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Mining Public Voices: Analyzing Suicide-Related Thoughts and Behaviors in YouTube Videos and Comments Using Topic Modeling

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Abstract. YouTube has become a common platform for sharing difficult experiences and sensitive information, including suicide-related thoughts and behaviors. This study analyzes YouTube videos and their comments using topic modeling to explore the common themes discussed within the online community. Our findings show that these videos and comments not only focus on personal stories but also provide encouragement and healthcare-related information, highlighting social media's role in health promotion and peer support. Given that millions of people use various social media platforms to discuss a wide range of topics, these platforms serve as a rich source of data. As such, YouTube videos and comments offer health services researchers a valuable source of public opinion data, providing insights into societal attitudes and perceptions that may differ from those collected through traditional research methods.

Keywords. Suicide, topic modeling, social media, mental health

1. Introduction

Suicide remains a critical global public health issue, impacting individuals, families, and communities. Its prevalence emphasizes the need for effective interventions and support. In today's digital culture, many turn to online platforms like YouTube, X, and Reddit to share personal experiences, including suicide attempts [1]. The anonymity and accessibility of these platforms enable individuals to seek help in ways that often differ from traditional face-to-face settings [2]. Therefore, an emerging area of research focuses on mining public opinion from social media to gain healthcare insights, providing a novel approach for capturing extensive data and reaching a broader audience [2–4].

Recognizing the value of social media as a source of diverse public opinion, our study examines stories of suicide-related thoughts and behaviours (SRTB) shared on

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YouTube, one of the most popular online platforms, with over 2.5 billion active users as of 2023 [5]. The purpose of this paper is to share the preliminary findings of our topic modeling study. By using topic modeling on YouTube video and comment data, we identified key themes in both the videos and comments, allowing us to explore the perspectives of individuals sharing personal experiences and the supportive communities around them. These findings provide insights into how social media can reach individuals who may not be accessible through traditional research methods and provide implications for research in our increasingly digitally connected healthcare landscape.

2. Methods

We focused on identifying key themes from two types of textual data related to SRTB collected from YouTube: video transcripts and comments. We began by retrieving relevant videos through searches using six representative keywords, then cleaned the collected data for effective theme identification. Next, we applied a standard topic modeling method to find an initial set of salient topics, which we further revisited to combine them into groups that cover the same themes.

2.1. Data Collection

Collection of relevant video transcripts was carried out using the 'tuber' R package [6] and the 'youtube-transcript-api' Python package [7]. From our preliminary investigation, we selected six most relevant keywords: 'my suicide story,' 'my suicide attempt,' 'my suicide,' 'suicide thoughts,' 'my suicide thoughts,' and 'I tried to kill myself.' The resulting list of videos was then reviewed to remove duplicates and distinct outliers.

2.2. Data Preprocessing

To ensure the following topic modeling algorithm accurately extracts underlying themes without being hindered by irrelevant or noisy text, we programmatically cleaned both transcripts and comments by removing meaningless words and characters, such as stop words and special symbols. We also applied stemming, converting words to their root forms (e.g., 'running' became 'run'), which facilitated grouping similar words. Finally, we filtered out words that occurred too frequently or too infrequently, as these could skew the analysis and lead to misleading results.

2.3. Topic Modeling and Postprocessing

Topic modeling is a machine learning technique used to identify underlying themes across a collection of documents, revealing topics that best describe the content of the entire corpus. Among various algorithms, we chose Latent Dirichlet Allocation (LDA) due to its popularity and suitability for our use case [8]. It assumes that each document is a combination of topics, with each topic represented by a distribution of words [8]. Since our videos often cover multiple topics, LDA was more appropriate than other techniques, such as BerTopic, which assume a single topic per document [9]. Our initial attempt showed that applying LDA directly to full-length video transcripts did not effectively capture themes due to the variable lengths of the transcripts. To address this, we split each transcript into documents of fewer than 500 words. While LDA can identify topics with minimal human guidance, the resulting clusters may overlap and vary slightly due to the algorithm's inherent randomness. Therefore, we qualitatively evaluated the keywords and sample videos from each group to refine the topics into related themes.

3. Results

Six searches yielded 3,606 videos, of which 997 were eligible for inclusion after removing 2,015 irrelevant and duplicate videos. From our manual categorization, it was identified that these videos featured personal experiences of SRTB in the form of self-video blogs (14.8%), experiences of losing family or friends (13.1%), health agency or organizational channels featuring people with lived experiences (12.6%), and news or information about SRTB (59.3%). Out of the 997 eligible videos, 639 had transcripts accessible and 74 videos were identified as outliers, leaving 565 videos for topic modeling analysis with an average length of 14.9 minutes.

While we used all 565 videos for transcript analysis, we present only our preliminary findings on the five most prominent themes and limit our comment analysis to 33,277 comments from 21 hand-picked videos covering these topics. This decision was driven by the large volume of comments and computational limitations. Even after cleaning the data, the total number of words we had to process remained extremely large. The video word count was reduced from 1,358,110 to 365,266, with 3,516 unique words. The data cleaning of the collected comments resulted in 30,875 comments, reducing the word count from 1,227,094 to 428,100, with 4,747 unique words.

3.1. Salient Trends in Video Transcripts and Comments

As shown in Figure 1, the most prominent keywords from the videos and comments were similar, including life, feel, help, health, family, friends, and suicide. However, we also found notable differences between the two datasets: words related to communication (e.g., talk, look) were more prominent in the videos, while words related to encouragement (e.g., happy, hope) were more prevalent in the comments.

Figure 1. Word clouds showing key terms from the videos (left) and comments (right).

3.2. Video Transcript Topic Modeling Results

From 565 video transcripts of 365,266 processed words, we identified 35 topics, then grouped them into 11 non-mutually exclusive themes. This paper presents five prominent themes: 1) finding hope despite pain; 2) relationship and losing someone by suicide; 3) attempt leading to death or near death; 4) addiction and substance use; 5) religion.

Table 1. Salient themes from the video transcripts and their representative words.

Themes	No. Videos	Identified representative words
1) Finding hope	247	life, happy, pain, love, hope, moment, reason, find, try
2) Relationship	242	leave, dad, brother, mom, sister, friend, family, love
3) Attempt	141	die, end, death, life, hell, guilt, violence, shame, leave, pain
4) Addiction	63	drink, medication, alcohol, depression, addiction, drug
5) Religion	57	god, jesus, lord, christ, spirit, sin, bible, pray, purpose

3.3. Comment Topic Modeling Results

We identified 11 topics from 30,875 comments. A careful review of the keywords and sample comments resulted in the identification of four mutually exclusive themes: 1) appreciation towards sharing and encouraging help seeking; 2) showing empathy through sharing one's struggles; 3) healthcare experience; 4) religion.

Table 2. Salient themes from the comments and their representative words.

Themes	No. Comments	Identified representative words
1) Appreciation and encouragement	19,605	stay, strong, hope, happy, share, help, thank
2) Empathy	5,199	feel, understand, live, pain, talk, tell, good
3) Healthcare experience	4,314	depression, mental, health, anxiety, medication
4) Religion	1,757	god, jesus, christian, lord, believe, pray, bible

4. Discussion and Conclusion

Through topic modeling of video transcripts and comments, we found that YouTube videos go beyond personal stories, highlighting individuals' efforts to find hope, factors contributing to SRTB, and experiences with healthcare and religion. Our analysis of comments confirmed that sharing stories on YouTube can lead to positive outcomes, with a dominant theme of appreciation for the individuals' courage to share difficult stories and encouragement for help seeking. These findings highlight the role of social media in fostering supportive communities, consistent with the current literature [2,10].

Despite the overall positivity fostered by encouragement and empathy, we also identified that it could have a negative impact by triggering re-experience of the trauma as noted in hate speech or unfiltered language in the user comments. These concerns highlight how social media can act as a double-edged sword, offering both benefits and harms [11]. In addition, while social media can make peer support and the exchange of healthcare information more accessible, it also poses risks of misinformation, highlighting the need for educational efforts and consistent community monitoring [12].

Overall, our study suggests that social media can be a valuable data source, providing a broader range of perspectives that may be difficult to capture in traditional research settings. This has important implications. First, social media data can contribute to a more holistic understanding of stigmatized topics, such as SRTB. Research in this area has traditionally been challenging, requiring careful safety planning before conducting research. Additionally, approximately 50-60% of people refrain from disclosing SRTB to others [13]. As such, leveraging social media data can enhance our understanding of these sensitive topics while minimizing ethical challenges. Second, social media is a valuable tool for gauging and monitoring public attitudes. For example, X (Twitter) has been useful in generating information on trends in public concerns during the COVID-19 pandemic [14]. When policymakers have a better and more comprehensive understanding of public perspectives, they can make decisions that accurately reflect the needs and interests of the population. This leads to better-informed policies that resonate with the people they are intended to serve.

As online communities continue to grow, understanding their role in health communication and public engagement is becoming increasingly important. This type of study offers a valuable avenue for gathering diverse perspectives and integrating public voices. Such an approach can support researchers, policymakers, and healthcare administrators in understanding public opinions on specific topics and developing targeted interventions to address particular healthcare issues. While capturing a broader range of perspectives through social media is encouraged, it is also important to acknowledge the biases and limitations inherent in this data. Researchers must therefore continue exploring multiple data sources to capture a wider range of perspectives and strive for a more comprehensive understanding of public needs.

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