A Pilot Study to Understand Preferences for the Design of Social Media Dashboards Among Students in Health-Related Disciplines

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Abstract

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Interactive data dashboards are effective tools that help researchers perform data analysis and identify patterns in large amounts of health-related social media data sets. However, people interested in using dashboards to explore health-related social media data may have different research questions and different backgrounds, such as different data analysis and interpretation skills. Hence, it is questionable what dashboard design could meet the different needs of people from different health-related domains. In order to find the answer, I did a pilot study using interviews with six graduate students. First, I developed a data dashboard containing topic modeling results and an interactive visualization using tweets containing covid-related keywords.

Then, I conducted structured interviews with graduate students in Biomedical and Health Informatics and Nursing. I inductively coded the interview transcripts to identify different needs between groups. Finally, I provide suggestions for dashboard design improvements and recruitment suggestions for larger-scale research of better dashboard designs for research using social media data.

The study results might generate dashboard and visualization design suggestions that make topic modeling and social network analysis dashboards fit the needs of people in different health-related fields. This study may also pave the way for larger-scale research of better dashboard designs for research using social media data.

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1 INTRODUCTION AND BACKGROUND

Social media data is publicly available and have been used in many health-related research studies. However, given the quantity and the unstructured texts in these social media data, it is often challenging to process them. Topic modeling and social network analysis are commonly seen in social media data analysis methods. Codes and tools performing these analyses have different ways of displaying the results and require different levels of knowledge and interpretation interpretive skills from users.

Data dashboards are tools that can provide an overview of what users need to know from data [1]. A purposefully and carefully designed social media data dashboard might serve as a tool to help interested users analyze social media data and interpret the results without difficulty and misunderstanding.

In this study, I focused on users in different health-related fields. I aimed to find their needs in designing a social media data dashboard containing topic modeling and social network analysis. People interested in using a social media data dashboard to explore health-related social media data might have received different training in processing, analyzing, and interpreting data. Walny et al. [2] observed different actions used to read network visualizations and showed that the errors in performing visualization tasks could be reduced. It is questionable what social media dashboard design could meet graduate students' needs in different health-related disciplines and reduce the difficulty in use and interpretation. Therefore, I conducted a pilot study to evaluate the usefulness of a designed dashboard that generates social network analysis visualization and topic modeling results on Covid Twitter data for graduate students in different health-related fields and explore the barriers and needs when they use the same dashboards. The evaluation results might generate

design implications and help design larger-scale research of better dashboard designs using social media data.

In the next section, I provide details on the usage of social media data in health-related research, explanations of the two methods used to facilitate analysis of social media data (topic modeling and social network analysis), and benefits and issues in data dashboard designs.

1. 1 Usage of social media data in health-related research

According to the definition from Kaplan and Haenlein [3], social media is "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0", and "Web 2.0" means "content and applications are continuously modified by all users in a participatory and collaborative fashion." Applications like Facebook, Twitter, and Reddit are all considered social media.

As seen in previous literature, social media data have great potential for health promotion and are widely used in research. Social media data is valuable in the field of public health. Edo-Osagie et al. [4] identified several domains of Twitter application in public health, including surveillance, event detection, etc., from 95 articles. Schillinger, Chittamuru, and Ramírez proposed a SPHERE (Social media and Public Health Epidemic and REsponse) framework exploring the function of social media during an epidemic [5]. The framework [5] includes social media as contagion, as vector, as inoculant, as treatment, for surveillance, and for disease control and mitigation. Researchers may use social media data to observe behavior changes and identify or predict disease outbreaks [5]. They may also use social media data to analyze how people use social media communities to support each other with the same disease [5].

Social media also provide valuable data sources for diagnosing disorders. Lejeune et al. [6] found that the use of social media data was promising in diagnosing psychotic disorders according to their systematic literature review of articles using social media data and machine learning to diagnose psychotic disorders.

1.2 Social media analysis

Social media analysis is "an emerging interdisciplinary research field that aims at combining, extending, and adapting methods for the analysis of social media data" [7]. Stieglitz et al. [8] proposed a four-step framework for social media analysis, including discovery, tracking, preparation, and analysis. Discovery represents the discovery of "latent structures and patterns"; tracking represents the "decision of data source, approach, method, and output"; preparation represents collecting data and preparing and preprocessing the data for analysis; and analysis represents different approaches used to analyze social media data [8]. Topic modeling and social network analysis are commonly used methods to analyze social media data.

1.2.1 Topic modeling

Topic modeling is "a statistical model to determine abstract 'topics' that occur in a collection of documents" [9]. It is frequently used in text data analysis to uncover hidden topics repeatedly appearing in documents [9]. Latent Dirichlet Allocation (LDA) [10] is one of the most frequently used methods [11] in topic modeling.

The algorithm considers each document to be a bag of words. The algorithm also considers that documents are composed of topics, and topics are composed of words. A topic number must

be set to use the algorithm, which means the number of topics appeared in the set of documents. In brief, the algorithm focuses on the probability that a topic exists in a document and the likelihood that a word exists in a topic [12]. The algorithm first randomly assigns words in each document to topics. It generates two tables. One table counts the appearance of each word in each topic, and the other measures the appearance of each topic in each document. Then, the algorithm loops through each vocabulary in each document. It assumes that the topic assignment is correct, except for this looped word. Using the two probabilities mentioned above, the algorithm assigns the current word to a new most relevant topic. The algorithm continues its iteration until it reaches a steady state.

LDA is also frequently used for social media data analysis since each post can be considered a document. For example, SV et al. [13] used LDA to discover major aspects Indians talked about in Covid-19 booster doses related tweets. There are pre-written libraries in many programming languages that help construct an LDA model, such as gensim [14] and sklearn [15] in Python. Writing codes to utilize these packages require some programming skills. Although there are tools like Stanford Topic Modeling Toolbox [16] and jsLDA [17], these tools still need users to have different levels of knowledge of the algorithm and display topic modeling results in different formats.

Manual qualitative coding for these social media posts is time-consuming and relies heavily on expert coders [18]. If the coding process involves multiple coders, finding another coder with similar professional levels and willingness to participate in coding is difficult, especially when the dataset is large [19]. In addition, if the measure of intercoder reliability is below the acceptable level, it takes more time to make concessions for un-agreed codes. In contrast, using LDA allows consistent processing for all the data and generates results faster than humans,

especially when the data set is large. However, before running the LDA algorithm, the input data must be carefully processed in order to get accurate and meaningful LDA results. The input texts need to remove stopwords, perform word stemming, and so on [20].

1.2.2 Social network analysis

A social network is "a set of actors, or other entities, and a set or sets of relations defined on them" [21]. In social network analysis, people often plot a social network analysis visualization, which uses graph-theoretical concepts to understand social phenomena [22]. Many studies have used social network analysis on social media. For example, Kim and Hastak used social network analysis to analyze characteristics of online social networks on Facebook after a disaster, the 2016 Louisiana flood [22]. Through the study of degree distributions, betweenness centralities, and other metrics in social network analysis, they found that individuals and organizations played different roles in social networks [22].

Various tools and software can do social network analysis, such as Gephi [23], NetworkX library in Python [24], etc. However, each one has its own pros and cons. On several software comparisons platforms, such as Capterra [25] and TrustRadius [26], these reviews were written by people with different jobs and used for various purposes. The reviewers valued different pros and cons. For example, one user found that the documentation about how to use Gephi needs to improve, while the other user found Gephi to be easy to use [27]. Hence, a social network analysis tool designed for specific purposes and specific users may be easier to use and meet the needs of this particular user group.

1.3 Social media data dashboard

There were multiple dashboards designed for business usage, but now there are dashboards intended for the field of public health [28]. Using a dashboard allows for easy results checking. It is common in academia and business that a person other than the people who do the analysis double-check the results to ensure the correctness of the results. When asked to do a data analysis task, people might have different preferences or skills. For example, some prefer Excel, while others use Python, R, or other methods. Depending on the tools and analysis packages used, the results might be different or displayed differently, making it hard to check other people's work. However, using a dashboard would allow easy checking for analysis results. Users could change specific settings to reproduce the results. Users could easily document how they do the analysis. In addition, dashboards could support decision-making by "identifying trends, patterns, and abnormalities" in data [28].

However, it is challenging to create an effective dashboard and a social media dashboard. Dashboard users who consider themselves professional analysts are good at interacting with and interpreting the data, while other users might have limited analysis and interpretation skills [29]. Hence, a successful dashboard design requires a lower barrier to entry [29].

2 METHODS

I split the method section into two main parts. In the first part, I will discuss dashboard development. Participants will use the dashboard in the interview and will be able to interact with this dashboard. Then, I will describe methods used for pretesting, recruiting participants, conducting interviews, and data analysis. From the data analysis results, I may find different needs

of participants in different disciplines using this social media data dashboard and generate future design suggestions.

2.1 Dashboard development

2.1.1 Collect data

First, I collected tweets related to Covid-19 on Twitter. I applied for Twitter API's research access [27], and Twitter approved the request. Twitter API [27] enables programming access to tweets and related information, such as received likes, replies, etc. I searched the keyword "covid" on Twitter's search box to see which covid-related keywords are popular among these tweets and could be used in tweet streaming filters. I looked at the top nine tweets in the search results and found keywords "covid", "Covid", and "COVID". Then, I used Twitter API [27] and twarc [30] to extract tweets using the search rule that tweets containing keywords of "covid" OR "Covid" OR "COVID" and written in English. Twarc [30] is a Python library that extracts Twitter data from Twitter API and saves the extracted tweets in JSONL format, similar to JSON format.

2.1.2 Preprocessing data

I preprocessed Twitter data using Python. I extracted tweet contents, tweet id, user id, referred tweet type, referred user id, and counts of retweets, replies, likes, and quotes for each tweet from the JSONL file. Other irrelevant fields were ignored.

I used the following steps in preprocessing the tweet content. First, I parsed each tweet into a list of words using spaces between words and converted each word into smaller cases. Next, I removed hashtags and referred usernames by eliminating words starting with "@" or "#" and

removed links by eliminating words starting with “http” or “www.”. Then, I removed punctuation and non-alphabetic characters from each word. Finally, I removed stopwords from NLTK [31]. Stop words are a set of words that are commonly seen but meaningless on their own, such as “is”, “are”, etc. I stored the preprocessed tweet contents next to the original tweet. I only replaced the refereed username with the symbol “@” in the original tweet.

I reformatted the tweet information into two five-hundred-row CSVs for faster data retrieval and to avoid the problem of the computer crashing. All the generated files were stored on my computer for data security.

2.1.3 Develop the dashboard

The data dashboard is a web application. Once the application starts, a login page will appear. If the entered username and password are correct, the application will direct the user to the main page of the data dashboard as shown in Figure 1 in the next page. The main page is split into three panels. The left panel contains settings. The central panel includes a social network analysis visualization. Below the visualization is a topic modeling results section containing the top 10 words in each topic. The right panel contains two sample tweets from each topic.

I used Flask [32] in developing the data dashboard. Flask is a lightweight Python framework used for creating web applications, and it is especially suitable for small projects, since it is easier to use than other sophisticated frameworks, such as Django [33]. I also used Hyper Text Markup Language (HTML), Cascading Style Sheets (CSS), and JavaScript to make the dashboard. HTML set the dashboard's skeleton; CSS specified each element's look in HTML, and I used JavaScript to generate a social network analysis visualization.

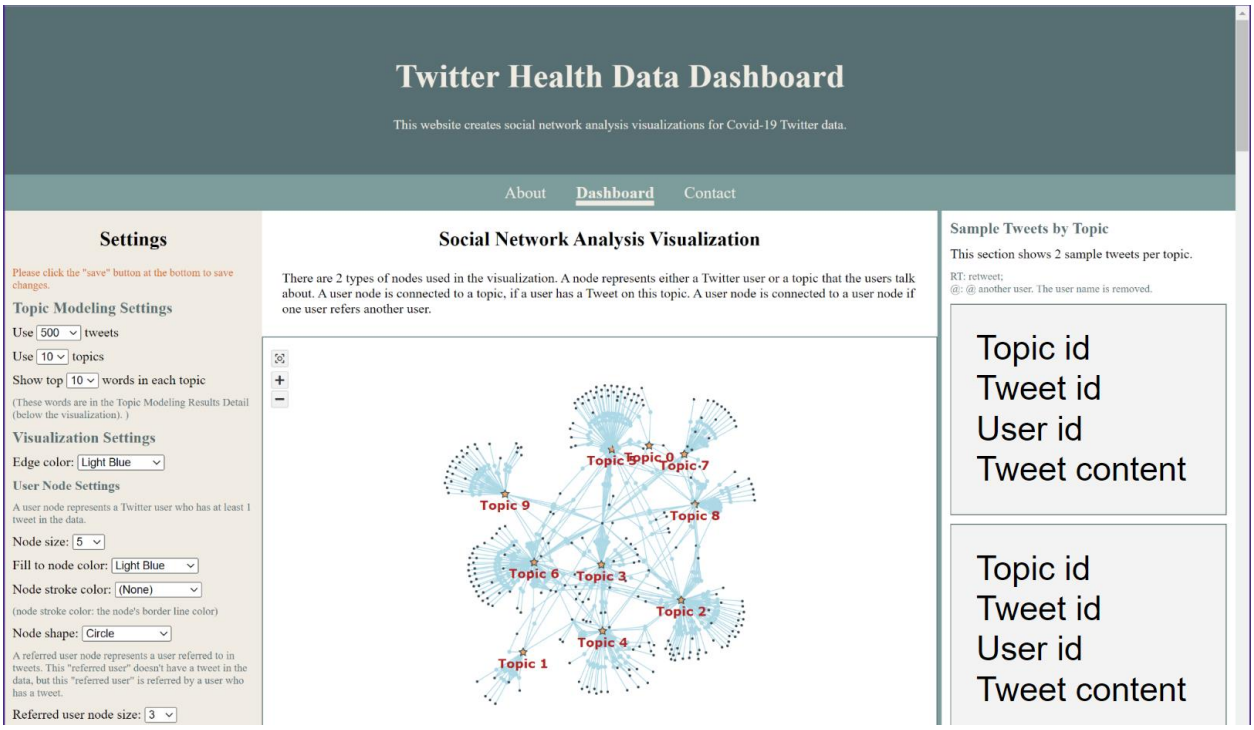

Figure 1. The main page of the dashboard. Each sample tweet block is hidden to avoid disclosing actual tweets.

I did not deploy the dashboard on a public website for data security reasons. Users used the dashboard in the interview through the remote control function in Zoom. The dashboard ran on my computer, and the remote control allowed users to control my screen and interact with the dashboard.

In the sections below, I will provide detailed explanations of topic modeling results and the social network analysis visualization.

2.1.4 Generate topic modeling results

Users could select the number of tweets used and the number of topics for topic modeling on the upper left panel. When a user submits the changed setting, a Python script will read

processed topic modeling results from the local computer and send results to the dashboard to display to reduce page loading time. The visualization and the topic modeling results detail part in the main panel and the sample tweets on the right will be changed accordingly. The topic modeling results detail could also be changed using the show top 10 words in each topic part in the setting.

I used gensim's LDA model [14] in the Python script and fed the model with preprocessed tweet content and topic number. For each topic, the model output a list of words within this topic, and the words were ordered from the most likely words to the least likely. Each tweet was assigned to a most likely topic. I stored these results and saved two tweets in each topic in text or CSV format.

2.1.5 Create social network analysis visualization

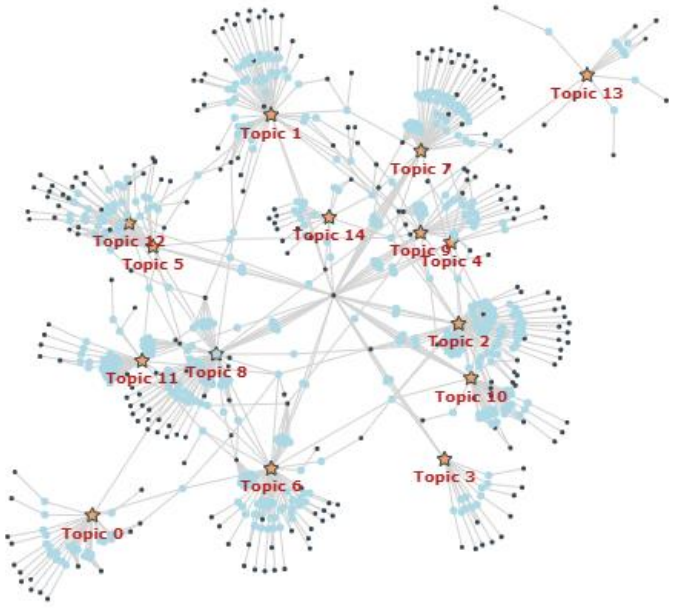

Figure 2. Social network analysis visualization

The social network analysis visualization is located in the dashboard's center as shown in Figure 1 on page 19. Figure 2 above is a zoom-in view of the visualization using fifteen topics.

There are two types of nodes. One represents a Twitter user and has a circle shape, while the other represents a topic and has a star shape. There are two types of user nodes. The light blue circles represent a Twitter user who has at least one tweet in the collected dataset. A light blue circle is connected to at least one start, which represents that the user's tweet is on this topic. A user may have multiple tweets and are about different topics. Hence, a blue circle may connect to multiple stars. Circles with charcoal-like colors represent users who do not have a tweet in the dataset but are referred to in other users' tweets. If a light blue circle is connected to a charcoal circle, it means a Twitter user refers to another user in his or her tweets. A user may have multiple tweets and may refer to several users. Hence, a blue circle may connect to multiple charcoal circles. If a user is referred by another user and has a tweet, this user will still be colored in blue.

The visualization setting on the left panel (see Figure 1 on page 19) not only allows users to change the display of the visualization but also serves as the legend of the visualization. It shows nodes' current colors, shapes, and sizes. The edges are links between nodes, and the color is changeable.

I created the social network analysis visualization using AnyChart [36], which is a set of JavaScript libraries allowing interactive visualizations to embed in web applications. I passed the nodes and edge information in JSON format to a function in AnyChart to create the interactive visualization. The visualization could be zoomed in or zoomed out using the plus and minus buttons on the visualization. Users could also drag nodes to change the visualization.

2.1.6 The setting panel

Figure 3 below shows a zoomed-in view of the dashboard's setting panel. The setting panel contains a topic modeling setting and a visualization setting. Changes in the topic modeling settings will alter every panel, while the visualization settings only change the visualization in the dashboard's center. Hence, the topic modeling setting appears before the visualization setting.

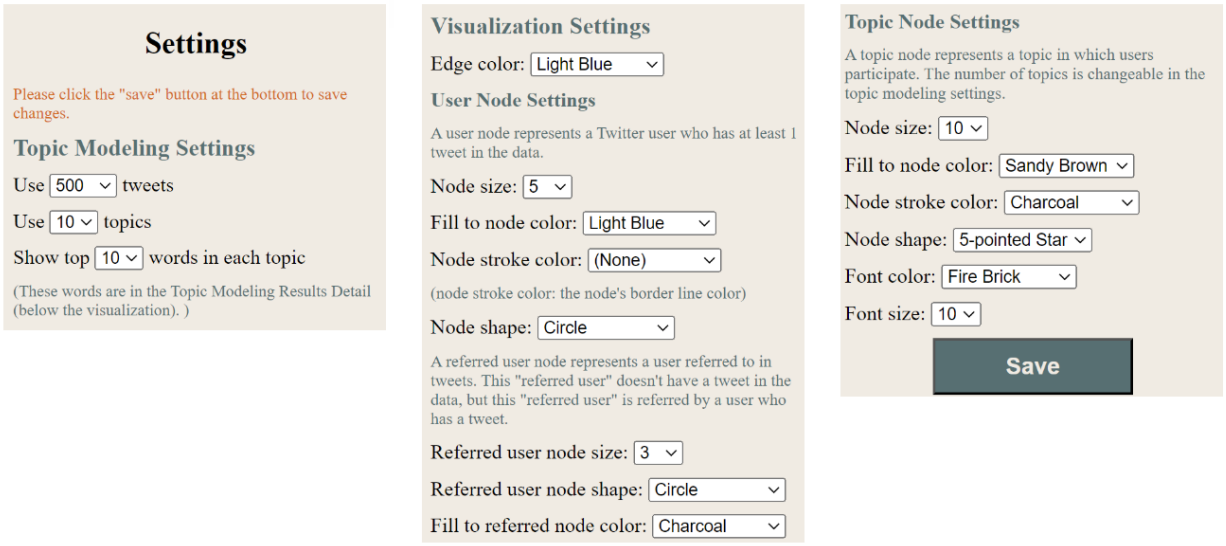

Figure 3. The setting panel

The visualization setting has edge colors, user node, and topic node settings. The edge color setting appears on top of the visualization setting, because users are only allowed to change the color of these edges. In contrast, users could customize more about the nodes. Users might ignore the edge setting, if it is below the node setting. User nodes are more complicated than topic nodes, as mentioned earlier, since there are two types of user nodes. In addition, there are more user nodes than topic nodes. Thus, the topic node setting appears below the user node setting. Users could

change the node size, colors, and shape in each node setting. Users could also change the font color and size below each topic node in the topic node settings.

2.2 Interview methodology

After developing the data dashboard, I conducted pretests for the whole interview process until the methods and results were satisfactory. I revised the dashboard and interview strategies based on the results of the pretests and started the main test.

2.2.1 Recruitment strategy

Since I aim to analyze the needs of people in different health-related fields, when they are given the same dashboard, I recruited people from two different fields. I used a convenience sample of six graduate students at the University of Washington in either Biomedical and Health Informatics (n=3) or Nursing (n=3) due to time and resource constraints. A snowball sampling method [35] was used in recruiting for the same reason and a small sample size. I sent known graduate students in Biomedical and Health Informatics and Nursing about the study by email and the recruitment form in Google form as shown in Appendix A and B respectively. Then I asked if they could direct my study recruitment information to people who they know and might be interested in participating. Despite the speed of recruiting, this snowball sampling might lead to a biased sample. The participation was voluntary and no compensation was given.

If people were interested in participating, they could reply to my email or fill in the recruitment form. For people who only responded to the email, I sent another email to ask the participants to fill in the recruitment form. The recruitment email and form contain details about

the study and my contact information for questions and concerns. An information sheet in the recruitment form allows participants to read and sign.

The recruitment form also collected the participant's name, email, field of study, and whether the participant was a graduate student at the University of Washington. I only used the names and email information for follow-up emails to schedule an interview time. The field of study and whether the participant is a graduate student at the University of Washington was used to check whether the participant was within the sample selection criteria. Participants may fill in their gender identity in the recruitment form, but it is optional. This study received permission from Institutional Review Board before recruiting.

2.2.2 Interview process

I used Zoom to conduct interviews. Since my participants are graduate students at the University of Washington, they might be familiar with Zoom, as many courses and seminars are offered through Zoom. Virtual interviews also reduce people's time and cost in traveling to a specific location [36].

There were three parts in the structured interview. The structured interview allows me to compare results from participants easily, since they were all asked the same questions. Appendix B includes the full interview details.

If the participant had not signed the information sheet and submitted it in the recruitment form, I briefly talked about my study and resent the participant the recruitment form. I asked them to submit it at the beginning of the interview.

- **Introduction**: I introduced myself and briefly explained my study first. Then, I asked participants whether they agree to record the interview and explained I might use anonymous quotes from them. If the participant still agreed, then I started recording.
- **Interview questions before interacting with the dashboard:** In this part, I asked participants what are some possible questions they might be interested in researching or exploring if they have access to the Covid Twitter data. In addition, I asked about participants' familiarity and previous experiences with topic modeling and social network analysis.
- **Interact with the dashboard:** Participants were asked to explore the dashboard on their own and talked about their feelings while exploring for approximately five minutes. Participants were then, asked to interpret the visualization. Next, participants were asked to talk about their overall feelings about this dashboard-using experience, including things they like, things they don't like, and how likely they would use this dashboard or something similar in the future.
- **Closing**: This part gave participants chances to talk about other things they would like me to know.

Before participants saw the dashboard, I asked them what they would be interested in researching if they could access Covid tweets. They were also asked what barriers they might encounter when using tweet data. After using the dashboard, I asked participants whether it helped answer their research questions before seeing the dashboard and why. These questions aimed to determine what participants need for a data dashboard for their research using social media data.

The think-aloud method [37] was used when participants explored the dashboard. The technique allows participants to talk about what they are thinking while interacting with the

dashboard. The method will enable me to discover what participants genuinely think about the dashboard and identify barriers and hesitation they encountered.

2.2.3 Interview data analysis

Participants' answers were audio recorded and Zoom automatically generated transcripts for the recording. Two interview questions (question 1.2.1 and 1.3.1 in appendix C) asked participants to rank their familiarity levels with topic modeling and social network analysis, with one being not familiar and five being very familiar. One question (question 2.7.1 in appendix C) asked participants to rank the likelihood to use the dashboard or tools similar to this dashboard in the future from one (not likely) to five (very likely). These numeric answers were extracted and stored in Excel. The mean and variance will be reported in the results section. It is likely that people with different familiarity with these concepts would have different expectations and needs when it comes to the use of the same data dashboard.

Empirical coding [38] was used for analyzing qualitative interview data. My objective was to identify the different needs of people with different backgrounds. First, I extracted what participants talked about during their dashboard exploration section (question 2.2 in appendix D) and answers to questions about the dashboard (question 2.3 to 2.7.2). Question 2.2 asked participants to use the think-aloud method [36] while they were exploring the dashboard. Question 2.3 asked participants to interpret the visualization. Questions 2.5 and 2.6 asked participants about what liked and disliked about the dashboard. Answers for 2.7.2 implies what features could be added to the dashboard to fulfill participants' need when they need to use social media data for their research. These questions and answers were concatenated together for content analysis, since participant not only talked about things they liked and disliked when they answered questions 2.5

and 2.6, but they also mentioned these things when they explore the dashboard and tried to interpret the visualization.

After extracting the answers to these questions, I re-listened to the audio and corrected the automatically generated transcript from Zoom. Sentences and phrases that were irrelevant to the study like “er” or “how do you make this dashboard” were removed. Then, I manually read through these paragraphs and identify initial categories. I constructed three major categories, what people liked, what could be changed, and what could be added. Next, I revisited transcripts and added code alongside the words. These codes belonged to the three initial categories. I reviewed all the codes and made sure I used the same code for the same issue. The codes were also reclassified into the three initial categories. Then, I reread the transcripts and used the revised codes. I created a table in Excel representing the code used by participants. The results were summarized in the results section below.

2.2.4 Pretests

I recruited three participants to participate in the pretest. They were not included in the main test. They checked whether the study information and interview questions were straightforward and whether they could access the recruitment form and dashboard smoothly. I adjusted the interview questions and dashboard looking based on the pretest results. No changes were made after the revision after the pretests.

3 RESULTS

This study recruited six participants, three studied biomedical and health informatics, and three studied nursing. All six participants were graduate students from the University of Washington. Most participants (n=5) have no experience with topic modeling (question 1.2.1. mean=1.3 out of 5, var=0.7). The average familiarity level with social network analysis is 2.2 out of 5, with a variance of 0.6 (question 1.2.2). More than half of the participants (n=5) have heard about social network analysis but have no practical use experience. The familiarity level of participants in different disciplines is shown in Table 1 below.

Table 1. Participants' familiarity level with topic modeling and social network analysis

	Topic modeling familiarity level (1 not familiar to 5 very familiar)	**Social network analysis familiarity level (1 not familiar to 5 very familiar)**
All participants (n=6)	Mean: 1.3 Variance: 0.7	Mean: 2.2 Variance: 0.6
Participants in biomedical and health informatics (n=3)	Mean: 1.0 Variance: 0.0	Mean: 2.3 Variance: 0.3
Participants in nursing (n=3)	Mean: 1.7 Variance: 1.3	Mean: 2.0 Variance: 1.0

Most participants (n=5) mentioned that they were likely to use this dashboard or something similar to this one in the future (question 2.7.1: mean=4.0 out of 5, var=2.4). The average

willingness level for participants in biomedical and health informatics (mean=4.7, var=0.3) was higher than those in nursing (mean=3.0, var=4.3).

The qualitative coding results were classified into three major categories: what people liked, what could be changed, and what could be added.

3.1 What people liked

Most participants (n=5) mentioned that they liked the setting panel which allow them to change the visualization and topic modeling model to their preference. Half of the participants also mentioned that they like the display of sample tweets and topic modeling results, which helped them understand the topics. These displays also helped them to have a general idea of what these tweets talked about. One participant thought the colors used in the visualization and the visualization itself were visually appealing. The summary of what people like about the dashboard is shown in Table 2 below. The table only counts thoughts from more than one participant.

Table 2. What participants liked about the dashboard

What people liked	Biomedical and Health Informatics (n=3)	Nursing (n=3)	Total (N=6)
The setting panel	3	2	5
The display of sample tweets and topic modeling results	1	2	3

3.2 What could be changed

Participants' ideas about what in the dashboard could be improved were categorized into three categories: topic modeling results detail, visualization, sample tweets, and settings. These subcategories were based on the four sections in the dashboard, as shown in Figure 1 on page 19. An overview of what participants' think could be changed is listed in Table 3 below.

Table 3. What participants' disliked about the dashboard

What could be changed	Biomedical and Health Informatics (n=3)	Nursing (n=3)	Total (n=6)
Need separators between words in topic modeling results	2	3	5
The location of topic modeling results could be changed	1	1	2
Confusion about terms in the settings	3	3	6
Unnecessary information in sample tweets	2	0	2

3.2.1 Topic modeling results detail

In the dashboard, the section titled topic modeling results detail displayed the top words in each topic, and it was located below the visualization. For example, the top frequent words in topic one could be "covid", "pfizer", "use", "mrna", etc. These words were displayed horizontally on the right of their topic id and separated by space. Three participants mentioned that the way to

show words in each topic could be changed. Twi participants said it was inconvenient to scroll up and down to look at words in each topic and come back to the visualization. It would be more convenient if this section could be on the right of the visualization instead of below the visualization. One participant suggested that it would be more convenient to see the list of words in a topic when she could hover over a topic node.

In addition, five participants mentioned that adding separators like semicolons between words would help them read and understand the top words in each topic. Some participants said that they tend to read the list of words into a sentence, even they later recognized these were just separate words.

3.2.2 Settings

All six participants needed clarification on some of the setting choices on the left panel of the dashboard. The height of nodes in the visualization could be changed through the “node size” setting. Two participants thought “node size” referred to the number of nodes displayed in the visualization or were unsure about its meaning at first glance. The dashboard used choices of node size in numbers, such as three, five, etc. The larger number refers to larger nodes. One participant mentioned that she had no idea about how large a node was with a node size of three. It would make more sense to her if the node size selection used terms like small, medium, or large as choices. Although the node size was changeable through the setting panel, one participant asked whether the size of each node had a specific meaning or representation in the visualization.

The “node stroke color” in the setting changed the borderline color of each node in the visualization. Although a line of explanation for the “node stroke color” was displayed on the

setting panel, it was still hard to understand for participants. All six participants were either unsure about the meaning of the “node stroke color” or asked me about it during the interview.

Half of the participants mentioned that sometimes they needed to scroll down the page to click the button at the bottom of the setting panel to update the setting. They would like to save the changes in the setting conveniently. One participant mentioned she would like the visualization and the results to change automatically after each selection instead of clicking the save button.

3.2.3 Sample tweets

There were two sample tweets per topic in the sample tweets section. Each sample tweet block contains a user id, tweet id, topic id, and tweet content. Two participants from biomedical and health informatics mentioned that the user and tweet id were useless and distracted them from viewing the sample tweet content. They said they only wanted to see the topic id and the tweet content.

3.2.4 Visualization

The visualization in the dashboard's center had three buttons allowing users to return the visualization to its initial place, zoom in, and zoom out. Participants could also move the visualization by clicking on the white space of the visualization and then dragging it. Zoom in and zoom out could also be done using two fingers on a keyboard pad. One participant thought it would be more convenient if all these actions could be done by buttons, such as using buttons to move the visualization to the left or right.

3.3 What could be added

Most participants (n=5) expressed that they would like to use the dashboard on different data sources, such as Reddit data or Twitter data with different keywords or varying time ranges. One participant said he would like to see changes in the visualization with time changes for tweets extracted by the same rule.

One participant asked how I decided on the keywords in extracting tweets for a specific interest. She wanted to know how to choose the correct keywords to filter social media data to research a particular problem. It would be convenient if the dashboard generates a set of suggested keywords for tweet extraction after the user enters a few words about their interest.

Twitter users use jargon and abbreviations in their tweets. Three participants said they were unfamiliar with these terms and would like to know their meanings. It would be convenient to show the jargon dictionary in the dashboard or display the explanation when hovering over the vocabulary.

Two participants from nursing said they would like the dashboard to summarize each topic in short sentences or one or two words. It was inconvenient to look at the topic modeling results and sample tweets sections together to figure out the meaning of each topic and remember these topics to look at the visualization. One found it hard to summarize the topic by only looking at the information given in the dashboard.

Half of the participants said they would like a filter function in the topic modeling results detail section to see if certain words of interest appeared in any topics. They expressed their interest in exploring Covid social media data but were also interested in more specific topics about Covid, such as Covid vaccination or recovering from Covid.

One participant suggested marking organizations and individuals in different colors in the visualization, because it was interesting to see whether they talked about different topics.

Table 4. What could be added to the dashboard

What could be added to the dashboard	Total (n=6)	Biomedical and Health Informatics (n=3)	Nursing (n=3)
Classify misinformation or disinformation	2	0	2
Tutorial or explanation to terms in settings	6	3	3
Explanations for jargon and abbreviations	3	1	2
Summarize topics in one or two words	2	0	2
Use different data	5	2	3
Filter keywords in topic modeling results section	3	1	2

Two participants would like an automatic classification function that could identify tweets with misinformation or disinformation and mark users sending or retweeting these tweets. Participants in nursing tended to be more concerned about misinformation and disinformation in Twitter data than biomedical and health informatics participants. Guess and Lyons define misinformation as information "constituting a claim that contradicts or distorts common understandings of verifiable facts "[39]. Disinformation is defined as "a subset of misinformation that is deliberately propagated" [39][40]. One participant said she recognized tweets include

misinformation while looking at the sample tweets. She was curious about the spread of misinformation or disinformation and the pattern of users spreading these tweets. One participant also mentioned she would like to exclude these tweets from the analysis.

In the sample tweets section, some tweets include links to outside websites. One participant expressed curiosity about where these URLs would be directed and the websites' contents. The summary of what could be added to the dashboard is summarized below in Table 4.

4 DISCUSSION AND CONCLUSIONS

In this study, I generated dashboard design implications for a dashboard using social media data and suggestions for larger-scale research of better dashboard designs using social media data. In addition, participants expressed their interest in using this tool in the future. Larger-scale research for better dashboard designs is needed before the tool could be put into use.

4.1 Limitations

Limitations of this study include a small sample size and a biased sampling method. The sample size was too small to facilitate conclusions about differences in the observations and suggestions made by graduate students in Biomedical and Health Informatics and Nursing. The sampling methods used in this study do not result in a random sample. Furthermore, only one annotator coded the interview transcript and decided on the coding scheme. A secondary coder could increase the rigor of the qualitative coding process.

4.2 Dashboard design implications

From this study, I identified three design considerations for dashboards using social media data: (1) add interactivity; (2) considering the gap in mental models; and (3) providing insights in text.

4.2.1 Add interactivity

Overall, users liked the interactivity of the dashboard. Interacting with the settings panel in the dashboard allowed users to customize the results on the dashboard to their preferences. Users may use the dashboard for different research questions or have different visual preferences than the creator, I. One participant said she felt the visualization looked better after she changed the default color settings. Wexler [41] pointed out that he had seen organizations spend a lot of effort to prepare numerous versions of the same visualization in slide decks, and interactivity could solve this issue.

4.2.2 Consider the gap in mental models

It is likely that a dashboard includes multiple sections, and these sections may not be displayed in a linear order. Users like to know which part they should look at first and what is the recommended order of looking at the information on the dashboard. A tutorial about how to get started with the dashboard would be helpful for users who use the dashboard for the first time.

There could be a gap in the mental model [42] between designers and users. Mental models are “personal and internal representations of external reality that people use to interact with the world around them“ [42]. Each individual might have their own mental model, and people may

have different understandings and expectations when they are using the same dashboard. Functions and terms that were obvious to the dashboard designer were not as obvious to the users. Users may feel hesitant to use certain features if they are unsure about the terms or do not understand what this function does. Hence, the way to phrase these terms and display these functions need careful consideration.

There are two ways to reduce the gap in the mental models between designers and users. One way is to make the design closer to users' mental models. The designer could make the wording and the function design similar to those in other applications that users frequently used. The other way is to change users' mental models, such as by providing more instructions to users about how to use the dashboard and the meaning of each term used. However, which tools graduate students in health-related disciplines use may need further research.

4.2.3 Provide insights in text

During the interview, some participants were hesitant to interpret the visualization. One mentioned that she did not do topic modeling or social media analysis before and was unsure how to interpret the visualization. She wants to see some guiding text to help summarize the findings.

In addition, only a few participants noticed that a user was referred by many different users in different Covid-related topics in the center of the visualization, as shown in Figure 2 on page 20. Users might have different backgrounds and interpretation skills. Providing explanations in words might help some users gain insights they missed. Hence, the dashboard must show how to interpret the information or the visualization.

Srinivasan et al. mentioned an emerging interest in incorporating automated insights and natural language generation (NLG) into visualization tools, which means having the tool

automatically generates texts of insights in natural language for a set of data or a visualization [43]. NLG is defined as "the task of generating text from underlying non-linguistic representation of information" [44][45]. Automated insights and NLG would allow users to quickly pick up insights from the data and underline facts that users might miss.

To add an automatic visualization interpretation text, the creator may create a text template summarizing the visualization. For example, the visualization could highlight nodes that have more connections and provide sentences like "Topic <topic id> located in <location such as upper right and center> has the most tweets." or "User <user id> located in <location> is referred by more users (users=<the number of users referred this user in their tweets>)." The visualization could also provide more facts, such as the average number of topics a user participates in, the average number of tweets per topic, etc. However, whether the guiding text provided to users is helpful, and how to display the interpretation text, may require further study.

4.2.4 Different needs for graduate students in biomedical and health informatics and nursing

Although the sample size in this study was too small to unequivocally assert a difference between participants in biomedical and health informatics and nursing, it may still be worthwhile to consider what the study findings may suggest about the influence of discipline on ability to interpret topic modeling results in the context of this study.

As shown in the results, only participants in biomedical and health informatics thought some information in the sample tweets section of the dashboard was meaningless to them. Graduate students in biomedical and health informatics were exposed to various analysis tools or supporting applications developed for different purposes. In their courses, they also learned about theories in informatics. Hence, even when they use a tool like a dashboard, they evaluate its design

using what they learned in class. There is perhaps a question of whether people in health-related disciplines with more informatics background care more about the displayed information that they do not know how to use or think it is not meaningful compared to people with less informatics background.

The average likelihood of using the dashboard or similar tools in the future for participants in biomedical and health informatics is higher compared to participants in nursing. According to the technology acceptance model [46], perceived usefulness and ease of use influence users' acceptability. Participants in biomedical and health informatics might think the dashboard is easier to use and more helpful than nursing participants. The dashboard creator myself had a background in biomedical and health informatics. The gap in the mental model between myself and other graduate students in biomedical and health informatics is likely smaller than between me and nursing students. Hence, biomedical and health informatics participants found the dashboard easier to use.

Only participants in nursing mentioned they needed the dashboard to classify misinformation and disinformation for them. Perhaps nursing students are more concerned about patient safety or more aware of the potential dangers of reading inaccurate information on the Internet.

Further research with larger samples is needed to better understand whether these differences do indeed exist, and the factors that may underlie these differences.

4.3 Suggestions for larger-scale research of better dashboard designs using social media data

In this pilot study, I ran the dashboard on my computer and allowed participants to access the dashboard through remote control. Participants encountered delays when they interacted with the dashboard, and not only were these delays uncomfortable for participants, but they also took time in the interview. Hence, I suggest deploying the dashboard on the Internet for future dashboard design studies.

Furthermore, interviewing and interacting with the dashboard requires participants to commit more time than filling out a survey. It was difficult to recruit participants for a forty-minute interview without using any recruiting platform and without giving any compensation. Hence, using a recruiting platform and compensating participants would make the recruiting process easier.

Although recording applications automatically transcribe the audio to words, it still takes researchers time and effort to re-listen to the audio and correct the transcription. Some interview questions could change to questions in surveys before and after the interview.

When I asked them to interpret the visualization in the interview, participants recognized more features they disliked and features could be added. Hence, asking participants to use the dashboard in a scenario similar to the real world, such as finding an answer to a small research question, would strengthen the evaluation of the dashboard and the assessment of user needs.

4.4 Future directions

In this pilot study, participants provided valuable insight about things that could be changed or added to the dashboard. If time permits, I will incorporate their suggestions into the dashboard

development. I will (1) revise the display of the topic modeling detail results section; (2) add a filter function in the topic modeling detail results section to allow users to filter topics containing certain words; (3) add explanations for common Internet jargon; (4) add a function to allow users to import their data, or add a portal to allow users to connect to other social media data retrieval portals; (5) change the wording in the setting panel; (6) allow users to choose what type of information to show in the sample tweets; (7) change the location of the "save" button in the setting panel; (8) add a few sentences about how to interpret the visualization; and (9) create a dashboard tutorial.

It is unclear which type of dashboard tutorial works best for people in different health disciplines. A long and detailed tutorial document that explains everything and provides examples may work for some people, but others might prefer a lightweight tutorial. In addition, some might like to read through the tutorial before using the dashboard, while others might want to interact with the dashboard first and check the tutorial later based on their needs. I might create different tutorials in formats such as videos and documents and explore people in various health disciplines' preferences for these tutorials.

Graduate students in biomedical and health informatics and nursing may use or receive training in different analysis tools. The interface of these analysis tools is very different. A survey about analysis tools they used and preferred may help improve dashboard design by making the dashboard design similar to tools they are familiar with and like.

After revising the dashboard, I would modify the research design, retest the dashboard's usability, and identify what works and what does not. I would recruit more participants and use statistical tests to analyze the difference between graduate students in different health-related fields.

4.5 Conclusion

In this study, I focused on graduate students in different health-related fields and aimed to find their needs in designing a social media data dashboard containing topic modeling and social network analysis. I generated dashboard design implications and suggestions for larger-scale research of better dashboard designs using social media data. This research could be helpful to others who are interested in developing social media data dashboards for students in health-related disciplines.

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Appendices

Appendix A: Recruitment email content

Hello,

My name is Wei Fan and I am a BHI MS student mentored by Dr. Annie T. Chen in the BIME Department at UW. I am conducting a study that aims to learn how graduate students in different health-related disciplines use a dashboard containing an interactive social network analysis visualization for Covid-19 Twitter data. I am inviting people to participate in this study.

If you decide to volunteer for this study, your participation will consist of a one-on-one structured Zoom interview that will take approximately 40 minutes of your time. During the interview, you will be asked to complete a few tasks to explore the dashboard and answer some questions such as your previous experience (if any) in using topic modeling or social network analysis, what worked, and what is not convenient. The tasks include things like changing the color in the visualization, choosing a different number of topics, etc. You do not need to have prior experience with either topic modeling or network analysis. With your permission, I would like to audio-record the interview to ensure accurate transcription and analysis. With your permission, I would also like to use some of your quotes anonymously in my thesis. This study has been reviewed and received ethics clearance through the UW Human Subjects Division.

If you are interested in participating, please fill in this Google form [link]. I will then send a confirmation email indicating that you have been signed up for one of those times and provide you with further information about the study. If you have any questions, please don't hesitate to contact me (XXXX@uw.edu). If you have to cancel your appointment, please email me (XXXX@uw.edu) or text me at +1 (XXX) XXX XXXX.

Thank you!

Sincerely,

Wei Fan

MS student in Biomedical and Health Informatics at UW

Email: XXXX@uw.edu

Phone: +1 (XXX) XXX XXXX

Appendix B: Recruitment form

The form is created in Google form and questions with "*" are required.

Page 1 of 2:

Thank you for interested in participating in my research! I am recruiting a few participants to test and use a Twitter data dashboard.

Please read through the next section to see the full consent form and information of the study.

Contact or Questions: Wei Fan, XXXX@uw.edu, +1 (XXX) XXX XXXX

Your email will be collected for future interview scheduling.

Please read the information below. Please click "I agree" if you agree to the information below. Feel free to ask me any questions regarding the information below. *

UNIVERSITY OF WASHINGTON

CONSENT FORM

Wei Fan

Biomedical & Health Informatics,

Biomedical Information and Medical Education,

Telephone number: +1 (XXX) XXX XXXX,

Faculty advisor: Dr. Annie T. Chen

PURPOSE OF THE STUDY

The purpose of this study is to explore the utility of a dashboard featuring a social network analysis visualization for Covid-19 Twitter data and analyze the differences in dashboard use among graduate students with different related health backgrounds. The study results might generate dashboard and visualization design suggestions that make topic modeling and social network analysis dashboards fit the needs of people in different health-related fields. This study may also pave the way for larger-scale research of better dashboard designs for research using social media data.

STUDY PROCEDURES

You will be one of 15 graduate students in health-related majors to use this dashboard. I will conduct a one-to-one Zoom interview with you and ask you complete a few tasks to explore the dashboard. You will also be asked to answer a few related questions, such as previous experience in topic modeling, which part of the dashboard you like/dislike, etc. I will record the interview and perform qualitative analyses of the interview results.

RISKS, STRESS, OR DISCOMFORT

Some people might have negative emotions when they see Covid-19 tweets. You will be acknowledged the dashboard uses Covid-19 Twitter data and the participation is voluntary. You may leave at any time.

BENEFITS OF THE STUDY

Participants will be able to try this dashboard. The knowledge generated from this research might inform better future dashboard design for health-related social media data.

CONFIDENTIALITY OF RESEARCH INFORMATION

The link between your identifiers and the research data will be destroyed at the end of the study.

USE OF INFORMATION AND DATA SHARING PLANS

Your data will only be shared between me and my committee. Your interview answers might be summarized and presented in my thesis. Your quotes might be used in my thesis anonymously.

OTHER INFORMATION

You may refuse to participate, and you are free to withdraw from this study at any time without penalty or loss of benefits to which you are otherwise entitled. If you wish to withdraw, please contact the researcher listed on page 1 of this consent form.

RESEARCH-RELATED INJURY

If you think you have been harmed from being in this research, contact Wei Fan by email weif3@uw.edu or using cell phone number +1(XXX)-XXX-XXXX.

Subject's statement

This study has been explained to me. I volunteer to take part in this research. I have had a chance to ask questions. If I have questions later about the research, or if I have been harmed by participating in this study, I can contact the researcher listed on the first page of this consent form.

If I have questions about my rights as a research subject, I can call the Human Subjects Division at (206) 543-0098. I will receive a copy of this consent form.

[checkbox] I agree

Sign* [short answer text]

Date* [Month, date, year]

Page 2 of 2:

Name* [Short answer text]

Email* [Short answer text]

I am a graduate student in UW. *

If you are not a graduate student in UW, you may not be eligible for participating.

[checkbox] yes

What's your field of study in UW? *

If you are in neither of these majors, you may not be eligible for participating.

[Mutiplie choice option 1] Biomedical & Health Informatics

[Mutiplie choice option 2] Nursing

What's your gender identity?

[Mutiplie choice option 1] Female

[Mutiplie choice option 2] Male

[Mutiplie choice option 3] Trans Male

[Mutiplie choice option 4] Trans Male

[Mutiplie choice option 5] Other. Please specify in the next question

[Mutiplie choice option 6] Prefer not to say

If your gender identity is not listed above, what's your gender identity?

[Short answer text]

The interview will be conducted through Zoom. Do you need any help in Zoom installing or using Zoom?

[Mutiplie choice option 1] Yes

[Mutiplie choice option 2] No

I have approximately 40 minutes for an interview in the next 2 weeks (April 17 - May 5) and am interested in participating in the study.

[Mutiplie choice option 1] Yes

[Mutiplie choice option 2] No

Thank you for filling in this form! I will contact you soon!

Appendix C: Interview guide

The interview contains four parts, from part zero to part three. The first part is just an introduction, and the last part is a closing. Part one asked

Part 0 Introduction

Hello <name>, Thank you for participating in this interview! My name is Wei Fan, an MS student in the BIME department. In this interview, we will talk about your previous experience in data analysis and let you use a covid-19 Twitter data dashboard.

Q 0.1: Would you mind if I record this interview? I will later change the recording into text and reported the aggregated data results in my thesis. For example, I would mention things like half of the participants mentioned that they found the dashboard useful. I might also paraphrase some of your answers in quotes, but I will anonymize your name to, for example, participant 1.

[Answer 0.1]

The interview would take approximately 40 minutes. Please let me know if at any time you want to take a break or stop!

Q 0.2: Are there any other questions before we start?

[Answer 0.2]

Part 1 Interview questions

Q1.1.1: What are some possible questions you might be interested in researching or exploring if you have access to the Covid Twitter data?

[Answer 1.1.1]

Q1.1.2: What would you do to find these answers?

[Answer 1.1.2]

Q1.1.3: What would you do to find these answers?

[Answer 1.1.3]

Q1.2.1: On a scale from one to five, how familiar are you with topic modeling? One is not familiar and five is very familiar.

[Answer 1.2.1]

Q1.2.2: [If Answer 1.2.1 > 1] Could you please briefly talk about your previous experience with topic modeling?

[Answer 1.2.2]

Q1.3.1: On a scale from one to five, how familiar are you with social network analysis? One is not familiar and five is very familiar.

[Answer 1.3.1]

Q1.3.2: [If Answer 1.3.1 > 1] Could you please briefly talk about your previous experience with social network analysis?

[Answer 1.3.2]

Part 2 Interact with dashboard

In the next section, I would let you interact with a Covid data dashboard I made. I will use the remote control function to grant your access to the dashboard.

Q2.1: Have you used remote control before?

[Answer 2.1]

If answer 2.1 is no, I would briefly explain the remote control. Remote control is a function in Zoom that allows you to remote control your screen. Now could you please try to move my cursor?

The dashboard might take some time to load in remote control mode. This is the dashboard you are going to use. I will briefly introduce this dashboard to you.

This is the main page of the dashboard. In the center, you can see a social network analysis visualization using Covid Twitter data. Each circle is a user node representing a Twitter user, and each star is a topic node representing a topic that a user participates in. The link between the user node and the topic node is an edge, and it means this user has a tweet that talked about this topic. A user may have multiple tweets on different topics, and hence, a user node could link to multiple topic nodes.

There are lighter blue nodes and darker blue user nodes. The light blue nodes represent a user who made at least one tweet, while the charcoal circle nodes represent a user who did not has a tweet but was referred to by another user in their tweets. The link between a light blue node and a charcoal node represents that the user represented in blue referred to the user represented in the charcoal node in one of his or her tweets.

The visualizations could be changed by changing the setting on the left panel. Under this visualization, you can see the top n words in each topic. The topic classification is based on Latent Dirichlet Allocation topic modeling. In brief, the algorithm classifies each tweet to a most likely topic based on the words in each tweet. The top frequent words in each topic can be seen in this part. On the right side, it displays some sample tweets by topic.

Q2.2: Next, I will give you 5 minutes to explore the dashboard on your own. We will use the talk-aloud method. Please talk about what you are thinking while exploring the dashboard.

[Answer 2.2]

If the participant did not change any setting during Q2.2, I would ask them to change the user node color to lavender. I would ask some participants to change the topic modeling settings to use 500 tweets and 15 topics and show the top 10 words in each topic. This step makes sure every participant has the same topic modeling setting before the next question.

Q2.3: How would you interpret the current visualization? Please feel free to change the visualization settings to help you interpret.

[Answer 2.3]

Q2.4: Does the dashboard helpful for answering your questions at the beginning of the interview (Q1.1.1)? The question about some possible questions you might be interested in researching or exploring if you have access to the Covid Twitter data.

[Answer 2.4]

Q2.5: Which part of the dashboard do you like? Why?

[Answer 2.5]

Q2.6: Which part of the dashboard you do not like? Why?

[Answer 2.6]

Q2.7.1: On a scale from one to five, how likely you will be using this dashboard or something similar in the future? One is not like and five is very likely.

[Answer 2.7.1]

Q2.7.2: Why?

[Answer 2.7.2]

Part 3 Closing

Thank you very much for your time and participation in this interview! It's very helpful for my thesis! Is there anything you would like me to know before we end this interview?

Thank you so much for participating in this interview and research!