Computational Thematic Analysis of Online Communities

by

Robert P. Gauthier

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Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner:	Shion Guha, Ph.D. Assistant Professor, Faculty of Information, University of Toronto
Supervisor:	James R. Wallace, Ph.D. Associate Professor, School of Public Health Sciences, University of Waterloo
Internal Member:	Samantha Meyer, Ph.D. Associate Professor, School of Public Health Sciences, University of Waterloo
Internal Member:	Mary Jean Costello, Ph.D. Research and Evaluation Scientist, Homewood Research Institute Adjunct Appointment, School of Public Health Sciences, University of Waterloo
Internal-External Member:	Daniel Harley, Ph.D. Assistant Professor, Stratford School of Interaction Design and Business, University of Waterloo

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The remainder of this statement identifies the published and submitted papers on which I was the first author that make up my Chapter 2, Chapter 3, and Chapter 4 and declares the contributions made by both myself and my co-authors.

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Contributor	Conceptualization	Methodology	Software	Validation	Formal analysis	Investigation	Resources	Data Curation	Writing - Original Draft	Writing - Review & Editing	Visualization	Supervision	Project administration	Funding acquisition
Robert P. Gauthier	●	●	●	●	●	●	●	●	●	●	●			
Mary Jean Costello	●			●						●				
James R. Wallace	●	●		●			●			●		●	●	●

CRediT author statement 1. Contributors to the paper presented in Chapter 2.

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Contributor	Conceptualization	Methodology	Software	Validation	Formal analysis	Investigation	Resources	Data Curation	Writing - Original Draft	Writing - Review & Editing	Visualization	Supervision	Project administration	Funding acquisition
Robert P. Gauthier	●	●	●	●	●	●	●	●	●	●	●			●
James R. Wallace	●	●		●			●			●		●	●	●

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Contributor	Conceptualization	Methodology	Software	Validation	Formal analysis	Investigation	Resources	Data Curation	Writing - Original Draft	Writing - Review & Editing	Visualization	Supervision	Project administration	Funding acquisition
Robert P. Gauthier	●	●	●	●	●	●	●	●	●	●	●			●
Catherine Pelletier				●	●					●				
Laurie-Ann Carrier				●	●					●				
Maude Dionne				●	●					●		●		
Ève Dubé	●	●		●	●		●	●		●		●	●	●
Samantha Meyer	●	●					●	●		●			●	●
James R. Wallace	●	●	●				●		●	●	●	●	●	●

CRediT author statement 3. Contributors to the paper presented in Chapter 4.

Abstract

Public health researchers can use thematic analysis to develop human understandings of health topics from the lived experiences discussed in online communities. However, thematic analyses of online communities are difficult to conduct because large data sets amplify the resource intensity and complexity of the common phases: Data Collection, Data Familiarization, Coding, and Theme Review. Researchers can manage this amplification by integrating computational techniques that facilitate scalable interaction with large data sets when they converge with tasks completed during a thematic analysis.

My thesis' research explored barriers to integrating computational techniques into thematic analysis through three research questions: RQ1. Could computational techniques be used within a thematic analysis to assist with the analysis of online communities' data? RQ2. How might tools be developed to not require programming expertise when integrating computational techniques as part of thematic analysis tasks? RQ3. How does a computational thematic analysis that integrates computational techniques compare with a traditional manual thematic analysis? To address these questions, I used a three-staged approach where I first piloted integrating techniques in a thematic analysis of addiction recovery. I then designed artifacts based on my pilot experience that allow qualitative researchers without programming expertise to integrate techniques. Finally, I deployed my artifacts with public health researchers to explore integration's impact on their real-world thematic analyses.

During my Pilot Stage, I conducted a topic-guided thematic analysis of two Reddit addiction recovery communities. Performing this analysis contributed a demonstration of integrating Latent Dirichlet Allocation topic modelling, a computational technique, to guide my reflexive thematic analysis by sampling interesting places in online discussion data sets for coding. Additionally, I discussed how integration benefited my data familiarization by facilitating the identification of patterns while being limited due to balancing metric optimization with interpretive usefulness when creating topic models.

In my Design Stage, I created my Computational Thematic Analysis Workflow and Computational Thematic Analysis Toolkit to build upon my pilot stage experiences and support qualitative researchers. My workflow provides researchers with guidance on planning a reflexive thematic analysis of online communities that integrates computational techniques. Similarly, my toolkit supports qualitative researchers by implementing computational techniques as reusable tools in a graphic user interface that integrates into thematic analyses without requiring programmer expertise.

My Deploy Stage investigated the impact of integrating computational techniques by collaborating with public health researchers studying COVID-19 news article comments.

The researchers independently performed two inductive thematic analyses, one of which used my Computational Thematic Analysis Toolkit. I then work with the researchers to compare their processes and results. From this comparison, I identified that integrating computational techniques to facilitate multiple data interactions aided the analysis by enabling different interpretations. Additionally, despite both analyses developing a convergent set of themes, computational technique integration had subtle influences leading to divergent analysis processes and coding approaches.

The contributions from my three stages have collective implications for qualitative research, human-computer interaction, and public health. My work provides qualitative researchers with demonstrations and tools that support integrating computational techniques to research online communities. My research created a base workflow and toolkit that human-computer interaction practitioners can support and extend to facilitate the integration of computational techniques into qualitative methods. Additionally, I addressed calls in human-computer interaction research to include qualitative perspectives in work that impacts qualitative researchers. Finally, public health researchers can use my guidance and toolkit to manage the amplification of resource intensity and complexity to perform thematic analyses on the lived experiences discussed in online communities. As researchers identify online communities' perspectives on new and existing health issues, they can develop health interventions that impact people represented by online communities.

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Chapter 1

Introduction

Online communities, such as those on Reddit, are places where people make discussions of lived experiences a part of their everyday lives. Public health researchers can access and explore online communities to identify different perspectives, challenges, and potential interventions (Eysenbach, 2005; Heldman et al., 2013) for both health topics, such as addiction recovery (Gauthier et al., 2022), and determinants of health, such as parenting (Ammari et al., 2018). In addition, public health researchers can study online communities' discussions for alternative perspectives on issues, such as vaccination (Rotolo et al., 2022) and Lyme disease (Mankoff et al., 2011), to learn the language and norms needed to interact with communities outside the current public health system (Heldman et al., 2013).

Public health researchers can use thematic analysis to explore online communities because it excels in complex areas involving lived experiences (Braun and Clarke, 2006). Thematic analysis is a flexible qualitative research method used to develop, analyze, and report qualitative themes from data (Boyatzis, 1998; Braun and Clarke, 2006). At the same time, thematic analysis is complex because researchers need to consider and customize multiple flexible guidelines based on the research's context (Aronson, 1995; Boyatzis, 1998; Braun et al., 2019). Similarly, thematic analysis is resource-intensive due to involving iterative cycles of reading and interpreting data (Boyatzis, 1998; Braun and Clarke, 2006). Consequently, the scale of online communities' data amplifies thematic analysis' complexity and resource intensity beyond researchers' capacity making it difficult to perform (Braun and Clarke, 2006; D'Agostino et al., 2017).

Qualitative researchers can manage this amplified complexity and resource intensity by integrating computational techniques that facilitate interaction with data and converge with thematic analysis tasks. Data science researchers have analyzed large data sets by applying computational techniques to process data into human digestible chunks, such as using natural language processing and topic modelling to interpret word patterns and discussion topics (Ammari et al., 2018; Maier et al., 2018). Furthermore, human-computer interaction researchers have begun exploring how applying computational techniques can converge with qualitative methods' tasks, such as topic model interpretation aligning with grounded theory's open coding (Baumer et al., 2017; Muller et al., 2016).

However, three barriers prevent qualitative researchers from simply integrating computational techniques into their thematic analyses. (1) Technique integration has not been described for thematic analysis contexts, as benefits and limitations need to include qualitative perspectives (Baden et al., 2021; Chen et al., 2018). (2) Integrating techniques historically requires expertise with programming languages, such as Python or R, making implementation difficult (McCallum, 2002; Rehurek and Sojka, 2010). (3) Techniques traditionally have post-positivist origins, focus on uncertainty reduction, and quantitative metrics making integration's impact on thematic analysis processes and results unknown and concerning (Jiang et al., 2021).

My thesis explores this integration and its barriers by conducting a three-staged approach of PILOT, DESIGN, and DEPLOY situated in public health research. First, I conducted my PILOT STAGE where I performed a thematic analysis of two online addiction recovery communities guided by computational techniques. Second, I ran my DESIGN STAGE where I implemented the Computational Thematic Analysis Toolkit (CTA Toolkit) to facilitate non-programmers' integration of computational techniques. Finally, I performed my DEPLOY STAGE by collaborating with qualitative researchers to compare two independent thematic analyses of COVID-19 news articles' online comments, one using my CTA Toolkit and the other using a manual approach. During this stage, I discussed the impact of integrating computational techniques on thematic analysis processes and results.

1.1 Positionality Statement

I based my thesis on my experiences at the intersection of human-computer interaction (HCI), qualitative research, and public health. I completed a Master of Science at the University of Guelph in the School of Computer Science and worked for several years as a software developer. During this time, I was taught about HCI, developed programming skills, and learned the value of including the perspective of domain experts. I then joined the University of Waterloo's School of Public Health Science to complete a Doctorate of Philosophy. During my Doctorate, I took courses and provided teaching assistant support that increased my knowledge and experience with public health research, qualitative methods, health informatics, and HCI applications of computational methods. These experiences developed the skills I used to critically reflect on integrating computational techniques and implement my toolkit from HCI, Qualitative, and Public Health perspectives.

Similarly, my experience with this combination of fields led to my thesis' focus on reflexive thematic analysis. Thematic analysis is a commonly referenced qualitative method in HCI research. Additionally, I liked that thematic analysis can provide a voice to communities impacted by public health issues, such as people suffering from addiction, who I want HCI research to treat as more than just data points for quantification.

Additionally, I combined my pragmatic worldview with my experience to choose to include researchers supported by my work. In my Pilot Stage I collaborated with an addiction recovery researcher, who provided real-world feedback on whether my themes aligned aspects of addiction recovery journeys. Similarly, I collaborated with multiple qualitative vaccine hesitancy researchers with experience performing thematic analyses for my Deploy Stage. Their perspectives provided a foundation for comparing analysis processes and results to identify real-world integration impacts. Including public health researcher perspectives in these stages encouraged my thesis' focus on supporting qualitative researchers.

1.2 Thesis Statement

By following a Pilot, Design, and Deploy approach situated in public health research, my thesis bridges Human-Computer Interaction (HCI), Qualitative Methodology, and Public Health to study integrating computational techniques into thematic analysis of online communities. My stages' results defends the following statement:

> *Qualitative researchers performing thematic analyses of online communities can make use of computational techniques to help manage the complexity and resource-intensity of analyzing large data sets.*

In support of this statement, my thesis focuses on three research questions that explore barriers that make integrating computational techniques into thematic analysis of online communities difficult:

RQ1. Could computational techniques be used within a thematic analysis to assist with the analysis of online communities' data?

RQ2. How might tools be developed to not require programming expertise when integrating computational techniques as part of thematic analysis tasks?

RQ3. How does a computational thematic analysis that integrates computational techniques compare with a traditional manual thematic analysis?

1.3 Research Contributions

My thesis contributes demonstrations, discussions, and artifacts that support integrating computational techniques into thematic analyses of online communities. Table 1.1 and this section summarizes how my three stages' contributions align with my three research questions (RQ1-3).

RQ1. Could computational techniques be used within a thematic analysis to assist with the analysis of online communities' data?

During my PILOT STAGE, Chapter 2, I conducted a topic-guided thematic analysis of Reddit addiction recovery communities. In this work I repurposed Ammari et al. (2018)'s use of Latent Dirichlet Allocation (LDA) topic modelling (Blei et al., 2003) as a tool to help me locate sample discussions that guided my reflexive thematic analysis (Braun and Clarke, 2006). My approach was inspired by both exploratory mixed methods (Creswell and Plano Clark, 2018) and purposive sampling (Hoeber et al., 2017) in that the modelling activity occurred first as a separate step and focused on located samples of interesting data for the thematic analysis.

By conducting this stage, I described how integrating LDA topic modelling to perform purposive sampling helped guide my analysis by locating useful samples from across subreddits' large data sets that discussed lived addiction recovery experiences. I also discussed the benefit of identifying insightful hints as I conducted the LDA topic modelling, such as the support acronym IWNDWYT, that primed my thematic analysis by familiarizing myself with the data. Additionally, I discussed how conducting my integration involved navigating and limiting quantitative metric-based optimization because the pursuit of optimal models distracted from whether models were qualitatively useful. Furthermore, I theorized that there was potential to use understandings developed during thematic analysis to contextually inform decisions made as part of computational techniques, allowing

Table 1.1: Thesis Contributions

Research Questions	Stages	Description	Contribution
RQ1: Could computational techniques be used within a thematic analysis to assist with the analysis of online communities' data?	**Pilot** "I Will Not Drink With You Today": A Topic-Guided Thematic Analysis of Addiction Recovery on Reddit (Gauthier et al. CHI'22)	I used a computational technique, Latent Dirichlet Allocation topic modelling, to guide a reflexive thematic analysis of addiction recovery communities.	**C1** A demonstration using topic modelling to purposively sample data for my analysis and a discussion the benefit of helping identify insights and the limitation of needing to balance metric optimization against interpretive usefulness.
RQ2: How might tools be developed to not require programming expertise when integrating computational techniques as part of thematic analysis tasks?	**Design** The Computational Thematic Analysis Toolkit (Gauthier & Wallace GROUP'22)	I conceptualized, designed, and implemented the Computational Thematic Analysis Workflow and Toolkit.	**C2** A description of my CTA Workflow that guides where computational techniques can augment thematic analysis and my CTA Toolkit artifact that researchers without programming expertise can use to apply these techniques in practice.
RQ3: How does a computational thematic analysis that integrates computational techniques compare with a traditional manual thematic analysis?	**Deploy** Agency and Amplification: A Comparison of Manual and Computational Thematic Analyses by Public Health Researchers (Gauthier et al. GROUP'23)	I conducted a case study comparison of two thematic analyses, where each was performed independently by public health researchers and one used the Computational Thematic Analysis Toolkit.	**C3** A demonstration and discussion how using the toolkit to integrate computational techniques impacted a thematic analysis by facilitating the interpretation of data and subtly influencing the analysis' steps and coding.

an interdisciplinary 'meeting in the middle' where the strengths of both techniques can be used to address each other's weaknesses.

Reflecting on this stage's approach and contributions provided a foundation that I expanded upon during my Design Stage (Chapter 3) and Deploy Stage (Chapter 4). First I observed that the activities involved in my integration did not all provide value to my thematic analysis and required skills that restricted who could perform integrations. For instance, my approach required first replicating standard technique implementations, which were not a source of qualitative insights and required programming expertise, before being able to apply contextual activities, such as token cleaning and model evaluation, that did provide insights. Additionally, my experiences highlighted to me the need to thoughtfully consider how computational techniques are interpretative tools that become part of tasks driven by a messy iterative thematic analysis process rather then as solutions or replacements for the human researcher. For instance, assuming that topic models' quantitative metrics show how well it represents a data set can lead to pursuit of the 'perfect' model and distracts from the human researchers who conducting subjective activities, involving concepts such as bias, values, and choices Aragon et al. (2022); Vaughan and Wallach (2021), during all parts of an analysis. These reflections also guided me to literature that described barriers preventing the integration of computational techniques into qualitative methods, particularly the unmet need to consider how to include qualitative researchers and their perspectives in integration research Baden et al. (2021); Chen et al. (2018); Jiang et al. (2021), which motivated my **RQ2** and **RQ3**.

RQ2: How might tools be developed to not require programming expertise when integrating computational techniques as part of thematic analysis tasks?

For my Design Stage (Chapter 3) I conceptualized, designed, and implemented my CTA Toolkit. I started by conceptualizing the Computational Thematic Analysis Workflow (CTA Workflow), which reconfigured reflexive thematic analysis into a set of conceptual phases accomplished by practical tasks that are augmentable by using different computational techniques. To realize my conceptualization, I designed my CTA Toolkit to focus on: (a) supporting the CTA Workflow to enable conducting my preferred reflexive thematic analysis; (b) assisting with challenges common to multiple types of thematic analysis to be useful beyond reflexive thematic analysis; (c) avoiding programming activities so that a new audience of researchers without programming expertise can use computational techniques; and (d) making toolkit operations recorded and transparent to give researchers' freedom to creatively explore different ways that computational techniques can manipulate their data.

To implement my design, I programmed my CTA Toolkit in Python as a graphical user interface that reduces the difficulty of using computational techniques. My implementation also stored data in an extendable format and automated common data transfer operations to allow users without programming expertise to reuse data across different tools.

Creating the CTA Workflow provided researchers who use thematic analysis a framework to consider whether to integrate computational techniques. Although focused on a reflexive thematic analysis, inspired by Braun and Clarke (2006), my CTA Workflow is transferable to other thematic analysis approaches by re-configuring conceptual phases and practical tasks, such as changing where theme development occurs or introducing inter-rater reliability tasks. Similarly, my CTA Toolkit enabled qualitative researchers without programming expertise to integrate computational techniques into their thematic analyses. Additionally, rather than focus on a single computational technique integration path, such as spaCy's lemmatization (Honnibal et al., 2020) and then LDA Blei et al. (2003) which assumes the data involves long texts that provides sufficient density, I included additional tools, such as nltk's snowball stemmer (Bird et al., 2009) and biterm (Yan et al., 2013) for shorter text, that researchers to explore as part of their iterative analysis process. Such approaches are by no means the only possibilities so I designed the toolkit to be open source and expandable, which has supported additional techniques being introduced since the original publication of the toolkit, such as an undergraduate research assistant adding a tool to conduct modelling and sampling using non-negative matrix factorization (Lee and Seung, 1999). As a result, more qualitative researchers can now perform thematic analyses of online communities by integrating computational techniques. Additionally, the CTA Toolkit provides a base from which qualitative researchers can explore what such integrations mean for the thematic analysis method and contribute to investigating impacts as part of my **RQ3**.

RQ3. How does a computational thematic analysis that integrates computational techniques compare with a traditional manual thematic analysis?

During my Deploy Stage (Chapter 4), I collaborated with five qualitative public health researchers and my supervisor to deploy my CTA Toolkit. Together we conducted a case study comparison of two independent thematic analyses of comments collected from COVID-19 news stories. One team of qualitative researchers conducted a computational analysis using my toolkit, while the other team performed a manual analysis using random sampling. I collected descriptions of both analyses' research process and results. I compared these descriptions to identify two impacts of integrating computational techniques into an inductive thematic analysis.

First, computational techniques facilitated multiple interaction patterns that aided interpretation during the thematic analysis. One pattern was using topic modelling to perform purposive sampling to interact with and interpret specific pieces of data. Another pattern was interacting with the visualization of computation techniques' application across the data set, such as word summaries created to visualize natural language processing and topic visualizations created to review iterative modelling, from which researchers could interpret general patterns. Facilitating multiple types of interaction that aid interpretation had beneficial impacts on the thematic analysis by diversifying where codes and themes can originate and broadening researchers' understanding of the data and phenomena.

Second, integrating computational techniques had subtle influences on the analysis process. The manual analysis followed a bottom-up process that coded for specific events in the data before grouping codes into more general themes. On the other hand, the computational analysis followed a top-down approach that coded for patterns occurring across the data before deriving more specific themes. Despite following different processes and using different coding types, both analyses' results converged as a comparable set of themes, raising the questions for future research that investigates whether the subtle influences are beneficial or disruptive.

1.4 Background

Thematic Analysis is a flexible method that researchers can use to explore complex research areas by developing and reporting qualitative themes (Boyatzis, 1998; Braun and Clarke, 2006). Braun and Clarke (2006) explained that researchers develop themes by iteratively reading and interpreting data. Additionally, researchers customize their thematic analysis process to suit different research aims (Aronson, 1995; Boyatzis, 1998; Braun et al., 2019). As a result of these characteristics, thematic analysis is widely used across multiple disciplines (Braun et al., 2019).

Conducting a thematic analysis is an iterative process in which phases are customized to suit the research questions being asked and the data sources being investigated (Aronson, 1995; Boyatzis, 1998; Braun and Clarke, 2006). Braun et al. (2019) proposed that approaches to thematic analysis can be fit into three different schools: (1) Codebook Thematic Analysis, where the aim is to use sets of themes which have been determined in advance (from existing codebooks or theory) to direct a structured analysis approach; (2) Coding Reliability Thematic Analysis, where the aim is to identify accurate themes that can provide domain summaries and analytical inputs/outputs; and (3) Reflexive Thematic

Analysis, where the aim is to interpret the data in a way that is contextual, coherent, compelling, and grounded in the data. Additionally, approaches to performing thematic analysis range from adhering closely to a school's philosophy and guidelines to more pragmatic approaches that focus on what researchers considered essential to their project, rather than the philosophy behind any particular school (Aronson, 1995; Braun et al., 2019). Despite having different aims, thematic analysis approaches involve several common phases: Data Collection, Data Familiarization, Coding, and Theme Review (Aronson, 1995; Boyatzis, 1998; Braun and Clarke, 2006).

In my Pilot and Design Stages I focused on applying a reflexive thematic analysis approach, inspired by Braun and Clarke (2006), to online community discussions in support of my interest in inductively developing themes that interpret online discussions of lived experiences. Additionally, during these studies I focused on the common phases to make my work transferable to other approaches. Focusing on common phases also facilitated my Deploy Stage, where I collaborated with researchers who used a less formal pragmatic analysis approach to their own inductive thematic analyses.

1.4.1 Why is Analyzing Online Communities Challenging?

Thematic analysis of online communities, such as those on Reddit, needs to account for the scale of data created by the hundreds of people interacting in discussions and accessing content from multiple points in the lifetime of the communities. Braun and Clarke (2006) explained how thematic analysis's iterative nature makes it a resource-intensive method that favours using smaller data sets. Similarly, thematic analysis's customizability makes it complex to plan and perform (Aronson, 1995; Boyatzis, 1998; Braun et al., 2019). Performing thematic analysis of online communities is challenging because the scale of online communities' data sets amplifies the analysis' resource intensity and complexity (D'Agostino et al., 2017). This amplification manifests in each of the common phases, where researchers have to choose from a limiting set of options that decreases the flexibility of thematic analysis when applied to online communities.

During **Data Collection**, researchers need to identify an appropriate data set that is small enough to interact with during all subsequent phases of the analysis using a reasonable amount of resources (Boyatzis, 1998; Braun and Clarke, 2006). However, online communities involve data sets that are too large to be manually interacted with. One approach is to collect a data from a limited period, such as a subreddit's hot list on a specific day (D'Agostino et al., 2017) or only several weeks of data (Ahmed et al., 2017; Gooden and Winefield, 2007). Another approach is to randomly sample an archived data set for a manageable number of discussions (Attard and Coulson, 2012). However, with both of these approaches data is being discarded before any interaction with data can occur which limits researchers' ability to make choices about what data is included in the analysis.

Data Familiarization involves identifying potential patterns that can range from being quite simple and easy to identify, such as reoccurring words, to more complex and harder to identify, such as reoccurring topics of discussion (Braun and Clarke, 2006). Additionally, when patterns are identified they can range from being within a single key source to occurring across multiple sources, both of which are important when exploring the individual and shared experiences discussed by a community. In any thematic analysis, researchers face a trade-off between resources spent and number of potentially useful patterns identified (Braun and Clarke, 2006). The scale of online communities amplifies the impact of this trade-off because there are more potential sources and patterns that could be considered despite the available resources not increasing. One option is for researcher to only familiarize with a small selection of data, collected using methods such as limited period sampling (Ahmed et al., 2017; D'Agostino et al., 2017; Gooden and Winefield, 2007) or random sampling (Attard and Coulson, 2012). However, this option favours identifying patterns that reoccur within one of the selected sources and limits researchers ability to identifying potential patterns from across the multiple sources.

During **Coding**, researchers need to balance assessing patterns to develop codes against their available resources (Boyatzis, 1998; Braun and Clarke, 2006). Assessing patterns during coding is important for thematic analyses, as relevant patterns provide a basis for developing codes related to research questions and identify interesting places to dig deeper into the data. However, assessing patterns can also distract researchers, as some patterns turn out to be less relevant and take up analysis resources. Additionally, maintaining a balance is important because incomplete coding of data can result in codes and themes that are merely extracts of data patterns rather than being an analysis of the data (Braun and Clarke, 2006). Unfortunately, the scale of online community discussions amplifies the number of reoccurring patterns, such as repeated phrases and topics of discussion, which makes maintaining this balance challenging. This results in researchers spending more resources finding and assessing whether patterns are relevant, which takes away resources needed to develop relevant patterns into codes.

Theme Review is challenging because researchers do not have enough resources to compare their themes against all data from an online community. As a result, this phase may be limited to the coded data or skipped, which is difficult to notice because many papers don't mention review or state they reviewed themes but not how (Attard and Coulson, 2012; D'Agostino et al., 2017). However, limiting or skipping theme review decreases a thematic analysis' quality. For instance, missing the confirmations and contradictions that

Table 1.2: Mapping of common phase of thematic analyses to support tasks that can integrate computational techniques to handle the scale of online communities' data.

		Support Tasks		
		Data Management	Pattern Identification	Sampling
Phase	Data Collection	•		
	Data Familiarization	•	•	
	Coding	•	•	•
	Theme Review	•		•

theme review can provide reduces the richness of an analysis (Braun and Clarke, 2006). Alternatively, the scope of this phase may focus on a specific sample or set of informants beyond the coded data (Ahmed et al., 2017; Gooden and Winefield, 2007). However, focusing the scope of the review can cause developed themes to be contextual to only certain individuals or specific points in time rather than to the online communities. As such, being forced to choose between a limited, skipped, or focused theme review reduces the flexible nature of thematic analysis.

1.4.2 How could Computational Techniques Assist?

Integrating computational techniques into thematic analyses can help qualitative researchers manage challenges associated with scaling to online communities' large data sets. Computational techniques can be used to: collect and manage data; identify potential patterns of interest in data; point to data where patterns of interest are occurring; and view where patterns of interest occur across data sets (Baumer et al., 2017; Evans and Aceves, 2016; Muller et al., 2016). However, computational techniques do not provide a human perspective on the context of the research or the communities behind the data (Baden et al., 2021; Feuston and Brubaker, 2021; Jiang et al., 2021). As such, critical computing researchers have begun integrating qualitative thinking into researchers mitigate bias, respect user groups, and consider social conditions during the development of data sets and models as they use computational techniques (Aragon et al., 2022; Cambo and Gergle, 2022; Papakyriakopoulos et al., 2021; Saxena et al., 2022; Vaughan and Wallach, 2021).

The interpretation of computational techniques with qualitative thinking provides a common ground that can be used to integrate computational techniques into qualitative tools and considering where in an analysis it is appropriate to integrate computational techniques. Aligning the characteristics of computational technique with thematic analysis tasks we can consider integrations best suited to assisting researchers, not replacing entire phases or researcher roles (Feuston and Brubaker, 2021). In pursuit of this assistance, computational techniques could be integrated as three support tasks that can assist with thematic analyses' common phases (see Table 1.2).

In the **Data Management** support task, researchers can integrate computational techniques to interact with online communities' large data sets, such as discussions. Qualitative researchers are already taking advantage of computational techniques (e.g., web scrapping utilities in NVIVO (QSR International Pty Ltd, 2021) and application programming interfaces (APIs) to data archives, such as pushshift.io (Baumgartner et al., 2020) and Tweepy (Roesslein, 2020)) to collect online communities' large data sets. Integrating additional techniques, (e.g, virtual tables using SQLite (Hipp, 2020) and data wrangling using pandas (pandas development team, 2020)) assist researchers by enabling them to view and manipulate large data sets. Similarly, integrating natural language process (NLP) implementations, such as the NLTK, can assist researchers with summarizing and managing text portions of large data sets (Bird et al., 2009). Leveraging the Data Management support task during all four common phases of thematic analyses can help researchers maintain the scale of the data sets as they consider what is interesting and conduct their analysis.

Integrating computational techniques into the **Pattern Identification** support task can assist researchers by visualizing data and helping identify potential patterns. Researchers can use NLP techniques (e.g., lemmatization and term frequency counting) to observe patterns involving what words are present in text data and how common or uncommon those words are (Bird et al., 2009; Honnibal et al., 2020). Similarly, researchers can use topic modelling techniques (e.g., Latent Dirichlet Allocation (Blei et al., 2003), biterm (Yan et al., 2013), and non-negative matrix factorization (Lee and Seung, 1999)) to process large sets of data into topics made up of machine-identified feature associations, often co-occurring words. Such modelling can also identify locations in the data set that contain features associated with these topics. Topic-associated features and locations in the data set can be used by researchers to identify patterns and assess whether contexts in which the patterns occur are of interest to the analysis (Baumer et al., 2017). The Pattern Identification support task helps thematic analysis researchers explore patterns from across online communities' data sets during **Data Familiarization** and **Coding** phases. Additionally, this support task's assistance with determining which patterns are interesting for the analysis helps manage resources during the Coding phase.

During the **Sampling** support task, qualitative researchers can integrate computational techniques to conduct purposive sampling (Hoeber et al., 2017; Marshall, 1996). Purposive sampling's goal is to locate appropriate samples for exploring researchers' qualitative analyses. To accomplish this goal, researchers use their ongoing data explorations and subject matter expertise to inform and justify selection approaches customized to their analyses (Hoeber et al., 2017; Marshall, 1996). Hoeber et al. (2017) proposed integrating exploratory search to support purposive sampling from large datasets. Similarly, the topic modelling techniques (e.g., Latent Dirichlet Allocation (Blei et al., 2003) and biterm Yan et al. (2013)) that can explore and understand data sets through topic-based patterns (Evans and Aceves, 2016) can be reused to locate topic-based purposive samples that correlate with patterns of qualitative interest (Baumer et al., 2017; Muller et al., 2016). In a topic modelling-based purposive sampling, researchers first create a topic model that aligns with patterns of interest and then apply the topic model to the data set to identify a subset of the data where these topics are likely to occur. Additionally, researchers can enhance their analyses' transparency by describing which assumptions and patterns of interest directed the techniques utilized during the sampling task. Researchers can use the Sampling support task during the **Coding** phase to locate purposive samples and focus their analysis resources on data that is likely relevant to their thematic analysis. This support task can also support researchers during the **Theme Review** phase by identifying purposive samples based on alternative assumptions or discarded patterns when assessing how well themes apply beyond the coded data.

1.4.3 What Barriers Prevent Integrating Computational Techniques?

Integrating computational techniques into thematic analysis is difficult due to three barriers: (1) Computational techniques are traditionally described for quantitative application and need to be re-described for qualitative contexts (Baden et al., 2021; Chen et al., 2018); (2) The techniques either require self-implementation or the use of programming libraries, such as NLTK (Bird et al., 2009), spaCy (Honnibal et al., 2020), Gensim (Rehurek and Sojka, 2010), pandas (pandas development team, 2020), and SQLite (Hipp, 2020), which provide a high degree of flexibility at the cost of restricting usage to researchers with programming expertise; and (3) The unknown impact of using techniques that have traditionally focused on satisfying post-positive worldviews, such as focusing on the novelty of the technique or creating optimal models based on generalized quantitative metrics, on thematic analysis' process and results (Jiang et al., 2021). My thesis explores these barriers to understand how qualitative researchers could integrate computational technique to the benefit of their thematic analyses of online communities.

Public health offers an interdisciplinary research intersection (Kivits et al., 2019) where these three barriers can be explored from both computational and qualitative perspectives.

First, public health is highly contextual, which pushes any integrations being explored to be customized according to the thematic analyses' needs. Second, qualitative public health researchers develop extensive subject matter and method expertise as part of researching health care issues, which can be leverage when: critically reflecting on approaches to integration; considering the design of tools to support researchers; and discussing how integration impacts analysis process and results.

1.5 Thesis Overview

Collectively, my thesis explores how integrating computational techniques can augment performing thematic analyses of online communities that investigate public health research questions. The remainder of my thesis includes a chapter for each stage and a conclusion chapter.

In Chapter 2, I present my Pilot Stage, where I integrated topic modelling to guide a thematic analysis of online addiction recovery communities. In Chapter 3, I present my Design Stage, where I created my CTA Toolkit that implements computational techniques so that qualitative researchers can integrate them into thematic analyses. In Chapter 4, I present my Deploy Stage, where I compared two thematic analyses conducted by public health researchers, one of which used the CTA Toolkit, to interpret the impact of integrating computational techniques on processes and results.

Finally, in Chapter 5, I summarize my findings from my three stages and their contributions to exploring the augmentation of thematic analysis of online communities by integrating computational techniques. I then discuss my contributions' broader implications for (1) Qualitative Research; (2) Human-Computer Interaction; and (3) Public Health. In addition, I discuss the limitations I navigated while developing my contributions and recommendations for future work that can build upon my contributions.

Chapter 2

Pilot Stage – "I Will Not Drink with you Today": A Topic-Guided Thematic Analysis of Addiction Recovery on Reddit

2.1 Abstract

Recovery from addiction is a journey that requires a lifetime of support from a strong network of peers. Many people seek out this support through online communities, like those on Reddit. However, as these communities developed outside of existing aid groups and medical practice, it is unclear how they enable recovery. Their scale also limits researchers' ability to engage through traditional qualitative research methods. To study these groups, we performed a topic-guided thematic analysis that used machine-generated topic models to purposively sample from two recovery subreddits: *r/stopdrinking* and *r/OpiatesRecovery*. We show that these communities provide access to an experienced and accessible support group whose discussions include consequences, reflections, and celebrations, but that also play a distinct metacommunicative role in supporting formal treatment. We discuss how these communities can act as knowledge sources to improve in-person recovery support and medical practice, and how computational techniques can enable HCI researchers to study communities at scale.

2.2 Introduction

Recovery from substance addiction (American Psychiatric Association, 2013) can involve long and difficult journeys (White, 2007). A key component of those journeys is having a strong network of peers who can support a person as they work towards a healthy, productive, and meaningful life (Beattie and Longabaugh, 1997; Boisvert et al., 2008; Humphreys, 2003; Kelly et al., 2009). Common sources of this support are health professionals, rehabilitation programs, and 12-step programs like Alcoholics Anonymous (AA) or Narcotics Anonymous (NA). However, several barriers can prevent people from participating in these groups, like physical distance, lack of cultural similarity to peers, the stigma surrounding addiction, and a program's appeal (Costello et al., 2019; Doukas, 2011; Humphreys, 2003; Masson et al., 2013). As a result, many seek out less formal support communities through social networking platforms like Reddit or Facebook (Graham et al., 2018; McQuaid et al., 2017). However, since these communities have developed outside of existing support groups and clinical practice, it is unclear whether they provide appropriate and effective support to those who seek it.

Our work investigates what is discussed in online peer-to-peer communities that have formed around addiction recovery and contributes an understanding of how these communities support their members' recovery journeys. We focused our inquiry on the use of Reddit (www.reddit.com), a pseudonymous social networking site where communities can discuss sensitive topics that people may not feel comfortable disclosing face to face or on sites were they are personally identifiable, like Facebook (Marwick and Boyd, 2011). We investigated discussions in two subreddits, `r/stopdrinking` and `r/OpiatesRecovery`, where people can seek out advice about recovery from addiction to two common substances, alcohol and opiates (Canadian Substance Use Costs and Harms Scientific Working Group., 2018).

To understand how these online communities support recovery, we built on previous Human-Computer Interaction (HCI) research (e.g., Ammari et al., 2019, 2018; Pappa et al., 2017; Park and Conway, 2018) by developing computationally-supported qualitative research methods (Muller et al., 2016). In particular, we addressed key drawbacks of existing research in this space, arising from the tension between the time intensity of qualitative research goals and the scale of online communities. That is, existing research has commonly resorted to: 1) sampling only a small set of posts from each community to enable human researchers to develop a qualitative understanding of the materials (e.g., Wadley et al., 2014); or 2) focusing on quantitative analysis (e.g., Ammari et al., 2019) and losing much of the 'thick' understanding of these communities (Braun and Clarke, 2006).

In this work, we applied computational techniques to perform a 'topic-guided thematic analysis' of discourses on recovery subreddits. First, we used Latent Dirichlet Allocation (LDA) (Blei et al., 2003), an unsupervised topic modelling technique, to develop models for each subreddit from four years of posts. We used these models' topics to generate purposive samples (Creswell and Plano Clark, 2018; Hoeber et al., 2017) by identifying related keywords and representative threads from both subreddits. We then performed reflexive thematic analysis (Braun and Clarke, 2006) on our purposive samples' threads to develop and review our themes. During our analysis, we performed inductive coding and grounded our interpretations in the communities' original contexts by looking at associated threads on Reddit's website. This combination of unsupervised topic modelling, purposive sampling, and reflexive thematic analysis enabled us to develop qualitative understandings of these communities while sampling from more than 150,000 threads. We present the results of our analysis in terms of two research questions: 1) How are stories used for addiction recovery in these Reddit communities?; and, 2) How do community members support each other's recovery?

Our research contributes an empirical understanding of the discussions people on recovery journeys are having online, and the information they have sought and shared on social networks at a large scale. We show that the communities comprise experienced members, are perceived as accessible, and provide a channel for sharing lived experiences such as personal stories, advice on common problems, and emotional support. These resources are leveraged by people experiencing addictions, their family, and their friends. Further, we show that Reddit enables meta-discussions that help people from under-represented groups navigate in-person programs, for example women seeking women mentors, and people struggling with references to 'a higher power' in 12-step programs. In discussing these findings, we describe how our themes provide a holistic understanding of addiction recovery that includes online communities, and can inform practice for both mutual aid programs and healthcare practitioners. Finally, we reflect on the effectiveness of computational techniques in supporting the development of a qualitative understanding of online communities.

2.3 Related Work

Experts today view addiction recovery as an ongoing journey that requires a variety of supports to enable those in recovery to "...develop a healthy, productive, and meaningful life." (White, 2007, p. 236). While professional treatment programs vary in implementation, they often share common elements such as an emphasis on education, development of coping skills, and management of co-occurring symptoms such as post-traumatic stress disorder (American Psychiatric Association, 2013). In many programs, emphasis is placed on support and mentorship through mutual aid groups, which may involve participation in well known 12-step groups, like AA and NA, or alternative groups, such as Self-Management And Recovery Training (SMART) and Moderation Management (MM) (Costello et al., 2019; Humphreys, 2003). That is, the formation of a lasting, positive, behaviour-dependent, and supportive network of peers is considered a key component of long-term success (Beattie and Longabaugh, 1997; Boisvert et al., 2008; Humphreys, 2003; Kelly et al., 2009).

There is a growing body of work in the HCI literature that examines how structured online health communities can provide this support network, facilitate emotional support and information exchange (Eysenbach, 2005), and help their members manage health challenges (e.g., Huh and Pratt, 2014; Mamykina et al., 2010). Notably, these structured communities have been found to be helpful for those with chronic conditions, including addiction (Bergman et al., 2017; O'Leary et al., 2018; Rahman et al., 2014; Shen et al., 2015; Winzelberg et al., 2003; You et al., 2016, 2015). To date, this research has largely focused on structured communities, such as InTheRooms (Bergman et al., 2017; Rubya and Yarosh, 2017a,b) and MedHelp (Chuang and Yang, 2012; MacLean et al., 2015), and has found that they offer similar benefits to in-person support groups, such as AA and NA (Bergman et al., 2017).

However, these structured online health communities also have drawbacks. They are often accessible only to those with registered accounts, potentially deterring people, and their friends and family, from accessing needed support. They also may place an emphasis on certain topics, perspectives for successful treatment, or belief systems that do not work for everyone (Humphreys, 2003; Kelly and White, 2012). For example, InTheRooms places an emphasis on the 12-step programs AA and NA (InTheRooms, 2019), whereas MedHelp's focus on connecting people with medical professionals emphasizes experts' opinions (Vitals Consumer Services LLC, 2019). For these reasons, there is growing interest in understanding what kind of support open-access online health communities on platforms like Reddit provide their members.

Further, the scale of these open-access online communities makes them difficult to study. Previous HCI research has begun exploring approaches to computer-supported qualitative research methods (e.g., Ammari et al., 2019, 2018; Chen et al., 2018; Evans and Aceves, 2016; Muller et al., 2016). Nevertheless, researchers investigating addiction tend to make one of two compromises in their approach: 1) they sample a small subset of posts from each community to enable human researchers to develop a qualitative understanding of the materials (e.g., D'Agostino et al., 2017; Sowles et al., 2017; Wadley et al., 2014), limiting their studies from including the years of discussions that members of the communities have access to, or 2) they focus on quantitative analysis (e.g., Pappa et al., 2017; Park and Conway, 2018; Tamersoy et al., 2015) limiting much of the 'thick' understanding of these communities that qualitative analysis could have developed (Braun and Clarke, 2006).

In our work, we make two contributions towards understanding the benefits of online communities focused on recovery: We first demonstrate use of computational methods for qualitative analyses of online communities' discussions, called a 'topic-guided thematic analysis', to overcome limitations of existing methods. We then perform an analysis on two addiction recovery communities on Reddit, describe how they support addiction recovery, and show how they help people from under-represented groups navigate in-person programs.

2.3.1 Analysis of Online Communities, Computational Support, and Sampling

One of the most significant challenges of studying online communities is their scale: each community is potentially comprised of hundreds of thousands of posts from tens of thousands of people over a period of years. Thematic analysis is a time-intensive method, due the amount of reading, re-reading, and reviewing involved, that aims to explore and develop understandings of complex data (Braun and Clarke, 2006). The scale of large online communities both amplifies the amount of time needed for analysis and makes finding data that contain interesting aspects difficult. Research to date often overcomes this challenge through different approaches to *sampling*; such as, selecting posts from a small time period (Wadley et al., 2014) or those associated with 'hot topics' at a given point in time (D'Agostino et al., 2017). For instance, Wadley et al. (Wadley et al., 2014), in their investigation of `r/StopSmoking` chose a sample frame of the 732 posts made during April 2014, and then randomly selected 100 posts from within that sample for manual coding. While these sampling approaches enable manual coding of the data, they also have substantial limitations: for instance, they limit researchers' opportunity to familiarize themselves with the data and develop a contextual understanding of the communities, and can exclude data from dominant or seasonal trends (Marshall, 1996).

Computational techniques provide an opportunity to overcome these sampling limitations, and enable an in-depth, qualitative understanding of online discourse (Evans and Aceves, 2016; Muller et al., 2016). For example, Latent Dirichlet Allocation (LDA) (Blei et al., 2003), an unsupervised modelling approach that can identify latent topics and associated threads within an online community (Maier et al., 2018), can be used to purposively sample (Creswell and Plano Clark, 2018; Hoeber et al., 2017) discourses for analysis. Researchers have employed the use of computational methods to derive a variety of topics from large data corpi for some time (e.g. (Baumer et al., 2017; DiMaggio et al., 2013; Dinakar et al., 2012; Eickhoff and Wieneke, 2018; Mejova et al., 2017; Nelson, 2020)). LDA has been particularly useful to HCI researchers in identifying latent topics in Reddit communities (e.g. Ammari et al., 2019, 2018; Pappa et al., 2017; Park and Conway, 2018), and has been described by Ammari et al. (Ammari et al., 2018) as part of a 'roadmap' for using computational techniques to better understand social relationships online.

Inspired by their work, we further develop this roadmap with a focus on a qualitative, *human* understanding of online discourse. We applied computational techniques to perform a 'topic-guided thematic analysis' of discourses on Reddit, where unsupervised LDA is used to sample for a thematic analysis. Our approach parallels explanatory mixed methods designs (Creswell and Plano Clark, 2018), and explores the use of computational techniques to augment human researchers' abilities, as described by Muller et al. (Muller et al., 2016).

The use of LDA to purposively sample for thematic analysis has several advantages. First, our two LDA models use the breadth of each corpus of threads ($144,422$ threads from `r/stopdrinking` and $14,079$ threads from `r/OpiatesRecovery`) which allows topics to emerge from all threads, rather than from a small sample. Second, LDA assumes that each thread comprises a mixture of topics, enabling the identification of secondary and/or latent topics (Blei et al., 2003), which aligns with how Reddit threads can involve multiple people contributing different viewpoints on both initial posts and subsequent responses. Third, purposive sampling via LDA enables identification of multiple threads for each topic, providing us opportunities to iteratively validate the models for human semantic sense (Maier et al., 2018) and to identify the samples needed for thematic analysis.

2.3.2 Open-Access Online Communities and Addiction Recovery

Large communities exist on open-access platforms around issues like addiction (D'Agostino et al., 2017). In particular, research has shown a large degree of participation on social networking platforms for topics like smoking cessation (Wadley et al., 2014) and diabetes (Newman et al., 2011). Previous work has also shown that online communities possess the same treatment mediators present for in-person group support (D'Agostino et al., 2017). For instance, Q&A participation in online communities has been found to be motivated by altruism and efficacy; known mediators for in-person mutual aid groups that are associated with an increased likelihood of recovery (Oh, 2012). As such, these open-access online communities can be considered to be mutual aid groups.

Additionally, pseudonymity fosters disclosure in online forums, particularly for sensitive topics like addiction (Schmitt and Yarosh, 2018; Yarosh, 2013), diabetes (Newman et al., 2011), and pregnancy loss (Andalibi and Forte, 2018). That is, people are often less willing to discuss sensitive topics when those discussions are linked to their real identities on platforms such as Facebook or LinkedIn (Newman et al., 2011). On the other hand, platforms that support or even encourage various degrees of anonymous participation, like Reddit, have been found to be supportive of these sensitive discussions (Ammari et al., 2018; Andalibi et al., 2016; Nagel and Frith, 2015). The freedom to post anonymously has been shown to enable discussions of mental health (Andalibi et al., 2017; Berry et al., 2017b), parenting issues (Ammari et al., 2018), and sexual abuse (Andalibi et al., 2016).

However, the peer-to-peer nature of these open-access online mutual aid groups, and their lack of medical authority, raises questions surrounding whether the information and advice are appropriate in the context of addiction (D'Agostino et al., 2017; Oh, 2012). That is, should these forums be officially recommended by health professionals as a place to find support? Initial work has suggested several limitations of online communities. For instance, community members may largely be new to sobriety, and advice provided by these groups may be harmful rather than helpful (Costello, 2019; Sowles et al., 2017). Similar concerns arise from the perspective of members seeking help, for instance Rubya and Yarosh (2017b) found that community members may be less likely to self-disclose information in online meetings than when meeting face-to-face, and that geographic differences make communication less effective, or may even lead to conflict. Barrett and Murphy (2020) found that online meetings were not perceived as being more accessible than face-to-face meetings, and were perceived as being less effective and of lower quality.

Further, much of the work that seeks to understand these communities is focused on the perspective of clinicians, such as looking for themes from diagnostic tools (D'Agostino et al., 2017; Gaur et al., 2018), clinician expertise-based recommendations (Huh and Pratt, 2014), analyzing discussions to find addiction mechanisms and treatment methods that can be assessed for clinical validity (Chancellor et al., 2019; Jha and Singh, 2020), and categorizing users into clinical diagnoses (Lu et al., 2019; Tamersoy et al., 2015; Zampieri, 2018). While valuable, clinician perspectives may not always align with community members' values (Berry et al., 2017a).

To address this gap in our understanding, we performed analyses of two active addiction-support subreddits. We show that the topics discussed align with the support identified in the healthcare literature (Beattie and Longabaugh, 1997; Boisvert et al., 2008; Humphreys, 2003; Kelly et al., 2009), and are consistent with a positive, supportive network of peers. Further, we found that these open-access online communities serve a meta-communicative role in helping people to navigate difficulties with in-person groups, such as women seeking women mentors, and people struggling to accept religious aspects of AA.

2.4 Method

We chose to study two subreddits because we initially sought to establish both similarities and differences across recovery communities. However, as our analysis progressed, it evolved to focus on exploring themes that were generated from our interpretation of both subreddits' discussions. Such an evolution is expected when performing thematic analysis using an inductive coding process (Braun and Clarke, 2021).

We investigated two active addiction recovery subreddits focused on alcohol addiction (`r/stopdrinking`) and opiate addiction (`r/OpiatesRecovery`), retrieving corpa from `pushshift.io` (Baumgartner et al., 2020). These subreddits were selected because: they address recovery from use of two different classes of substances that are stereotyped as legal (alcohol) and illegal (opiates) and are current concerns of public health (on Drug Abuse, 2019), they were the largest recovery subreddits we could find for each substance, they are publicly accessible, and they are active in terms of number of community members and posts.

We used thematic analysis to create in-depth understandings of the behaviour we observed in both subreddits. Thematic analysis enabled us to develop 'thick' understandings of the subreddits' community discussions and to generate results that are accessible for both researchers and the general public, while also capturing unanticipated insights (Braun and Clarke, 2006). To perform the thematic analysis, we first built LDA models for each subreddit and used those models to purposively sample (Creswell and Plano Clark, 2018; Hoeber et al., 2017) threads for each topic. Our LDA models used the full corpus of texts ($144,422$ threads from `r/stopdrinking` and $14,079$ threads from `r/OpiatesRecovery`) to develop 16 topics for each subreddit. 20 discussion threads were selected from each topic in each of our two 16-topic LDA models, providing a total sample of 640 threads (composed of 640 submissions and 7828 comments). We then performed a reflexive thematic analysis (Braun and Clarke, 2006) where we inductively coded the sampled discussions, in their living state on Reddit, and used our codes and samples to develop our themes.

Our iterative approach comprised three phases: data gathering, LDA topic modelling, and thematic analysis (section 2.4). The code used to support each activity was written in Python, and is included in the supplementary material.

2.4.1 Data Gathering and Ethical Considerations

As addiction recovery is a sensitive topic, we took additional steps to consider the ethical implications of our work and to protect the communities that we were interested in

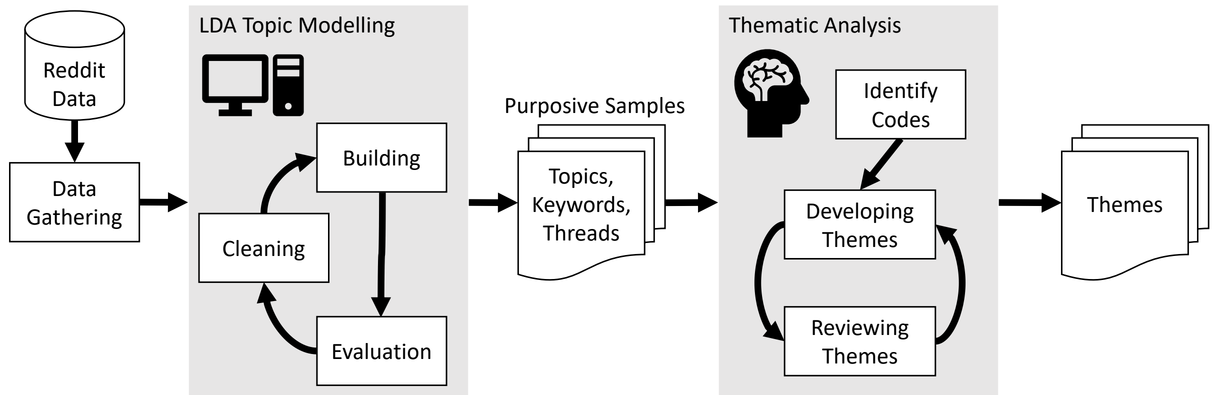

Figure 2.1: To perform our thematic analysis, we first collected Reddit data from 2014 to 2017 for `r/stopdrinking` and `r/OpiatesRecovery`. We then developed LDA topic models for each subreddit by iteratively cleaning, building, and evaluating the generated models, which produced proposive samples made up of keywords and threads for each topic. Finally, we performed the core of our thematic analysis by iteratively identifying codes, developing themes, and reviewing themes with the topics, keywords, and threads from our LDA model.

learning from. We reviewed Reddit's terms of service and the rules and FAQs of both of the subreddits to confirm that data was open for public use, though they did not explicitly allow use for research purposes. We included all publicly available threads from the `r/stopdrinking` and `r/OpiatesRecovery` subreddits created during 2014 to 2017 ($144,422$ threads and $14,079$ threads respectively). We chose the start point of January 1, 2014 and the end point of December 31, 2017 based on our desire to allow behaviours that might be seasonal to occur multiple times and what was available when we started performing the analysis in the summer of 2018. Data for submissions and comments was downloaded from `pushshift.io` in json format (Baumgartner et al., 2020).

We used discussion threads as our unit of analysis because we intended to examine entire threads for our thematic analysis, to preserve the context of each submission and its responses. Threads were recreated by merging `title` and `text` fields by `submission id` for both the submission and any associated comments. The downloaded data was also used to identify URLs as well as aggregated to find thread counts and distinct `user id` counts by `date`. Other non-aggregate information was not extracted or used from the dataset to respect both the community members' privacy (i.e., classifying and categorizing community members risks inferring private information (Wachter and Mittelstadt, 2019)) and limitations of `pushshift.io` (Baumgartner et al., 2020) as a snapshot of posts on Reddit (e.g., archived karma scores often do not match those currently on the website).

All published quotes are paraphrased from existing non-deleted posts to preserve pseudonymity. To respect the choice of community members who chose to delete content, we did not include deleted posts in our thematic analysis. Deleted content was identified manually when reviewing threads on Reddit for thematic analysis. We paraphrased by breaking quotes down into their thematic analysis codes, then manually constructed a new quote. We then compared against the old quote for consistency, and Googled it to ensure anonymity.

Our study design received full approval from our institution's research ethics board, and is consistent with guidelines from the HCI community for protecting pseudonymous research participants (e.g., Bruckman, 2002; Markham, 2012) and transparency in qualitative research (Talkad Sukumar et al., 2020).

2.4.2 LDA Topic Modelling

LDA topic modelling involved three iterative sub-phases: cleaning, building, and evaluation. These sub-phases ultimately produced two models: one for each subreddit. Each model comprised 16 topics, keywords, and a list of associated threads that we used as purposive samples for our thematic analysis. Although we cannot release the final cleaned datasets or generated models, since they contain non-paraphrased text data that could be used to identify community members, our code and a summary of outputs is available in Appendices section A.2, section A.3, and section A.4.

Cleaning

Our cleaning process emphasized human interpretability (Baumer et al., 2020; Maier et al., 2018), an important consideration given our goal was to create purposive samples for thematic analysis by a human researcher (e.g., Baumer et al., 2020; Muller et al., 2016). Our initial cleaning approach consisted of: 1) lemmatization and part of speech identification (Jacobi et al., 2016) using spaCy (Honnibal et al., 2020); and 2) English stop word filtering, as well as filtering out words that were not nouns, verbs, adjectives, and adverbs (Jacobi et al., 2016) using NLTK (Bird et al., 2009) and Mallet (McCallum, 2002). This kind of 'light cleaning' improves the interpretability of models, but does not impact their stability (Schofield et al., 2017; Schofield and Mimno, 2016).

In subsequent cleaning iterations we noticed repetition of common acronyms within models' topics. To reduce this duplication and allow the LDA modelling to treat all representations as being the same word, we expanded a number of general and domain-specific acronyms (e.g., ‘fyi’ to ‘for your information’ and ‘wd’ to ‘withdrawal’) to their full form. We also observed that frequently occurring words, particularly adjectives, were causing a high level of overlap between topics. To reduce this overlap, we removed both adjectives and words that appeared in more than 25% of threads. To further improve performance, we also removed words that occurred in fewer than 20 threads using Gensim (Rehurek and Sojka, 2010) and masked out external links (e.g., ‘http://....’).

Building

We built an LDA model for each subreddit using Gensim 3.8 (Rehurek and Sojka, 2010). For metadata parameters we set the number of passes to 100 along with both alpha and eta to auto, to allow each model to infer its own asymmetric topic distribution from the corpora (Rehurek and Sojka, 2010). We then built 10 separate LDA models for each subreddit, using the generated dictionaries and corpora, and selected the model with the maximum coherence score from the 10 generated models (Appendices section A.2, section A.3, and section A.4).

We set the number of topics in each model to 16, based on pilot runs that indicated the topic coherence had plateaued; previous research has found that topic models with higher coherence score correlate to human-interpretable topic groups (Maier et al., 2018; Newman et al., 2010; Röder et al., 2015). We selected 16 topics for each subreddit because, although opiates recovery plateaued earlier at 9 topics, we wanted to gather a similar sized sample from each subreddit to allow our thematic analysis to consider each community equitably (Appendix section A.4).

Evaluation

We then iteratively fine-tuned the LDA topic models (Maier et al., 2018). We used the models to categorize the available threads and inspected the distribution between different topic groups. We reviewed the models, their topic terms, and the topics’ associated threads to assess their reliability (Maier et al., 2018), coherence (i.e., C_V (Röder et al., 2015)), and, most importantly, whether the topics were interpretively useful (Baumer et al., 2020) to both the authors and a separate pilot group of 12 HCI researchers. During these reviews we reflected on whether additional cleaning was required. During early iterations, we also tried using Jaccard’s distance as a measure of topic similarity (Ammari et al., 2018). However, as we adjusted our cleaning process the Jaccard’s distance measures approached

1.0 for almost all identified topics, and so we did not ultimately use it to guide our topic modelling. Instead, we relied on our semantic interpretation of generated topics, consistent with our need to inform our thematic analysis.

Purposive Sampling

To purposively sample we used each subreddit's LDA model to retrieve 20 representative `submission id`s for each of the 16 topics, giving a total of 640 threads for analysis. We identified representative threads by calculating the probability of each topic occurring in each thread, and selected the 20 threads with the highest probability. We then generated URLs for each `submission id` that could access the discussion threads. We accessed each thread through Google Chrome to ground our analysis in the context of the Reddit communities. The 320 `r/stopgaming` threads were composed of 3302 comments with a median of 7 comments per thread (mean = 10.32). The 320 `r/OpiatesRecovery` threads were composed of 2526 comments with a median of 6 comments per thread (mean = 7.89).

2.4.3 Thematic Analysis

For our reflexive thematic analysis (Braun and Clarke, 2006) we took the realist stance that the continued existence of these subreddits implies a perception of value by their communities and that seeking to understand addiction recovery is a complex process with many different contributing processes and possible outcomes. To focus on the experiential knowledge of the subreddits, we used inductive coding rather than try to force the behaviour of the communities into current understandings of addiction recovery or categorize the communities' members.

We based our reflexive thematic analysis approach on the 6 phases described by Braun and Clarke (2006). The familiarization phase occurred as part of the LDA topic modelling. Using what was learned from familiarization, the first author then worked with the purposive samples to identify codes and to develop and review themes. The first author read each thread in its original context on Reddit to understand what data-driven codes were present. The first author iteratively compared the threads and codes to develop themes (Appendix section A.5); for example, the common code pair 'seeking information' and 'providing information' was combined with codes for different types of seekers, such as 'Atheists' and 'Female', and support group sub-codes, such as 'overwhelmed' and 'fear of stigmas' to develop the theme 'Navigating 12-Step programs'. Threads could contain multiple codes, codes could contribute to multiple themes, and thus threads could also contribute to multiple themes. The first author gathered supporting quotations for each theme from multiple threads that contributed supporting codes. Finally, the first and third authors reviewed the themes by looking at additional threads from each subreddit to confirm that they were present and came to agreement that the themes fit the data.

To consider the individual researcher positions inherent in qualitative research, such as our reflexive thematic analysis, we conducted group reflections with the first, second, and third authors on the identified themes (Creswell and Plano Clark, 2018). During these group reflections we discussed the topics used for sampling, the themes developed, the example quotes, and the first author's experiences and thoughts from interacting with content on a sensitive subject. We did not seek to establish inter-rater reliability, since it is inconsistent with reflexive thematic analysis as described by Braun and Clarke (2021), and because there was a single coder and "codes are the process not the product" of our work (McDonald et al., 2019). The final two phases, developing/reviewing of themes and producing of the report, occurred jointly between the first and third authors. The first author brought forward immersive experience from the previous phases and the third author provided experience communicating to the intended HCI audience.

2.5 Results

An initial review of the subreddits identified that both were active and growing over the four-year period in terms of distinct user names and active threads (section 2.5). We defined a distinct user name as one with at least one submission or comment within the month, where over the entire four year period `r/stopdrinking` had $58,407$ distinct user names compared to $10,668$ for `r/OpiatesRecovery`. We defined an active thread as any with at least one new submission or comment during the month, where over the entire four year period `r/stopdrinking` had $144,422$ active threads, and `r/OpiatesRecovery` had $14,079$.

2.5.1 How are stories used for addiction recovery in these Reddit communities?

Our thematic analysis revealed that the communities engage in a range of discussions related to addiction and recovery, including stigmatized and personal areas, such as relapse, body weight, personal finances, and legal trouble. We now describe how discussions on these subreddits used stories to share experiences, provided peer encouragement, established the consequences of addiction, and exposed substance related concerns (Table 2.1).

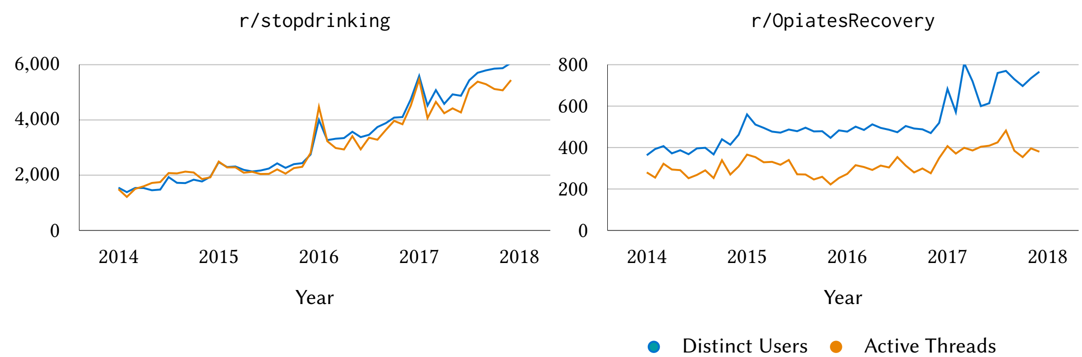

Figure 2.2: Distinct users and active threads for `r/stopdrinking` (right) and `r/Opiates-Recovery` (left) showing that both counts are experiencing an upwards trend over time for both subreddits.

Table 2.1: Example themes that show diverse discussions related to addiction and recovery occurring on the subreddits. Includes themes identified and paraphrased example quotations from the subreddits.

Theme	**Sub-Themes**	**Paraphrased Example Quote**
Sharing Experiences	Self Reflections	"Reading *This Naked Mind* and thinking about my feelings and what alcohol took from me has been enlightening. I was able to establish a critical perspective that showed me how warped my thoughts had subconsciously become."
	Sharing Failures Sharing Successes	"I remember how much I struggled at 4 months and how I couldn't understand why it wasn't getting easier to resist the cravings. Now that I'm at 6 months I am finally understanding why everyone means then they say the cravings don't go away they just change. Thankfully now, despite it being a shitty week, I am not thinking about using as my first thought. Remember it does get easier, so don't give up."
	Waking Up	"Still experiencing the occasional vivid dream of taking pills. I guess its because it was so prominent in my life for so long. What sucks most is that after these dreams the craving is so strong. At least I am starting to feel disappointed in the high even even in the dream."
Peer Support	Check-ins	"Day 5, Monday Night. Really wanted to drink but I resisted!"
	Encouragement	"exercise works wonders! try different activities like yoga and working out. keep up the good effort!"
	Solidarity	"It's great how our lives don't have to be like that anymore!"
Consequences	Benefits of Recovery Costs of Recovery	"I am trying to find rehab or detox facilities in the southern US that will take my government issued insurance. Does anyone have any suggestions?"
	Harm from Substance Use	"I saw in the newspaper that someone got picked up for their 5th dui. This made me think about my own duis from several years ago and realize how great it is to be free of both alcohol and the legal system."
Substance Related Concerns	Pain Management	"I'm worried that visiting my doctor about my illness will end up with me continuing my normal scripts AND/OR I might end up on something else that is also addictive"
	Socializing	"It's super bowl season and while we aren't huge into sorts my significant other and I do like the cultural aspect. What do people suggest as bars are clearly now off the table?"

Sharing Experiences

The most frequent theme that emerged from our analysis focused on community members sharing experiences with one another through stories. This theme is consistent with previous work (e.g., Wadley et al., 2014), as the sharing of stories serves as a way for people to relate to each other and to learn from others' successes and failures. These stories served as an opportunity to self-reflect or relate to others, often through comparing their lives to books or movies (Table 2.1, Sharing Stories). Other stories would discuss common experiences, such as dreams about drinking:

> "I was so relieved when I finally realized it was in a dream. At first I thought it was impossible that I was in the middle of my 1st glass of beer. I felt that I had fallen off the wagon and thought I may as well enjoy the beer or maybe it was a dream like last time. Then I realized it really was a dream!"

These stories also often described how community members fought against internal monologues debating substance use, and reflected on what caused a relapse to both seek out help and serve as a warning to others:

> "After 3 months I relapsed today. It wasn't even on my former drug of choice. So others know it was not worth it as I feel regret for my choice in addition to how shitty I feel when on opiates. The only upside is that this destroyed any remaining belief in my mind that opiates are amazing. I feel like what used to comfort me now disgusts and depresses me. I feel like I'm poisoning myself.
>
> Not feeling sober sucks and I can't wait for this to be over again"

Peer Support

We also observed that community members were supportive of one another — including messages of solidarity, encouragement, affirmation, and celebration. This theme highlights and reminds us that the community is participating in each others' journeys of recovery. For example, the previous quote describing a relapse after three months provided an opportunity for another community member to encourage the original poster towards recovery:

> “Remember that you were clean for all those days so they were not a waste. These things happen as we all have ups and downs. Sometimes from the downs we can see what we’re missing and improve next time. Keep smiling, keep your spirits up, and keep going.”

Another form of peer support we noted was reoccurring ‘open check-in threads’, where any community member could mark sobriety milestones in their recovery journey. These threads serve a similar purpose to the ‘chips’ or ‘sobriety coins’ that are handed out during in-person 12-step programs to mark sobriety milestones such as 24 hours or 1 month, but also could be more frequent, such as daily, weekly, monthly, or around holidays. Comments on these check-in threads were often as short as “*Day 50!*”, but also could be multiple paragraph stories describing the community member’s current situation. In addition to open check-in threads, community members created personal threads where they shared events like birthdays as personal milestones where they recommitted to sobriety and were celebrated by the community:

> “Thirty Nine! I’m 39 years old today and I’m less then a week from 1 year sober. I feel like a million bucks. Quitting drinking with y’all was so worth it.”
>
> >> “Sobriety is such a great birthday present that you gave yourself. Happy Birthday!”

Throughout threads involving peer support, we observed an unusual acronym/phrase in `r/stopdrinking`: “IWNDWYT”, or “I will not drink with you today”. Several variations on this acronym and its full form were observed throughout the threads, including “IWNDWY” (i.e., I will not drink with you), “IWND” (i.e., I will not drink), and “IWND (anymore) WYT” (i.e., I will not drink anymore with you today). We saw the acronym used to respond to stories of both successes, such as not drinking after the death of a loved one, and struggles, such as returning to the community after experiencing a relapse. We observed that members from `r/stopdrinking` used this acronym to express solidarity with each other in both good and bad times of living in recovery.

Consequences

In addition to community members encouraging and supporting one another, discussions often covered the consequences of substance use and of recovery, including interactions with the legal system, financial costs, academic costs, loss of social connections, and quality of life. While the two subreddits often focused on different consequences, such as drinking and driving for `r/stopdrinking` and drug court for `r/OpiatesRecovery`, the general theme of consequences covered positive, negative, and confusing aspects of both addiction and living in recovery.

In threads that discussed negative consequences, we observed community members expressing relief that they had either already worked through the consequence or no longer had to worry about a consequence of addictive substance use now that they were living in recovery (Table 2.1). We also observed members receiving peer advice on how to handle the negative consequences that had occurred in the past or that they currently faced:

> "Was finally arrested for a theft from a long time ago. Was back when I stole to feed by my H addiction and I knew consequences would eventually catch up to me. I was glad that I wasn't scared of jail withdrawal thanks to being clean."
>
> >> "It's good that you're clean as judges like to see that. Be sure to find a decent lawyer and don't be tempted to relapse"
>
> >> >> "Yep, I definitely plan to be honest about my past to the court and explore my options with my lawyer. In Jail I was even offered pills and I was proud that I was able to say No!"

The cost of recovery was a negative consequence frequently discussed on Reddit. These discussions covered insurance, drugs, and rehab facilities, and highlighted the financial burden to stopping use; especially when medicated withdrawal is necessary. Conversely, in threads that focused on the positive consequences of recovery, people would discuss how much money they had saved due to living in recovery, for example:

> "When I see how much I saved I can't help but think it's awesome to not be wasting money on alcohol. I won't drink with you today."

We also observed the communities discussing how being in recovery had brought about confusing consequences such as impacts on body weights in `r/stopdrinking`:

> "Has anyone else experienced weight loss from no longer drinking?"

>> “Yeah, I found it weird how even though I was eating more chocolate bars I still lost weight during my first few months. I also found that tracking my diet was easier when I wasn’t binge eating in the middle of the night while blackout drunk”

While the question and response suggested a loss of weight, we saw many different perspectives throughout the thread, including this response where a member discussed weight gain and raised changing exercise routines:

>> “Believe it or not I have gained weight. Also, I’ve been having better workouts and am pumped! Has anyone else noticed they can increase the weights they lift more rapidly? I know it keeps me motivated to keep checking in.”

We came to understand that Reddit enabled community members to develop a better understanding of their own experiences by comparing them to the consequences experienced by others. Overall, this theme illustrated how the discussion of consequences took on a variety of forms, were largely personal in nature, could provide direction to other members in navigating their own path to recovery.

Substance Related Concerns

In both communities we observed discussions that were focused on concepts that were tightly connected to the substance’s context. Members of `r/OpiatesRecovery` were often concerned about managing acute and chronic pain, frequently associated with a recent injury or planned surgery. For example:

“I was in the same situation as you early in my recovery. When I went to the doctor I told them that I was allergic to codeine so that they wouldn’t consider giving me any. Instead they have me this awful syrup I had never heard of before. It didn’t work for me but luckily someone else I know in recovery is a nurse who directed me to tessalon perles. It doesn’t work very well but at least it was something. I think there’s other over the counter options as well as long as you don’t abuse them.

If your doctor knows you’re struggling with opiates and they still prescribed this to you, then just take it as recommended and be careful. If they don’t know then I’d say try to find a way to ask them for something that is non-narcotic.”

The urgent and fearful tone of the concerns highlighted to us that it is important to consider the beliefs of the community when treating the individual, such as the perception that effective pain management drugs are opiates, and therefore pain treatment introduces opportunities to relapse; either through a person taking the drugs in good faith to treat pain, or through the temptation to obtain a legal prescription to feed an addiction. As these concerns were raised in `r/OpiatesRecovery`, we saw that the community would respond with sharing stories and support, and sometimes provide advice on alternative drugs that could be explored with the help of a physician.

Discussions with similar fearful tones were observed in `r/stopdrinking`. However, rather than pain management, these discussions were focused on concerns around socializing. For instance, we observed a fear of choosing between risking relapse and maintaining social commitments :

> "So I'm part of a group trip planned for Ireland, However now that I'm in recovery I'm growing increasingly nervous about the planned pub visits where the rest of the group will be drinking. I know I can avoid drinking normally but I'm scared it will be different when I'm in a different place. Any suggestions you might have would be appreciated. Thanks."

Another concern was that recovery stigma was driving a wedge into existing friendships:

> "I found out that some friends went out last Saturday and didn't invite me because they thought that I don't like to drink beer. I miss going out with them and I feel excluded just because I've stopped drinking."

Reading multiple threads with similar concerns highlighted to us that the social context of alcohol consumption complicates the struggle that can occur when community members seek to balance their existing social networks with their recovery. The community would try to be supportive and offer suggestions when social concerns were raised. The suggestions commonly included taking time to develop a personal plan for the situation and establishing a trusted in-person social network in order to be able to provide support. These suggestions show the community seeking to help members learn skills that can both help them handle the current situation as well as be reused during their recovery journeys. Another type of suggestion was to consider alternative activities that the entire social group could enjoy. This type of suggestion highlighted to us how the `r/stopdrinking` community tries to encourage members to look past their fears and develop and maintain healthy connections to their friends rather than fixating on the stigma that addiction creates a wall between you and your friends.

Table 2.2: Example themes that show what the community members are discussing to support each other's recovery. Includes themes identified and paraphrased example quotations from the subreddits.

Theme	Sub-Themes	Paraphrased Example Quote
Social Relationships and Activities	Filling a Void	"Since I stopped drinking my life has felt empty. What do you suggest to handle the boredom?" >> "You got to fill that emptiness! You can get started with anything you wanted to try in the past. It might be hard starting but motivation will come if you try."
	Group Activities	"During the movie club we chat while watching the linked stream in sync as best as we can."
	Healthy Activities	"I picked up cross-training, biking, and running. I also found myself enjoying golf."
	Leisure Activities	"If you're bored trying reading Game of Thrones. With five currently out and thousands of pages it will keep you occupied a while."
Sharing Knowledge and Lived Experience	Family and Friends	"tl;dr my older sibling is addicted to opiates and I have no idea how to help them."
	Managing Addiction Managing Consequences Managing Recovery Managing Withdrawal	"I know exercise sucks to get started during withdrawal but believe me when I say you will feel better after you finish. I read this is because of runner's high where the body releases endorphins which helps the opiate receptors feel less starved."
	Understanding Addiction Understanding Recovery Understanding Withdrawal	"I can't understand how any amount of alcohol can be good for us as since I stopped drinking recently and I feel way healthier. Does anyone know if the claim the moderated drinking extends your life has been refuted by science? I can't believe this claim."
Supporting Formal Treatment of Addiction	Female Support	"I want to find a group that has members who have common ground with me as a young female if possible."
	Higher Power Concerns	"After going back to NA I remember why i stopped. I just cant figure out how to reconcile not believing win god with the 12-steps. I know if supposed to be spiritual not religious but i just have such a hard time with how that works in my head."
	Newcomer Support	"As long as you go to an AA meeting you're at the best one. Any meeting should welcome you."

2.5.2 How do community members support each other's recovery?

During our thematic analysis, we saw indications that Reddit made it possible to have discussions that may be difficult to address in person, and that the ability to share information easily through URLs fostered sharing both within the recovery communities and from outside groups. The sharing nature of Reddit was observed to be particularly supportive in discussions on social relationships and activities, knowledge seeking, and in supporting formal treatment of addiction (Table 2.2).

Social Relationships and Activities

Community members sought out suggestions for new activities, taking advantage of the subreddit's accessibility and the community's collective experience. This theme is particularly important because, for many living in recovery, previous social relationships and activities were formed around their drug of choice, leaving a void to be filled and many opportunities for relapse. It also mirrors recovery programs which seek to maintain balance, structure, and routine in a person's daily life (Busse et al., 2015; National Institute on Drug Abuse, 2018). Responses frequently included links to related content, such as music videos on YouTube. The discussions would often be initiated by a request, such as:

> "The local methadone clinic, while pricey, helped me stay off heroin for 6 days and is saving me money. In other news I wanted to see if anyone had any new music suggestions for when I'm feeling down. I've been wanting to find new music to help with my boredom. Thanks for any suggestions you can give. I'm really liking this site and am glad that I was shown it by a friend."

While many sought out advice for off-line activities, we also observed that community events that provided members with online activities that helped to fill voids in their social lives such as Book and Movie clubs (Table 2.2). These events were often synchronous, such as in the case of movie nights, and provided members a sense of being together. Other events were less tightly-coupled, such as book or reading clubs, where members would post about a shared reading assignment over a 1-week period.

Sharing Knowledge and Lived Experience

Many people came to the subreddits as a step towards gaining a better understanding of addiction and recovery. This desire for knowledge came from community members living in recovery, as well as those more generally impacted by addiction in some way, such as family or friends, or those actively using (Table 2.2). These discussions highlighted to us that the Reddit platform enables knowledge to be sought, distributed, and discussed by the community. Responses to questions often included formal sources of information, like scientific research results, therapy approaches, new discoveries in the media, and the experiences of others, and was supported by the ability to directly link to content online via URLs. Additionally, some members disclosed that they felt the sense of anonymity provided by Reddit helped make them feel more open to sharing their personal experiences:

> "I hear you. While I like NA I find Reddit's real anonymity provides me something which makes me feel free to share more personally."

For family and friends, Reddit also provides a venue for advice, and access to a community with lived experience, that may not otherwise be accessible. Many used the platform as a way to reach out for advice on how to approach a loved one's recovery:

> "My older brother lost his job a year ago. I figured out he has been binge drinking all the time and I want to help. Can someone who can relate to this give me some advice?"

On both subreddits we observed community members responding to questions like these with their lived experiences. We also saw the original posters respond with thanks, showing that these two Reddit communities were considered a valuable knowledge source by outsiders who had been impacted by addiction. We also noted responses that referred people to other subreddits or external organizations such as:

> "I suggest you check out r/AlAnon as they have resources for family and friends of people with alcohol problems. We're the people with those problems here."

These responses showed us that the subreddits could act as a knowledge bridge that connected community members living in recovery with others impacted by addiction. These responses also showed us that the subreddits exist within an ecosystem of both online and in-person groups that are interconnected with one another through a multitude of addiction recovery journeys.

Throughout the discussions we also saw indications that the communities wanted their members and any readers to be aware that their lived experiences supplemented professional expertise rather than replaced it. For instance, when discussing treating withdrawal and any symptoms, community members frequently mentioned that they where not medical experts and that that the experiences they described should be discussed with a care provider:

> "That medicine can help with sleeping but it is actually an anti-psychotic, To use it you seriously need to talk with your doctor more. I took it for years but I was always under supervision. While I was glad to get off it a few months ago how you use it and stop using it is individual and you really need to talk to your doctor about what is right for you."

Similarly, when discussing experiences with the justice system they would emphasize that they were not lawyers and contacting proper representation was important. From these discussions we learned that the communities acknowledged limitations of their experiential knowledge and sought to cooperatively contribute to their members' addiction recovery journeys rather than replace other contributors.

Supporting Formal Treatment of Addiction

We observed widespread efforts to support formal treatment, such as detox clinics, and 12-step mutual aid groups, such as AA and NA, in both subreddits. Community members encouraged one another to seek out and make use of these supports as part of living in recovery. Also, both subreddits served as a platform for members with concerns about these groups to seek out advice from the rest of the community. In these cases, we postulate that Reddit's pseudonymity helped members to seek out this advice without risk to their in-person relationships. For instance, we observed a member raise concerns about the in-person nature of AA and NA violating their anonymity when seeking advice about how to handle a relapse:

> "While I am involved in twelve step programs for both alcohol and opiates many of the people there are connected to my halfway which makes me worried my family will be called or that I might get kicked out"

Since the subreddit is pseudonymous and separate from the AA and NA groups, it allows community members to discuss their questions and concerns. In these cases, the subreddits offer access, through the Reddit platform, to a large supplementary group of peers that can offer assistance in navigating 12-step groups.

In other cases, the subreddit helped members struggling with aspects of the 12-step programs, such as how to seek out advice on how to participate. In particular, we noted examples where women (e.g., Table 2.2, Supporting Formal Treatment of Addiction) and atheists/agnostics sought advice on how to participate in 12-step mutual aid groups that are predominantly male focused, and founded by people with a belief in a higher power:

> "While I respect that everyone has different beliefs that may involve religion it just isn't for me. When I see higher power I have a hard time accepting that it's not a reference to God. Any suggestions?"

The discussion about the above quote included responses such as the following that the original poster responded to with thanks:

>> “When I was in a similar situation I found the following quote by Jung helpful:

God is the name by which I designate all things which cross my path violently and recklessly, all things which alter my plans and intentions, and change the course of my life, for better or for worse.”

We also observed discussions that emphasized difficulties when discussing such concerns at AA meetings due to perceptions of judgment:

“Someone at my AA meeting was explaining how your higher power doesn’t have to be god. However when I looked around there was a lot of head shaking and silent judgment. What was going on with this? Is there something I’m not understanding?”

>> “Some meetings involve a lot of God talk to the point it makes some people think AA is religious. When someone explains how to take the steps less literally that is when the silent judgment happens (which is unfortunate).”

>> >> “Thank you!”

In addition, members expressed concern over being stigmatized in-person by users of other substances. For example, one community member who wanted to attend in-person 12-step meetings felt stigmatized because they were an opiate user instead of an alcoholic:

“Why are good meetings so hard to find? I’m new to abstinence from opiates and the first NA meeting I tried to go to landed me in the middle of the ghetto. When I tried to broaden my search in a meeting finder app to include AA meetings but then I got rejected because I identified as a heroin addict instead of an alcoholic. So I tried only looking at NA, but I once again ended up at a meeting location that was in a tiny room, in the ghetto, and had no parking.

Why are these meetings so hard to find?? I can’t understand this since I live in a large city. Does anyone else find they have to bend over backwards to find a god damn meeting to attend??”

Multiple community members responded with advice, such as:

>> “You could try identifying yourself as an alcoholic and just not mentioning that you are a drug addict until you feel out the meeting for mentions of drugs.”

Seeing concerns and responses like these showed us that the Reddit platform was enabling community members to have pseudonymous meta discussions about AA and NA that might be viewed as inappropriate at the meetings themselves. In all of these cases the community was supportive of its members, and tried to work through their concerns with a focus on finding what could best support their recovery.

2.6 Discussion & Implications

Our results show a considerable depth of support and richness of lived experience present in online communities that largely mirrors best practice from the medical community. These findings contrast existing work by showing diversity in community members and their lived experiences. For instance, previous work has raised concerns that members may be new to sobriety or may give inappropriate or harmful advice (e.g., Rubya and Yarosh, 2017b; Sowles et al., 2017). Indeed, we identified that discussions on Reddit enable communication between different groups impacted by addiction, including those with years of recovery experience, those just starting out on their own journeys, and family members and friends. Community members often raised concerns about sensitive, addiction-related issues such as withdrawal, body weight, legal trouble, and personal finances. We also observed discussions covering concepts such as stories, seeking advice, and informational support (MacLean et al., 2015; Rubya and Yarosh, 2017a,b; Wadley et al., 2014; Yang et al., 2019a).

Our results also show the important meta-communicative role that these communities play in supporting formal treatment of addiction. Community members provided encouragement to seek out help, advice on navigating 12-step programs like AA and NA, and helped others as they struggled with differences in norms and values. These discussions were particularly valuable for under-represented groups like women struggling with a lack of female mentors, and for atheists/agnostics with concerns about references to a higher power. These examples provide a valuable counterpoint to past work which has found that online communities may be perceived as being less effective and of lower quality than face-to-face meetings (Barrett and Murphy, 2020), and that individuals may be less willing to disclose sensitive information online (Rubya and Yarosh, 2017b). This contrast suggests the communities play a distinct and important complementing role by supporting queries that may be difficult to address in person.

These observations add to a growing body of research (e.g., Ammari et al., 2018; Andalibi et al., 2016; Newman et al., 2011; Yang et al., 2019b) that shows how Reddit provides a distinct environment where members feel comfortable seeking out a network of support, and where they can share personal or stigmatized experiences that they wouldn't necessarily disclose with in-person groups. We now discuss implications of this work for both research and practice moving forward, and reflect on the usefulness of topic-guided thematic analysis in conducting the analysis.

2.6.1 Implications for Addiction Recovery Programs Online and Offline

Our analysis shows how communities on Reddit provide mediators for positive recovery outcomes identified in the literature, like access to recovery role models, abstinent contingent social support, and an environment that increases commitment to recovery (Beattie and Longabaugh, 1997; Humphreys, 2003; Kelly, 2017; Moos, 2007). For example, we observed that check-in threads provide a useful parallel to 12-step meetings and enable community members to mark milestones together and celebrate successes. Members explore new recreational activities and strategies to handle difficulties such as social changes, and experienced members act as mentors, matching the role that they would play for in-person 12-step programs. Similarly, communities help members develop new friendships through social activities, such as movie nights, reading circles, and song sharing groups. These elements correspond to emphases on in-person mutual aid groups like education, development of coping skills, and management of co-occurring symptoms (American Psychiatric Association, 2013).

The similarity between online and in-person support groups, and the substantial number of active members and discussions on Reddit, raises the question of whether in-person groups, such as AA and NA, might benefit from the online communities' lived experiences. In-person groups are typically much smaller than the 6000 people we observed engaged online in `r/stopdrinking`, with about 17 members on average (Office, 2019). These groups may also benefit from the many different perspectives online, including access to underrepresented groups, that may not always be present in-person. Our results show how the large community and body of experiential knowledge work as a supplementary resource for in-person mutual aid groups, and highlights opportunities for HCI to help people leverage these resources moving forward.

The potential benefits of online communities to people who attend in-person aid groups are myriad. For instance, more regular peer support like daily check-in threads may be impractical in person, but may benefit some members. Shared activities, like synchronous online movie watching, may be valuable to those who typically attend in-person meetings but have difficulty finding in-person alternatives to substance use. Mentors may not have the resources they need to advise other members, but may find those resources online through shared stories, frequently asked questions about consequences, or more niche concerns such as those around pain management.

Thus, there is an opportunity for HCI researchers to make the valuable lived experience from online groups more readily available to in-person groups. For example, addiction treatment specialists could use Reddit's experiential knowledge to create and share a curated selection of frequently asked questions, advice, and activities for in-person addiction treatment programs. Computational techniques, like those used in our analysis, may be particularly effective in identifying concepts of interest and potential alternative treatments (e.g., Chancellor et al., 2019).

2.6.2 Expert Use of Online Experiential Knowledge

Our analysis also shows how communities like `r/stopdrinking` and `r/OpiatesRecovery` exist alongside of the medical profession and traditional mutual aid groups. These communities are dedicated to responding to questions and discussing sensitive issues, and are an important source of patient expertise and lived experience (Unruh and Pratt, 2008). For example, we observed discussions on consequences of recovery, which included concerns about addiction recovery treatment costs and risks involving insurance, drugs, and rehab facilities. The separation from medical expertise is both a strength and weakness. We saw that these communities help people on their journeys of recovery by discussing sensitive and highly personal issues such as pain management alternatives, different consequences of addiction and recovery, and getting the right support from formal treatment. Although the communities make efforts to be clear they are not sources of medical expertise, providing advice may also mean that inappropriate, out-of-date, or even incorrect information is being shared, and that there is potential for harm (D'Agostino et al., 2017; Eysenbach, 2005; Huh et al., 2013) — particularly when discussing medication, e.g., incorrectly changing dosages could lead to overdosing. By understanding that patient expertise and medical expertise are complimentary (Hartzler and Pratt, 2011; Huh et al., 2012) they can be used together to to gain a more holistic understanding of addiction recovery journeys.

Bridging treatment specialists into these communities is a tempting way for HCI research to contribute clinical knowledge to the discussions. For instance, previous work has focused on how to weave specialists' expertise into online communities (Huh and Pratt,

2014) and the potential to supplement posts with clinician validation (Chancellor et al., 2019). However, when learning from and interacting with these communities, it is important for both researchers and specialists to be respectful and non-judgmental as not dismiss patient expertise or disrupt community norms and rules; they are valuable safe spaces for members that serve a collaborative role in recovery journeys.

An alternative approach informed by our research is to consider what support these communities want from specialists, and what clinicians can gain from an understanding of the issues discussed. For example, we identified that pain management is a common concern in `r/OpiatesRecovery`. People discussed being afraid to see a doctor about an illness out of a fear that they begin using an addictive substance again. They also discussed how to interact with medical providers in ways that could avoid common prescriptions, and to seek out alternative treatments. The communities' online discussions can be additional sources of patient experiences for medical training approaches, such as narrative medicine (Milota et al., 2019) and situated learning (Lee et al., 2018) which enhance awareness and empathy, to help practitioners better understand and respond to the experiences and needs of patients impacted by substance use disorders. Similarly the discussions of social isolation in `r/stopdrinking` could serve as an additional source of patient experiences for therapists being trained on how to emphasize with and assist patients attending recovery programs. HCI practitioners working in the social computing space can play a valuable role by developing new tools that can help experts access this experiential knowledge in ways that respect the anonymity of online communities.

2.6.3 Topic-Guided Thematic Analysis

Finally, in reflecting on our topic-guided process, we found that the opportunity to 'prime' our thematic analysis with a qualitative understanding of topics was invaluable. The LDA topics helped us sample in a way that allowed us to develop both general themes, like sharing stories (Wadley et al., 2014), but also novel and nuanced themes that are specific to the context of addiction recovery, such as difficulties with pain management and supporting formal treatment of addiction. This process aligned with our goal of obtaining a 'thick' understanding (Braun and Clarke, 2006) of the communities' experiential knowledge of addiction recovery, while mitigating challenges of scalability when studying very large online communities. We argue that use of LDA to guide thematic analysis provided two key benefits: 1) the work performed as part of the LDA modelling process was informative in itself, and 2) purposive sampling based on generated topics improved our thematic analysis.

First, we found that the *iterative* nature of the process, and human involvement in developing and interpreting the model was invaluable to our thematic analysis. While our topic modelling activities leveraged computational techniques (i.e., left side of section 2.4), a human researcher played a substantial role in iteratively cleaning data, building models, and evaluating their utility. For instance, we first became aware of the 'IWNDWYT' acronym when cleaning data, which prompted us to pay more attention to it later on. When evaluating models, we noticed that optimizing around quantitative measures like coherence (Röder et al., 2015) and Jaccard's distance did not yield a single solution, but did give us an opportunity to engage with and reflect on topics from multiple perspectives.

Second, we believe that purposively sampling from each topic improved our thematic analysis (i.e., right side of section 2.4). Sampling from each topic ensured that a range of data was represented in our thematic analysis, rather than simply those that were 'hot' on a given day (e.g., D'Agostino et al., 2017; Marshall, 1996; Wadley et al., 2014). Sampling an equal number from each topic also ensured that a range of data was represented, compared to, for instance, a random sample (e.g., Wadley et al., 2014). Topics often provided invaluable 'hints' for thematic analysis, and ultimately some translated directly to themes (e.g., Sharing Experiences), some were combined into broader themes (e.g., Activities, Consequences), and even topics that were less coherent provided data to code and helped us develop and review our themes.

To realize such benefits we needed to consider whether LDA modelling was an appropriate technique for our research questions and intended methods. We determined that because our unit of analysis, discussions, is long-form text with multiple authors and multiple co-occuring topics, LDA was an appropriate method for purposive sampling. However, for other analyses and research contexts, a different choice of topic model may be more suitable. For instance, for discussions on Twitter data is more sparse and biterm modelling (Yan et al., 2013) or LDA with author aggregation (Hong and Davison, 2010) are likely to better capture latent topics. Similarly, if the topic models were intended to provide a baseline for deductive theme and code identification, then techniques with enhanced within-topic aspect identification, such as Attention-based Aspect Extraction (He et al., 2017), should be considered.

Our work fits within a larger body of computational social science research that explores how technology can help qualitative understanding by human researchers (e.g., Evans and Aceves, 2016; Muller et al., 2016). We demonstrated a specific application of thematic analysis where computing *supports*, not replaces, a human researcher. Indeed, we believe there are opportunities to more deeply integrate computational techniques into thematic analysis phases like identifying codes, developing themes, and reviewing themes (section 2.4). In the interest of transparency (Talkad Sukumar et al., 2020), and to enable others to expand on our work, we have shared our full source code in the paper's supplementary materials.

2.7 Limitations

As qualitative research, our work develops an understanding of addiction recovery communities on Reddit and the topics that they discuss. These methods have the advantage of allowing us to engage with materials from the 'wild', derive themes from our observations, and to validate our findings within their original context. However, the choice to carefully study two subreddits focused on substance use also has limitations, particularly when generalizing to the broader addiction recovery community, or when comparing to communities centred on, for example, weight loss, fitness, or mental health. For instance, substance-specific issues like stigma and local legality for alcohol or opiate use differ from those for smoking or foods. In this work, we intentionally focused on understanding the under-explored supports for substance use on Reddit, and while we identified themes like stories and seeking advice that have also been found in contexts like smoking cessation (e.g., Wadley et al., 2014), additional research is required to examine similarities and differences across communities for the many distinct, but related, medical diagnoses grounded in addiction.

We also needed to manage some limitations of our topic modelling approach, and to balance model optimization with our ultimate goal of performing a *qualitative* analysis of discussions in these communities. As Baumer et al. (2017) notes, the models we generated needed to provide "scaffolding for human interpretation." We came to understand the importance of *good enough* models which provide new perspectives of the data, and the trap of searching for the *best* model. In short, perfect was the enemy of useful. To develop the models we used best practices for LDA analysis (Maier et al., 2018), including practices for data cleaning, and selecting a number of topics for each model based on maximizing its reliability and coherence scores. We also discussed pilot models as a group and identified features of the data that were making topics both interpretable and uninterpretable. These discussions informed our tokenization, lemmatization, and filtering of stop words, frequent terms, and infrequent terms. However, the interpretive nature of both model development and thematic analysis are simultaneously a strength and a limitation of our methods (Baumer et al., 2017; Muller et al., 2016).

Finally, another limitation is that we have little information about the people who posted online, or their motivations for doing so. Since Reddit is a pseudonymous community, we cannot infer any direct relationships between accounts, or between accounts and people. We therefore are limited in our ability to accurately generate descriptive statistics, like the number of posts or threads created by any individual, or to more fully explore interactions between individuals in these communities. We also can only consider those who posted in the forums, and have no means of understanding how others use this information (i.e., lurkers (Nonnecke and Preece, 2000)), or whether individuals sought support through other means like in-person 12-step groups or other online communities (Cohn et al., 2019).

2.8 Conclusions & Future Work

Our work shows how online communities such as Reddit support addiction recovery. It provides an understanding of the issues discussed in these communities, how they take advantage of pseudonymity and an online format to support one another, family, and friends, and the stories, advice, and emotional support that they share. We also identified that these online communities play a role in helping people navigate personal concerns about 12-step programs. Our results can be used by the HCI community, addiction recovery programs, and healthcare practitioners to develop a more holistic understanding of how online peer-to-peer communities are leveraging the Reddit platform around sensitive and health-related issues such as addiction recovery.

Our work also further explores the application of computational techniques to support qualitative research (Evans and Aceves, 2016; Muller et al., 2016). We built on the 'roadmap' set out by Ammari et al. (Ammari et al., 2018) to gain insights into the needs of stigmatized groups, like those in addiction recovery, via social networks. We show how the complementary use of computational and qualitative techniques, in this case the use of topic modelling to purposively sample for thematic analysis, can yield insights into the types of discussions occurring online at scale, and allow human researchers to more deeply engage with those discussions. We expect to see tighter integration of qualitative research and computing moving forward, and that our work can serve as one model of partnership between human- and machine-guided analysis techniques. As a next step towards making these models more accessible to qualitative researchers, we are currently developing an open-source graphical toolkit for topic-guided analysis of online discussions, called the Computational Thematic Analysis Toolkit (e.g., Gauthier and Wallace, 2022).

2.9 Acknowledgements

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Chapter 3

Design Stage – The Computational Thematic Analysis Toolkit

3.1 Abstract

As online communities have grown, Computational Social Science has rapidly developed new techniques to study them. However, these techniques require researchers to become experts in a wide variety of tools in addition to qualitative and computational research methods. Studying online communities also requires researchers to constantly navigate highly contextual ethical and transparency considerations when engaging with data, such as respecting their members' privacy when discussing sensitive or stigmatized topics. To overcome these challenges, we developed the *Computational Thematic Analysis Toolkit*, a modular software package that supports analysis of online communities by combining aspects of reflexive thematic analysis with computational techniques. Our toolkit demonstrates how common analysis tasks like data collection, cleaning and filtering, modelling and sampling, and coding can be implemented within a single visual interface, and how that interface can encourage researchers to manage ethical and transparency considerations throughout their research process.

3.2 Introduction

Many researchers seek to develop a qualitative understanding of the activities taking place online, and have explored use of computational methods to help them overcome the volume, velocity, and variety of data found in those communities. In building on the strengths of qualitative and computational methods, researchers hope to enable a qualitative understanding of activities at scale that is not possible with traditional methods through a synthesis of techniques. For instance, the literature has explored augmenting qualitative techniques with natural language processing (Evans and Aceves, 2016) of text, use of computational techniques like topic modelling (e.g. (Baumer et al., 2017; DiMaggio et al., 2013; Dinakar et al., 2012; Eickhoff and Wieneke, 2018; Mejova et al., 2017; Nelson, 2020)) to support data sampling (Hoeber et al., 2017), and development of classifiers to support humans in coding (Chen et al., 2018).

However, substantial barriers exist to this synthesis of methods in practice. For instance, researchers must be experts in qualitative research methodologies, like Grounded Theory (Strauss and Corbin, 1997) or Thematic Analysis (Braun and Clarke, 2006), as well as computational techniques, like topic modelling (Blei et al., 2003), all of which require extensive training. Further, myriad ethical considerations need to be made when working with online community data, like whether the communities being studied have an expectation of privacy, the community's and their platform's terms of use, and balancing the need for transparent research practices with potential harm to the communities being studied (Bruckman, 2002; Fiesler et al., 2020; Markham, 2012). Finally, researchers must navigate all of the these challenges across a number of separate tools; current software was not designed to support computational and qualitative methods in a single interface. Indeed, they must perform the substantial, iterative, and often tedious work associated with both qualitative research and computational methods; like data familiarization, cleaning, modelling, development of themes, and revisiting and iterating on those tasks when results are deemed unsatisfactory.

To overcome these barriers, we developed the *Computational Thematic Analysis Toolkit* which brings together elements of reflexive thematic analysis and computational methods under one cohesive, visual interface that is accessible to non-programmers. Our toolkit supports common analysis tasks like data collection from online communities (e.g., Baumgartner et al., 2020), cleaning and filtering, modelling and sampling, and coding (e.g., Braun and Clarke, 2006). In presenting our toolkit, we first define a conceptual workflow based on the many similarities between qualitative analysis and computational methods. We then present the toolkit's implementation for each analysis task. We also pay particular attention to guidance from the HCI literature on the integration of computational and qualitative research methods (e.g., Baumer et al., 2017; Chen et al., 2018; Jiang et al., 2021; Muller et al., 2016), and how this guidance was implemented in our design.

3.3 Related Work

The Computational Social Science community has begun to explore the substantial similarities between qualitative analysis and computational methods. For instance, Muller et al. (2016) notes ‘convergences’ between the two approaches to research; both are grounded in data, involve the creation of codes or features, are highly iterative, and that results are ultimately interpretive in nature. In discussing these similarities, they raise the question of whether hybrid methods might provide complementary benefits; that is “What if we could enjoy the virtues of both ways of inquiring?” (Muller et al., 2016, p.3).

Yet, despite their similarities, the tools used to support these different methods remain separate, and play distinct roles in their respective analyses. Qualitative researchers use a variety of tools (Jiang et al., 2021) including office software, such as Excel (Microsoft Corporation, 2021) and Google Docs (Google LLC, 2021), as well as more specialized software like NVivo (QSR International Pty Ltd, 2021), Atlas.TI (Scientific Software Development GmbH, 2021), or MAXQDA (VERBI Software, 2021). These tools typically have visual interfaces and are designed to play a supporting role rather than be the subject of analysis.

In contrast, computational tools typically require programming experience, like Mallet (McCallum, 2002), Gensim (Rehurek and Sojka, 2010), and TensorFlow (Abadi et al., 2016). They include both stand-alone software, as well as programming libraries that can be used alongside other tools. And while these libraries are often powerful and adaptable, there is some ‘assembly required’ before they can be used for analysis. Especially when compared to qualitative tools, computational tools play a central role in analysis; they are often integral to the analysis itself, rather than seen as supporting a human researcher.

Currently, this dichotomy in tools is a barrier to the integration of qualitative analysis and computational methods. They require different kinds of expertise. They are integrated with different tasks of their respective methods. It is also hard to transfer data between different tools, particularly given the highly iterative nature of both approaches to research. Thus, in this work, we consider how such techniques can be best integrated to support qualitative analysis of online communities. In particular, we focus on reflexive thematic analysis, as defined by Braun and Clarke (2006).

3.3.1 Thematic Analysis and Computational Sampling

One of the most significant challenges to performing thematic analysis of online communities is how their scale impacts sampling and the time intensity of analysis (Boyatzis, 1998; Braun and Clarke, 2006); each community potentially comprises hundreds of thousands of posts from tens of thousands of people over a period of years. One approach to dealing with this size is to sample. For instance, researchers frequently use random selection (Attard and Coulson, 2012) or convenience sampling, such as a date-window (Ahmed et al., 2017; D'Agostino et al., 2017; Gooden and Winefield, 2007; Rodgers and Chen, 2005), to obtain a sample that is small enough for human analysis. However, by doing so researchers risk missing interesting parts of the data before they can familiarize themselves with the data, perform coding, or review themes.

As such, computational techniques can assist with sampling and analysis tasks. Topic modelling techniques like Latent Dirichlet Allocation (LDA) (Blei et al., 2003) have been identified by the research community as a potential avenue for engagement with such large data sets (Ammari et al., 2018; Chen et al., 2018; Evers, 2018; Maier et al., 2018; Muller et al., 2016). In particular, researchers have begun exploring how topic models can be used to provide a lens into the data, be used to identify latent themes (Maier et al., 2018; Poursabzi-Sangdeh et al., 2016), and to produce useful samples from large scale data (Baumer et al., 2017; Hoeber et al., 2017; Muller et al., 2016). If chosen wisely, computational techniques can assist with qualitative sampling strategies, such as purposeful sampling and theoretical sampling (Marshall, 1996), and can help researchers develop an understanding of complex issues.

However, researchers also do not want computational methods to simply automate their interaction with the data; they want to maintain autonomy, intimacy, and ownership of their qualitative analysis (Jiang et al., 2021). In response to these needs, the research community has explored how humans might guide topic modelling techniques like LDA (El-Assady et al., 2018, 2019). Thus, there is a need for tools that support computational approaches to thematic analysis, but maintain the human researcher's role as the driver of analysis. In this work, we develop a conceptual framework for how qualitative and computational methods can be bridged in the context of reflexive thematic analysis, and create a toolkit that implements that framework.

3.3.2 Ethical and Transparency Considerations

Alongside the methodological and technical progress made by the research community, there has been a growing recognition that computational social science researchers need to actively consider the impacts of their processes, artifacts, and results (Densmore et al., 2020). That is, "ethics exist within a social context" (Williams, 2003, p. 77) and are intertwined with social considerations about how our research is performed and how it is used. In particular, research on digital communities can not be done in a one-size-fits-all manner (Fiesler et al., 2020). While once such data might have been considered 'public' and safe, the research community now acknowledges that its use can put community members at risk (Bruckman, 2002; Markham, 2012). As such, there is a need for researchers to responsibly handle such research data, and for tools that support them in doing so.

There is also a growing recognition of the importance of transparency in Computational Social Science research, as well as within the broader HCI community (e.g., Talkad Sukumar et al., 2020; Vornhagen et al., 2020; Wacharamanotham et al., 2020). Transparent reporting strengthens the rigour and trustworthiness of research (Pratt et al., 2020; Talkad Sukumar et al., 2020; Tuval-Mashiach, 1027). It helps others understand, evaluate, and build upon published work. It can also help the researchers *themselves*: it can help them familiarize themselves with, interpret, and reflect on the myriad decisions they make when working with data. Decisions like what data were captured and not captured? What was filtered during cleaning? And which topic models were created and why?

Despite transparency's importance, there remains little agreement on how it should be supported in research tools. When navigating epistemological tensions between interpretivist social science and positivist computational science perspectives there is often an emphasis on tying transparency to *replication* despite it being an inappropriate for many qualitative research studies, which instead seek to establish *trustworthiness* (Pratt et al., 2020). Indeed, complete transparency may also be inappropriate in some contexts. For instance, research involving marginalized or stigmatized groups may necessitate reduced transparency through paraphrasing (Bruckman, 2002) or fabricating data (Markham, 2012). Thus, in developing our toolkit, we sought to embody these values within its design, and to show how ethical and transparency considerations might be embedded into the tools themselves.

3.4 Computational Thematic Analysis

Grounded in Braun and Clarke's (Braun and Clarke, 2006) six-phase model of reflexive thematic analysis, we wanted to explore how computational techniques could play a larger role in supporting analysis by human researchers. To do so, we started by considering the commonalities, or 'convergences' (Muller et al., 2016), between thematic analysis and the computational methods used by the data science and machine learning communities. In

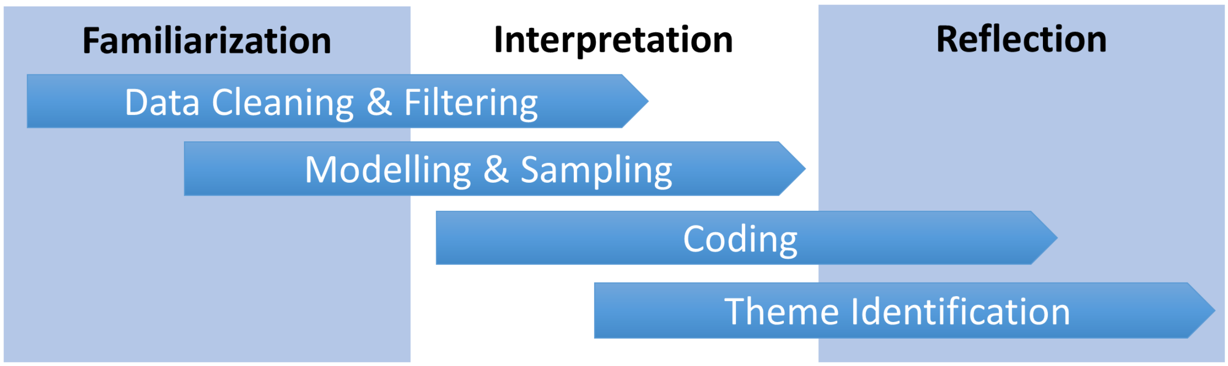

Figure 3.1: Our Computational Thematic Analysis workflow. In moving from data collection to writing their final report, researchers progress through three conceptual stages of work: familiarization, interpretation, and reflection. To do so, they perform the practical tasks of data cleaning and filtering, modelling and sampling, coding, and theme identification. Like thematic analysis and computational methods, this workflow is highly iterative, and is not a linear process; researchers may shift between any conceptual stage or practical task.

particular, we considered similarities between how models and themes were developed, interpreted, and then used to identify patterns in the data (Braun and Clarke, 2006; Raschka, 2015). We then developed a hybrid workflow (Figure 3.1) that scaffolds the practical tasks associated with these analyses into three abstract, conceptual stages: familiarization, interpretation, and reflection.

We emphasize that while Figure 3.1 shows these conceptual stages and tasks in a linear manner, they are in practice highly iterative, and tasks frequently overlap. That is, as when performing thematic analysis or computational methods, researchers are likely to jump between conceptual stages and tasks as their analysis develops. For instance, a researcher might choose to code parts of their data during familiarization, and then sample before generating themes. In this way, the stages and tasks provide a guideline of how an analysis progresses, rather than a strict process that must be followed. We now overview each stage, and their relationships to the work performed in thematic analysis and computational methods.

Familiarization

Regardless of whether researchers are approaching their analysis from the perspective of thematic analysis or computational methods, they must first familiarize themselves with the data; they need to confirm that they've collected appropriate data, spend time understanding it, and identify patterns (Braun and Clarke, 2006). In our workflow, familiarization encompasses tasks like data collection and inspection from thematic analysis, and pre-processing and exploration from computational methods. Computational techniques can augment these traditional thematic analysis tasks by automating aspects of data cleaning, providing an overview of collected data, and better enabling researchers to familiarize themselves with semantic, or word-level, patterns in the data.

Interpretation

Interpretation is how researchers turn their familiarity with data into their own ideas. It involves tasks like sampling, generating initial codes, searching for themes, and theme identification from thematic analysis, and modelling and sampling from computational methods. The primary benefit of a hybrid model for these tasks is that computational techniques, like topic modelling, can be used iteratively by researchers to generate models, latent patterns within those models, and consider how the patterns suggest new assumptions and/or impact existing assumptions about their analysis (Chen et al., 2018; Evers, 2018; Muller et al., 2016), giving them access to a larger variety of patterns to investigate in later stages of thematic analysis. These techniques can also improve researchers' ability to describe the contextual nature of their assumptions and how their assumptions might influence their analysis.

While drawing a definitive line between familiarization and interpretation is difficult due to the highly iterative and overlapping nature of thematic analysis, it can be helpful to consider familiarization as being more focused on *semantic* patterns, such as reoccurring words or phrases, whereas interpretation then seeks to transition to more abstract understandings or *latent* patterns, such as reoccurring topics of discussion.

Reflection

Reflection is where researchers consider whether their interpretations line up with the data, their experiences interacting with the data, and with their broader understanding of the domain of interest. It includes tasks like reflecting on codes, reviewing themes, and writing the final report. While we did not implement any computational techniques to support this aspect of thematic analysis, we posit that they may be used to suggest alternative interpretations of the data, for instance through summarization or counterfactuals.

3.5 The Computational Thematic Analysis Toolkit

To explore how our hybrid workflow and lessons learned from the literature might be embodied in a visual interface, we developed the *Computational Thematic Analysis Toolkit*. Imported data is visualized, cleaned, filtered, sampled in an interactive setting that enables rapid, iterative exploration and analysis. To support the inherent flexibility of our hybrid workflow, the toolkit's design is modular, where changes made at one stage of analysis are immediately reflected in the others, enabling researchers to shift between tasks as they progress between the familiarization, interpretation, and reflection stages of analysis.

Our toolkit supports each of the conceptual stages identified in our workflow (Figure 3.1), with each task assigned its own tab: Data Collection, Data Cleaning & Filtering, Modelling & Sampling, and Coding. The Data Collection tab enables researchers to download a data from various sources. The Data Cleaning & Filtering tab enables researchers to inspect, clean, and filter the data. The Modelling & Sampling tab enables researchers to locate data of interest for their thematic analysis. In particular, it involves applying machine learning approaches to the data to create and visualize samples of potential interest. The Coding tab provides a central location to develop, apply, and review codes by using data identified during both sampling and manual data inspection.

To maintain control of research data we implemented our toolkit as a standalone application instead of as a web application. We implemented our toolkit using Python 3 due to the wide availability and interoperability of packages for computational techniques, visualization, and user interfaces. Reddit data was obtained from pushshift.io's web API (Baumgartner et al., 2020). Individual data analysis components were implemented using pandas (pandas development team, 2020), spaCy (Honnibal et al., 2020), NLTK (Bird et al., 2009), Gensim (Rehurek and Sojka, 2010) and biterm (Tretzmuller, 2021). The toolkit's GUI was implemented using wxPython (Dunn, 2021), with visualizations supported by Matplotlib (Hunter, 2007), wordcloud (Mueller, 2021), and mpl-chord-diagram (Fardet et al., 2021). The toolkit's full source code and installation instructions are available at https://osf.io/b72dm/.

3.5.1 Data Collection

To focus on the data, we moved from data collection being a code-oriented workflow to a visual interface that displays the data directly (Figure 3.2), similar to existing analysis software like *Tableau* where data is imported into a large collection that can then be visually modified or inspected. This approach also parallels computational tools like *Jupyter*

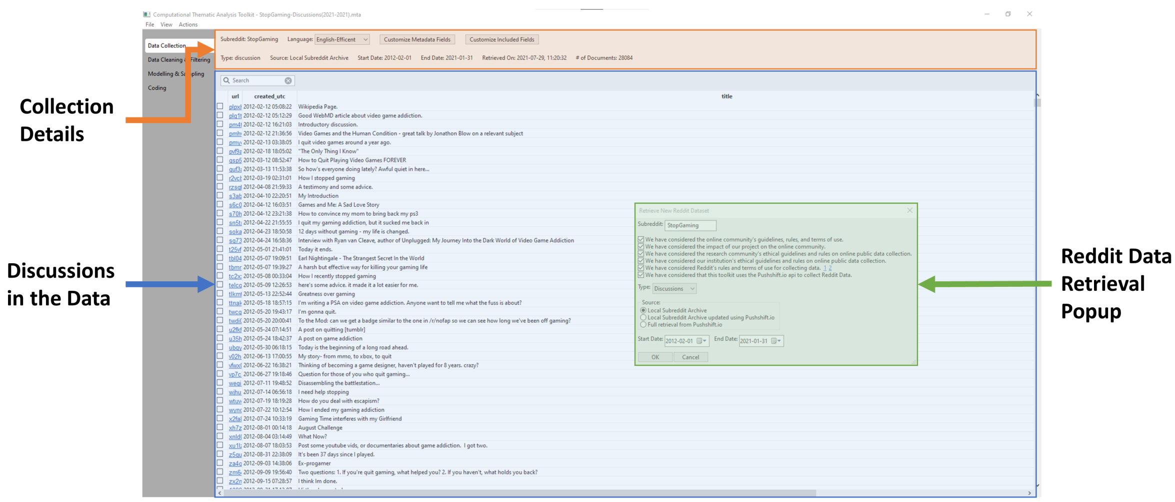

Figure 3.2: Our toolkit's Data Collection tab provides a visual interface for imported discussion data. We automated the importation workflow, to enable researchers to pull data from sources like Reddit or Twitter without needing to write code while respecting each platform's terms of use, as well as the individual community's expectations for use of their data. Once imported, the data is available in for use in each of the other tabs.

Notebook, albeit with a less programming-centric metaphor for interaction. Our toolkit automates many aspects of connecting to data APIs for platforms such as Reddit and Twitter through visual dialogues, and enables researchers to directly import data from previous projects.

Importing Data

A typical data import workflow includes four steps: (1) Import the submissions, (2) Import the comments that responded to those submissions, (3) group the submissions and comments using their `id` and `submission_id` fields, respectively, to form discussions and (4) select fields from those discussions for analysis. Each of these steps involves nuanced decisions, for instance, initial submissions and responses may fall on different sides of the defined time period for sampling. The workflow also needs to account for some fields being out-of-date when pulling from sources like pushshift.io, since they rely on snapshots taken shortly after a submission is created. For instance, fields like `author`, `created_utc`, `title`, `selftext`, and `body` are less likely to change after the archive was created, whereas fields like `score` (upvotes and downvotes) and `num_crossposts` tended not to be reliable in the archive.

To handle this complexity we developed an automated workflow for Reddit discussions, so that submissions and their responses are automatically grouped together when imported based on a given time period. We only include submissions made after the defined start time, and responses to those submissions that were made before the defined end time. We also selected a default subset of more stable fields to import, based on those we found useful during our thematic analyses: `URL`, `created_utc`, `title`, `text`, and `body`. However, acknowledging that thematic analysis by definition requires flexibility, the included fields are all modifiable. To be transparent about these concerns, the import dialogue includes warnings for each field that is unreliable when pulled from an archive.

Ethical Considerations and Retrieval Costs

Ethical considerations are also deeply integrated with how data is first imported into the toolkit. We began by recognizing that there is no one-size-fits-all approach to handling these ethical considerations (Fiesler et al., 2020), and that our toolkit should encourage researchers to navigate their ethical choices rather than rigidly enforce a single set of decisions for all analyses. We then reviewed the literature and identified the following general opportunities for design: (1) communities' position on the use of their data by researchers, (2) ethical guidelines and rules of institutions, governments, and the research community (Bruckman, 2002; Densmore et al., 2020; Munteanu et al., 2019), (3) the need to respect community actions such as moderation, (4) the need to respect individuals' actions such as deleting posts and/or accounts, and (5) the terms of use and capacity of the platforms we use to retrieve the data.

To encourage researchers to actively reflect on the five considerations above, the toolkit's data retrieval dialog implements friction in the form of confirmation check boxes. For example, in the case of Reddit, we implement multiple ethics confirmation check boxes (Figure 3.2), which provoke researchers to consider and reflect on how their analysis might impact different groups, including the community being studied, the research community, and Reddit.

We also implemented local caching of data to help reduce the amount of requests made to the platforms' APIs, and to improve the performance of computational techniques. However, even though this caching is technically permitted by both Pushshift and Reddit, it can be in tension with respecting the actions of both communities and individuals. That is, the cache might become out-of-sync, and contain posts that have been moderated by the community, or deleted by the person who made them. To help researchers identify and manage out-of-sync data, our toolkit links each discussion to its online source, providing a means of manually confirming which posts should be included in the analysis.

3.5.2 Data Cleaning & Filtering

We also developed a visual interface for cleaning and filtering tasks (Figure 3.3), and to enable researchers to become familiar with and interpret various patterns during their thematic analysis. In addition to these tasks being prerequisites for later computational techniques and machine learning tasks (Raschka, 2015), tight integration of cleaning and filtering into a thematic analysis workflow facilitates the discovery of semantic patterns in the data. Our interface also provides opportunities to support transparency and interpretability of the computational aspects of the thematic analysis process.

Our toolkit includes a default data cleaning workflow, based on off-the-shelf tools available in Python. Imported data is tokenized using NLTK (Bird et al., 2009). Tokens are then converted into both a stemmed form, using NLTK's SnowballStemmer (Bird et al., 2009), and a lemmatized form as well as tagged for parts-of-speech, and stop words status, using spaCy's pre-trained model (Honnibal et al., 2020). The toolkit then computes descriptive data for each token, and stores them into pandas dataframes (pandas development team, 2020), including number of occurrences, number of discussions containing each token, and tf-idf. Should a researcher choose, each of these steps is modifiable.

Token-based Analysis

To support data cleaning and familiarization, our toolkit's Data Cleaning & Filtering tab (Figure 3.3) provides list views for each token's part-of-speech, frequency, and tf-idf score. These views show how NLP is being used to interpret the data, and enable researchers to question underlying assumptions and fine-tune default settings before moving on to modelling and sampling tasks. These views are automatically updated when data is loaded and as filtering rules are adjusted. Search boxes enable researchers to quickly search the list for known words.

In developing and using the toolkit, we also found that visual inspection and review of these steps can inform qualitative analysis of data. While originally this interface was focused on helping us conduct modelling, as our toolkit evolved we found that the filtering and cleaning tasks enabled us to identify semantic patterns in the data. That is, looking at these lists also helped us familiarize ourselves with the data for our thematic analysis. For instance, these lists can be helpful in identifying domain-specific nouns that can be used as

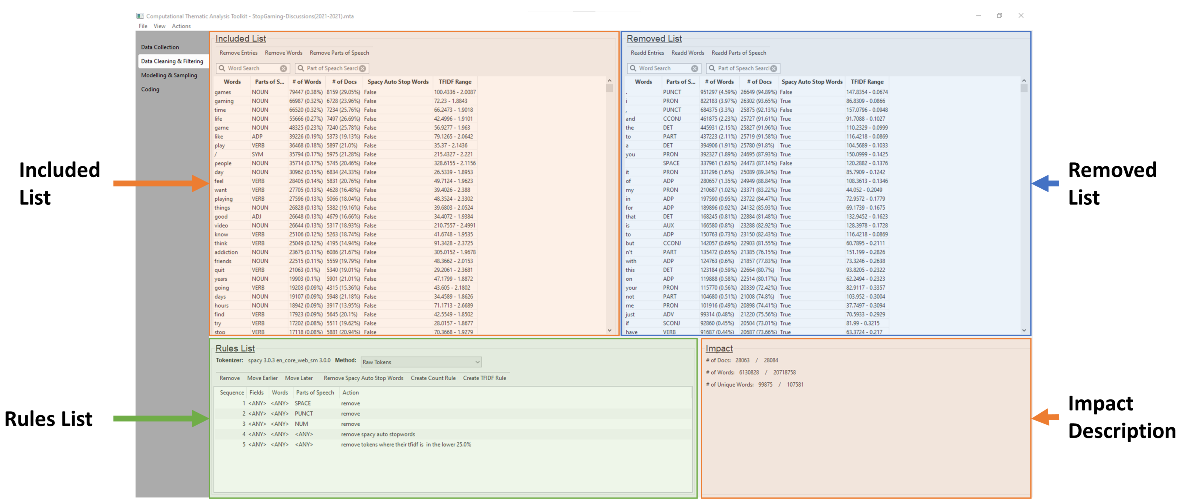

Figure 3.3: Our toolkit's Data Cleaning & Filtering tab presents a summary of tokens present in the imported data. Researchers can use two list views to inspect and reflect on words included and removed by the data cleaning process. They can also manually fine-tune filters. We also developed a rules list that shows the cleaning and filtering steps applied, including their order, to assist with interpretability and transparency of the research process. To further transparency, our toolkit shows the impact filtering has on the data in terms of word counts and discussion counts to highlight the amount of data removed.

features in any models used to inspect the data, or for coding and theme development. We have found that the list of *removed* words is equally useful in reflecting on and questioning underlying assumptions of our analysis.

Supporting Explainability & Transparency

When using computational methods like *Juypter Notebooks*, analysts are initially aware of why a word was included or removed from their model(s), since each step is performed manually. However, much of this work becomes hidden when it is automated, making it difficult to determine which tokens had been included or removed, and in which order operations were applied. To make these decisions more transparent we implemented a rules list (Figure 3.3) that visualizes each operation and the order in which they are applied. To be transparent about the impact of filtering on the data, we also provide summaries of how many discussions, words, and unique words are present after all of the filtering rules have been applied.

3.5.3 Modelling & Sampling

Once the researcher has familiarized themselves with semantic patterns in the data, our Modelling & Sampling tab (Figure 3.4) provides functionality to help them identify and interpret latent patterns. It enables researchers to quickly generate, inspect, and interpret samples from computational models of their data. Researchers can generate unique models in separate tabs across the top of the display using random sampling, or purposive computational techniques like LDA and biterm, for long and short text, respectively. As models are generated, they are also visualized on the right-hand side of the screen, with samples shown in the bottom left, where they may be inspected by the researcher.

Visualizing Models

While much of the topic modelling literature has focused on statistical evaluation of models (Ammari et al., 2018; Arun et al., 2010; Blei et al., 2003; Mimno et al., 2011; Newman et al., 2010; Röder et al., 2015), when we tried to implement such measures into our qualitative research process we found that they were very abstract, difficult to explain, and difficult to apply. Additionally, we did not find a clear consensus on what metrics to use to optimize a model since each had their own strengths and weaknesses. We instead decided to focus on visualizing the model, to enable researchers to more rapidly understand, refine,

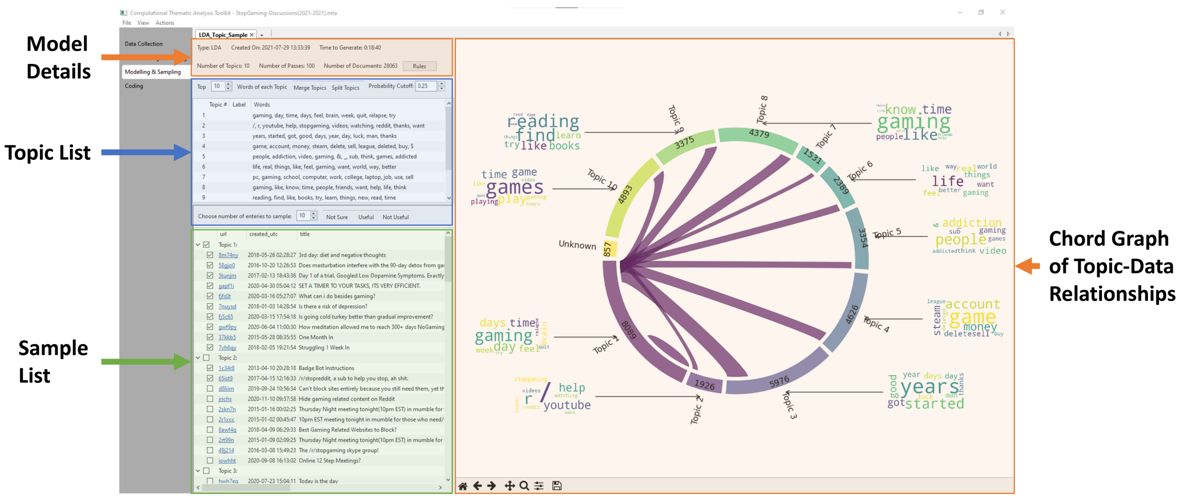

Figure 3.4: The Modelling & Sampling Tab enables researchers to create topic models of the data set and visualize them using our chord graph. The graph shows topics, their respective keywords, and the portion of discussions shared with each other topic. Researchers may also label and merge topics created by the model before selecting discussions from the generated sample for coding and theme development.

and enhance their topics for qualitative interpretation (El-Assady et al., 2018, 2019). By evaluating the models visually we found that we could generate models that are 'good enough' to hone in on interesting data, rather than getting caught up in trying to create an optimal model for some quantitative metric that didn't ultimately improve the thematic analysis.

In particular, our visualizations focused on both topic-discussion and topic-word relationships. Initially, we tried including pyLDAvis (Sievert and Shirley, 2014), a popular visualization for LDA models that shows whether topics overlap and how different words contribute to each topic. However, we found that it didn't help us explore how words interrelated between topics or identify when discussions might contain to multiple topics — particularly important questions when performing a thematic analysis. To better support these aspects of thematic analysis, we decided to implement our own visualization.

We created a chord graph (Figure 3.4) where each topic is represented by an arc, with its length corresponding to the portion of discussions it represents. Each arc is then labelled with a name and a word cloud containing the most relevant keywords for each topic. The visualization is also interactive. Researchers can click on any topic arc to view chords corresponding to discussions in common with other topics. Researchers can then mouse over other topics to make comparisons between more than one topic at once. Topics can also be named and merged by the researcher, as they familiarize themselves with the model and data. By default, topic names are blank so that they may be created by the researchers rather than the model (Jiang et al., 2021).

Identifying Samples

To facilitate sampling, our toolkit uses the generated models to identify sets of discussions to be used as samples for thematic analysis using the following steps: (1) The topic model is used to calculate the probability that each topic is present within each discussion. (2) A sorted list is created for each topic, with the most representative discussions at the top of the list. (3) Any discussion with a probability lower than the cutoff is dropped from each topic's list. (4) An 'unknown' topic is formed using any discussions whose topic probabilities are all below the cutoff. (5) For the 'unknown' topic, discussions are sorted based on *lowest* maximum probability to seek out discussions that the model is least confident in. (6) The top discussions from each topic are then included in the samples.

These samples are visualized in a list that shows each of the fields of the discussions on the lower left hand side of each Modelling & Sampling tab (Figure 3.4, Sample List). Researchers can interactively control how many discussions are sampled for each topic, and flag documents that they find useful or not-useful.

3.5.4 Coding

The Coding tab (Figure 3.5) facilitates researchers' interpretation of data through reviewing discussions, taking notes and applying codes. Rather than this tab using additional computational techniques, such as AI coders, we focused on providing researchers access to discussions identified manually, in the data collection tab, as well as from model-derived samples. This approach aligns with the goal of 'supporting serendipity' to maintain researchers' agency in the thematic analysis process (Jiang et al., 2021). Our toolkit supports three coding activities: reviewing discussions, applying codes, and writing notes.

Discussions are gathered when a researcher checks off desired discussions on the's activity during Data Collection and Modelling & Sampling tabs. Any discussion that a researcher has checked off is made available for coding in a list at the top the screen. Researchers can also search and toggle which discussions are displayed, based on those flagged as useful, unsure, and not useful. When a discussion is selected, the lower portion

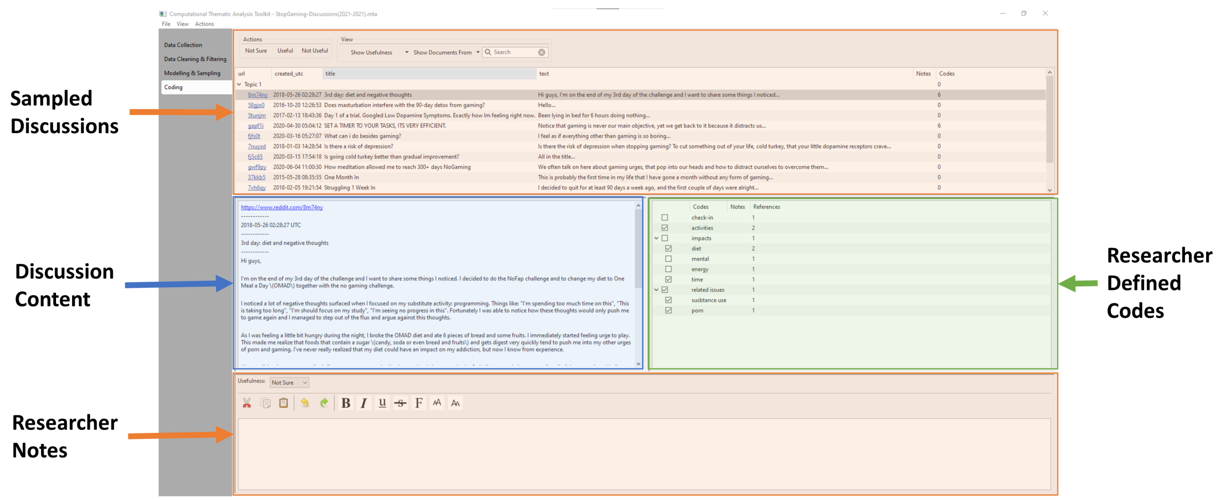

Figure 3.5: Our toolkit's Coding tab displays a list of discussions along with, upon selecting a discussion, showing the discussion's collected fields, a list of codes researchers can assign to the discussion, and a text editor where researchers can make and review any notes about the discussion. Adding codes to a discussion can be done by either by checking off existing codes used in other discussions or creating new codes.

of the screen is used to perform coding: the full discussion content is displayed, codes can be applied, and researcher notes can be attached.

This coding tab is designed to mirror existing qualitative research software like NVivo (QSR International Pty Ltd, 2021) and Atlas.TI (Scientific Software Development GmbH, 2021). As researchers review each discussion, they can apply self-defined codes to them. Researcher-defined codes are displayed in a pane to the right, along with the number of discussions that have been tagged with that code. To support note taking, the coding interface provides a rich text interface with common word processing functions at the bottom of the screen.

3.6 Discussion

Our toolkit integrates support for qualitative and computational research methods within a single software interface. We built on the 'convergences' between qualitative and computational methods (Muller et al., 2016), and from those convergences derived a computational thematic analysis workflow and a visual interface that enables non-technical researchers to engage in its methods. As the first implementation of these ideas, we hope that our toolkit can spark discussion in the field, and in particular, discussion around two aspects of its design: the interpretive role of computational support for qualitative analysis, and how to provide built-in support for ethical and transparent research.

When integrating qualitative and computational techniques, we embraced Baumer et al.'s (Baumer et al., 2017) view that models provide "scaffolding for human interpretation" and the importance of one or more *good enough* models which provide new perspectives of the data, rather than a singular, "best" model as an objective truth. Similarly, we emphasized a visual approach to model evaluation, eschewing quantifications like coherence (Mimno et al., 2011; Newman et al., 2010; Röder et al., 2015) or Jaccard's distance (Ammari et al., 2018). These visualizations intentionally show data that was *not* associated with a topic to help researchers keep in mind that models are imperfect, and should be questioned and interpreted.

We also considered calls for ethical design and use of computational methods from the research community, and notably Jiang et al. (2021). We acknowledge these risks, but also feel that computational techniques can help to identify different understandings of a phenomenon, often in ways that may not be immediately accessible to a human researcher alone. To mitigate these concerns, we emphasized transparency — we designed our toolkit to support transparent reporting within each conceptual stage and practical analytic task to strengthen the rigour and trustworthiness of the research (Talkad Sukumar et al., 2020; Tuval-Mashiach, 1027).

3.7 Limitations

We designed our toolkit around *reflexive* thematic analysis (Braun and Clarke, 2006), however other variations of thematic analysis (or more generally, other qualitative research methods) may not be as well supported by it. We believe that much of our toolkit's core functionality can be useful for different methods, and we designed it to be modular and flexible. But, if one wanted to, for example, begin with a qualitative analysis (i.e., coding) and then use those codes to create a supervised model for topic classification, then the current toolkit would not provide adequate support.

Further, additional research and development will be required to show the toolkit's efficacy in practice. This research will need to focus on both specific features and the general utility of the toolkit. For instance, novel features like our chord graph visualization require further study. Future work could perform comparative evaluations of our visualization and pyLDAvis (Sievert and Shirley, 2014) to elucidate their respective strengths and weaknesses. We also anticipate performing hands-on field studies with qualitative researchers to better understand our toolkit's use in practice.

Finally, and perhaps most significantly, we acknowledge that the ethical and transparent treatment of research data, and indeed the methods themselves, are a rapidly evolving research area. Our implementation is itself therefore a limitation of this research. In developing our toolkit, we sought to embody the values of transparency and ethical conduct into the software's design. Sometimes that meant adding friction, like when prompting researchers to pause and think about the potential consequences of their actions. We did this intentionally to align with what we felt were emerging best practices; but this area of research is rapidly evolving and future work is likely to develop new best practices.

We also want to explicitly resist any notion of situating our toolkit as 'ethical', or the false dichotomy of other tools as 'unethical'. We instead acknowledge there are ethical risks involved when conducting research into online communities. Due to these risks, we aimed to make our tool provoke ethical considerations which enable researchers to take control of their own ethics in research process. However, our implementation is certainly not perfect, nor complete. We only hope that it can serve as a working example and a point of critique for how ethics and transparency can be more deeply integrated into the software used to perform Computational Social Science.

3.8 Conclusion

In this work we set out to explore how computational techniques can augment human qualitative analysis, with a focus on reflexive thematic analysis. To do so, we developed the Computational Thematic Analysis toolkit to explore different types of support, and how those supports might be extended to researchers without expertise in computational techniques. We also embedded ethical considerations of data analysis into the toolkit, with the goal of encouraging researchers to consider the potential impacts of their research on the communities they study, and to support research transparency through records of both the decisions made for both qualitative and quantitative methods.

Finally, this research was exploratory by nature, intended to explore some of the 'big effects' (Neustaedter and Sengers, 2012) in designing for a hybrid qualitative and computational analysis. Our toolkit implements software features to support several tasks as defined in our Computational Thematic Analysis workflow, but unexplored supports, particularly in later tasks like 'theme identification', may also prove useful. For instance, future work might explore how counter-factuals can prompt a qualitative researcher to consider new perspectives on the themes that they had developed, or how summarization techniques might be used to help define and name themes later on in an analysis. We hope that by sharing our code under an open source license that this work can serve as a platform for the exploration of these ideas in future work.

3.9 Acknowledgements

We thank the University of Waterloo Games Institute and its members for their constructive feedback. This work was made possible by NSERC Discovery Grant 2015-06585 and the Ontario Graduate Scholarship.

Chapter 4

Deploy Stage – Agency and Amplification: A Comparison of Manual and Computational Thematic Analyses by Public Health Researchers

4.1 Abstract

Computational techniques offer a means to overcome the amplified complexity and resource-intensity of qualitative research on online communities. However, we lack an understanding of how these techniques are integrated by researchers in practice, and how to address concerns about researcher agency in the qualitative research process. To explore this gap, we deployed the Computational Thematic Analysis Toolkit to a team of public health researchers, and compared their analysis to a team working with traditional tools and methods. Each team independently conducted a thematic analysis of a corpus of comments from Canadian news sites to understand discourses around vaccine hesitancy. We then compared the analyses to investigate how computational techniques may have influenced their research process and outcomes. We found that the toolkit provided access to advanced computational techniques for researchers without programming expertise, facilitated their interaction and interpretation of the data, but also found that it influenced how they approached their thematic analysis.

4.2 Introduction

Recent progress in artificial intelligence and machine learning research has prompted the human-computer interaction research community to question how computational techniques should be used to perform data science. They've noted, for instance, that computational techniques converge with qualitative research activities like coding and theme creation, and can help researchers overcome human limitations like the time required to (manually) study massive online data sets (Baumer et al., 2017; Muller et al., 2016; Rodriguez and Storer, 2020). While the theoretical benefits of these partnerships are compelling, we have a limited understanding of whether they are ultimately beneficial, how they might improve research practices, or whether they may have some unintended side-effects or limitations.

To date, the human-computer interaction research community has developed prototype tools (e.g., Baumer et al., 2020; Gauthier and Wallace, 2022)), and spoken to qualitative researchers about their perceptions, beliefs, and attitudes towards AI (e.g., Feuston and Brubaker, 2021; Jiang et al., 2021)). Critical computing researchers have also begun integrating qualitative traditions, such as reflexivity and context awareness, into quantitative computational methods to mitigate bias, respect user groups, and consider social conditions during the development of data sets and models (Aragon et al., 2022; Cambo and Gergle, 2022; Papakyriakopoulos et al., 2021; Saxena et al., 2022; Vaughan and Wallach, 2021). However, we currently lack hands-on experience with these tools, and a sense of how they might be used in practice, particularly by researchers without programming experience.

To explore how these partnerships play out, we asked two teams of public health researchers to independently perform thematic analyses on the same data set; one performed 'manually' using a traditional process, and one performed 'computationally' using the Computational Thematic Analysis (CTA) Toolkit (Gauthier and Wallace, 2022). Each team started with the same set of 613,666 comments from English Canadian news sites and independently performed an inductive thematic analysis to answer research questions about the perception of COVID-19 during the period of January – July 2020. After both teams had finished, we compared each team's process and results.

In presenting the results of our case study we describe how each analysis followed a different inductive and iterative process — the manual analysis team used a bottom-up process defined by the human activities, whereas the computational analysis team interacted used a top-down process defined by the toolkit modules. Despite these differences, each analysis produced coding trees with similar, overlapping themes. Reflecting on these results, we discuss implications of qualitative researchers' use of the toolkit to perform thematic analysis:

1. The toolkit lowered the threshold to use computational techniques, and enabled non-programmers to conduct their qualitative research;
2. It simultaneously 'raised the ceiling' (Ledo et al., 2018) of their efforts, and facilitated their interaction and interpretation of the large data set;
3. However, we also show how use of the toolkit influenced their research process, and discuss implications of this influence for future research.

4.3 Background

Our work is situated at the intersection of three active research areas: thematic analysis, computational social science, and toolkit research. In particular, we examine how techniques from computational social science (e.g., Blei et al., 2003; Yan et al., 2013) can be used to address known challenges in applying qualitative research methods like reflexive thematic analysis to large, online data sets (Braun and Clarke, 2006; D'Agostino et al., 2017). To do so, we were particularly interested in understanding how toolkit-based research might help us understand some of the implications of deploying computational tools to domain experts in a practical setting (e.g., Gauthier and Wallace, 2022; Ledo et al., 2018). We now outline related research that describes: (1) challenges in extending traditional qualitative methods to online data, (2) the potential benefits of computational techniques for these analyses, and (3) how toolkit-based research can be used to explore their utility through real world deployments.

4.3.1 Thematic Analysis

Thematic analysis is a flexible research method that is used to develop, analyze, and report qualitative themes present within data (Boyatzis, 1998; Braun and Clarke, 2006). Being a flexible method means there is not one correct approach to performing a thematic analysis; instead there are multiple sets of adaptable guidelines aligned under three schools: reflexive, codebook, and coding reliability. Further, within these schools, thematic analyses can be performed with different levels of formality, ranging from adhering closely to an established procedure, such as *reflexive (Braun and Clarke, 2006)* or *codebook (Boyatzis, 1998)*, to less formal approaches like *pragmatic* thematic analysis (Aronson, 1995).

A consequence of this flexibility is that planning and performing a thematic analyses is complex. Researchers need to consider multiple interconnected aspects of their research such as: its context and objectives; the researcher's position, assumptions, and experiences; research constraints, such as time, money, and people; and which reliability mechanisms are appropriate (Braun and Clarke, 2021; McDonald et al., 2019). These complexities are compounded by the iterative nature of thematic analysis which requires researchers to repeatedly read and code data, and develop and refine themes which contextually integrate their experience and practical knowledge (Boyatzis, 1998; Braun and Clarke, 2006).

And when working with online communities, this complexity is even more severe. Researchers need to consider their data's origin and scale . They also need to navigate trade-offs between the amount of data included in their analysis and the resources required to analyze it (Braun and Clarke, 2006; D'Agostino et al., 2017).

A common strategy to manage these challenges is sampling to reduce the amount of data processed for analysis. For instance, researchers frequently use random selection (Attard and Coulson, 2012) or convenience sampling, such as a date-window (Ahmed et al., 2017; D'Agostino et al., 2017; Gooden and Winefield, 2007; Rodgers and Chen, 2005), to obtain a sample that is small enough for human analysis. However, these sampling techniques risk discarding interesting data before they can be considered by expert researchers (Marshall, 1996). Thus, researchers have turned to computational strategies, such as purposive sampling (Hoeber et al., 2017), to mitigate these challenges while simultaneously enabling them to engage with data in detail and interpret themes from large data sets.

4.3.2 Computational Social Science

The human-computer interaction research community has recently begun to explore 'convergences' between machine learning and qualitative methods: the collection of empirical evidence, iterative interaction with data, and the use of different lenses to interpret it (Baumer et al., 2017; Chen et al., 2018; Muller et al., 2016; Rodriguez and Storer, 2020). To date, these convergences have manifested through research that explores how computational techniques like topic modelling (e.g., Blei et al., 2003) and exploratory search (White and Roth, 2009) can support qualitative researchers in identifying interesting samples (Gauthier et al., 2022; Hoeber et al., 2017) and latent topics (Maier et al., 2018; Poursabzi-Sangdeh et al., 2016). These techniques are particularly compelling because they are interpretive, and can be grounded in researchers' expertise and practical knowledge (Marshall, 1996).

However, qualitative researchers also do not want computational techniques to simply automate their interaction with the data; they want to maintain autonomy, intimacy, and ownership of their analysis (Jiang et al., 2021). There are also open questions around how these influences manifest because computational techniques have been primarily developed and validated by computational researchers without sufficient input from qualitative researchers with domain expertise (Baden et al., 2021).

Moreover, the integration of computational social science techniques into qualitative research is incomplete (Baden et al., 2021; Jiang et al., 2021). While the aforementioned research has developed narrow technical prototypes that explore individual computational techniques, they have yet to deeply explore their use in practice, by domain experts. Developed tools also frequently rely on programming knowledge and assume a process grounded in data science, which makes it difficult to combine and validate technique use within a qualitative research pipeline (Baden et al., 2021).

To address this gap, the human-computer interaction research community has called for work that bridges the gaps between the computational and qualitative communities to establish common ground and explore where and how computational techniques can provide meaningful value to the social science (Baden et al., 2021; Chen et al., 2018). Our work contributes to closing these gaps by deploying a toolkit to an existing research group actively engaged in addressing a pressing real world public health research question.

4.3.3 Toolkit-based Research

In human-computer interaction research, toolkits provide opportunities to explore a 'bold vision of the future' and enable access to new solution spaces (Ledo et al., 2018). Toolkits can be developed and deployed by researchers to empower new audiences through access to tools; to explore concerns and research gaps identified in the literature, like those surrounding agency (Baden et al., 2021; Jiang et al., 2021); and to understand how they integrate with current practice. During our toolkit deployment, we focus on two toolkit evaluation strategies identified by Ledo et al. (2018): *demonstrations* and *usage*.

Demonstrations explore what can be done with a toolkit and enable researchers to describe which paths of least resistance it facilitates (Ledo et al., 2018). They use methods like case studies in real world contexts to describe how toolkits can be used as unexpected situations occur (e.g., MacIntyre et al., 2004; Seyed et al., 2015). They help to identify thresholds and ceilings — a person's ability to get started, and how much they can achieve with a toolkit (Ledo et al., 2018) — both of which contribute to understanding how and where a toolkit can be used in complex solution spaces (Myers et al., 2000).

Usage evaluations explore who can use a toolkit and frequently include end users as valuable stakeholders (Ledo et al., 2018). They take advantage of methods like take-home studies to understand how stakeholders appropriate and use toolkits over time while

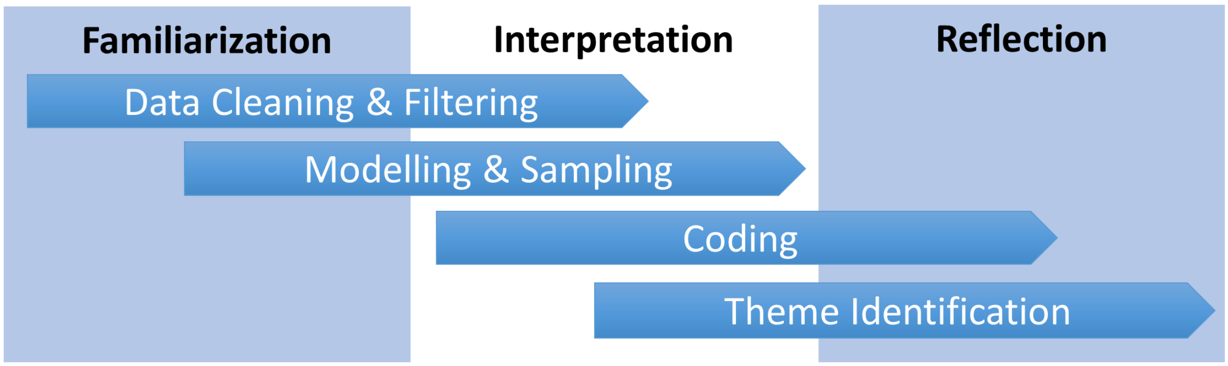

Figure 4.1: Gauthier and Wallace (2022)'s workflow that was used to focus the development of the toolkit. In moving from data collection to writing their final report, researchers progress through three conceptual stages of work: familiarization, interpretation, and reflection. To do so, they perform the practical tasks of data cleaning & filtering, modelling & sampling, coding, and theme identification. Like thematic analysis and computational methods, this workflow is highly iterative, and is not a linear process; researchers may shift between any conceptual stage or practical task.

developing new workflows (e.g., Bomfim et al., 2020; Judge et al., 2010). Similarly, usage evaluations provide opportunities to reflect on how people's behaviour differs with the introduction of a toolkit (e.g., Bostock and Heer, 2009; Hill and Gutwin, 2004). They are useful for exploring complex design spaces, like thematic analysis of large data sets, where integration of computational techniques has been theorized but is not yet fully established.

In this work, we explore both demonstration and usage through a case study of holistic use of a toolkit that supports thematic analysis. By deploying the toolkit with a team of domain experts, we sought to better understand its thresholds and ceilings, and how it can be used to solve complex tasks. We also explored how the toolkit may influence their analysis process and outcomes.

4.4 The Computational Thematic Analysis Toolkit

The Computational Thematic Analysis Toolkit (Gauthier and Wallace, 2022) was designed to enable non-programmers to use computational techniques to perform thematic analysis of online community data. In developing their toolkit, Gauthier and Wallace created a cohesive, visual interface that integrates Braun and Clark's (Braun and Clarke, 2006) reflexive thematic analysis phases with tasks common to data science (Figure 4.1). To support these various activities, the toolkit comprises interconnected modules that researchers can freely move between as they iteratively familiarize themselves with their data, interpret it, and reflect on their findings:

- The **Data Cleaning & Filtering module** enables researchers to visualize collected data and how NLP techniques may interpret it through fields like included and removed tokens, part of speech, and NLP summaries, such as frequency and TF-IDF range. This module also enables researchers to interactively review and change the filtering rules being applied to the data, and the impact of those changes on the above fields.
- The **Modelling & Sampling module** enables researchers to identify and interpret latent patterns in the data using computational techniques, such as biterm topic modelling (Yan et al., 2013). Once generated, researchers may label, merge, or remove topics, and visualize models as word lists and chord graphs. When a suitable model has been decided on, it may be used to purposively sample threads for further analysis.
- The **Coding module** enables researchers to manually code data, in an interface similar to qualitative data analysis software like NVIVO, MaxQDA, or Atlas TI. Researchers may choose from a list of sampled data, and develop a code tree by creating, modifying, and/or deleting codes.
- **Theme Identification** is supported through two modules. The **Reviewing module** enables researchers to create and review themes and codes through a network visualization. The **Reporting module** enables researchers to select and track the sources of quotations for the themes and codes developed in previous modules.

We deployed and iterated on version 0.8 of the Computational Thematic Analysis Toolkit (Gauthier and Wallace, 2022). The toolkit's full source code and installation files are available at https://osf.io/b72dm/

4.5 Methods

To understand how the Computational Thematic Analysis Toolkit might influence research in practice, we performed a field comparison of two thematic analyses; one conducted through manual methods, and the other with computational methods (Figure 4.2). The two thematic analyses were performed independently, by expert teams, and with an inductive, realist perspective on the same set of real-world data. The manual team was asked to perform the analysis using their normal process. The computational team was asked to use the toolkit as they saw fit and told that it was not intended to replace their research, rather to provide a scaffold of tools to support their interaction with the data. Each team then reported on their process and findings, allowing us to compare and contrast each analysis and to develop an understanding of how the toolkit influenced the analysis.

The two analyses were conducted by teams of public health researchers, who were tasked with describing online discourses related to the generation and spread of rumours, misinformation and disinformation on COVID-19 in Canada. Both teams belonged to the same public health research group associated with the Canadian Immunization Research Network (CIRN), and were seeking the ability to perform end-to-end analysis themselves after unsuccessfully working with an external team of AI consultants. Additionally, the public health research group: had not been involved in the toolkit's development; had research questions motivated by an emerging public health need; had expertise in conducting inductive thematic analyses; and had already collected data for their research questions.

Each team analyzed the same set of 613,666 English comments from Canadian news sites. This data set was collected by the CIRN team between January and June 2020 from a variety of Canadian news sites, including: CBC news, The Cape Breton Post, The Chronicle Herald, The Globe and Mail, The Halifax Examiner, The National Post, The Time Colonist, The Toronto Star, The Toronto Sun, The Tyee, and The Vancouver Sun. Thus, the members of both analysis teams were familiar with the data set.

4.5.1 Our Research Teams

Our research team comprised three sub-teams, each focused on a distinct task: toolkit development, computational analysis, and manual analysis. The members of both analysis teams came from a public health research group and had common experience conducting thematic analyses.

- The **manual analysis team** was responsible for using their research group's normal processes to conduct a thematic analysis of the shared data set and comparing the results of their manual analysis against the computational analysis. The team consisted of the third author, who is a trainee in anthropology, fourth author, who has a MSc in Public Health (Health Promotion and Program Evaluation) and investigates prevention, health promotion, communication, and misinformation, and sixth

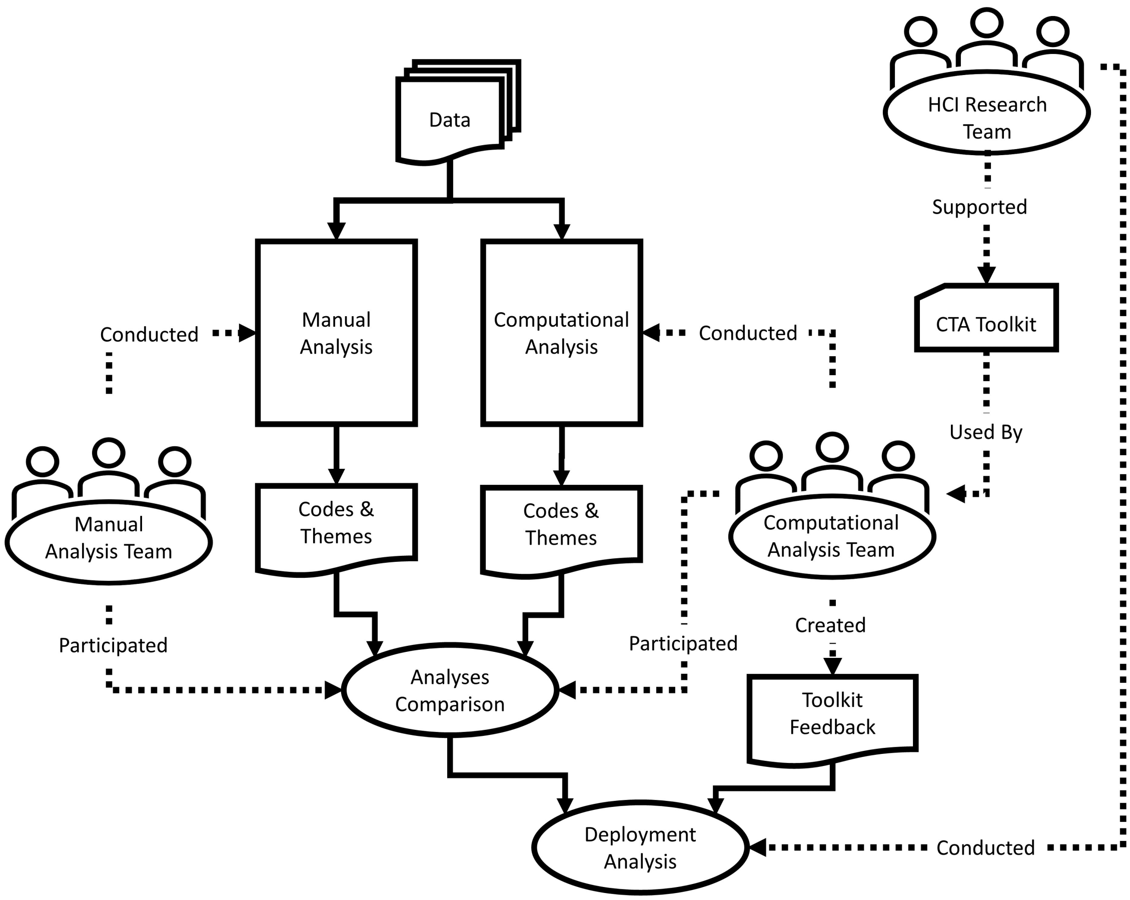

Figure 4.2: Three research teams were involved in our case study. (1) The manual analysis team performed an inductive thematic analysis using their traditional methods. (2) The computational analysis team performed a thematic analysis using the Computational Thematic Analysis Toolkit (Gauthier and Wallace, 2022). (3) The HCI research team was responsible for technical support, and comparing the processes and outcomes of each thematic analysis.

author, who has a PhD in public health and focuses on using qualitative methods to investigate the role of trust in Canadians' use of immunization and who was the principle investigator for funding acquisition. The third and fourth authors focused on developing and comparing results, while the sixth author assisted with preparing the data set, coordinating inter-team communications, and distributing results. Because of their inter-team communication role, the sixth author stayed at arms length during analysis tasks, such as coding, and comparison.

- The **computational analysis team** was responsible for conducting a thematic analysis using the Computational Thematic Analysis Toolkit, comparing the results of their computational analysis against the manual analysis, and providing feedback based on their experience. This team consisted of the second author, who has an MSc in Public Health and who researches prevention, vaccine hesitancy, social listening, and media coverage, and the fifth author, who has a PhD in medical anthropology and who specializes in using qualitative methods to investigate the socio-cultural field surrounding infectious diseases prevention. The second author acted as the primary analyst and the fifth author provided continual consultations throughout the analysis.

- The **HCI research team** provided technical support to the computational analysis team through training and bug fixes. They did not participate in the thematic analysis, but were responsible for analyzing the results of each and interpreting feedback from the other two teams. This team consisted of the first author, who is a PhD Candidate in public health and has software development, human computer interaction, and reflexive thematic analysis experience, and the seventh author, who is a professor and human-computer interaction researcher.

4.5.2 Data Collection & Analysis

To analyze the case study, we first gathered information about each analysis: (1) the processes, regarding what steps were performed and the activities that occurred during these steps; (2) the outputs, which consisted of themes and coding trees created during the analyses. We also collected (3) toolkit usage data from (a) the computational analysis team's journals, that described their thoughts as they used the toolkit; (b) a saved toolkit workspace, that captured the data used, the state of each module, and the actions that lead to these states; and (c) emails with the HCI research team, that describe activities in need of support during the analysis.

We then used the gathered data to describe both analyses' processes and outputs. To describe the analyses' processes, each analysis team summarized their notes taken while planning and conducting the analyses. These notes were then used by the HCI research team to create analysis process diagrams. In addition, for the computational analysis, the HCI research team added details of toolkit usage by triangulating the analysis' process with the toolkit usage. To describe the analyses' outputs, both analysis teams created coding trees, that capture the connections between themes and codes, as well as a description of each theme. These coding trees and the descriptions of themes were then integrated into tables by the HCI research team.

Finally, we compared the two analyses to identify similarities and differences. To compare the analysis, both analysis teams participated in a group discussion that went over both team's analyses' outputs and how these were created and used. For process, The HCI research team then triangulated discussion notes with the descriptions of the two analyses to identify similarities and differences during both high level process steps and low level activities. For themes and codes created, the analysis teams summarized their discussions, which the HCI research team triangulated with the analyses' outputs to create a table of the overlap between topics.

4.6 Results

In this section we present both the manual and the computational thematic analysis. First, we describe both analyses in terms of: (1) each team's analysis process and the activities performed; and (2) each team's results which are made up of themes and coding trees. We then identify similarities and differences by comparing the two processes and the team's results.

4.6.1 Manual Analysis

The manual analysis team followed a three step iterative process to analyze the 613,666 comments (Figure 4.3): (1) independent inductive coding, using 150 randomly selected comments; (2) group discussions, to establish and revise a coding framework; and (3) apply coding framework to a sample of 2,000 randomly selected comments. By the last iteration of this process the team created six main themes, one secondary theme, and a four level coding tree that links the codes to these themes (Table 4.1).

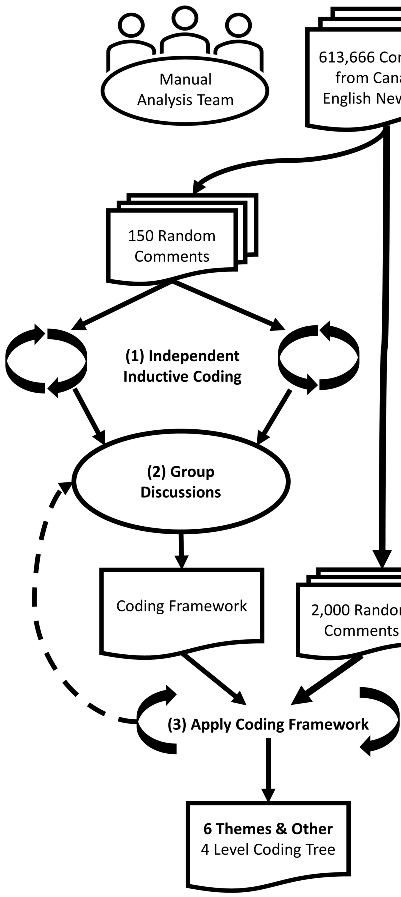

Figure 4.3: The manual analysis team followed an iterative, three-step process : (1) Independent Inductive Coding, using a random sample of 150 comments; (2) Group Discussions, to establish and later revise a coding framework; and (3) Apply Coding Framework, using a random sample of 2,000 comments. The process created a four level coding tree that group codes using six main themes and one secondary theme.

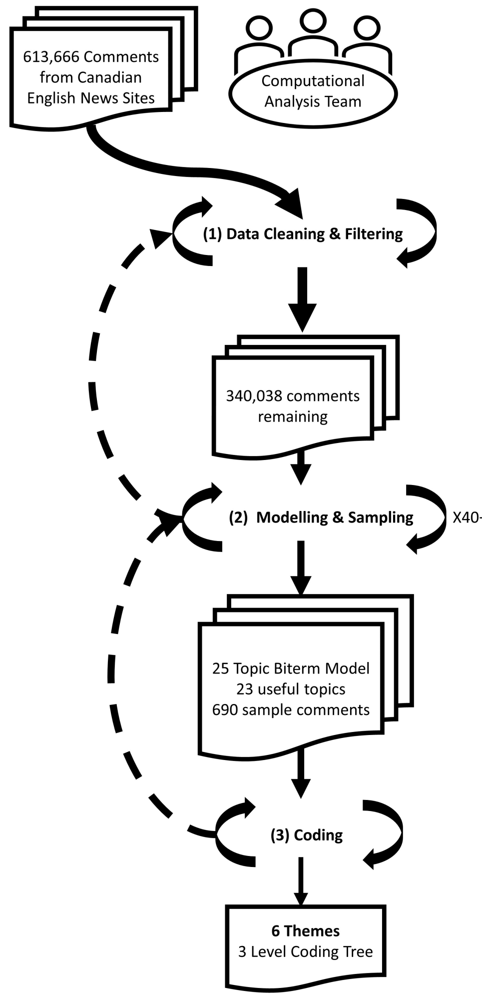

Figure 4.4: The computational analysis team followed a separate, iterative, three-step process: (1) Data Filtering & Cleaning, which reduced the data from 613,666 to 340,038 comments; (2) Modelling & Sampling, which resulted a biterm topic model, and reduced the data down to a sample of 690 comments; and (3) Coding, during which they created a three level coding tree and developed six themes.

Independent Inductive Coding

The team first inductively coded a sample of 150 randomly selected comments. Two team members independently read the comments to develop context and then coded the comments to iteratively develop and identify initial codes, themes, and meanings that provided initial perspectives on the data set and how it could be analyzed. For instance, as a researcher read over the comments, they identified the general themes: criticism, frustration, and opposition from another user. As these general themes re-occurred, they created specified codes based on the subject matter of the comments, such as ageism, racism, stigma, discrimination, and xenophobia. The team completed an estimated 4 hours of coding the initial 150 comments on day 6. In the end the group of themes was combined into the theme CRITICISM with sub-themes corresponding to whom the comment was being critical towards, such as TOWARDS USER, TOWARDS EXPERTS, or TOWARDS GOVERNMENTS.

Group Discussions

The team then initiated group discussions after (1) independent inductive coding and as an iterative activity when new codes were created during (3) applying coding framework. During these discussions, the team discussed how their codes apply to the data. The team held their initial discussion on day 6 for an estimated 4 hours and spent a further 2 hour of time meeting meeting to revise and finalize their coding framework over the course of step 3. For instance, they discussed examples from CRITICISM TOWARDS USER and whether they were identified as a CORRECTION OF FACTS TO ANOTHER USER ensure that both coders were able to consistently distinguish between them. These discussions also helped the team to create and refine their common coding framework, which they used as a foundation for rest of the analysis. For instance, they discussed how DISINFORMATION was an important theme during the pandemic on social media and how they could identify it, leading to the creation of codes for MINIMIZATION OF THE VIRUS, CONSPIRACY THEORIES, and TROLL.

Apply Coding Framework

Finally, the team coded a sample of 2,000 randomly selected comments to assess code coverage, identify needed revisions, and themes. Two team members divided and deductively coded the comments using the common coding framework. Additionally, when the team identified the need for additional codes or revisions to existing codes they iterated back to (2) group discussions to revise their framework, and then resumed applying it to the sample. The team spent an estimated 14 hours on this step and finalized their application of codes and revising their coding tree on day 20. At the end of the process the they had developed a four level coding tree that grouped their codes under six main themes and one secondary theme (Table 4.1).

Table 4.1: Manual Analysis Coding Tree, made up of four levels. Six main themes and one Other theme make up the first level. Levels two, three, and four consist of codes that contributed to the themes.

1. **CRITICISM**
   Comments expressing an opinion on different aspects of the COVID-19 pandemic (sanitary measures, experts' opinions, authorities' decisions, media). This theme is divided into sub-themes, depending on who is targeted by the comment (another user, the experts, the population, the government or the media).

   1.1 **Towards User**
   - 1.1.1 Critical of those in favour of sanitary measures
   - 1.1.2 Critical of those in opposition to the sanitary measures/pandemic
   - 1.1.3 Correction of facts to another user
   - 1.1.4 Hateful comment
     - 1.1.4.1 Racism towards an individual
     - 1.1.4.2 Ageism
     - 1.1.4.3 Discrimination
     - 1.1.4.4 General insult
   - 1.1.5 Comment in agreement with another user

   1.2 **Towards Experts**
   - 1.2.1 Lack of trust in experts
   - 1.2.2 In agreement with the experts

   1.3 **Towards the Population**
   - 1.3.1 On non-compliance with sanitary measures
   - 1.3.2 Racism towards a group
   - 1.3.3 General criticism / discouragement
   - 1.3.4 encouragement

   1.4 **Towards Governments**
   - 1.4.1 USA / International
     - 1.4.1.1 In disagreement with the decisions
     - 1.4.1.2 Insult to Donald Trump
     - 1.4.1.3 In accordance with political decisions
   - 1.4.2 Canadian
     - 1.4.2.1 Poor budget management during the pandemic
     - 1.4.2.2 Poor management of the pandemic
     - 1.4.2.3 Good management of the pandemic
     - 1.4.2.4 Lack of confidence in the government
     - 1.4.2.5 In accordance with the government's decisions
     - 1.4.2.6 Insult to politicians

   1.5 **Towards Medias or the News**
   - 1.5.1 In agreement
   - 1.5.2 In disagreement

   1.6 **Towards Companies**

2. **DISEASE**
   Comments about the characteristics of COVID-19: transmission, origin of the virus, prevention and treatment, vaccines, statistics (cases/deaths), and screening.

   2.1 **Virus Transmission**

   2.2 **Screening - Testing**

   2.3 **Statistics/Deaths/Cases**

   2.4 **Origin of the Virus**
   - 2.4.1 Discrimination
   - 2.4.2 Racism

   2.5 **Prevention and Treatments**

   2.6 **Immunization/Vaccine**

3. **SANITARY MEASURES**
   Comments related to public health measures and recommendations. The theme is divided according to the view expressed by users (agree or disagree with the measure).

   3.1 **Confusion / Inconsistency of Measurements**

   3.2 **Skepticism About the Effectiveness of Measures**

   3.3 **In Accordance with the Measures**
   - 3.3.1 Wearing the mask

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Table 4.1 – continued from previous page

- 3.3.2 Border closure
- 3.3.3 Loss of employment / return to the labour market
- 3.3.4 Conditions of workers in general
- 3.3.5 Lockdown and curfew
- 3.3.6 Closing of non-essential businesses
- 3.3.7 School and child care closures
- 3.3.8 Opening of non-essential businesses
- 3.3.9 Opening of schools and childcare services

3.4 **Disagree with the Measures**

- 3.4.10 Wearing the mask
- 3.4.11 Border closure
- 3.4.12 Opening of the borders
- 3.4.13 Physical distancing
- 3.4.14 Lockdown and curfew
- 3.4.15 Closing of non-essential businesses
- 3.4.16 School and child care closures
- 3.4.17 Opening of non-essential businesses
- 3.4.18 Opening of schools and childcare services

4. **IMPACTS OF THE PANDEMIC**
Comments related to the impacts of the health measures and the management of the pandemic on different sectors of activity or social aspects (each represented by a sub-theme). The sub-themes are: work (health care workers, telecommuting, job loss, working conditions), societal impacts (school, long-term care, children, vulnerable populations), economic impacts and environmental impacts.

4.1 **About the World of Work**

- 4.1.1 Conditions of health care workers
- 4.1.2 Remote work
- 4.1.3 Loss of employment / return to the labour market
- 4.1.4 Conditions of workers in general

4.2 **Social Impact**

- 4.2.1 Impact on the education system
- 4.2.2 Propagation and death of the elderly / CHSLD
- 4.2.3 Impacts on children
- 4.2.4 Impacts on people with disabilities
- 4.2.5 Impacts on Aboriginal communities

4.3 **Economic Impacts**

4.4 **Environmental Effects**

5. **DISINFORMATION**
Comments related to conspiracy theories, downplaying the severity of the pandemic/virus and trolls.

5.1 **Minimization of the Virus**

5.2 **Conspiracy Theories**

5.3 **Troll**

6. **INFORMATIVE COMMENT**
Comments where informative content is shared and where users exchange information.

6.1 **Argument/Information between Users**

6.2 **Sharing References/Articles**

OTHER
Comments that are off-topic, not related to COVID-19 or not belonging to any of the previous themes.

1 **Out of Order**

4.6.2 Computational Analysis

The computational analysis team followed a three step process (Figure 4.4): (1) Data Filtering & Cleaning, to investigate words being used in comments and to focus what data computational techniques used; (2) Modelling & Sampling, to identify interesting patterns and generate useful samples of comments; and (3) Coding, using the samples to create their codes and themes. By the last iteration of this process they had created six themes and a three level coding tree that links the codes to these themes (Table 4.2). Throughout these three steps, the second and sixth authors spent an estimated five hours training and familiarizing themselves with the toolkit and four hours consulting with one another.

Data Cleaning & Filtering

The team first iteratively inspected, cleaned, and filtered the words being included and removed. To make these choices, they interpreted the lists of words through the lens of their knowledge of the vaccine discourse topic and data set to determine relevance to COVID-19 commentary. When they encountered unfamiliar words, they looked at comments that used the word to expand their understanding. Words were excluded that either occurred fewer than 20 times or were considered to be 'noise', such as conjunctions, interjections (e.g., 'oh', 'ah'), insults, and misspelled words. They also removed the names that were not connected to public figures of interest.

Over the course of their analysis, the team created a contextually useful set of 578 filtering and cleaning rules that reduced the data down to 340,058 comments. They used these rules to create a total of 46 models, exploring different rules' impact on the words in the data. The team spent an estimated 8 hours iteratively adding rules and inspecting included and removed words over the first 15 days of the analysis.

Modelling & Sampling

The team then iteratively constructed models to interpret and sample data for thematic analysis. They configured model-specific parameters, such as number of topics and passes for biterm, and then inspected the generated models, and removed, merged, and labelled topics, selected comments for later coding, and considered potential codes. After learning from each model, they returned to either the first step, to perform additional word filtering and cleaning, or to build new models with adjusted parameters (such as number of topics). The team completed generating models after 15 days and an estimated 15 hours.

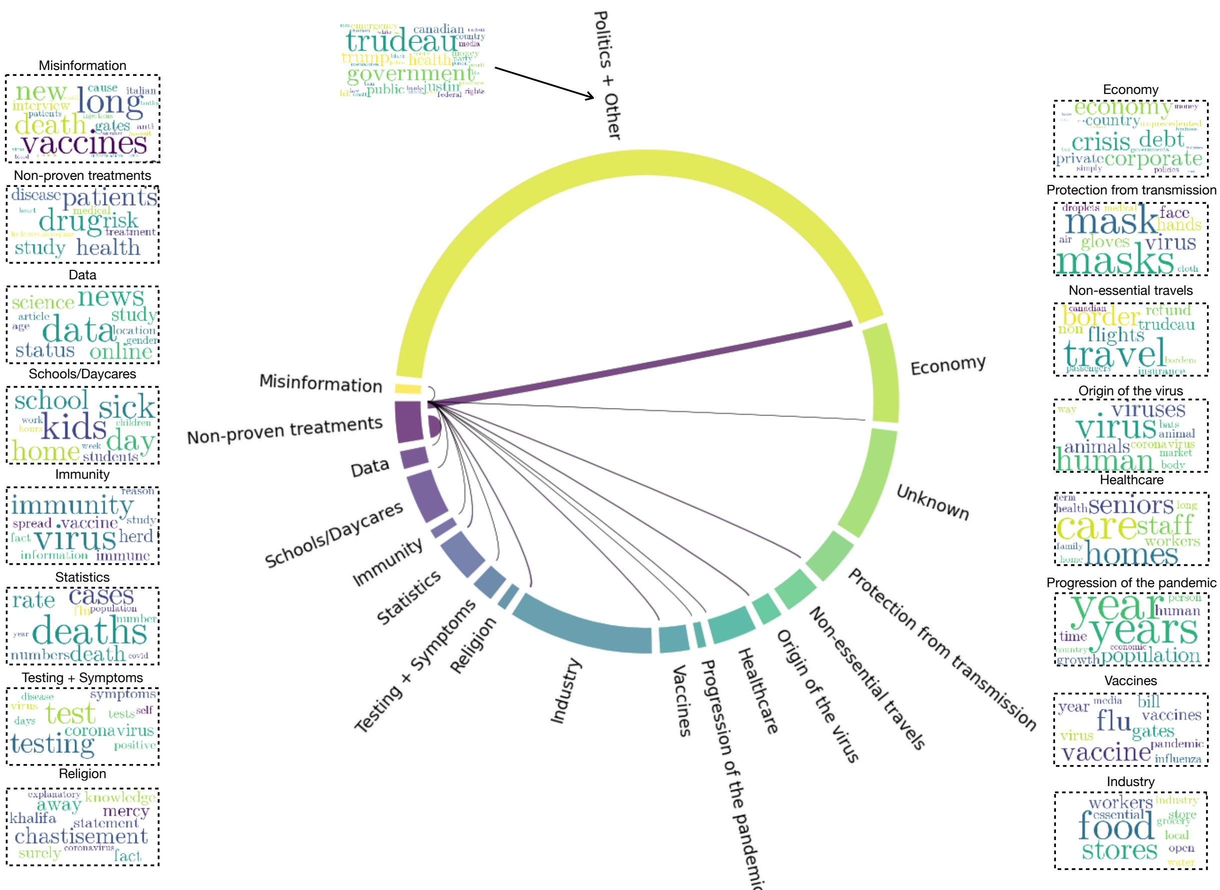

Figure 4.5: A chord diagram of Model 41, which the computational analysis team used to derive their code tree. Each topic show the human created labels. Within the Computational Thematic Analysis toolkit, these chord diagrams are interactive: topic labels can be clicked on to show/hide word clouds of topic keywords, and mousing over arcs for each topic shows chords that represent document overlap.

After more than 46 iterations, the team selected model 41 as a foundation for their coding activities (Figure 4.5). Although they generated model 41 on day 14, the team considered it more contextually valuable than models from further iterations on days 14 and 15. Model 41 was a biterm model generated with 25 topics and 500 passes and the team felt that its topics were cohesive and useful for the context of their vaccine hesitancy research area. After they had inspected and interpreted the model, 23 topics remained that were useful for identifying comments for the third step.

Coding

Finally, the team created and applied codes to develop themes and a coding tree. First, they used model 41 to sample 30 comments from each of its 23 topics, for a total of 690 comments. They then inductively coded the comments by iteratively selecting and interpreting each comment. After completing all coding iterations, they had created and applied 38 codes. Using these codes, they created a document that describes a three level coding tree that grouped the codes under six themes (Table 4.2). The team spent an estimated 17 hours coding and finished their analysis on day 25 of the analysis.

Table 4.2: The coding tree generated by the computational analysis team. It was a three-level tree, with six themes present in the first level. Levels two and three consist of codes that contributed to each theme. Codes that originated from interpreting topics from a model during step 2 are denoted by ⋆. Codes that originated from coding comments during step 3 are denoted by †. Other codes and themes were developed when organizing the coding tree.

1. **USER SHARING OPINIONS**
   Comments expressing an opinion. It is divided into 3 subtopics: opinion on the management of the pandemic by the authorities, criticism of the media and criticism of people not complying with preventive measures.
   - 1.1 Opinion on the Management of the Pandemic†
   - 1.2 Criticism of Media†
   - 1.3 Criticism of People Not Complying with Preventive Measures†
2. **DISEASE**
   Comments related to the characteristics of COVID-19: origin of the virus, transmission, symptoms, perceived risk, methods of protection against transmission, testing, immunity, and progression of the virus.
   - 2.1 **Origin of the Virus**⋆
     - 2.1.1 China
     - 2.1.2 Animals
     - 2.1.3 Made by human
     - 2.1.4 Act of God (Religion)⋆
   - 2.2 Protection from Transmission⋆
   - 2.3 Testing⋆
   - 2.4 Immunity⋆
   - 2.5 Progression of the pandemic⋆
   - 2.6 Transmission†
   - 2.7 Symptoms†
   - 2.8 Risk†
3. **PREVENTION AND TREATMENT**
   Comments on ways to prevent or treat COVID-19, including unproven or alternative treatments and vaccines.
   - 3.1 Vaccines⋆
   - 3.2 Non-Proven Treatments⋆
4. **IMPACTS OF THE PANDEMIC**
   Comments about the impacts of health measures and pandemic management on different sectors of activity or social aspects (each represented by a sub-theme). The sub-themes are: school/daycare, industry and business, interpersonal relationships, travel industry, health system, economy and stigma/racism.
   - 4.1 Impacts of COVID-19 on Schools/Daycares⋆
   - 4.2 Impacts of COVID-19 on Industries and Businesses⋆
   - 4.3 Impacts on Interpersonal Relationships†
   - 4.4 **Non-Essential Travel**⋆
     - 4.4.1 Impacts on travellers and airlines
     - 4.4.2 Preventive measures for travellers
     - 4.4.3 Border closure
   - 4.5 **Healthcare**⋆
     - 4.5.1 Long term care
     - 4.5.2 Healthcare workers
     - 4.5.3 Equipment
   - 4.6 **Economy**⋆
     - 4.6.1 Financial aid
     - 4.6.2 Economic crisis/debt
   - 4.7 Stigma and Racism†

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5. **TYPES OF INFORMATION**
   Comments where informational content is shared. It is divided into 2 subtopics: statistics/data on COVID-19 (cases, deaths) and misinformation.

   5.1 Statistics & Data⋆

   5.2 Misinformation⋆

6. **NOT NECESSARILY RELATED TO COVID-19**
   Comments related to politics (provincial, national and international). At the time of data collection, the political context was particular, both in Canada and in the United States (tensions between the Conservatives and the Liberals, Donald Trump). Although efforts were made to eliminate purely partisan comments during the data cleaning and filtering process, many remain and it is difficult to determine whether or not they are related to the pandemic. Finally, comments posted by trolls and off-topic comments are also classified under this theme.

   6.1 Politics†

   6.2 Troll/People Insulting Each Other†

   6.3 Other†

4.6.3 Comparison of Processes and Outcomes

Both analysis teams followed an iterative process and performed inductive coding throughout their analyses. However, when comparing their workflows and outcomes, we identified some (sometimes subtle) differences between the two groups. We now discuss these differences in terms of toolkit usage, differences in time, differences in process, and similarities and differences in outcomes.

Toolkit Usage

The CTA toolkit enabled qualitative researchers to learn applied skills, such as data cleaning and adjusting model parameters, and to tune and generate useful models. Such applied skills are needed when integrating existing computational techniques in a qualitative research process, as opposed to programming skills that are required to implement and refine computational techniques into usable tools. Additionally, this learning helped the researchers develop their contextual knowledge of how and when different techniques can be integrated with specific thematic analysis tasks. For instance, the computational analysis team chose to integrate the biterm topic model as a primer for coding, based on it grouping common word patterns, rather than as a replacement for the entire theme and coding process.

Alongside the applied skills, the computational analysis team developed contextual understandings of limitations of computational techniques as they used the CTA Toolkit. For instance, the team became aware that frequently repeated data, such as copy and pasted comments, can limit modelling techniques and distort model results, making it important to manage through both filtering and interpretation. Understanding of such limitations helps qualitative researchers avoid over-reliance on computational techniques which, while useful tools to interact with data, are not replacements for domain expertise or a human researcher's interpretive abilities.

Differences in Time

The manual analysis team completed approximately 24 hours of work over 25 days. They estimated that work was distributed between several analytical sub-tasks:

- ∼4 hours Coding their initial data set of 150 comments
- ∼6 hours Group Discussions

- ∼14 hours Applying their coding framework to 2000 random comments

On the other hand, the computational analysis team reported working for approximately 49 hours, spread over a 30-day period in which they were also working on several ongoing, unrelated projects. The team provided further estimates for analytical sub-tasks:

- ∼5 hours Initial orientation with the toolkit
- ∼8 hours Data Cleaning & Filtering
- ∼15 hours Modelling & Sampling
- ∼17 hours Coding
- ∼4 hours Participating in team consultations

The team also reported that some of this time was spent exploring different software features (e.g., token filtering and topic modelling) and that in some cases the toolkit was less mature than the commercial software they typically use (i.e., NVIVO (QSR International Pty Ltd, 2021)). In particular, the CTA toolkit's coding interface lacked features such as multi-comment coding and visualizations for code hierarchy, was less polished than commercial software, and was delivered to the team with a few performance-impacting bugs that were quickly addressed by the development team, but which slowed the analysis team down.

Differences in Process: Top-Down vs Bottom-Up

The computational analysis team used a top-down process where they: (1) followed the toolkit's large-to-small data handling approach that reduced the amount of data from 613,666 comments down to 690 comments; (2) aligned their steps to match the toolkit's modules and integrated human activities into each step (Figure 4.4); and (3) started coding by covering multiple comments and then revising their coding to capture specific comments' context. This top-down process jump-started the team's interpretation of recurring patterns in the data *before* creating the codes. The toolkit's word list visualizations (Data Filtering & Cleaning) helped the team identify recurring topic keywords from across the data like 'Trudeau', 'masks', 'money', and 'businesses'. They then looked for reoccurring keywords across different models (Modelling & Sampling) to identify topics like IMMUNITY, VACCINES, STATISTICS, and PROTECTION. The team's interpretation of these recurring topics and keywords were the origin points of 15 codes in their final tree, such as 2.2 Protection from Transmission (denoted by $\star$ in Table 4.2).

On the other hand, the manual analysis team used a bottom-up process where they: (1) followed a small to large data handling approach, that included 150 comments at first and added 2000 comments; (2) defined their steps by the human analysis activities (Figure 4.3); and (3) started their coding by capturing specific comments' contexts and then refining the coding to cover multiple comments. They relied on developing specific codes for individual comments and multiple encounters before grouping recurrences. For example, they created nine subcodes to capture comment-specific sanitary measures before grouping them into two mirrored parent codes, 3.3 In Accordance with the Measures and 3.4 Disagree with the Measures, that specify two different recurring contexts).

These two approaches lead to subtle differences in the teams' coding processes. First, each team interpreted codes in different ways. For instance, in the context of mask use, the computational analysis team considered the discussion of masks sufficient to assess whether the code 2.2 Protection from Transmission occurred. On the other hand, the manual analysis team needed to interpret whether each comment's context aligned with agreeing or disagreeing with masks to fit one of the sub-codes 3.3 In Accordance with the Measures or 3.4 Disagree with the Measures. Second, the computational analysis team maintained their coding focus by grouping potentially similar comments based on model 41's interpreted topics group to provide structure. In comparison, the manual analysis team had to reset focus between different comment types encountered during coding until they developed an internal interpretation of similar comment groupings. During the comparison, the teams decided that the computation analysis coding process was easier to perform while the manual analysis coding supplied more specific details about the data.

Similarities in Code Trees

Both analysis teams created coding trees that organized the inductive codes, developed during their interactions with the data. In these structures the themes were the first level and any additional level consisted of codes connected to the theme. Both teams used their coding trees for two purposes: to consistently apply their codes across the data; and to ground communication when discussing themes and codes, both within the teams during their analyses and across teams when comparing the analyses.

In both coding trees the themes were positioned as parent nodes and overlapped by covering the same ideas despite having slightly different names and descriptions (Table 4.3).

Table 4.3: Overlap between manual and computational analysis themes.

		Manual Analysis Themes						
		Criticism	Disease	Sanitary Measures	Impacts of the Pandemic	Disinformation	Informative Comment	Other
Computational Analysis Themes	Users Sharing Opinions	●						
	Disease		●	●				
	Prevention and Treatment	·		●				
	Impacts of the Pandemic				●			
	Types of Information					●	●	
	Not Necessarily Related to COVID-19	●				●		●

The teams stated in their comparison summary that these differences were expected and perfectly normal for two independent inductive thematic analyses, as developing the themes from data involves subjective description of ideas. Based on the similarities between the two code trees, the teams felt that the toolkit had helped the computational analysis team develop real themes.

Differences in Code Trees

However, when debriefing, the analysis teams also acknowledged that different coding tree structures had been created and used. The computational analysis' coding tree had three levels, was focused on general descriptions, and was useful for capturing common ideas from multiple comments under each code which made coding large numbers of comments easier. The manual analysis' coding tree had four levels, was focused on specialized descriptions, and was useful for describing the specific comments coded which made it time consuming to apply to large numbers of comments. Despite having different structures, the teams agreed that neither coding tree was invalid, rather the two trees provided distinct forms of utility and both could contribute to a successful thematic analysis.

We also identified a difference in how the coding trees were reported. The computational analysis team included indicators of where codes originated from, either topic model interpretation, coding, or code organization. This additional information provided transparency about how codes may connect to the interpretation of computational techniques. In comparison, the manual analysis team did not indicate code origin in their coding tree as all codes originated from human inductive coding.

4.7 Discussion: Agency and Amplification

We found that the CTA Toolkit provided access to advanced computational techniques for researchers without programming expertise, facilitated their interaction and interpretation of the data, but also that it influenced how they approached their thematic analysis. We now discuss how each of these findings can inform ongoing efforts by the human-computer interaction and machine learning research communities to integrate computational techniques into qualitative methods, like thematic analysis.

4.7.1 Opening Computational Techniques to Non-Programmers

The CTA Toolkit served as a scaffold upon which researchers could use computational techniques to develop interpretations of data (Baumer et al., 2017). By the end of their analysis, the team had tried more than 40+ combinations of model parameters and types. Similarly, the team explored NLP summary data, iteratively filtered words based on their context and usage, and observed the impact of that filtering on the generated models. The non-programmer, qualitative researchers used these computational techniques on their own, rather than through a third party such as an AI consultant who may not have the same understanding of the research area or objectives.

Several members of the human-computer interaction research community have raised the question of 'perfect' being the enemy of 'good' (Baumer et al., 2017; Gauthier et al., 2022). For instance, one might question whether these analyses were performed 'optimally', and whether the same tools may have yielded more accurate models in the hands of experts. However, our post-analysis comparison of themes and coding trees shows that both the computational and manual teams created similar results. Qualitative researchers could also use what they learned from the models to describe their choices, which contributes to establishing process transparency and the trustworthiness of analysis results (Pratt et al., 2020; Talkad Sukumar et al., 2020; Tuval-Mashiach, 1027).

Taken together, these activities demonstrate how tools can lower the threshold to use computational techniques during qualitative research (Baden et al., 2021; Jiang et al., 2021), establish common ground between computation and qualitative communities (Chen et al., 2018), and create space where further collaborations can benefit both fields (Baden et al., 2021; Chen et al., 2018). And so we suggest that with tools like the CTA toolkit there is a real opportunity to start applying computational techniques in practice, to better understand the actual challenges qualitative researchers face when performing computationally-supported research, and to refocus the human-computer interaction research community on solving them. That is, there is an opportunity to engage in truly human-centred data science.

4.7.2 Facilitating Interaction and Aiding Interpretation

The CTA toolkit also 'raised the ceiling' for thematic analysis of large, online data sets (Ledo et al., 2018). In follow-up discussions, the computational analysis team reported that the CTA Toolkit enabled them to focus their efforts on data interpretation. Iterations of filtering and modelling tasks enabled them to shift from a sample of 613,666 comments, to 340,038 comments, to an informative sample of 690 comments (i.e., purposive and judgmental sampling (Hoeber et al., 2017; Marshall, 1996)). The same models made it easier to locate topics of interest and groups of comments to code. The team also described how these computational tasks helped them to create meaning (Chen et al., 2018). For instance, the HEALTHCARE code (Table 4.2, 4.5) and its subcodes for LONGTERM CARE, HEALTHCARE WORKERS, and EQUIPMENT were interpreted from interacting with a topic model and its keywords like care, homes, seniors, staff, workers, health, long, term, home, family, and masks.

However, the CTA toolkit did not facilitate all of the analysis team's tasks. For instance, although it helped them clean and filter the data, removal or inclusion of words was too limited to manage some contextual signals and/or noise. As one example, synonyms for Canadian Prime Minister 'Justin Trudeau' like 'trudeau', 'trudeaus', 'trudo', and 'justintrudeau' all contributed to codes (Table 4.2, OPINION ON THE MANAGEMENT OF THE PANDEMIC and POLITICS). But this work had to be performed manually because the toolkit did not support finding and replacing synonyms. Similarly, comments were sometimes difficult to interpret when they referenced ideas that were specific to a subset of the data, such as a specific news organization, which topic-based sampling does not account for.

These limitations help to highlight that the ceiling can be raised, and to reveal how computational techniques can further amplify qualitative researchers' ability to interpret data. Data cleaning and filtering can be expanded to align with researchers' interpretative activities, such as enabling researchers to manipulate the data to represent their interpretation of the synonyms. Similarly, model generation and visualizations could occur more directly, and *collaboratively*, to facilitate researchers' interpretation (e.g., El-Assady et al., 2018). Coding and theme identification activities might further be supported by tools that help researchers reflect and reconsider relationships between data and their interpretations of it.

4.7.3 Influence of Computational Techniques on Research Process

Importantly, the computational analysis team felt that they maintained autonomy, intimacy, and ownership of their analysis (Jiang et al., 2021). Indeed, they reported that the CTA toolkit assisted with specific analysis tasks, particularly pattern identification and sampling (Feuston and Brubaker, 2021). We attribute this sense of control to the toolkit's design, which was intended to be flexible and support researchers' own styles and preferences (Gauthier and Wallace, 2022). Researchers have substantial agency in terms of choosing how and when to iterate, determining which models are useful, and quickly experimenting with different filters and models in a safe environment. The CTA toolkit made common data science tasks rapid, incremental, and reversible — key principles for intuitive and predictive interfaces (Kwon et al., 2011) — and, when tool limitations were encountered, researchers were able to fall back on their expertise and practical knowledge.

These findings demonstrate the potential of visual interfaces to enable non-programmers to use computational methods in their analysis. But our comparison of the teams' processes and outcomes also points to some previously unidentified side-effects. In particular, we observed differences in how each team sampled comments for inspection and coding, and how those codes ultimately translated into code tree artifacts.

First, while the two code trees produced by each team were similar, they arrived at them using quite different processes. This divergence was not a surprise — the CTA toolkit was designed to enable model-based sampling and bag-of-words pattern identification that is simply not feasible without the aid of computational techniques. However, it's currently unclear under which conditions one might prefer the top-down vs. bottom-up approaches taken by our two teams; are there circumstances under which a team would favour one over the other? Can computational techniques support a bottom-up analysis? Or perhaps they should be considered in a 'hybrid' fashion, similar to what was proposed by Muller et al. (2016). We leave these questions to future work.

Second, the trees themselves differed in the amount of detail present, and their use in supporting the thematic analysis. The code tree developed by the manual analysis team was more detailed, and was used throughout the process to foster common ground — at least in some sense, as a means to coordinate team members' coding activity (i.e., inter-coder reliability (McDonald et al., 2019)). On the other hand, the computational analysis team used the CTA Toolkit together and thus did not need to use the coding tree to develop internal common ground. The long-term implications of these differences are unclear: might they impact a team's ability to share, expand on, or otherwise further develop their results? Might they impact transferability or transparency?

These differences may be more insidious than the adoption concerns raised by Jiang et al. (2021), since they were not consciously raised or considered by researchers during the analysis, but were apparent in post-hoc comparisons of process and outputs. They also complicate calls to action, particularly those from Braun et al. (2019) and Braun and Clarke (2021), in supporting transparent reporting and rigour in qualitative research. That is, if researchers are unaware of how computational methods might influence their research, how can they adequately reflect and report on those influences?

4.7.4 Next Steps in Critical Computing Research

Finally, our case study provides an opportunity for the human-computer interaction and critical computing research communities to consider next steps in advancing computationally-supported qualitative research. Our research provides an opportunity to triangulate with contemporary findings like Jiang et al. (2021) and Feuston and Brubaker (2021) that interviewed qualitative researchers about their experiences, aspirations, and concerns. It also provides an opportunity for calls-to-action for cross-pollination between human-computer interaction and qualitative research communities: human-computer interaction researchers need to better understand qualitative methods (Baden et al., 2021; Chen et al., 2018; Feuston and Brubaker, 2021; Jiang et al., 2021), and qualitative researchers need to better understand computational methods (Aragon et al., 2022; Cambo and Gergle, 2022; Papakyriakopoulos et al., 2021; Saxena et al., 2022; Vaughan and Wallach, 2021).

Much of the contemporary discourse (e.g., Cambo and Gergle, 2022; Saxena et al., 2022; Vaughan and Wallach, 2021) still considers data science in a segregated context, where technical scientists with programming experience independently develop models before deploying them to a team of domain experts, stakeholders, or 'users' (Bradley et al., 2015). This segregation places an emphasis on 'eager AI' (Feuston and Brubaker, 2021) that then needs to be *interpretable* or *explainable*. It also emphasizes the mathematical optimality and pseudo-objectivity of models over their usefulness to domain experts, which the human-computer interaction research community has sought to address through concepts like computational reflexivity and model positionality (Cambo and Gergle, 2022). Given this segregation it is hardly surprising that, when asked, qualitative researchers raise concerns about about loss of agency in their analysis process (Feuston and Brubaker, 2021; Jiang et al., 2021).

Our work contributes to a growing body of research that seeks to more fully engage qualitative researchers in the design and use of ML and AI. To date, that research has primarily relied upon the development of prototype tools (e.g., Baumer et al., 2020) and interviews with domain experts (e.g., Feuston and Brubaker, 2021; Jiang et al., 2021). Our case study further builds on existing calls 'put tools in their place' (Feuston and Brubaker, 2021), and to consider how ML and AI can empower domain experts without requiring them to become experts in computer programming. We stress the need for additional research methods — particularly those that emphasize realism (Mcgrath, 1995) like case studies, autobiographical design, and research through design (Neustaedter and Sengers, 2012; Zimmerman et al., 2007) — to further our understanding of ML workflows.

4.8 Limitations

In this work, we conducted a study of two thematic analyses performed 'in the wild'. That is, two research teams with expert knowledge in public health engaged with a large data set obtained from Canadian media to answer pressing questions about vaccine hesitancy during the SARS-CoV-2 pandemic. Conducting such a case study provides a rich environment in which to explore a highly subjective and interpretive research process with an emphasis on realism at the expense of experimental precision and control (Mcgrath, 1995). And so, there are some inherent limitations and benefits to this approach:

First, a limitation of exploratory human-computer interaction research is that identifying appropriate participants is often a challenge, or even impossible, since such a target audience may not yet exist (Ledo et al., 2018). While qualitative research, and reflexive thematic analysis (Braun and Clarke, 2006; Braun et al., 2019) in particular, are extremely popular, valuable research strategies one might not consider our research team to be expert 'end users' for the Computational Thematic Analysis Toolkit (Gauthier and Wallace, 2022). That is, this was the research team's first analysis using the toolkit, and one would expect practices to evolve as they became more adept with it and gained experience with different data sets, analyses, etc.

Second, thematic analysis is an interpretive process (Braun and Clarke, 2006; Braun et al., 2019), and interpreting and comparing research outputs between two teams is extremely complex. It is difficult to argue that any one code tree is 'better' than another.

One also needs to consider what was learned during the analysis process itself, and there are many potential trade-offs between time spent on analysis and the researcher's depth of understanding, whether a researcher choose to explore themes in depth or breadth, and which perspectives they chose to explore and emphasize. In our case study, many internal and external factors also influenced the amount of time it took each team to perform their analysis, including: the time required by the computational team to familiarize themselves with the toolkit, differences in their research approach (e.g., single vs multiple coders), and real-world stressors like family commitments and other concurrent projects. All of these factors were beyond our control. Instead, we focused our analysis on the *research process*, and understanding how the manual and computational methods influenced it.

4.9 Conclusion

In this work we explored how the integration of computational techniques into thematic analysis plays out in real world research. Our teams conducted two independent thematic analyses of 613,666 online communities, one manual and one computational using the CTA Toolkit. We presented results that describe both analyses' process and outputs, and then compared them to identify their similarities and differences.

Grounded in this case study, we identified the benefits and opportunities of using computational techniques to augment qualitative analysis of large data sets. We showed how the Computational Thematic Analysis toolkit made computational techniques accessible to non-programmer researchers, and enhanced their ability to interpret large data sets. We also found that researchers maintained a sense of agency during the analysis, contrary to concerns raised in previous research, but showed how the tool subtly influenced how researchers approached their analysis. In discussing these findings, we shared provocations that future research should explore how to avoid these (potentially) insidious influences of computational methods, and incorporate real-world deployments of technology to understand how they play out in practice.

4.10 Acknowledgements

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Chapter 5

Conclusion

For my thesis, I explored opportunities for researchers to integrate computational techniques into their thematic analyses and how to address barriers that inhibit these integrations. First, I conducted a Pilot Stage where I demonstrated and discussed integrating LDA topic modelling to guide a reflexive thematic analysis of online addiction recovery communities. Then in my Design Stage, I created workflow and toolkit artifacts that facilitate researchers without programming expertise in integrating computational techniques into thematic analyses. Finally, for my Deploy Stage I collaborated with public health researchers to perform and compare two real-world thematic analyses to describe and discuss the impact of integrating computational techniques on research processes and results. Each of my three stages' contributions address a specific research question as summarized by Table 5.1. Considered together, my research's three stages support the thesis statement:

> *Qualitative researchers performing thematic analyses of online communities can make use of computational techniques to help manage the complexity and resource-intensity of analyzing large data sets.*

I began my work with a Pilot Stage (Chapter 2) where I performed a topic-guided thematic analysis of Reddit addiction recovery communities that explored my research question:

> RQ1. Could computational techniques be used within a thematic analysis to assist with the analysis of online communities' data?

Table 5.1: Thesis Contributions – replicated from Table 1.1

Research Questions	Stages	Description	Contribution
RQ1: Could computational techniques be used within a thematic analysis to assist with the analysis of online communities' data?	**Pilot** "I Will Not Drink With You Today": A Topic-Guided Thematic Analysis of Addiction Recovery on Reddit (Gauthier et al. CHI'22)	I used a computational technique, Latent Dirichlet Allocation topic modelling, to guide a reflexive thematic analysis of addiction recovery communities.	**C1** A demonstration using topic modelling to purposively sample data for my analysis and a discussion the benefit of helping identify insights and the limitation of needing to balance metric optimization against interpretive usefulness.
RQ2: How might tools be developed to not require programming expertise when integrating computational techniques as part of thematic analysis tasks?	**Design** The Computational Thematic Analysis Toolkit (Gauthier & Wallace GROUP'22)	I conceptualized, designed, and implemented the Computational Thematic Analysis Workflow and Toolkit.	**C2** A description of my CTA Workflow that guides where computational techniques can augment thematic analysis and my CTA Toolkit artifact that researchers without programming expertise can use to apply these techniques in practice.
RQ3: How does a computational thematic analysis that integrates computational techniques compare with a traditional manual thematic analysis?	**Deploy** Agency and Amplification: A Comparison of Manual and Computational Thematic Analyses by Public Health Researchers (Gauthier et al. GROUP'23)	I conducted a case study comparison of two thematic analyses, where each was performed independently by public health researchers and one used the Computational Thematic Analysis Toolkit.	**C3** A demonstration and discussion how using the toolkit to integrate computational techniques impacted a thematic analysis by facilitating the interpretation of data and subtly influencing the analysis' steps and coding.

To answer this research question, I implemented my topic-guided thematic analysis approach, which integrated LDA topic modelling (Blei et al., 2003) to perform purposive sampling (Hoeber et al., 2017) and guided a reflexive thematic analysis (Braun and Clarke, 2006). I applied my approach to develop themes focused on the experiential knowledge of addiction recovery journeys. Based on my experiences, I discussed the benefits of integrating LDA topic modelling. First, performing LDA modelling tasks with a qualitative mindset helped me develop informative hints that aided my coding. Second, the topics I created with the modelling identified interesting purposive samples for my thematic analysis. These benefits aligned with Chen et al. (2018)'s suggestion that qualitative researchers could experience qualitative benefits from performing machine learning tasks.

As part of this stage, I also identified and described limitations qualitative researchers need to navigate when integrating topic modelling techniques to manage the resource intensity of their thematic analyses. First, the temptation to seek out quantitative metric-optimized *best* models risks researchers losing sight of the interpretive nature of both model development and thematic analysis. Second, researchers need to integrate the context of their research as they consider topic modelling techniques' limitations. For instance, if the research is studying long text discussions with multiple topics, then LDA topic models (Blei et al., 2003), which work well on long text, were more suitable than biterm models (Yan et al., 2013), which are specialized for short text.

After completing this stage's thematic analysis, I reflected on whether other qualitative researchers could replicate and transfer my topic-guided thematic analysis approach to study other online communities to realize my thesis statement. During this reflection, I concluded that in the current state, researchers would need programming expertise to implement and modify the computational techniques used by my approach. This dependence on programming expertise limited my approach's accessibility and re-usability.

These benefits and limitations motivated my Design Stage (Chapter 3) that focused on making the integration of computational techniques into thematic analysis accessible and more qualitatively focused while answering my research question:

> RQ2. How might tools be developed to not require programming expertise when integrating computational techniques as part of thematic analysis tasks?

During this stage, I focused my design by creating the Computational Thematic Analysis Workflow (CTA Workflow), that customized reflexive thematic analysis (Braun and Clarke, 2006) into a set of cognitive phases accomplished by performing different practical tasks. Within the CTA Workflow, I identified convergences between thematic analysis tasks and computational techniques, inspired by my Pilot Stage and findings from background literature that describe other qualitative methods and machine learning convergences (e.g., Baumer et al., 2017; Evans and Aceves, 2016; Muller et al., 2016). In my workflow, these convergences highlight points where technique integration can augment thematic analysis tasks.

To support qualitative researchers applying my CTA Workflow and benefit from these point integrations, I designed and implemented my Computational Thematic Analysis Toolkit (CTA Toolkit) as a graphical user interface. My toolkit was designed to: (a) Implement computational technique integrations that support pattern identification and sampling to enable qualitative interaction with online community data sets at scale during common thematic analysis tasks; (b) Allow qualitative researchers without programming expertise to use integrated computational techniques; (c) Record toolkit operations transparently so that researchers have the freedom to creatively explore different ways that computational techniques can manipulate their data while still being able to reflect on their choices to help centre researcher's subjectivity and transparently report their analysis process. The CTA Workflow and Toolkit support my thesis statement by providing qualitative researchers reusable tools that mitigate the limitations from my Pilot Stage to facilitate integrating computational techniques into thematic analyses.

I then collaborated with qualitative public health researchers to perform my Deploy Stage (Chapter 4) where my CTA Toolkit was used in a real-world research project that investigated COVID-19 discourse in online news articles' comments. During this collaboration I explored the research question:

> RQ3. How does a computational thematic analysis that integrates computational techniques compare with a traditional manual thematic analysis?

In this stage, qualitative researchers performed two independent analyses, one computationally using my toolkit and one manually using their usual approach. These two thematic analyses were conducted pragmatically rather than reflexively. I then worked with the teams to compare their analysis processes and results, which I analyzed to discuss the impact of using my CTA Toolkit to augment thematic analysis by integrating computational techniques.

The comparison identified that although both teams' analyses were inductive and developed similar themes, technique integration had subtle influences on the computational analysis. These subtle influences shifted the computational analysis from a bottom-up process with data-specific coding to a top-down process with easy-to-apply generic coding. Within this top-down process, the team's interaction with news comments through multiple integrated techniques facilitated interpreting recurring patterns and a general sense of codes and themes. When reflecting on their process, rather than raising concerns about techniques having post-positivist influences Jiang et al. (2021), the team instead raised questions about the potential for additional computational techniques to help quantitatively assess whether coding summarized the full data set and to assist with knowledge translation efforts. This request highlights that the perspective that post-positivist influences should to be minimized is not the only perspective integration toolkits should be focused on supporting. Additionally, the team used topic models, generated when integrating computation techniques for sampling, as an assistive structure that supports developing and revising common codes by grouping topic-relevant comments. These findings support my thesis statement by showing that qualitative researchers used my CTA Toolkit to integrate computational techniques that facilitated interacting with data at scale while performing a thematic analysis of real-world online comments from new's discussion forums.

Developing my contributions at the intersection of qualitative research, human-computer interaction (HCI), and public health led to implications for all three fields. In qualitative research, my contribution of guidance and tools can assist researchers with planning new approaches and performing their online community research. For HCI, I addressed existing calls to action with my contributions to create a foundation for researchers seeking to support and expand the integration of computational techniques into qualitative methods. Finally, my contributions facilitate public health researchers applying the intersection of HCI and qualitative research to thematic analysis of health-related discussions to understand lived experiences and consider online community perspectives on public health issues.

5.1 Implications for Qualitative Research

My work provides qualitative researchers with a guidebook of how to integrate computational techniques to support thematic analyses of online communities. My descriptions & demonstrations of integrating computational techniques (C1 & C3) provide paths researchers can reuse when designing their own approaches to conducting thematic analyses of online communities by considering how the contexts, benefits, limitations, and impacts align with their research questions. Similarly, researchers can use my CTA Workflow (C2) to plan new integration paths customized to fit their reflexive thematic analyses. My guidebook focuses on integrating techniques to assist with specific tasks, such as pattern identification and sampling, which puts Feuston and Brubaker (2021)'s call for customizable task assistance over full automation into practice. My guidebook also provides real-world evidence to support Chen et al. (2018) proposal that the tasks involved with integrating computational techniques can be meaningful beyond model-building as qualitative researchers develop insights from iteratively interacting with the data.

Furthermore, qualitative researchers can use my guidebook as a starting point to reconsidered how they perform thematic analyses from other schools, such as codebook and coding reliability (Boyatzis, 1998; Braun et al., 2019), which involve both common and distinct tasks occur as part of difference processes. For instance, qualitative researchers seeking to perform a codebook thematic analysis could start by modify my CTA Workflow (C2) by: (1) adding new practical tasks for developing a codebook early in the workflow; and (2) revising existing phases and practical tasks to focus on applying the codebook. Then qualitative researchers can use the new workflow to consider how integrations in these practical tasks benefit, limit, and impact their thematic analysis based on differences from the CTA Workflow and it's reflexive thematic analysis origin. For instance, if seeking to develop themes that are full dataset summaries instead of reflexive stories, the appropriate way to use purposive sampling as part of creating and evaluate codes and themes would need to be examined. Additionally, where existing computational technique integrations do not provide the desired aid, researchers can use their new workflow to describe requirements from qualitative perspectives for HCI practitioners to design new integrations (Baden et al., 2021).

Qualitative researchers without programming expertise can use my CTA Toolkit (C2) to integrate computational techniques into their thematic analyses. Expanding the audience beyond programmers democratizes computational technique integration, realizing one of Ledo et al. (2018)'s toolkit goals. Additionally, my toolkit provides a foundation on which qualitative researchers can experiment and provide their perspectives on integrating computational techniques into thematic analyses, which helps address the lack of qualitative perspectives in integration research (Baden et al., 2021; Chen et al., 2018). Similarly, qualitative researchers can use my toolkit to experiment with integrating computational techniques to customize specific thematic analysis tasks and decide whether the assistance is suitable for their analyses, in line with Feuston and Brubaker (2021)'s recommendations.

My contributions also support researchers integrating computational techniques into other qualitative methods. Integrating computational techniques into thematic analysis assisted researchers with pattern identification and grounded the analyses in data (C1 & C3). This integration assistance aligns with Baumer et al. (2017); Muller et al. (2016)'s proposed that grounded theory methods (Strauss and Corbin, 1997) could benefit from integrating machine learning to leverage pattern discovery and data grounding convergences. Based on this alignment, it is reasonable that qualitative researchers could transfer integrating computational techniques to other qualitative methods when seeking to study online communities. To perform such transfers, researchers can reuse my guidebook's demonstrations & discussions (C1 & C3) and CTA Workflow (C2) to identify potential alignments, similar to what was described for other schools of thematic analysis. They can then consider whether customizing their method's tasks based on these alignments would potentially assist their qualitative study (Feuston and Brubaker, 2021). However this would be an intensive process as more methodological differences will occur when researchers move beyond thematic analysis leading to divergences that need to be considered as part of design a study that seeks to leverage computation technique integrations. However, when researchers do identify points of potential assistance that involve convergent tasks, they can select modules from my CTA Toolkit (C2) that support these tasks to experiment with computational technique integrations and assess impacts on their qualitative method.

Future work that builds on these implications can also explore how to nudge qualitative researchers to consider computational thematic analysis research as an additional box of tools that can be useful for specific thematic analysis tasks, not as a prescriptive best process for thematic analyses or qualitative studies. Of particular concern is the CTA toolkit's current state where the GUI's module order aligns with a possible integration path that was appropriate for *my* reflexive thematic analysis. In the Deploy Stage, my collaborators modified their process to follow the CTA toolkit's module order rather than using the modules to enhance their usual analysis process. While the researchers were still in the loop and had control of the customization the toolkit's influence appeared to become central to their process, which risks pushing the analyses becoming less human-centred (Aragon et al., 2022). To address these risks, qualitative researchers can leverage their perspectives and expertise to push for approaches that reduce tools' influence on processes. Some potential ideas to explore are: considering what sort of documentation would help clarify the role of the CTA Toolkit in integration, such as considerations and guidelines that nudge researchers to prioritize their own approaches; or describing novel interfaces that provide human control over how analysis processes are represented, such as a flow visualization that prompts researcher for the order of task and integrations instead of the CTA Toolkit's module tab list that may feel prescriptive.

5.2 Implications for Human-Computer Interaction

My work demonstrates the value of including qualitative researchers and their perspectives in research that integrates computational techniques into qualitative methods. Situating my Pilot Stage in the context of a real-world analysis of Reddit addiction recovery communities grounded my demonstration with a qualitative public health perspective. I used this context and perspective to guide my discussion of the benefits and limitations of integrating computational techniques (C1). Similarly, my collaboration with public health researchers for my Deploy Stage provided a pragmatic qualitative lens for studying integration in a real-world investigation of COVID-19 news article discussions. I used this lens to emphasize realism (Mcgrath, 1995) in my description & discussion of how computational techniques aided researchers' interpretations while having subtle influences on the process (C3). Also my work's lens demonstrates the appetite of qualitative researchers to make use of the large volumes of data being generated by online communities is real, particularly with understanding lived experiences and identifying diverse perspectives, which should motivate HCI to facilitate access via thoughtful integrations of computational techniques.

Including qualitative perspectives aligns my work with the call for HCI practitioners to include qualitative researchers at the centre of integration research (Baden et al., 2021; Chen et al., 2018). My work builds upon the efforts to survey qualitative researchers about thier perspectives on computational technique integration (Feuston and Brubaker, 2021; Jiang et al., 2021) by exploring messy real world contexts where execution of research involves pragmatic compromises and customization to meet external constraints. HCI researchers who build upon my work can collaborate with qualitative researchers who apply my guidebook (C1, C2, & C3) and deploy my CTA Toolkit (C2) in real-world thematic analyses. Such collaborations create a context for joining computational and qualitative perspectives on how integrating computational techniques assist or interfere with thematic analysis tasks. These joint perspectives can form a basis for HCI to create tool contributions that avoid disrupting the valued messy, interpretive, and iterative nature of qualitative methods (Feuston and Brubaker, 2021; Jiang et al., 2021).

Additionally, my contributions demonstrate that HCI practitioners can develop and deploy tool contributions (Wobbrock and Kientz, 2016) that make integrating computational techniques accessible. My CTA Toolkit (C2) implements computational techniques (e.g., NLP (Bird et al., 2009) and LDA topic modelling (Blei et al., 2003)) so that qualitative researchers without programming expertise can them integrate into thematic analyses to support interacting with online community data sets at scale. Deploying my CTA Toolkit with qualitative researchers demonstrated that my toolkit successfully facilitated integrating computational techniques into their thematic analysis and aided data interpretation without programming expertise being a prerequisite (C3). Using my CTA toolkit as a starting point, HCI practitioners can explore paths to implementing, customizing, and using integrations to assist rather than replace qualitative researchers (Feuston and Brubaker, 2021). HCI practitioners can build upon my work by: (1) enhancing existing computational technique integrations, (2) expanding integrations to explore aiding addition analysis tasks, and (3) extending support to methods to other thematic analysis schools and qualitative methods.

First, HCI practitioners can enhance my CTA Toolkit's existing integration of computational techniques to improve support for pattern discovery and purposive sampling. Developers could enhance these implemented techniques, such as integrating alternative visualizations of data (Baumer et al., 2020) or adding controls to enable researcher directed topic modelling (El-Assady et al., 2018, 2019). Alternatively, practitioners can implement other text processing techniques such as VADER (Hutto and Gilbert, 2014) a sentiment analysis tool into my toolkit to support qualitative researchers' interaction with additional interpretive dimensions as they develop codes and themes (Braun and Clarke, 2021). Other similar techniques for non-text data, such as images and videos, can also be integrated to help researchers' ability to analyze non-discussion online community data. Enhancing existing integrations and implementing new techniques would augment qualitative researchers' ability to interact with and sample online communities' data. Additionally, as part of these integrations, HCI practitioners should explore making integrated techniques transparent from a qualitative perspective. In my CTA Toolkit implementation, I offered transparency through technique-specific visualizations of the actions performed, impacts, and uncertainty of topics. These visualizations are simple "what you see is what you get" reporting approaches that would benefit from integrating more qualitatively focused interactivity and customization.

Second, HCI practitioners can expand my toolkit to investigate facilitating tasks other than pattern matching and sampling, such as code application. In my Deploy Study my collaborators' feedback included a desire for tools that describe how their codes apply across their data set. This feedback aligns with Feuston and Brubaker (2021)'s discussion of how classifiers may be appropriate for researchers that stabilize their codes relatively early in their process due to resource constraints. HCI practitioners investigating this area could expand my toolkit to integrate supervised text classifiers (Kowsari et al., 2019). Qualitative researchers' coding could provide the training data for these classifiers, allowing them to estimate code application across the data set and help researchers identify points of uncertainty through classifier feature explanations, facilitated by explanation frameworks like LIME (Ribeiro et al., 2016). Once implemented, HCI practitioners and qualitative researchers can perform collaborative deployments to assess whether pragmatical applying and interpreting classifiers assist or hamper the thematic analysis process. However, Jiang et al. (2021) and Feuston and Brubaker (2021) both reported that other qualitative researchers worry about using techniques like classifiers due to their emphasis on reducing uncertainty. As an alternative to extending with existing techniques, HCI practitioners can collaborate with qualitative researchers and use my toolkit framework as a platform for developing and integrating re-usable novel computational techniques for analysis tasks in need of support. These novel techniques would be designed and evaluated from the ground up with qualitative perspectives and values, which could help elevate the concerns around existing techniques' post-positive origins.

Third, HCI practitioners can extend my CTA Toolkit beyond reflexive thematic analysis to other schools (Braun et al., 2019) or other qualitative methods, such as grounded theory (Strauss and Corbin, 1997). Reconfiguring my toolkit's interface could support other schools of thematic analysis by aligning module orders with their workflows, such as moving themes and code development modules to be the first modules to support codebook thematic analysis (Boyatzis, 1998). Similarly, practitioners can investigate how my CTA toolkit's existing integrations can transfer to other qualitative methods by reuse modules to support tasks shared with thematic analysis, such as pattern identification. Additionally, practitioners can develop new modules that integrate computational techniques to expand and explore support for school-specific and method tasks, such as inter-rater reliability for coding reliability thematic analyses (Boyatzis, 1998) or theoretical sampling for grounded theory (Strauss and Corbin, 1997).

Regardless of direction, future work that builds upon my contributions needs to assess the impact of facilitating computational technique integration. My Deploy Stage showed that integrations have subtle influences, which need to be identified and understood for computational technique integration to be reusable and accessible.

5.3 Implications for Public Health

My thesis enables public health practitioners to perform thematic analysis of online communities to understand these communities' discussions of issues, such as addiction recovery (D'Agostino et al., 2017; Gauthier et al., 2022) and COVID-19 (Hughes et al., 2021). Understanding discussions of issues supports researchers' ability to develop context-sensitive interventions for population segments represented by these online communities (Eysenbach, 2005). I have demonstrated this impact by situating my contributed demonstrations and discussions of integrating computational techniques (C1 & C3) in two real-world public health research projects. From my Pilot Stage (Chapter 2), my results can help public health practitioners to empathize with and decide how to support members of online communities who are seeking to develop productive, healthy, and meaningful lives (White, 2007). In particular, public health practitioners can implement interventions that help doctors navigate the barrier of pain management concerns of people in recovery from opiate addiction and facilitate professionals learning from lived experiences of people's recovery journeys (Gauthier et al., 2022). Similarly, my public health collaborators' plan is to leverage the analysis performed using my CTA Toolkit during my Deploy Stage (Chapter 4). This analysis was the first step of an ongoing Canadian Immunization Research Network project to investigate online discourse that generates and spreads rumours, misinformation, and disinformation about vaccination in Canada.

Additionally, my work highlights that subject matter expertise is essential to conducting computational thematic analyses of online communities in public health contexts. As part of being human-centred (Aragon et al., 2022) and not deskilling experts (Sambasivan and Veeraraghavan, 2022), researchers' developing and applying subject expertise is central and needs to be supported by appropriate use of methods and tools, not replaced or minimized. My Pilot Stage's analysis was grounded in public health's knowledge of addiction and recovery journeys being about more then just abstinence White (2007), which pushed my findings to consider more than whether the communities use of technology was helping people were avoid relapsing or not. Likewise, addiction recovery knowledge was crucial to my reflections around the meaning of words and acronyms, such as IWNDWYT, which enabled contextual data familiarizing and modelling during the purposive sampling and pushed the integration towards supporting qualitative research rather then assuming it was providing findings in the data. Similarly, my Deploy Stage's collaborators used their knowledge of vaccine hesitance, combined with their qualitative method expertise, to chose their data set and drive their analyses, leading to the development of contextual themes that explored online perspectives about COVID-19.

Public health researchers can reuse and combine my work's qualitative research implications with their public health expertise. Applying my demonstrations & discussions (C1 & C3) and CTA workflow (C2) allow researchers to assess whether integration is appropriate for the questions and research contexts that are central to their analysis. When suitable, my CTA Toolkit (C2) can support researchers by providing accessible computational technique integrations without requiring programming expertise. Researchers can combine my contributions with their contextual public health expertise to control how computational techniques are integrated and customize their thematic analyses of online communities to suit their research questions about existing and emerging public health issues.

5.4 Limitations

My exploration of integrating computational techniques into thematic analyses of online communities involved navigating three areas of limitation. First, I considered the ethics of processing public data to guide my approaches to performing and supporting thematic analysis of online communities. Second, I focused on transferable over generalizable contributions due to my work's qualitative approaches and context. Finally, I pivoted my research approach based on real-world constraints.

5.4.1 Ethical Choices

During my research, I considered the ethics of working with online public data as I navigated facilitating thematic analyses of online communities. Since my work contributes to public health, I was particularly concerned about the potential harm data processing can have on the community members. One such harm is re-identification, where processing links public data back to people who expected to be anonymous. Re-identification can cause stigmatization and loss of support, particularly when processing data from communities discussing sensitive health issues (e.g., addiction and chronic diseases). Some ways re-identification can occur are publishing direct quotations, releasing models built out of public data, and unintended data breaches. (Bruckman, 2002; Markham, 2012)

In my Pilot Stage that analyzed addiction recovery communities, I minimized the risk of re-identification by publishing paraphrased quotations and topic summaries. These practices avoid providing enough public data to re-identify and stigmatize community members (Bruckman, 2002; Markham, 2012). Additionally, I limited myself to running any task on my local computer to avoid data breaches.

Similarly, I designed my CTA toolkit to be a local application so that any researcher conducting an analysis has control over the public data they are analyzing. I also avoided having my toolkit send data off to be processed using cloud computing, as that would send data outside the researcher's direct control. However, making these choices limited my integration and toolkit to computational techniques that are efficient enough to run on local computers.

5.4.2 Transferability over Generalizability

Thematic analysis is a flexible methodology that needs to be customized to suit different research contexts (Braun et al., 2019). As such, I cannot claim my integration description contributions will generalize to all thematic analyses of online communities. Instead, my work's contributions are situated in qualitative contexts so that they can be transferable as qualitative researchers consider how to integrate computational techniques into their thematic analyses of online communities.

Similarly, computational research continues to develop novel techniques that researchers could use to interact with large data sets. As a result, I cannot make a generalized claim that my contributed CTA Toolkit is the best option or will always work when integrating computation techniques into thematic analysis, as the techniques I implemented are not the only option. Instead, my CTA toolkit contributions are transferable by being designed so that developers can work with qualitative researchers to implement new tools and apply them to new contexts as they explore the integration of existing and future computational techniques. As researchers explore integrating and applying techniques in new tools in thematic analysis contexts, they need to reflect on the operational validity of transferring computational techniques into qualitative contexts (Baden et al., 2021). In my work, I provided transparency beyond a simple post-hoc inspection of technique outputs by showing researchers combinations of what their data set includes, how their data is being manipulated, and references to established uses of techniques. These combinations encourage researchers to reflect on and triangulate multiple aspects of the tools and make contextual assessments of operational validity.

Finally, my contributions do not focus on a specific online platform, such as Reddit. If my contributions were platform-specific, they could be invalidated when new platforms overtake old platforms, such as how Facebook overtook myspace's number of users in 2009 (JR Raphael, 2009). Instead, my contributions focused on performing and facilitating thematic analyses in online community qualitative research contexts, enabling them to be adjusted and transferred to similar communities.

5.4.3 Pivot to Remote Research

In my original proposal, I had intended to design a toolkit for a large wall display and deploy the toolkit in a series of in-person collaborations during which several researchers would perform thematic analyses. However, as I wrote my proposal for this work, the World Health Organization declared the COVID-19 pandemic, which increased the value of my contributions as online communities became more relevant as many formally in-person activities migrated online. As a result, my planned in-person research would have required researchers to take an unnecessary risk of infection. In response to this risk, I pivoted my Design Stage to make the CTA Toolkit able to run on researchers' computers and my Deploy Stage to a remote collaboration, which turned out to be a mixed blessing.

First, the pivot benefited my Deploy Stage's contribution by requiring that I create a more stable and polished version of my toolkit. This requirement was due to needing a toolkit that was easy to install and work with on remote researchers' computers rather than only on a local lab computer. However, this benefit came at the cost of increasing the development effort involved in my Design Stage.

Second, remote collaboration benefited my Deploy Stage by allowing the collaborating researchers to perform their analyses at their own pace in their real-world research environments, which enabled my stage to emphasize realism. However, remote collaboration increased the amount of effort required for the project. For instance, collaborators now needed to work through issues that could have been simple to handle in person by participating in virtual coordination meetings. As such, I chose to focus on comparing two analyses from a single larger remote public health research project to minimize the coordination burden on everyone involved.

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APPENDICES

Appendix A

Chapter 2 Study Material

A.1 Ethics Application

APPLICATION FOR ETHICS REVIEW OF RESEARCH INVOLVING HUMAN PARTICIPANTS

Please remember to PRINT AND SIGN the form and forward with all attachments to the Office of Research Ethics, EC5, 3rd floor.

A. GENERAL INFORMATION

1. Title of Project: Addiction Subject Matter Expert Topic Evaluation Study

2. a) Principal and Co-Investigator(s)
NEW As of May 1, 2013, all UW faculty and staff listed as investigation must complete the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans Tutorial, 2nd Ed. (TCPS2) prior to submitting an ethics application. The tutorial takes at least three hours; it has start and stop features.

Name	Department	Ext:	e-mail:

2. b) Collaborator(s)
NEW As of May 1, 2013, all UW faculty and staff listed as investigation must complete the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans Tutorial, 2nd Ed. (TCPS2) prior to submitting an ethics application. The tutorial takes at least three hours; it has start and stop features.

Name	Department	Ext:	e-mail:

3. Faculty Supervisor(s)
NEW As of May 1, 2013, all UW faculty and staff listed as investigation must complete the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans Tutorial, 2nd Ed. (TCPS2) prior to submitting an ethics application. The tutorial takes at least three hours; it has start and stop features.

Name	Department	Ext:	e-mail:
Dr. James R. Wallace	School of Public Health and Health Systems	30184	james.wallace@uwaterloo.ca

4. Student Investigator(s)

Name	Department	Ext:	e-mail:	Local Phone #:
Robert Gauthier	School of Public Health and Health Systems		rpgauthier@uwaterloo.ca	647-524-8404

5. Level of Project: PhD **Specify Course:**

Research Project/Course Status: New Project\Course

6. Funding Status (If Industry funded and a clinical trial involving a drug or natural product or is medical device testing, then Appendix B is to be completed):

Is this project currently funded? Yes

- If Yes, provide Name of Sponsor and include the title of the grant/contract: NSERC : NSERC : Dr. Wallace's NSERC Grant
- If No, is funding being sought OR if Yes, is additional funding being sought? Yes
  - Funding Name of Sponsor and title of grant/contract:
- Period of Funding: 2015-2020

7. Does this research involve another institution or site? Yes
If Yes, what other institutions or sites are involved:
Homewood Research Institute

8. Has this proposal, or a version of it, been submitted to any other Research Ethics Board/Institutional Review Board? No

9. For Undergraduate and Graduate Research:

Has this proposal received approval of a Department Committee? Not Dept. Req.

10. a) Indicate the anticipated commencement date for this project: 8/1/2018

b) Indicate the anticipated completion date for this project: 12/1/2018

section A.1 continued on next page ...

11. Conflict of interest: Appendix B is attached to the application if there are any potential, perceived, or actual financial or non-financial conflicts of interest by members of the research team in undertaking the proposed research.

B. SUMMARY OF PROPOSED RESEARCH

1. Purpose and Rationale for Proposed Research

a. Describe the purpose (objectives) and rationale of the proposed project and include any hypothesis(es)/research questions to be investigated. For a non-clinical study summarize the proposed research using the headings: Purpose, Aim or Hypothesis, and Justification for the Study. For a clinical trial/medical device testing summarize the research proposal using the following headings: Purpose, Hypothesis, Justification, and Objectives.
Where available, provide a copy of a research proposal. For a clinical trial/medical device testing a research proposal is required:
Purpose: the study seeks to improve understanding of addiction recovery by investigating public information available on the social media platform Reddit using automated data analysis tools.

Aim: The aim of the study is to work towards answering two research questions:

1) Does Reddit provide appropriate support for addiction recovery?

2) Can leveraging an LDA topic analysis approach generate meaningful topics in the sensitive area of addiction recovery?

Justification: Public social media platforms like Reddit play a role in addiction. As such it is a valuable data source for gaining a better understanding of what data is available and how it is being used could help improve addiction recovery approaches.

b. In lay language, provide a one paragraph (approximately 100 words) summary of the project including purpose, the anticipated potential benefits, and basic procedures used.
The study aims to understand what is being discussed on Reddit with regards to addiction and addiction recovery. The understanding will help to inform better addiction recovery decisions. The study will use subject matter experts in the addition treatment domain to analyse topics made up of terms and posts from Reddit.

C. DETAILS OF STUDY

1. Methodology/Procedures

a. Indicate all of the procedures that will be used. Append to form 101 a copy of all materials to be used in this study.

Focus group(s)
Audio-recording
Video-recording
Analysis of secondary data set or secondary use of information

b. Provide a detailed, sequential description of the procedures to be used in this study. For studies involving multiple procedures or sessions, provide a flow chart. Where applicable, this section also should give the research design (e.g., cross-over design, repeated measures design).
1) Participants will be welcomed and be provided with a consent form, once the participants fully understand the purpose of the study they will be asked to sign the consent form.

2) The participants will be provided machine generated topics in the form of word groups and example historical posts from Subreddits focused on addiction.

3) The experts will discuss the topics from an perspective informed by their expertise. this will include identification of useful information, identification, useless information, and providing a general labeling of the topics. The following questions will be used to focus this discussion:

3a) What topics were expected and present?

3b) What topics were unexpected and present?

4) After all topics have been discussed the experts will be asked to reflect on whether anything was missing that they expected to see reflected in the topics based on their expertise. The following question will be used to focus this discussion:

4a) What topics were expected and not present?

5) the participants will be asked if they have any other questions or concerns.

c. Will this study involve the administration/use of any drug, medical device, biologic, or natural health product? No

d. Will you be using, processing and/or storing any biological materials of human origin such as blood, tissue, cells or bodily

section A.1 continued on next page . . .

fluids?
No

2. Participants Involved in the Study

a. Indicate who will be recruited as potential participants in this study.
Non-UW Participants:
Adults

b. Describe the potential participants in this study including group affiliation, gender, age range and any other special characteristics. Describe distinct or common characteristics of the potential participants or a group (e.g., a group with a particular health condition) that are relevant to recruitment and/or procedures. Provide justification for exclusion based on culture, language, gender, race, ethnicity, age or disability. For example, if a gender or sub-group (i.e., pregnant and/or breastfeeding women) is to be excluded, provide a justification for the exclusion.

Potential participants are professionals in the addiction treatment domains recruited through the Homewood Research Institute. These participants will be subject matter experts through both formal education and work experience.

c. How many participants are expected to be involved in this study? For a clinical trial, medical device testing, or study with procedures that pose greater than minimal risk, sample size determination information is to be provided.

Approximately 2-6 participants working as a focus group

3. Recruitment Process and Study Location

a. From what source(s) will the potential participants be recruited?
Agencies
Businesses, industries

b. Describe how and by whom the potential participants will be recruited. Provide a copy of any materials to be used for recruitment (e.g. posters(s), flyers, cards, advertisement(s), letter(s), telephone, email, and other verbal scripts).
Rapport has been established with the Homewood Research Institute (HRI). Our study goals and values align with HRI's mission. Recruitment will occur internally to HRI through snowball sampling with our research contacts.

c. Where will the study take place? Off campus: prearranged public place that is convenient for participants

4. Remuneration for Participants
Will participants receive remuneration (financial, in-kind, or otherwise) for participation? No

5. Feedback to Participants

Describe the plans for provision of study feedback and attach a copy of the feedback letter to be used. Wherever possible, written feedback should be provided to study participants including a statement of appreciation, details about the purpose and predictions of the study, restatement of the provisions for confidentiality and security of data, an indication of when a study report will be available and how to obtain a copy, contact information for the researchers, and the ethics review and clearance statement.
Please see attached Feedback letter document.

D. POTENTIAL BENEFITS FROM THE STUDY

1. Identify and describe any known or anticipated direct benefits to the participants from their involvement in the project.
There are no known or anticipated direct benefits to the participants.

2.Identify and describe any known or anticipated benefits to the scientific community/society from the conduct of this study.
The study will provide a better understanding of what occurs in online social media platforms in the context of addiction recovery. This will help towards uncovering the needs of the addiction community as well as how social media impacts the recovery from addiction.

E. POTENTIAL RISKS TO PARTICIPANTS FROM THE STUDY

1. For each procedure used in this study, describe any known or anticipated risks/stressors to the participants. Consider physiological, psychological, emotional, social, economic risks/stressors. A study–specific current health status form must be included when physiological assessments are used and the associated risk(s) to participants is minimal or greater.

Minimal risks anticipated.
1) As these posts originate from online communities around addiction there is a possibility that the content may be uncomfortable in nature. The expectation is that this is low risk as professionals in the addiction domains will be prepared for such uncomfortable topics.

2) There is a unlikely possibility that even though the source is pseudnonymous the professionals identifying

section A.1 continued on next page . . .

characteristics of posts that suggest negative experiences with the very professionals participating. The information is already freely available online so this is considered a low risk as using good could result in the same information being found.

2. Describe the procedures or safeguards in place to protect the physical and psychological health of the participants in light of the risks/stressors identified in E1.
Each participant will:

- be provided with a summary of the study as well as a consent form in advance

- be encouraged to ask questions at any time.

- be verbally provided all the summary and consent form's information by the researcher.

Once the participant is certain and comfortable about the procedure, they will then sign the consent form, which they can freely withdraw from at any time.

Before the focus group the researcher will emphasize that healthy disagreement may occur but should not create negative feelings between participants.

During the focus group the researcher will provide light moderation and will intervene if the discussion becomes to heated with breaks or possibly halts.

Post focus group the participants will be reminded that the focus group may have shown conflicting ideas and that they should not take away negative opinions of each other based on the discussion.

F. INFORMED CONSENT PROCESS

1. What process will be used to inform the potential participants about the study details and to obtain their consent for participation?
Information letter with written consent form

2. If written consent cannot be obtained from the potential participants, provide a justification for this.
not applicable

3. Does this study involve persons who cannot give their own consent (e.g. minors)? No

G. ANONYMITY OF PARTICIPANTS AND CONFIDENTIALITY OF DATA

1. Provide a detailed explanation of the procedures to be used to ensure anonymity of participants and confidentiality of data both during the research and in the release of the findings.
The participants will be informed that all the documents and recordings that will be collected will be kept secured and completely confidential. The documents will be kept in in room LHN 1707 at University of Waterloo, which only the researcher have the access to the room and information. The recordings will be kept on a password protected computer at University of Waterloo.

2. Describe the procedures for securing written records, video/audio tapes, questionnaires and recordings. Identify (i) whether the data collected will be linked with any other dataset and identify the linking dataset and (ii) whether the data will be sent outside of the institution where it is collected or if data will be received from other sites. For the latter, are the data de-identified, anonymized, or anonymous?
Data will only be used for the purpose of this research and will be confidential. Consent to video and audio-recording of each focus group will be obtained for each participant for accurate transcription and analysis. The data will not be shared or linked with any other dataset outside the University of Waterloo. The name of the participants will not appear in any of the research papers or the interview. Each participant will be assigned non-identifying id and the mapping of participant to id will be stored in a separate location. These measures will keep the data will stay anonymous in the research paper.

3. Indicate how long the data will be securely stored and the method to be used for final disposition of the data.
Paper Records
  Confidential shredding after 7 year(s).
Audio/Video Recordings
  Erasing of audio/video recordings after 7 year(s).
Electronic Data

section A.1 continued on next page . . .

Erasing of electronic data after 7 year(s).
Location: secure cabinet and hard drive in locked room at the University of Waterloo

4. Are there conditions under which anonymity of participants or confidentiality of data cannot be guaranteed? No

H. PARTIAL DISCLOSURE AND DECEPTION

1. Will this study involve the use of partial disclosure or deception? Partial disclosure involves withholding or omitting information about the specific purpose or objectives of the research study or other aspects of the research. Deception occurs when an investigator gives false information or intentionally misleads participants about one or more aspects of the research study. No

Researchers must ensure that all supporting materials/documentation for their applications are submitted with the signed, hard copies of the ORE form 101/101A. Note, materials shown below in bold are normally required as part of the ORE application package. The inclusion of other materials depends on the specific type of projects.

Protocol Involves a Drug, Medical Device, Biologic, or Natural Health Product

If the study procedures include administering or using a drug, medical device, biologic, or natural health product that has been or has not been approved for marketing in Canada then the researcher is to complete Appendix A. Appendix A is to be attached to each of the one copy of the application that are submitted to the ORE. Information concerning studies involving a drug, biologic, natural health product, or medical devices can be found on the ORE website.

Please **check** below all appendices that are attached as part of your application package:

- Information Letter and Consent Form(s)*. Used in studies involving interaction with participants (e.g. interviews, testing, etc.)
- Data Collection Materials: A copy of all survey(s), questionnaire(s), interview questions, interview themes/sample questions for open-ended interviews, focus group questions, or any standardized tests.
- Feedback letter *
- Other - secondary data sets

* Refer to sample letters.

NOTE: The submission of incomplete application packages will increase the duration of the ethics review process.

To avoid common errors/omissions, and to minimize the potential for required revisions, applicants should ensure that their application and attachments are consistent with the *Checklist For Ethics Review of Human Research Application*

Please note the submission of incomplete packages may result in delays in receiving full ethics clearance.
We suggest reviewing your application with the Checklist For Ethics Review of Human Research Applications to minimize any required revisions and avoid common errors/omissions.

INVESTIGATORS' AGREEMENT

I have read the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans, 2nd Edition (TCPS2) and agree to comply with the principles and articles outlined in the TCPS2. In the case of student research, as Faculty Supervisor, my signature indicates that I have read and approved this application and the thesis proposal, deem the project to be valid and worthwhile, and agree to provide the necessary supervision of the student.

NEW As of May 1, 2013, all UW faculty and staff listed as investigators must complete the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans Tutorial, 2nd Ed. (TCPS2) prior to submitting an ethics application. Each investigator is to indicate they have completed the TCPS2 tutorial. If there are more than two investigators, please attach a page with the names of each additional investigator along with their TCPS2 tutorial completion information.

________________________________ ______________________
Print and Signature of Principal Investigator/Supervisor **Date**

Completed TCPS2 tutorial:
___YES ___NO ___ In progress

________________________________ ______________________
Print and Signature of Principal Investigator/Supervisor **Date**

section A.1 continued on next page . . .

Completed TCPS2 tutorial:
___YES ___NO ___ In progress

Each student investigator is to indicate if they have completed the Tri-Council Policy Statement, 2nd Edition Tutorial (http://pre.ethics.gc.ca/eng/education/tutorial-didacticiel/). If there are more than two student investigators, please attach a page with the names of each additional student investigator along with their TCPS2 tutorial completion information.

______________________________ ______________________
Signature of Student Investigator **Date**

Completed TCPS2 tutorial:
___YES ___NO ___ In progress

______________________________ ______________________
Signature of Student Investigator **Date**

Completed TCPS2 tutorial:
___YES ___NO ___ In progress

FOR OFFICE OF RESEARCH ETHICS USE ONLY:

________________________ ______________________
Julie Joza, MPH **Date**
Acting Chief Ethics Officer
OR
Nick Caric, MDiv
Research Ethics Advisor
OR
Karen Pieters, MPH
Research Ethics Advisor

ORE 101
Revised September 2016

A.2 r/stopdrinking's topic keywords and example posts

LDA TOPIC KEYWORDS	PARAPHRASED EXAMPLE QUOTES
external_link, book, watch, link, movie, reddit, song, comment, write, show	"During the movie club we chat while watching the linked stream in sync as best as we can."
sleep, run, play, exercise, hour, meditation, walk, hobby, watch, game	"It's rainy and I'm out of ideas. Anyone have any suggestions of things that can keep my hands and mind busy? :)"
bar, party, fun, plan, event, situation, hang, enjoy, weekend, date	"I found out that some friends went out last Saturday and didn't invite me because they thought that I don't like to drink beer. I miss going out with them and I feel excluded just because I've stopped drinking."
eat, beer, water, coffee, food, tea, craving, taste, wine, triumph	"I've been having fun by trying and enjoying so many different non-alcoholic drinks instead of just choosing the one with the highest alcohol amount"
link, external_link, comment, www_reddit, com_stopdrink, comment_http, amp_nbsp, author_post, title_link, ups_down	"See the comments for a table of top posts. Most Upvoted Comments ..."
relationship, alcoholic, wife, drive, talk, situation, call, advice, lose, car	"I saw in the newspaper that someone got picked up for their 5th dui. This made me think about my own duis from several years ago and realize how great it is to be free of both alcohol and the legal system."
family, mom, dad, kid, parent, child, son, brother, daughter, die	"Joining this sub helped give me reasons to not join in on the drowning of sorrows when my wife's mom died. That way I could be there for my wife."
money, school, college, pay, live, move, spend, class, save, student	"When I see how much I saved I can't help but think it's awesome to not be wasting money on alcohol. I won't drink with you today."
eat, body, weight, liver, lose, exercise, calorie, diet, health, food	"I found it weird how even though I was eating more chocolate bars I still lost weight during my first few months. I also found that tracking my diet was easier when I wasn't binge eating in the middle of the night while blackout drink"
meeting, aa, group, recovery, meet, talk, step, sponsor, program, share	"I want to find a group that has members who have common ground with me as a young female if possible."
step, aa, god, program, sponsor, higher_power, atheist, big_book, recovery, person	"While I respect that everyone has different beliefs that may involve religion it just isn't for me. When I see higher power I have a hard time accepting that it's not a reference to God. Any suggestions?"
congratulation, share, birthday, celebrate, man, guy, number, story, inspiration, badge	"I turned 45 years old yesterday and made it to 1 year. It was so worth it to quit drinking that I can image how winning the lottery feels."

section A.2 continued on next page ...

LDA TOPIC KEYWORDS	PARAPHRASED EXAMPLE QUOTES
alcoholic, alcoholism, drug, control, addiction, moderation, smoke, addict, question, drinker	"I can't understand how any amount of alcohol can be good for us as since I stopped drinking recently and I feel way healthier. Does anyone know if the claim the moderated drinking extends your life has been refuted by science? I can't believe this claim."
learn, feeling, thought, deal, mind, live, recovery, realize, point, person	"By reading This Naked Mind and thinking about my feelings and what alcohol took from me has been enlightening. I was able to establish a critical perspective that showed me how warped my thoughts had subconsciously become."
morning, wake, beer, bottle, tomorrow, hour, weekend, dream, bed, plan	"I was so relieved when I finally realized it was in a dream. At first I thought it was impossible that I was in the middle of my 1st glass of beer. I felt that I had fallen off the wagon and thought I may as well enjoy the beer or maybe it was a dream like last time. Then I realized it really was a dream!"
doctor, anxiety, withdrawal, detox, depression, medication, symptom, sleep, med, taper	"Has anyone used Klonopin before? My doctor perceived this new stuff instead of Librium."

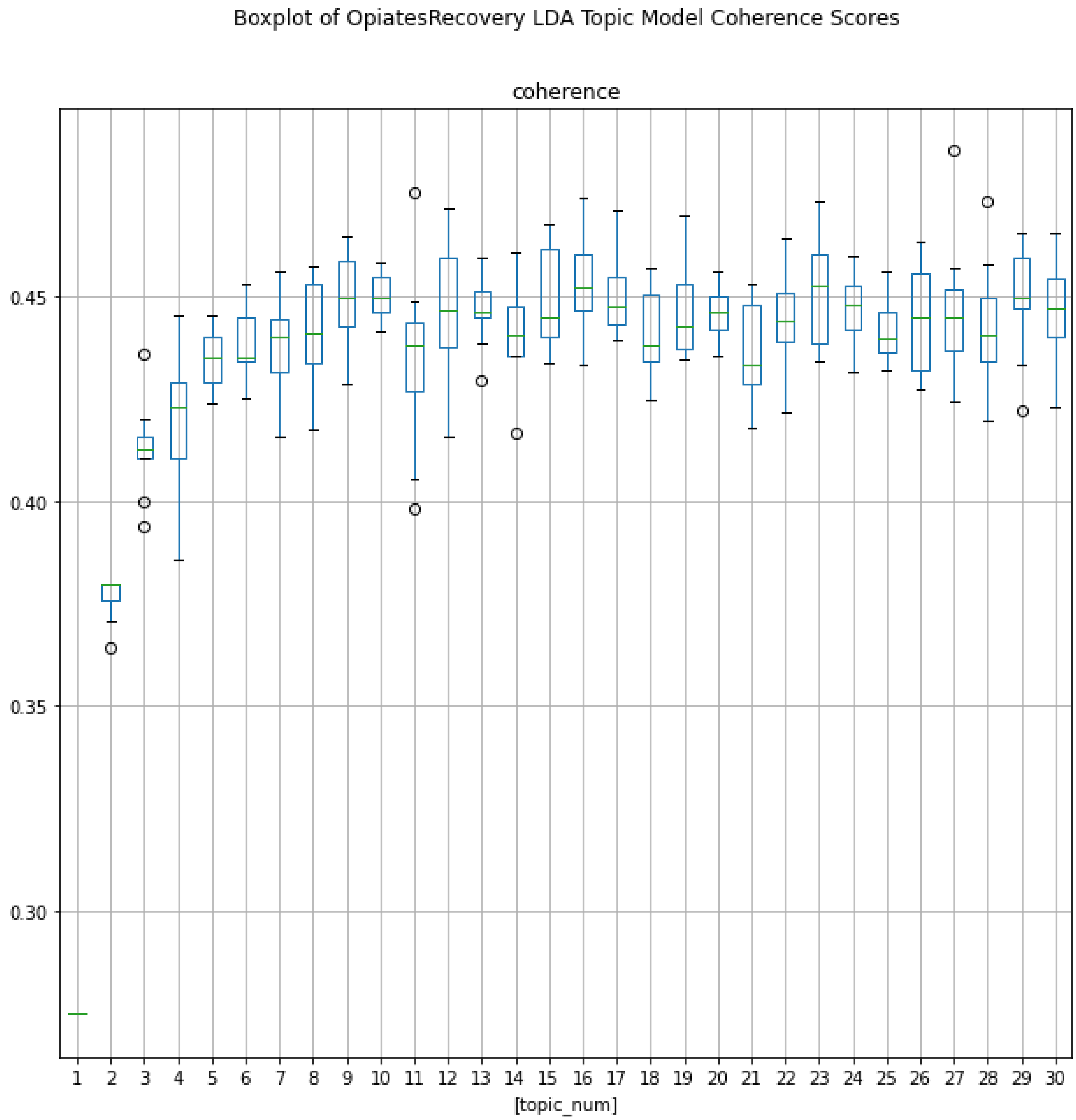
A.3 r/OpiatesRecovery's topic keywords and example posts

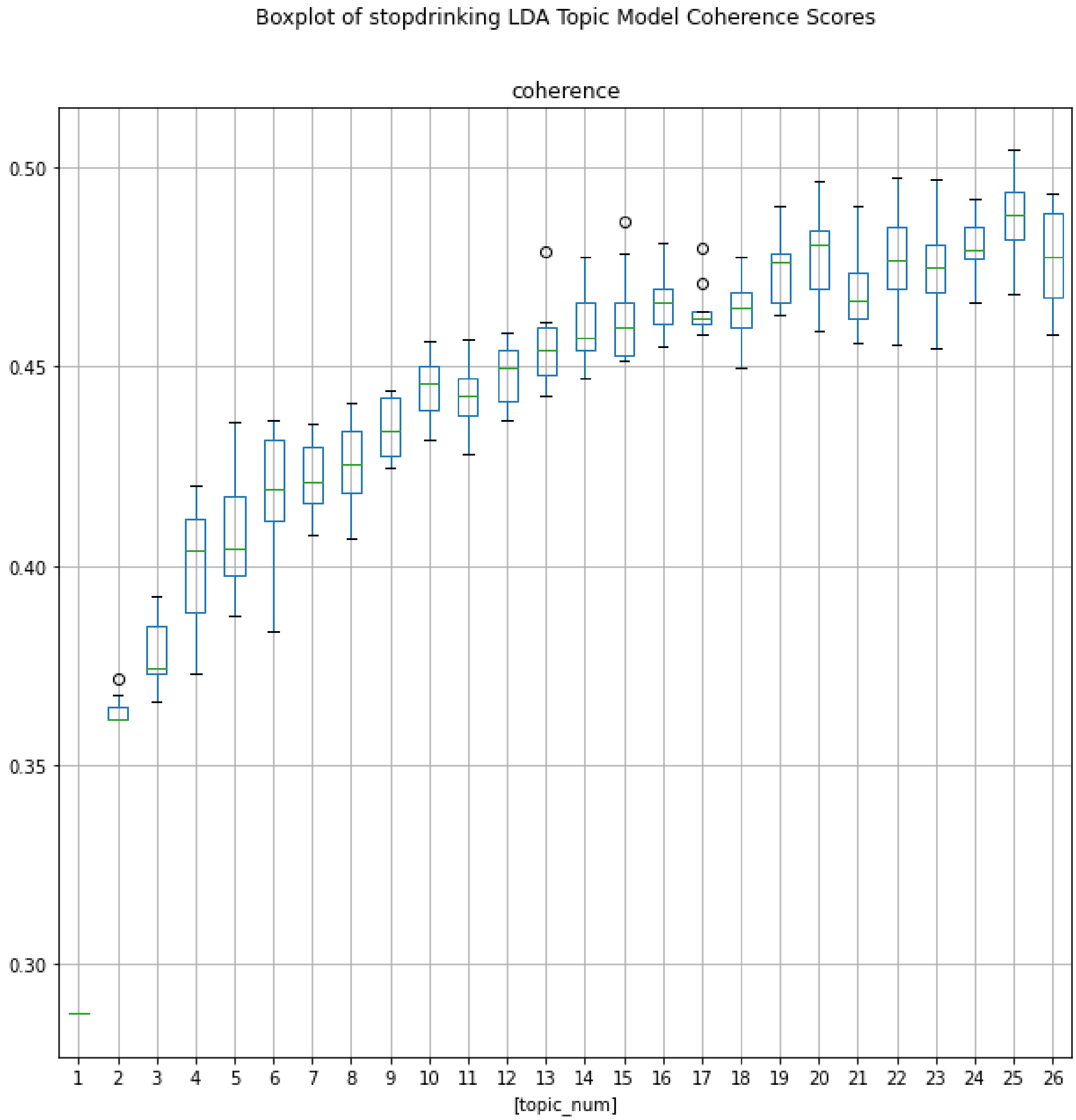
LDA TOPIC KEYWORDS	PARAPHRASED EXAMPLE QUOTES
paw, exercise, body, eat, energy, weight, food, gym, endorphin, vitamin	"I know exercise sucks to get started during withdrawal but believe me when I say you will feel better after you finish. I read this is because of runner's high where the body releases endorphins which helps the opiate receptors feel less starved."
external_link, watch, music, song, play, listen, video, game, enjoy, dude	"The local methadone clinic, while pricey, helped me stay off heroin for 6 days and is saving me money. In other news I wanted to see if anyone had any new music suggestions for when I'm feeling down. I've been wanting to find new music to help with my boredom. Thanks for any suggestions you can give. I'm really liking this site and am glad that I was shown it by a friend."
dream, jail, court, charge, wake, prison, record, arrest, probation, felony	"Here are some tips I found out about who can access my file during my experience getting a felony charge expunged..."
anxiety, depression, meditation, therapist, issue, therapy, emotion, psychiatrist, hang, symptom	"After 1 year sober I have bad panic attacks and anxiety. Does anyone else have the same sort of experience?"
drink, smoke, weed, alcohol, pot, drinking, substance, beer, program, smoking	"Does my recovery mean I have to sustain from alcohol forever? Recovery is great but I do wonder."
sponsor, program, group, aa, god, higher_power, share, meet, area, power	"While I am involved in twelve step programs for both alcohol and opiates many of the people there are connected to my halfway which makes me worried my family will be called or that I might get kicked out"
doctor, med, prescribe, surgery, medication, abuse, prescription, script, tramadol, option	"I'm worried that visiting my doctor about my illness will end up with me continuing my normal scripts AND/OR I might end up on something else that also addictive"
yesterday, morning, weekend, school, wake, tomorrow, last_night, house, tonight, eat	"Good morning to everyone. Had a great time yesterday with a girl and I look froward to seeing her again. It's almost been 50 days clean now! How are you all doing?"
wife, kid, husband, dad, test, child, story, son, baby, lie	"My amazing girlfriend has stuck with me and supported me after learning the lies I've been spewing. I'm so lucky to have her."
external_link, comment, agree, fact, opinion, question, disease, study, state, issue	"In my research on different areas of addiction I found reading research and dissertations really helped me better understand both my experience and the research..."
relationship, situation, lie, parent, mom, girlfriend, break, trust, girl, story	"tl;dr my older sibling is addicted to opiates and I have no idea how to help them"

section A.3 continued on next page . . .

LDA TOPIC KEYWORDS	PARAPHRASED EXAMPLE QUOTES
craving, struggle, congrat, sobriety, anymore, fight, moment, learn, hang, tomorrow	"I've been on that train as well this horrible January. Despite the similar demons I know you can do it. You already know it's not worth using from what you've experienced before. If it's really bad have someone you trust hold onto your paycheck for you."
rehab, treatment, program, insurance, facility, doctor, outpatient, pay, state, inpatient	"Being able to go to rehab is a fortunate opportunity.. Just make sure to participate, hang with the people who are really trying, learn more about yourself then you ever wanted to know, listen, laugh, read, and follow the recommendations when you leave. It will be great!"
methadone, mg, taper, dose, doctor, clinic, strip, vivitrol, wait, maintenance	"I've seen these insurance issues first hand with my boyfriend. Luckily while he's waiting he could set up with a primary care doctor who said they could get him into a suboxone treatment program or start him on vivitrol."
kratom, taper, mg, symptom, dose, habit, lope, oxy, kick, rl	"I ran out of my suboxone two days ago. does anyone know if I'm facing any withdrawals? I've still got some Valium and xanax. Could I space out these to try to eliminate any night withdrawals I might have?"
die, overdose, hospital, needle, wake, shoot, mom, turn, eye, arm	"So I've been off for 6 months and I don't even think about using H, other then remember how glad i am to no longer be using. However I still have a lot of redness and some small tracks on my arm. Anyone else tried getting rid of these small scars with the help of a dermatologist?"

A.4 Coherence Statistic Graphs for Pilot Model From Each Subreddit




Boxplot of stopdrinking LDA Topic Model Coherence Scores
coherence
0.50
0.45
0.40
0.35
0.30
1
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[topic_num]

A.5 Theme-Code Mapping

Themes	Sub Themes	Contributing Codes
Sharing Experiences	Self Reflections	Fear of Relapse, Self Reflections, Inner Monologue, Journey, Providing Information
Sharing Experiences	Sharing Failures	Current Situation, Relapse, Stress, Struggle between Addiction and Recovery, Negative Emotions, Providing Information
Sharing Experiences	Sharing Successes	Current Situation, Positive Emotions, Providing Information
Sharing Experiences	Waking Up	Dreams, Feeling of Failure, Positive upon Waking Providing Information
Peer Support	Check-ins	Daily, Holidays, Birthdays, Celebrating Success, Providing Support, IWNDWYT, Accepting Support
Peer Support	Encouragement	Current Situation, Negative Emotions, Providing Support, IWNDWYT, Accepting Support
Peer Support	Solidarity	Current Situation, Death, Positive Emotions, Providing Support, IWNDWYT, Accepting Support
Consequences	Benefits of Recovery	Weight Change, Money Saved, Improved Health, Positive Emotions
Consequences	Costs of Recovery	Treatment, Insurance, Cost, Time, Inpatient vs Outpatient, Social Changes
Consequences	Harm from Substance Use	Justice System, Money, Current Situation, Accepting Responsibility
Substance Related Concerns	Pain Management	Pain, Fear of Treatment, Current Situation, Seeking Information, Providing Information, Providing Support
Substance Related Concerns	Socializing	Social Events, Bars, Spots, Trips, Fear of Relapse, Stigma, Changes in Friendships, Internalized No Alcohol Stigma
Social Relationships and Activities	Filling a Void	Boredom, Seeking Activities
Social Relationships and Activities	Group Activities	Connecting to Each other, Book Clubs, Movie Night, Support Groups, Helping Others
Social Relationships and Activities	Healthy Activities	Exercise, Improving Diet, Non-Alcoholic Drinks
Social Relationships and Activities	Leisure Activities	Music, Art, Books, External Resources, Seeking Information, Providing Information, Connecting to Each other
Sharing Knowledge and Lived Experiences	Family and Friends	Family, Friend, Concern, Broken Relationships, Seeking Information, Providing Information, Suggesting Support Groups

section A.5 continued on next page ...

Themes	Sub Themes	Contributing Codes
Sharing Knowledge and Lived Experiences	Managing Addiction	Considering Recovery, Seeking Information, Providing Information, Suggesting Support Groups
Sharing Knowledge and Lived Experiences	Managing Consequences	Justice System, Healthcare, Scars, Current Situation, Seeking Information, Providing Information, Suggesting Talking to Lawyer, Suggesting Talking to Doctor
Sharing Knowledge and Lived Experiences	Managing Recovery	Exit Plans, Alternative Activities, Importance of Support Network, Importance of Honesty, Multiple Perspectives
Sharing Knowledge and Lived Experiences	Managing Withdrawal	PAWS, Withdrawal Symptoms, Anxiety, Depression, Fatigue, Tapering Off, Seeking Information, Providing Information, Suggesting Alternatives, Risks of Alternatives, Suggesting Talking to Doctor, Different Drug Names, Multiple Perspectives, CBT
Sharing Knowledge and Lived Experiences	Understanding Addition	Self-Reflections, Documentaries, External Resources, Defining Addiction, Multiple Perspectives
Sharing Knowledge and Lived Experiences	Understanding Recovery	Abstinence vs Moderation, Changing Social Groups, Multiple Perspectives
Sharing Knowledge and Lived Experiences	Understanding Withdrawal	Withdrawal, Seeking Information, Providing Information, Suggesting External Resources, Suggesting Talking to Doctor, Describing Withdrawal Symptoms
Supporting Formal Treatment of Addiction	Female Support	Support Groups, Female, Female Sponsors, Seeking Information, Providing Information
Supporting Formal Treatment of Addiction	Higher Power Concerns	Struggles with Support Groups, Higher Power, Stigma, Seeking Information, Providing Information, Reframing
Supporting Formal Treatment of Addiction	Newcomer Support	Struggles with Support Groups, Time Conflicts, Overwhelmed, Group Types, Sponsorship, Fear of Stigma, Seeking Information, Providing Information, External Resources, Role of NA, Role of AA

Appendix B

Chapter 4 Study Materials

B.1 CIRN Project Protocol

Created by Dr. Samantha Meyer with feedback from Robert P. Gauthier, Catherine Pelletier, Laurie-Ann Carrier, Maude Dionne, Ève Dubé, and James R. Wallace to guide the project within which Chapter 4's collaboration took place.

Research approach – protocol for analysis

1. Project Objectives

This plan serves to meet two objectives related to two existing projects:

1. Objective 1: Describe online discourses related to the generation and spread of rumours, misinformation and disinformation on COVID-19 in Canada (Dube CIHR 440293)
2. Objective 2: Apply and validate software that uses artificial intelligence to support qualitative researchers to analyze and interpret large datasets (Meyer CIRN; Gautier PhD)

We will **apply** the software to analyze existing CIHR data (Obj 1). We will then **validate** the software by comparing the computer analysis with human analysis (Obj 2). Through this process we will produce software that can be used freely to thematically analyze online qualitative posts to better understand the role of social media in vaccine acceptance.

The plan for analysis, as described below, will serve to meet both objectives. The data analysis itself, both human (sample of data collection) and via the toolkit (entire dataset), will provide results for the purpose of preparing a manuscript regarding rumours, misinformation and disinformation on COVID-19 in Canada (Obj 1). The availability of both human and toolkit analysis will allow us to compare outputs as a method for validating the toolkit (Obj 2) while also provide data output that draws on the lager dataset,

2. Data collection (complete)

Our exploratory approach involved collecting comment threads on news articles. News articles and comment threads are freely available and published digitally. The commenting feature on the site is a threaded format which allows users to not only reply to original posts (OP), but also to reply to the threaded replies (TR) under the OP. In addition, all TRs are indented under the OP and the atmark (@) identifies the specific comment a user is replying to, which will allow us to analyze exchanges.

Three online national news sources (*CBC News, The Globe and Mail* and *The National Post*) and 12 provincial newspapers (*The Times Colonist, The Tyee* and *The Vancouver Sun* for BC; *The Cape Breton Post*, *The Chronicle Herald* and *The Halifax Examiner* for NS; *The Toronto Sun* and *The Toronto Star* for ON; and *Le Devoir*, *Le Journal de Québec*, *La Presse* et *Radio-Canada Nouvelles* for QC) were included in our analysis. These news sources were selected because of either their high circulation and readership. In some cases they were chosen to reflect a range of opinions and perspectives on COVID-19 based on news type (tabloid vs. mainstream), audience (rural vs. urban) and political affiliation (right vs. left-wing position), rather than to be representative of the news coverage on the topic in Canada.

section B.1 continued on next page . . .

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Data in the present analysis were collected from January to June 2020. User comments were captured in the 15 selected newspapers at specific time corresponding to specific events:

- January 01-January 15, 2020 : The first cases of COVID-19 in China
- January 25-February 8, 2020 : The first cases of COVID-19 in Canada (BC and ON)/ WHO declares COVID to be a public health emergency of international concern
- February 27-March 3, 2020 : The first cases of COVID-19 in QC
- March 9-April 8, 2020: COVID-19 declared a pandemic by WHO, the first cases in Nova Scotia, the first death related to the virus in Canada and the lockdown
- May 4-May 31, 2020: The lifting of the control measures

Articles
Searches in newspapers websites were conducted using the following keywords: “coronavirus”, “COVID-19”, “Wuhan virus”, and “pandemic” in English and “coronavirus”, “COVID-19”, “virus chinois”, and “pandémie” in French. The searches were limited to 24 hours prior and after critical events identified in the timeline for retrospective analysis and every week for prospective analysis. News articles for the present analysis were included if they are a text-based news report, published between January to June 2020 and pertain to the COVID-19 pandemic. News articles were excluded if they are in a format other than text (i.e. audio, video or blog format).

Comment threads
User comments were extracted using Scraper v.1.7, a Google Chrome data mining extension to automate the data extraction process. Limits inherent to the website’s application programming interface (API) prevent the collection of any personal or identifying information. As such, we were not able to conduct analyses as they relate to demographic and user characteristics.

Data use for present analysis

A total of 2 484 717 comments were collected. An AI firm cleaned the sample from comments that did not include textual elements (e.g. gig, videos, emojis, etc.). It also cleaned the sample from comments that were not related to COVID-19 using the following keywords: corona virus, covid-19, covid, covid19, coronavirus, cov-19, 2019-ncov, corona, sars-cov-2, sras-cov-2. 1,082,890 comments were left in the sample after this cleaning process.

In order to focus on analysing the Enlsih content only, the comments were split into two CSV's based on the journal.

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The English journals were: 'English', 'Vancouver Sun', 'The Tyee', 'CBC News', 'The Time Colonist', 'Cape Breton Post', 'The Chronicle Herald', 'Toronto Sun', 'Toronto Star', 'Globe and Mail', 'Halifax Examiner', 'National Post'

The French journals were: 'French', 'Le Devoir', 'La Presse', 'Radio Canada Information', 'Le Journal de Québec'

This splitting created an English CSV of 613667 and a separate French CSV of 484571 comments

For the purpose of validation, we focused on English article only. Within the English CSV file use for analysis, the cells contained the following fields:

1. Post ID - the id of the news article (not unique as multiple comments may come from the same article)
2. Post Text - either the title of the news article or its contents (not unique as multiple comments may come from the same article)
3. Comment Time - the date of the comment or the date and time of the comment (field's time is populated inconsistently)
4. Comment ID - the unique id of each comment
5. Comment Text - the comment's text
6. In Reply To - seems to have been intended to show if a comment was in response to another (usually not populated so cannot assess the reliability of field)
7. Journal - the new site of the article that the comment came from.
8. Other fields were either generated by the AI firm (sentiment and categorization) or simply usually left empty making them uninterpretable by me

3. Approach to analysis

The analyses, as described below, will provide insight into the nature of vaccine discourses online (Obj. 1). However, the comparison of the outcomes of these separate analyses is the basis of software validation (Obj. 2).

For both analysts, there should be note-taking conduct as the process unfolds for the purpose of writing a detailed methods section for papers, and for validation. The toolkit analyst will likely identify fixes to be made with Gautier along the way. This should be documented.

<u>Human coding</u>

First, two researchers (M Dionne, L-A Carrier) will code 100 user comments inductively, in line with Obj 1., to develop a preliminary coding framework. MD and L-AC will code the first 100 independently and then review and discuss before finalizing a framework for the remainder of the analysis. The analysts will then code the remaining data using the framework, and consult to discuss the emergence of additional themes and devices. The framework will be refined

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iteratively throughout the analysis. Attention will be paid to identify racism, ageism, class discrimination, xenophobia and stigma.

Once the coding framework is agreed upon, a second sample of the data (n=2000 comments from the total of 1,082,890 comments) will be coded, allowing for the emergence of new themes. In order to remain true to the validation process (no input from the toolkit designers or toolkit analysts), the randomization and sample of selection will be completed by the human analysis team.

Toolkit coding

The toolkit will provide a scaffold of tools the researcher can use during their inductive analysis of the dataset. Throughout using the toolkit, it is expected that the researcher (C Pelletier) will perform similar tasks, team consultations (with E Dube), and discussions similar to the Human coding as the toolkit's was not designed to replace the researcher or the team but rather enable and enhance their ability to interact with the data at scale.

Functionality in the toolkit is as follows:

(1) The toolkit's Data Collection tab and Data Cleaning and Filtering tab provide the researcher an ability to interact with the data at scale by providing access to the raw data's contents, in terms of what comments looks like, as well summarizations that show the distribution of words in the dataset. Interacting with the data at scale is meant to help the research become more familiar with the data and begin forming ideas about their framework. Additionally, the Data Cleaning and Filtering tab allows the researcher to see what rules are helping tune what types of words the computational tasks will focus on when searching for signals that can be used to sample the data.

(2) The toolkit's Modelling and Sampling tab provides the ability for researcher to create a variety of purposive samples, using iterative topic models the seek to group data based on signals such as common word groupings in the comments, to provide a diverse set of models that capture samples of different sets of data. The researcher can use these samples to help them both further familiarize with the data as well as continue forming their inductive analytical framework.

(3) The toolkit's Coding tab and document review screens (accessed from the other tabs) provides the researcher with a place where data can be coded and reviewed in an iterative manner to develop, refine, and apply their analytical framework in the form of a concrete set of codes and themes.

(4) The toolkit's Reporting tab provides an interface to help the researcher choose quotes and keep track of which piece of data they came from for each code and theme and, if desired for ethical reasons, keep track of paraphrasing of these quotations to enable review with the research team about whether the paraphrase captured the original quotation properly.

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4. Data validation process

Following the analysis using human coding and the toolkit, we will compare the results to determine the extent to which the sample of data analyzed by humans is consistent with software outputs (nearing validation of the software). For Obj. 1, we will work with the two analysts to see what the different analyses tell us in relation to our question, both as they see the data and as part of a wider group discussion with all Co-investigators on the grant (e.g. making sense of the data for publication/KT). This will also help inform validation of the tool (Obj. 2). However, Obj. 2 will also be met by Gauthier will conducting interviews with the analysts and wider team members to elicit feedback on the software, its impact and effectiveness for performing automated thematic analysis, and any unaddressed needs for future development. These discussions will provide insight related to the feasibility and usability of the software for future analyses of big data as discourse regarding vaccine hesitancy.