use and further development of this method.

Visuals in Qualitative Research

Qualitative researchers value a range of sources of data, including text-based and non-text visual presentations such as photographs, video recordings, paintings, drawings, and models. In their definition of qualitative research, Saldaña and Omasta (2018) described a range of visual presentations as key types of qualitative data. Within published or presented qualitative research, visual displays may be most often found in approaches such as art-based or arts-informed research where a variety of visualizations may comprise or supplement research findings, and in research with process or theory-building aims, including grounded theory methods. A third area where visualization is common is research which focuses on place or space.

Examples of arts-informed research, where artistic expressions comprise the findings, range from Leavy's (2010) series of brief "tri-voiced poems" (p. 181), which merged aspects of interview transcripts, researcher interpretation, and prior research, to development of a live theater performance based on findings from research on pre-natal genetic screening (Hundt et al., 2010), to the large scale visual arts installation designed by Lapum et al. (2012) as a means of presenting findings from research on patients' experiences with open-heart surgery. Visual depictions of theory can be found in the work of Rosen et al. (2008) and Nicol et al. (2009). In a multi-stage study, Rosen et al. (2008) used review of prior research to develop a conceptual model in which they describe men's experiences with Peyronie's disease, a condition which potentially impacts sexual functioning. Following, the model was refined through consultation with an expert panel. Lastly, the authors conducted group interviews with men diagnosed with Peyronie's disease and used these results to further refine the model. Nicol et al. (2009) implemented a modified grounded theory approach, in which data were compared with an existing theory. The authors depicted their findings related to healthcare worker hand hygiene compliance by adding a contextual component to a standard diagram of the theory of planned behavior, a widely used framework for explaining and predicting health behaviors.

Visualization is also often applied in works where place or relational space informs or is used as a lens for viewing research findings. Pearce and Louis (2008) chronicled, in text and supporting visuals, use of modified technological mapmaking techniques to "better express Indigenous cultural knowledge of natural resources" (p. 107) in Hawai'i. These authors demonstrated how visual depictions of attributes of importance to indigenous peoples could enhance conventional maps including movement of the sun and tides. Noy (2008) demonstrated human relational mapping by detailing relationships among individuals recruited for research participation through snowball (referral) sampling. Noy's depiction has dual advantages in informing findings and enhancing transparency.

Conversations as Temporal Events

Through our review of aims and examples of visualization applied to qualitative research results, we found few examples where visual methods were implemented during analysis to mold and contribute to presentation of outcomes. More often, data were first condensed, then used in summary form to inform visual outcomes. However, the conversations which comprise qualitative interviews are an important source of raw data in qualitative research that potentially yields rich content. The conversation itself is an integral part of how people experience the world and refine their own ideas. When describing how people understand the self and others, Mulhall (2007) observed: "humankind is a kind of enacted conversation" (p. 58).

Omojola (2016) and Omojola et al. (2018) provided examples of visualization applied to conversations as raw data. Omojola (2016) demonstrated use of pictorial symbols to categorize focus group interview responses in a research study describing internet use in Nigeria. The researcher used a set of symbols as proxies for the range of responses to items, which allowed for creation of a matrix of responses by participants. This visual display allows many readers to quickly recognize areas of agreement and contrast by noting the proportion of matching items in each row of symbols. Omojola et al. (2018) expanded on this approach through use of color hues and shades to show two dimensions: content and strength of opinion. Categories of item responses were associated with specific color hues and the shade, from darker to lighter, indicated strength of opinion. As with the symbol approach described in Omojola (2016), color-coded findings facilitate quick comparison by readers, although this specific approach may be less effective for readers who do not uniformly perceive color and/or experience some visual disabilities.

Despite the richness of content associated with conversational data, even those visualizations that are closer to the data, such as those provided in Omojola (2016) and Omojola et al. (2018), lack detail related to some aspects such as time and word frequency. By their nature, conversations are dynamic interactions in which participants make changes to their behaviors, speaking patterns, and cognition based on their conversational partners (Richardson et al., 2008). Many content-focused treatments of qualitative data are not concerned with the multitude of conversational aspects of a discussion such as the speed of speech, interruptions from another speaker, and pauses. When analyses are based on condensing data and extraction of key themes, the flow of original conversations is lost, and readers often do not see where certain topics were discussed within these temporal events. Use of the stream graph method described in this paper facilitates graphing of both thematic content and emotions over the course of a conversation.

The research study that inspired this current work was an interview project to evaluate public school teachers' perceptions of mental health programs and policies within their school. This project was approved by the institutional review board of the authors' institute of higher learning. For this paper, the first author developed a way to visualize qualitative themes throughout a conversation using the R software package "ggplot" in conjunction with the function "geom_stream" for creating stream graphs, which are stacked volume charts that show multiple categories of events increasing or decreasing over time (Byron & Wattenberg, 2008; Havre et al., 2002). This process can capture, in a single graph, the overall flow of a conversation and important qualitative themes throughout. Not only are the timings of themes present, but large volumes of words within a chart visually denote longer stories or discussions versus times when responses are quick, and themes are interspersed between interviewer questions. The method proposed here for visualizing data includes components important to visual processing such as meaningful colors. The human brain processes color and meaning in an image in a fraction of a second (Potter et al., 2014), highlighting the importance of using colors for helping readers understand a visual.

Researcher Context

The first author was inspired to explore mental health practices in public schools through discussions with a relative who is a teacher in a K-12 setting and exposure to her academic advisor's focus on mental health research and programming. The worked example was pilot research which informed the author's dissertation study. The second author was drawn to this work due to her interest in use of technology for various aspects of the processes of qualitative inquiry. She is particularly motivated to advocate for increased use of open access software such as R, due to capability and availability for lower resourced institutions and researchers.

Methods

The stream graph method described here can be reproduced using a combination of Microsoft Excel, a widely available software program, in conjunction with open access programs. For this project, we utilized R (R Core Team, 2021) and RStudio (Rstudio Team, 2020). The data for this project consisted of text interview transcripts of K-12 teachers who were interviewed for a mental health evaluation project in their school. The semi-structured interview guide contained questions meant to gather information about attitudes and perceptions of mental health resources in schools. During the interviews conducted by the first author, it became clear this topic elicited an emotional response from many teachers. Qualitative coding of interview data was informed by methods used in a study of emotions conducted by Denham and colleagues (2004) in which the authors asked questions such as "what emotions do [participants] show?" and "how often and intensely do they display them?" (p. 325). A detailed and stepwise description of the methods used follows.

1. **Conduct participant interviews.** Interviews were conducted during a short period of time toward the end of a school year, often on the last day of school, at a building when teachers had free time to pack up their belongings, organize their classrooms, and meet with coworkers without having to manage students and teach. All interviews were based on the same semi-structured prompt sheet, although interview questions were not asked in a strict order, allowing for a more natural flow of conversation when needed.
2. **Transcribe participant interviews.** This was done by the first author by listening to audio recordings and typing content into a Microsoft Word document.
3. **Divide the text in each transcribed interview into meaning units**. Chenail (2012) described qualitative units as undivided entities that contain the

important qualities of text a researcher intends to analyze. Following this guidance, the first author categorized segments of text as distinct meaning units based on changes in emotion, then pasted one meaning unit per line in Microsoft Excel.

4. **Calculate length of time for each meaning unit with start, stop and total time**. This was done for each speaker in turn. A sample of meaning units were rechecked to ensure timings were accurate.
5. **Count number of words per meaning unit** using an IF equation in Microsoft Excel which can be found in Appendix 2.
6. **Code each meaning unit.** The first author used principles of thematic analysis, (Braun & Clarke, 2006), and expanded on the emotion coding scheme developed by Denham et al. (2004) to develop 13 codes which described distinct emotions, plus additional codes for neutral and interviewer. Additional description and examples of code applications are provided in the results section. Each segment was associated with one of the emotion codes, neutral, or attributed to the interviewer.[1] During this process, some meaning units were subdivided into shorter segments. The final outcome of the coding processes described in steps 3 – 6 was creation of an Excel sheet that showed meaning unit start time and total time, emotion code, and word count for the segment.
7. **Excel automatically matched codes to one of the 13 emotions** with a VLOOKUP function that can be found in Appendix 2.
8. **Summarize the frequencies and volumes of emotions** by generating tables using the PivotTable function in Excel.
9. **Create stream graph** by importing the Excel sheet to RStudio (RStudio, 2021) with R (R Core Team, 2021) and generating a stream graph using the streamgraph package. Sample R code is shown in the Appendix.

Results

In this section we first provide example excerpts and detail about occurrence and prevalence for the 13 emotion codes. Following the code definitions, we present a detailed description of a single stream graph, which illustrates a representative example of emotions prevalent across the interviews. This section concludes with consideration of other factors including speech speed and word volume.

Table 1 shows emotion codes in reverse order of prevalence, based on number of words associated with each code. The percent of associated words as a proportion of all transcript text is also shown. The most prevalent emotion code was "disappointed," followed by "empathetic." The least expressed emotion was "tired."

[1] An additional code denoted interviewer speech, which was coded for time but not emotion with the aim of providing a more precise overview of the conversation flow. Specifically, this allows readers to discern between a single uninterrupted response and multiple short responses to different questions.

Table 1: Word Volume Analysis

Emotions	Sum of Word Volume	Percentage of Word Volume
Tired	19	0.10%
Apologetic	33	0.17%
Teacher Pride	40	0.21%
Sad	53	0.28%
Judgmental	250	1.33%
Satisfied	460	2.44%
Confused	683	3.62%
Hopeful	858	4.55%
Frustrated	866	4.59%
Creative	976	5.17%
Concerned	1211	6.42%
Empathetic	1265	6.71%
Disappointment	1449	7.68%
Neutral	4393	23.29%
Interviewer	6310	33.45%
Grand Total	**18866**	**100.00%**

Emotion: Disappointment

Examples of Disappointment

As noted previously, the most expressed emotion across all eight interviews was disappointment. In these interviews, teachers expressed disappointment in a lack of resources, leading to a lack of responsiveness. For instance, Teacher 7 said, "kids were flagged at some point, and nothing was done because there's no resources for it," referring to students being identified as needing a mental health intervention. Explaining the official referral process, Teacher 8 mentioned, "the negative about it is there's not always a follow-up on what's going on."

Teachers did not express disappointment with specific staff in the school, but several felt disappointed to be losing grant-funded mental health workers: "so it's very sad to know that mental health has gone up in schools and that we're getting rid of somebody who helped with that," according to Teacher 3. Disappointment mostly related to a lack of resources, where schools had no ability to hire additional staff to manage student issues.

Frequency of Disappointment

Each of the eight participating teachers expressed some level of disappointment; disappointment was often expressed throughout the interview in response to various questions about the current state of the school's mental health programs and policies. Interview 7 had the highest proportion of disappointment; this emotion code was applied to 13.17% of total word volume.

Emotion: Empathic and Concerned

Examples of Empathy and Concern

In the stream graph analysis of the data, the fourth and fifth most common emotions were empathy and concern. Concern, in the stream graph analysis, was coded as an empathetic type of emotion, following Denham et al. (2004) who considered these to be conceptually related. In these interviews, teachers expressed empathy by working to see reasons for student issues rather than blaming the student. For instance, Teacher 3 said, "I think there's a lot of male students who have difficult home lives and … their needs aren't always being met, so it's very hard for them to concentrate in school," and Teacher 5 shared a similar insight: "a lot of students bring challenges to school and just have trouble coping to have a normal day."

As an example of concern, Teacher 8 expressed general distress about students: "I think it's unhealthy in general for the students to just feel the pressure that I think we put on them on a daily basis." Teacher 4 discussed an assignment in which she asked students to write about something important that happened over the course of the year, and expressed concern as many students wrote about depression, anxiety or even "shocking" scenarios such as "parent conflict and yelling and police being called."

Frequency of Empathy and Concern

Not all interviews had both empathy and concern, although each of the eight interviews had at least one empathetic emotion. Empathetic emotions occurred at various points throughout the interviews. In the stream graphs, increases as word use show up as colored spikes; spikes in empathetic emotions often accompanied longer stories about student distress which were told in response to several interview questions. The interview with the highest word volume of empathetic emotions was Teacher 3, with a word volume that was 7.24% concerned and 21.31% empathetic.

Emotion: Creativity

Examples of Creativity

One interview guide item directed interviewees to describe what they might do with unlimited funding to improve mental health for students in their school. This elicited many novel ideas and examples of language coded as creativity. A common suggestion among teachers was that schools needed more human resources; this reflected recent changes in funding and diminishment of available resources. One more creative idea offered by multiple participants was the need for unstructured free time for students to process their day, socialize with each other and talk to the teacher.

Teacher 5 mentioned, "Well, this is like very idealistic, [but with wraparound services] social workers were working around that and just giving tools to better motivate and provide positive support to their students, not through direct academic help." Teacher 3 mentioned a desire for a "program that comes through the social studies class and can really help kids get coping mechanisms to deal with [issues]." Peer groups was an idea generated by Teacher 1: "A peer … who's been through it, who knows how to navigate the situation or can give them advice. I really think that kids would benefit from that."

Frequency of Creativity

Teachers used creative language in each of the interviews. Creativity had the sixth-highest word volume overall. Creativity often appeared in interviews around the 500- to 600-second mark, and Interview 1 contained the most creative words, comprising nearly 12% of total word volume.

Other Emotions

Beyond the most common emotions, several other less frequent emotions appeared throughout interviews. One notable example is judgment, in which teachers sometimes described situations and judged students for factors seemingly beyond their control. Teacher 2 related a story of a student who often slept in class, and stated, "none of us allow that. And so, he's had to stand in the classroom." However, this was a rare example. Most of the interview text is empathetic toward students.

Another less frequent emotion was teacher pride, in which teachers expressed confidence that they knew their students best. Teacher 1 said mental health trainings for teachers would be helpful because, "we're the ones with the kids all the time. We're with them 100 percent of the time, so we know them best." This was another rarely coded emotion; more often, teachers expressed feelings of helplessness when dealing with students, which presented as frustration, concern, disappointment, and sadness.

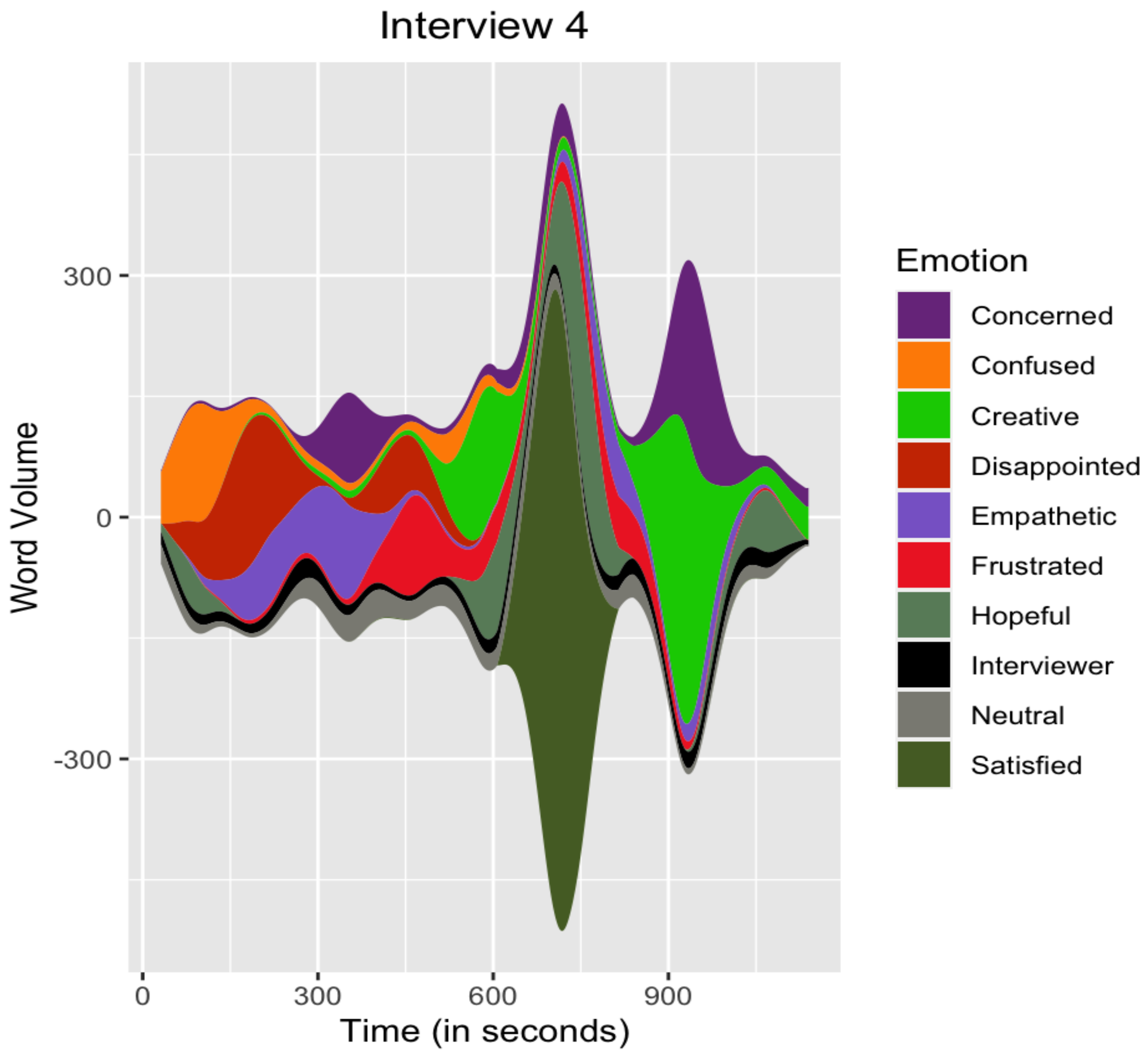
Apologies and confusion occurred rarely during interviews and were coded when teachers said something such as, "I apologize [for] not knowing a hundred percent" (Teacher 3) when unsure of the full details of a program at their school. Some interviewer questions led to teachers asking for clarification, such as: "Like a protocol, or how I would go about handling that?" (Teacher 5), or sometimes from not having a full understanding of the answer, such as, "I don't really know too much what happens after we've kind of sent them to their … counselor" (Teacher 4).

Sadness, feeling hopeful, and feeling tired are the remaining emotions, and each occurred less frequently than those discussed in detail. Another notably infrequent emotion was satisfaction, which comprised less than three percent of total word volume. Many questions asked teachers to describe current processes, programs and staff used to promote students' mental wellness, and few teachers felt programs were sufficient. Teacher 4 described a new mediation initiative with satisfaction: "I thought that they [the exercises] were really helpful," although overall, she noted that the school needs more staff, as, "it's a daily occurrence that there's someone coming to me with like, 'Can I see the guidance counselor? … I need to talk to someone about this.'"

Figure 1 shows Interview 4, described here in detail. The remaining seven stream graphs are shown in the appendix. Each stream graph is unique and provides a visual expression of the overall character of the interview. For each graph, the x axis shows word volume, and the y axis shows time in seconds. The key shows the color associated with each emotion code, as well as neutral (gray) and interviewer-contributed content (black). The first author chose color groups according to emotion types, such as reds for negative emotions and greens for positive emotions. Related emotions, such as the empathetic emotions, are reflected by different shades of the same hue.

Stream Graphs

Figure 1: Interview 4



The conversation with Teacher 4 began with regular alternating turns by interviewer and participant; in most instances participant responses are longer compared to interviewer turns. The participant provided primarily neutral responses in the first third of the interview, supplemented by brief expressions of confusion, indicated by the orange portions, as well as frustration, shown in red. As the interview progressed, empathetic emotions, indicated by purple hues, begin to appear, along with positive type emotions, shown in green. Roughly three quarters of the way through, the participant began to express frustration (indicated by brighter red) but concluded with a return to an empathic emotion (concern, purple).

This stream graph depicts both flow of emotions over the course of the interview and accompanying spikes in word volume. Spikes typically indicate long, uninterrupted periods of time in which the participant relayed a story to highlight their point. For instance, the large spike in green (satisfaction) which occurs between just before 600 seconds, is a description of a teacher's thoughts on meeting more frequently with her coworkers, and how the teacher anticipates they will be able to discuss student concerns more regularly with more time set aside for staff to meet before school.

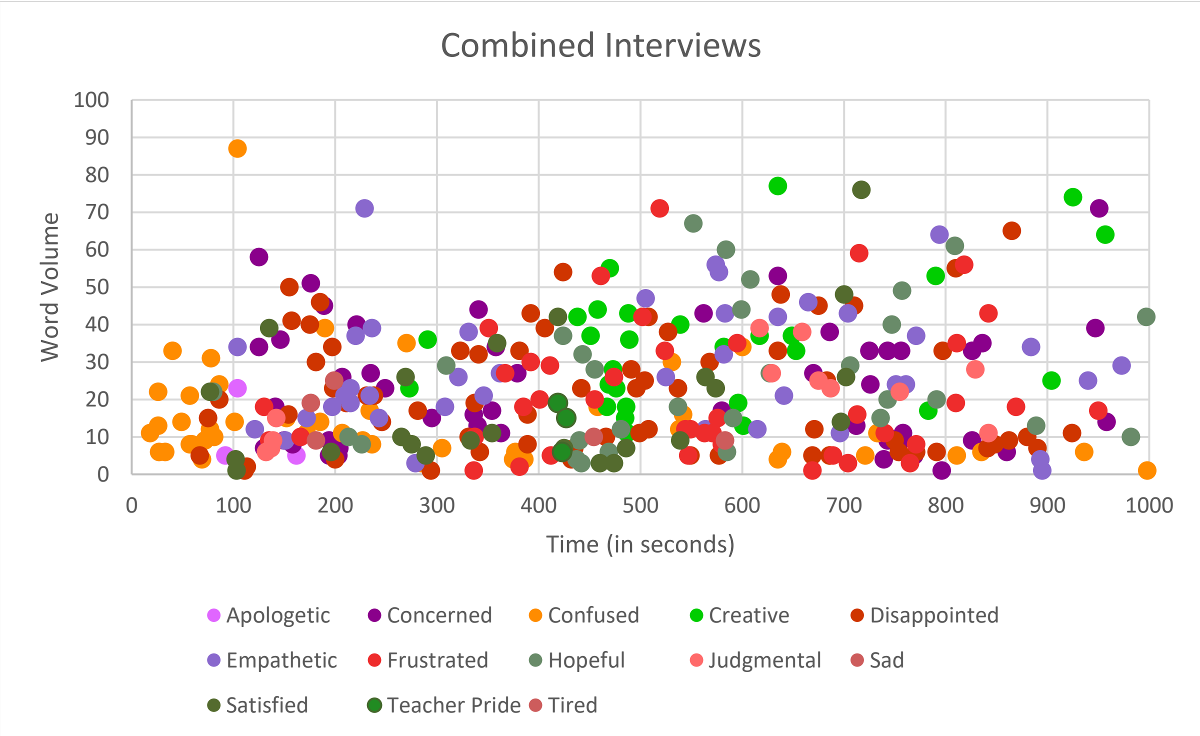
Speech Speed and Word Volume

When listening to interview recordings while coding and transcribing, the first author noticed the speed of speech varied with different teachers and responses. For example, when Teacher 8 was asked to describe the biggest issues facing students, the response consists of 47 words but takes a full 34 seconds, a rate of 83 words per minute. This is because Teacher 8 spoke slowly and paused several times to consider this response. By contrast, the same teacher provided a description of everyday problems facing students earlier in the interview, at 33 words over 18 seconds, or a rate of 113 words per minute.

Emotions over Time

To depict the emotional flow of the group of interviews, all interview active emotion timings (not including neutral or interviewer contributions) were combined into a single dot plot (Figure 2), created by a process of copying and pasting all emotions with their time stamps and word volumes into three columns, then using the Excel scatterplot function to generate a chart with one dot representing one emotion plotted at its time of occurrence in the conversation on the x axis and its word volume on the y axis. Many questions were associated with patterns of negative emotions or empathetic emotions. Additionally, confusion commonly occurs early in interviews, but less frequently otherwise.

Figure 2: Combined Interview Emotions



Discussion

In this "how to" paper, we have illustrated a novel visualization process through description and examples. This method, similar to the work of Omojola et al. (2018), relies on color but produces a visual image which incorporates the dynamic aspect of time along with coded information. These stream graphs combine aspects of re-presentation of data with interpretation to inform a visually compelling display. The graphs show ebb and flow of conversation in terms of interviewer-participant balance, emotional range, and length of responses, provide additional insight into the character of the data, enhance transparency of data analysis processes, and add an aesthetically appealing component to a research report.

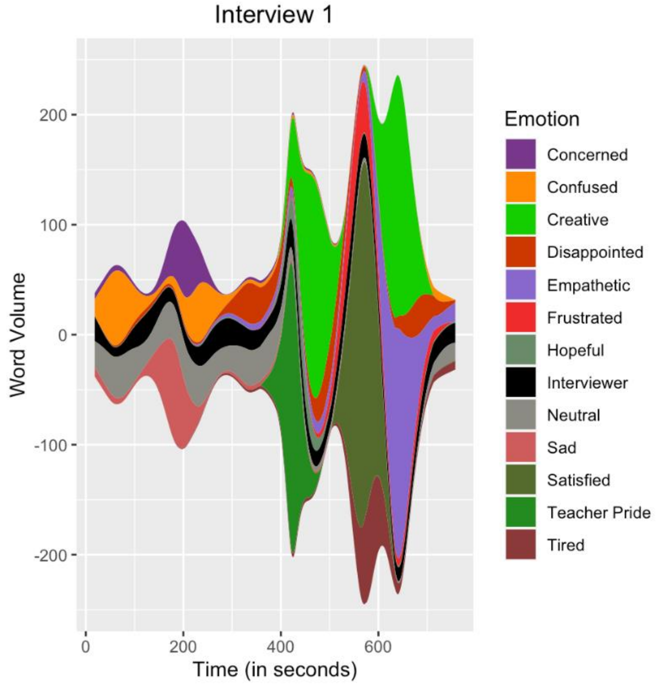
Along with providing a new alternative for visual display of qualitative data, the stream graph process might also provide researchers with insights during research study. The flow of emotions over an interview may be a proxy indicator of the level of familiarity or comfort between participant and interviewer. Often in this group of interviews, the early portion emphasizes informational (neutral) conveyances of data, and a greater range of emotions and higher volume responses occur later in the interview. Stream graphs of pilot interviews might provide researchers with additional insight about content, order, and pacing of guide items. Abundance of confusion may indicate the need to revise guide items. Speed of speech might indicate the need for additional effort or consideration or illustrate fatigue. Patterns across multiple interviews related to speed and length of responses might also point to the need for overall revision in the interview guide. Note that comparative use of stream graphs presume interview guide items are presented in identical order across the series of interviews.

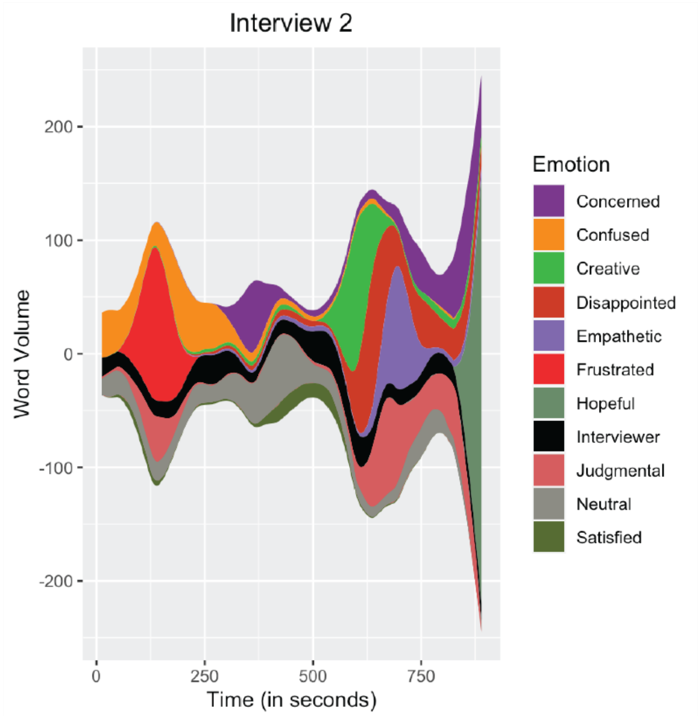
Stream graphs might additionally serve as a quick method to prompt recall and the ability to distinguish among the content or tone of a given participant interview. For example, in this series of interviews, Interview 2 had fewer words and fewer empathetic expressions when compared to the others. Interview 8, by contrast, had many more “red” emotions throughout, evidencing the participant’s enhanced level of disappointment and frustration.

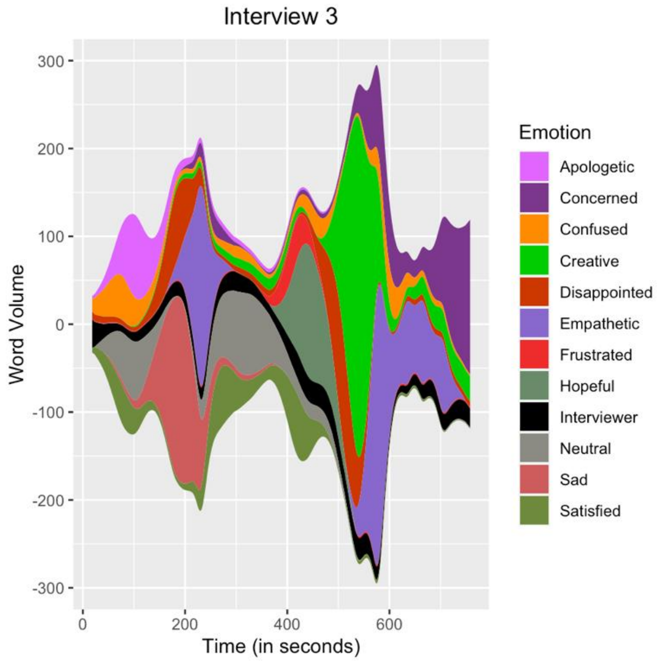
As with many technology-reliant processes, there are challenges associated with the creation of stream graphs. One of these is the need to efficiently associate timestamps with meaning units. For this project, a mobile phone app called Ultimate StopWatch (v. 2.7.0) for counting laps for athletes ended up being an ideal solution. This app compiles data line-by-line and allows for export into a comma separated values (CSV) file, which can be read by Microsoft Excel. Some specialized transcription software programs (e.g., Express Scribe; F4 or F5 Transcribe) may allow flexible application and export of time stamps, although these applications were not explored for this current study since transcription was completed in Microsoft Word. Another challenge is the lack of accessibility of color-based displays for persons who perceive color differently, including those who are colorblind. Use of black and white or grayscale patterns for stream fill may provide a partial solution in some contexts.

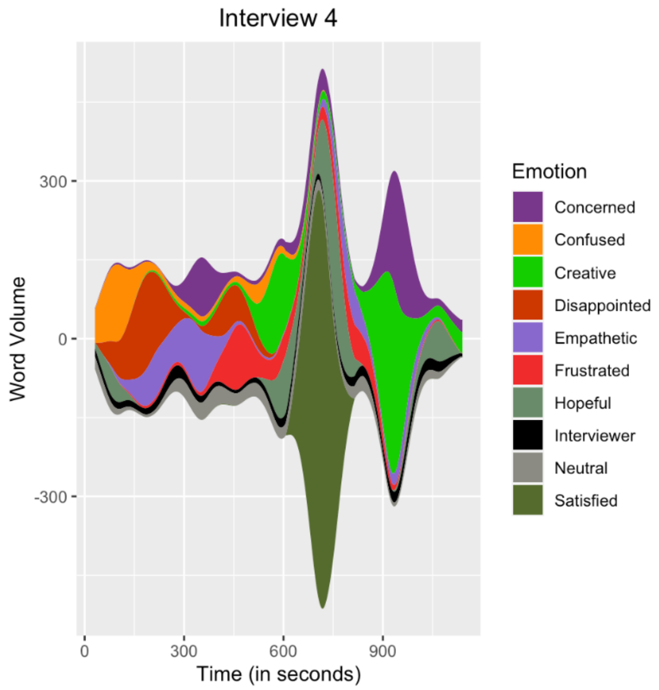
With practice, the data processing required to produce stream graphs can be completed with roughly the same amount of time and effort put toward creation of a standard text transcript. Although emotion-based codes were used in this study, stream graphs can be produced based on other aspects of content, delivery, or other attributes of interest in a research study. For example, if a participant alternates between past, present, and future activities, these three time points might comprise the codes of interest and be associated with contrasting hues. This process as described will create useful, comparable displays if data from most participants exemplifies multiple codes; otherwise, researchers are encouraged to be flexible and creative in their application of this technique. Given the increasing amount of data that many individuals encounter in their daily lives, supplementing research with engaging and meaningful visual displays is a method to potentially enhance understanding and increase the impact of your research.

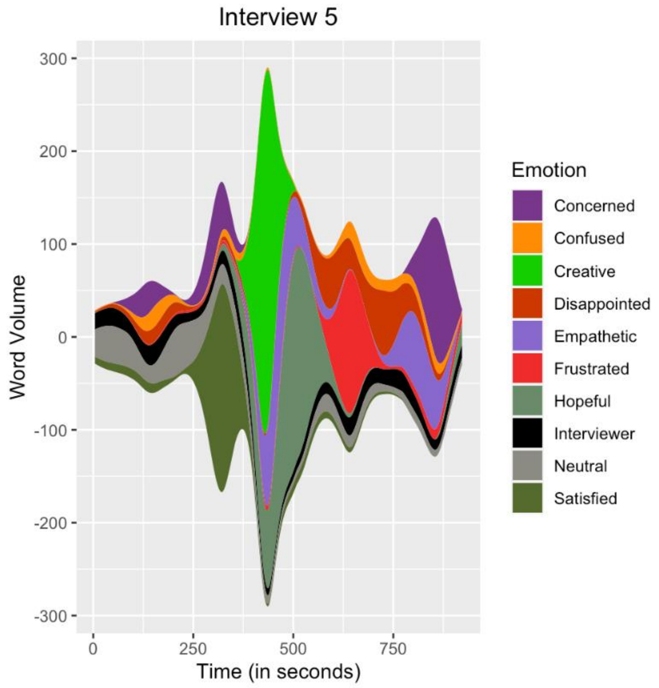
Appendix 1: Graphs

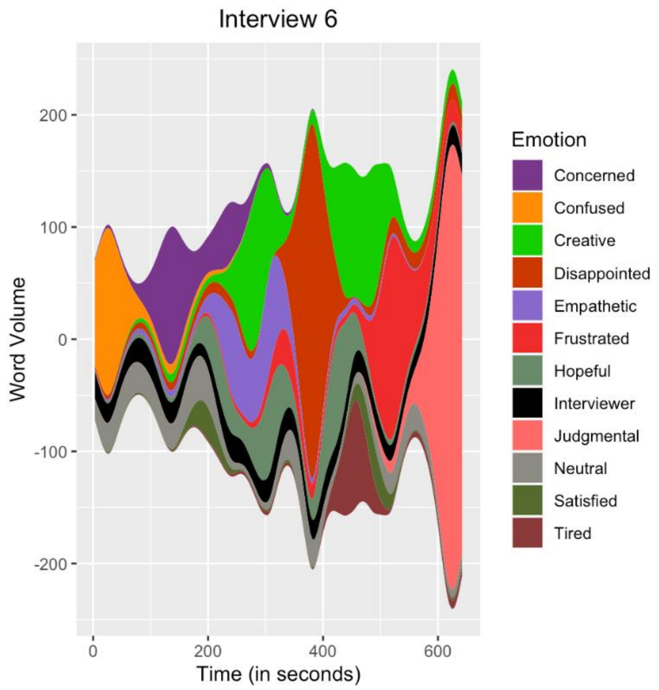




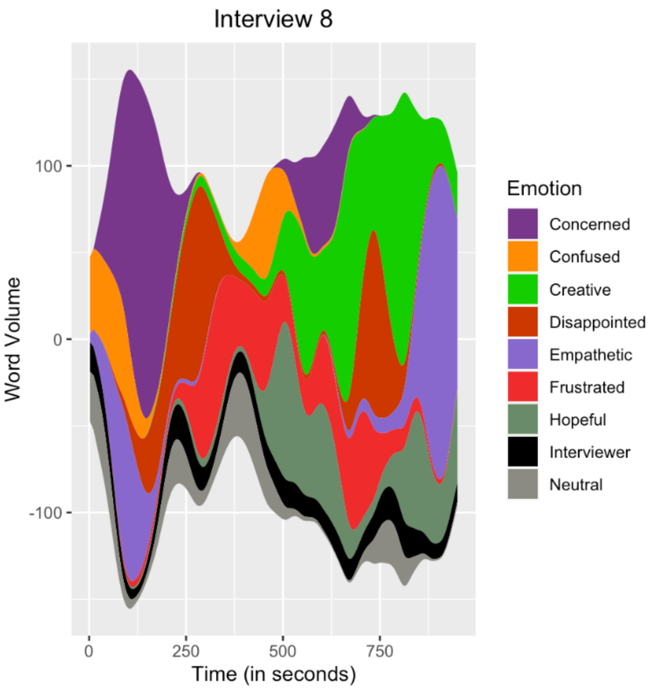

Interview 3
300
200
100
0
-100
-200
-300
Word Volume
0
200
400
600
Time (in seconds)
Emotion
Apologetic
Concerned
Confused
Creative
Disappointed
Empathetic
Frustrated
Hopeful
Interviewer
Neutral
Sad
Satisfied


Interview 4
300
0
-300
Word Volume
0
300
600
900
Time (in seconds)
Emotion
Concerned
Confused
Creative
Disappointed
Empathetic
Frustrated
Hopeful
Interviewer
Neutral
Satisfied


Interview 5
300
200
100
0
-100
-200
-300
Word Volume
0
250
500
750
Time (in seconds)
Emotion
Concerned
Confused
Creative
Disappointed
Empathetic
Frustrated
Hopeful
Interviewer
Neutral
Satisfied


Interview 6
200
100
0
-100
-200
Word Volume
0
200
400
600
Time (in seconds)
Emotion
Concerned
Confused
Creative
Disappointed
Empathetic
Frustrated
Hopeful
Interviewer
Judgmental
Neutral
Satisfied
Tired


Interview 7
Word Volume
200
100
0
-100
-200
0
200
400
600
800
Time (in seconds)
Emotion
Concerned
Confused
Creative
Disappointed
Empathetic
Frustrated
Hopeful
Interviewer
Neutral
Satisfied


Interview 8
Word Volume
100
0
-100
0
250
500
750
Time (in seconds)
Emotion
Concerned
Confused
Creative
Disappointed
Empathetic
Frustrated
Hopeful
Interviewer
Neutral

Appendix 2: Excel Equations and R Code

Excel		
Purpose	**Base Functions**	**Equation Example**
Count the number of words in a meaning unit.	LEN, TRIM and SUBSTITUTE	=IF(LEN(TRIM(A1))=0,0,LEN(TRIM(A1))-LEN(SUBSTITUTE(A1," ",""))+1)
Apply one of 12 emotions codes to a meaning unit.	VLOOKUP	=VLOOKUP([@[MeaningCode]],TableName[#All],2,FALSE).

R		
Purpose	**Base Functions**	**Code Example**
Load required packages.	if, install, pacman and p_load	if (!require("pacman")) install.packages("pacman") pacman::p_load(datasets, pacman, rio, tidyverse, ggplot2, RColorBrewer, ggstream)
Import data.	read	dat <- read.csv("file name.csv")
Create a stream graph.	ggplot and geom_stream	ggplot(data=dat,aes(time,word_volume, fill = emotion)) + geom_stream()

References

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Byron, L., & Wattenberg, M. (2008). Stacked graphs–geometry & aesthetics. *IEEE Transactions on Visualization and Computer Graphics, 14*(6), 1245–1252. https://doi.org/10.1109/TVCG.2008.166

Chenail, R. J. (2012). Conducting qualitative data analysis: Reading line-by-line, but analyzing by meaningful qualitative units. *Th Qualitative Report, 17*(1), 266–269. https://doi.org/10.46743/2160-3715/2012.1817

Denham, S., Caal, S., Bassett, H. H., Benga, O., & Geangu, E. (2004). Listening to parents: Cultural variations in the meaning of emotions and emotion socialization. *Cogniţie Creier Comportament, 8*(3–4), 321–349.

Dunlap, J. C., & Lowenthal, P. R. (2016). Getting graphic about infographics: Design lessons learned from popular infographics. *Journal of Visual Literacy, 35*(1), 42–59. https://doi.org/10.1080/1051144X.2016.1205832

Friendly, M. (2008). A brief history of data visualization. In C. Chen, W. Härdle, & A. Unwin (Eds.), *Handbook of data visualization* (pp. 15–56). Springer. https://doi.org/10.1007/978-3-540-33037-0_2

Havre, S., Hetzler, E., Whitney, P., & Nowell, L. (2002). Themeriver: Visualizing thematic changes in large document collections. *IEEE Transactions on Visualization and Computer Graphics, 8*(1), 9–20. https://doi.org/10.1109/2945.981848

Hundt, G. L., Byrnston C., Lowe, P., Cross, S., Sandall, J., & Spencer, K. (2010). Inside 'Inside View': Reflections on stimulating debate and engagement through a multimedia live theater production on the dilemmas and issues of pre-natal screening policy and practice. *Health Expectations, 14*(1), 1-9. https://doi.org/10.1111/j.1369-

7625.2010.00597.x

Lapum, J. L., Church, K., Yau, T. M., David, A. M., & Ruttonsha, P. (2012). Arts-informed research dissemination: Patients' perioperative experiences of open-heart surgery. *Heart & Lung, 41*(5), e4-e14. https://doi.org/10.1016/j.hrtlng.2012.04.012

Lamb, G. R., Polman, J. L., Newman, A., & Smith, C. G. (2014). Science news infographics: Teaching students to gather, interpret, and present information graphically. *The Science Teacher, 81*(3), 25. https://www.nsta.org/science-teacher#tab

Leavy, P. (2010) Poetic bodies: Female body image, sexual identity and arts-based research. *LEARNing Landscapes*, *4*(1), 175-187. https://doi.org/10.36510.learnland.v4i1.370

Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: An expanded sourcebook* (2nd ed., pp. xiv, 338). SAGE.

Miles, M. B., Huberman, A. M., & Saldaña, J. (2015). *Qualitative data analysis: A methods sourcebook* (3rd ed.). SAGE.

Mulhall, S. (2007). *The conversation of humanity*. University of Virginia Press.

Nicol, P. W., Watkins, R. E., Donovan, R. J., Wynaden, D., & Cadwallader, H. (2009). The power of vivid experience in hand hygiene compliance. *Journal of Hospital Infection, 72*(1), 36-42. https://doi.10.1016/j.jhin.2009.01.021

Noy, C. (2008). Sampling knowledge: The hermeneutics of snowball sampling in qualitative research. *International Journal of Social Research Methodology, 11*(4), 327-344. https://doi.org/10.1080/13645570701401305.

Omojola, O. (2016). Using symbols and shapes for analysis in small focus group research. *The Qualitative Report, 21*(5), 834-847. https://doi.org/10.46743/2160-3715/2016.2388.

Omojola, O., Odiboh, O., & Amodu, L. (2018). Opinions as colors: A visual analysis technique for modest focus group transcripts. *The Qualitative Report, 23*(8), 2019-2035. https://doi.org/10.46743/2160-3715/2018.3349

Patel, Z., Patel, C., Oreper, J., Patel, H., & Sajedeen, A. (2020). Healthcare professionals' perceptions of infographics within medical information response letters. *Therapeutic Innovation & Regulatory Science, 54*(6), 1382–1387. https://doi.org/10.1007/s43441-020-00164-w

Pearce, M. W., & Louis, R. P. (2008). Mapping indigenous depth of place. *American Indian Culture and Research, 32*(3), 107-126. https://doi.org/10.17953/aicr.32.3.n7g22w816486567j

Peters, E., Dieckmann, N., Dixon, A., Hibbard, J. H., & Mertz, C. K. (2007). Less is more in presenting quality information to consumers. *Medical Care Research and Review, 64*(2), 169–190. https://doi.org/10.1177/10775587070640020301

Peters, E., Hibbard, J., Slovic, P., & Dieckmann, N. (2007). Numeracy skill and the communication, comprehension, and use of risk-benefit information. *Health Affairs, 26*(3), 741–748. https://doi.org/10.1377/hlthaff.26.3.741

Potter, M. C., Wyble, B., Hagmann, C. E., & McCourt, E. S. (2014). Detecting meaning in RSVP at 13 ms per picture. *Attention, Perception, & Psychophysics, 76*(2), 270–279. https://doi.org/10.3758/s13414-013-0605-z

Richardson, D., Dale, R., & Shockley, K. (2008). Synchrony and swing in conversation: Coordination, temporal dynamics, and communication. In: *Embodied communication in humans and machines* (pp. 75–94). Oxford University.

R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Rose, G. (2014). On the relation between 'visual research methods' and contemporary visual culture. *The Sociological Review, 62*(1), 24–46. https://doi.org/10.1111/1467-954X.12109

Rosen, R., Catania, J., Lue, T., Althof, S., Henne, J., Hellstrom, W., & Levine, L. (2008).

Impact of Peyronie's disease on sexual and psychosocial functioning: Qualitative findings in patients and controls. *Journal of Sexual Medicine, 5*(8), 1977-1985. https://doi.org/10.1111/j.1743-6109.2008.00883.x

RStudio Team. (2020). *RStudio: Integrated development for R*. RStudio, PBC, Boston, MA. http://www.rstudio.com/

Saldaña, J., & Omasta, M. (2018). *Qualitative research analyzing life.* SAGE.

Scagnoli, N., & Verdinelli, S. (2017). Editors' perspective on the use of visual displays in qualitative studies. *The Qualitative Report, 22*(7), 1945–1963. https://doi.org/10.46743/2160-3715/2017.2202

Verdinelli, S., & Scagnoli, N.I. (2013). Data display in qualitative research. *International Journal of Qualitative Methods, 12*(1), 359-381. https://doi.org/10.1177/160940691301200117

Yarbrough, J. R. (2019). Infographics: In support of online visual learning. *Academy of Educational Leadership Journal, 23*(2), 15. https://www.abacademies.org/journals/month-august-year-2019-vol-23-issue-2-journal-aelj-past-issue.html

Author Note

Emily S. Nelson is a postdoctoral scholar at Case Western Reserve University. She received her PhD from Kent State University. Her research goals are to improve the readability and comprehension of data through visualizations and to more equitably include underrepresented voices in health research. Her research interests include education, mental health, and community health. Please direct correspondence to: emilynelson515@gmail.com.

Sheryl L. Chatfield is associate professor of public health at Kent State University and the co-coordinator of the Kent State graduate certificate in qualitative research. She received her PhD from the University of Mississippi and concurrently completed the graduate certificate in qualitative research at Nova Southeastern University. Dr. Chatfield is very interested in use of visual expressions to share results from qualitative and mixed methods research. Please direct correspondence to: schatfi1@kent.edu.

Article Citation

Nelson, E. S., & Chatfield, S. L. (2022). A conversation in time: A new concept for creating stream graphs for qualitative data visualizations. *The Qualitative Report, 27*(11), 2605-2622. https://doi.org/10.46743/2160-3715/2022.5713