AI-Driven Sentiment Trend Analysis: Enhancing Topic Modeling Interpretation with ChatGPT

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Abstract. Understanding the sentiment trends of large and unstructured text corpora is essential for various applications. Despite extensive application of sentiment analysis and topic modeling, extracting meaningful insights from the vast amount of textual data generated on social media platforms presents unique challenges due to the short and noisy nature of the text. In this study, we propose a methodology for analyzing sentiment trends in social media, including data collection, data preprocessing, sentiment analysis, social network graph construction, and topic modeling interpretation using ChatGPT. By integrating ChatGPT with topic modeling techniques such as LDA and BERTopic, we aim to enhance the interpretability of sentiment-related topics and gain deeper insights into sentiment trends in social media conversations. Through a case study focusing on parental hesitancy toward child vaccination, we illustrate the applicability and utility of our proposed methodology in real-world social media analysis scenarios, demonstrating its effectiveness in topic modeling interpretation and enhancing understanding of social media discourse. The integration of ChatGPT and BERTopic yielded improved topic interpretation for the short text of large corpus based on the coherence score of the original posts and generated description of the topic, ultimately reducing the cost and time required for topic interpretation by humans.

Keywords: Sentiment analysis · Social network analysis · Topic modeling and Interpretation · BERTopic · ChatGPT

1 Introduction

Social media has gained popularity as a tool to communicate, exchange, and share ideas and information. Various natural language processing (NLP) and machine learning (ML) tools have been developed to analyze social networks. These tools investigate people's behavior when accessing information, perform

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sentiment analysis on specific topics, and utilize topic modeling to uncover latent semantic structures of textual data [1].

Topic modeling has emerged as a powerful analytical tool for understanding and deciphering public discourse on social media. One of the challenges of topic modeling is the short and noisy nature of social media texts, such as posts or comments. These texts often contain abbreviations, slang, emoticons, hashtags, and other informal expressions that make it difficult for traditional topic models to capture the semantic meaning and coherence of the topics. The objectives of the topic modeling interpretation process include understanding and explaining the topics discovered by a topic modeling technique. These tasks are recently often addressed by ChatGPT, a Large Language Model (LLM) based on the Generative Pre-training Transformer (GPT) model [4] that can generate natural language texts according to a given prompt or question. Such an approach provides human-readable summaries of the topics and gives answers to questions and clarifications about the topics.

In this study, we propose a methodology that leverages sentiment analysis, social network graph analysis, and topic modeling and interpretation using ChatGPT to improve understanding of the content and trends of large and unstructured text corpora extracted from social media. Specifically, in a case study, we study social media to characterize parental hesitancy toward child vaccination in the United States before and during the COVID-19 pandemic.

Vaccine hesitancy is a significant public health issue associated with infectious disease outbreaks and reduced vaccination coverage rates. Data from around the world indicates that vaccine hesitancy is prevalent in over 90% of countries [15]. This hesitancy can be seen concerning all routine or specific childhood vaccines, with influenza and HPV vaccines having the highest hesitancy rates among parents [16]. The national survey in 2019 [21] showed that around 25% of parents expressed significant concerns regarding vaccinating their children. Despite being a complex matter influenced by various factors, social media platforms such as Twitter (X) have been identified as potential drivers of vaccine hesitancy.

This study scrutinizes communication patterns and social structures based on X users and their relationships through networks and graph theory, sentiment analysis of posts, and topic modeling and interpretation. The research's significance lies in its potential to identify key actors and communication patterns in social networks. Our study corroborates the findings of previous studies [23,24], indicating that ChatGPT provides valuable insights into topic modeling if prompted accurately. Here, we employ ChatGPT to interpret topics generated by Latent Dirichlet Allocation (LDA) and Bidirectional Encoder Representations from Transformers Topic (BERTopic) to reduce the cost efficiency and time for interpreting topics of a large corpus. Moreover, we apply multiple prompts engineering techniques to enhance ChatGPT results. The contribution of this study can be summarized as follows:

- Integrating topic modeling techniques, including LDA and BERTopic, with the ChatGPT model to model and interpret topics from a social media corpus without involving domain experts.

- Collecting over $650K$ posts in the context of child vaccination discourse, aiming to investigate attitudes before and during the pandemic.
- Extracting mentioned and quoted networks from collected posts to explore the role of influencers and sources of information on public attitude.

In this study, we specifically address the following research questions:

- **RQ1:** How do people react before and during disruptive events on social media?
- **RQ2:** How does the construction of social network graphs, including mentioned and quoted networks, contribute to understanding the source of the sentiment in social media?
- **RQ3:** Does the proposed methodology, which integrates the approach of topic modeling and ChatGPT, enhance the interpretability of sentiment-related topics in social media?

The remainder of this manuscript is organized as follows. Section 2 discusses related works and previous studies. Section 3 describes our proposed methodology. Section 4 shows the results, findings, and discussions. Finally, Sect. 5 presents the conclusion and future works.

2 Related Works

Sentiment analysis, social network analysis (SNA), and topic modeling and interpretation are the methods that can be used to analyze the interactions and information flow within these online communities. Besides social media, some studies explored the factors contributing to vaccine hesitancy among parents conducting questionnaires or surveys [6,8,11,13].

Sentiment analysis is used to explore vaccine hesitancy and anti-vaccination reactions from post contents [18,22]. Moreover, public sentiments on X are also examined regarding vaccines and vaccination before and during the COVID-19 pandemic across multiple languages. The study [26] revealed a notable shift towards positive sentiments in public attitudes towards vaccines during the pandemic compared to pre-pandemic sentiments. On the other hand, SNA is considered to study the influence of the COVID-19 pandemic on Saudi users' posting behavior to identify key information sources and influencers [1]. In another study [25], semantic network analysis was employed to analyze $139,433$ posts and identify 420 vaccine X influencers. The results suggest that locating social media influencers efficiently identifies and targets vaccine-hesitant communities online.

Topic modeling has emerged as a powerful analytical tool for understanding and deciphering social media discourse such as X. Researchers have applied topic modeling techniques such as LDA [2] and BERTopic [14] to identify and categorize prevalent themes and discussions related to different applications. For instance, Ljajić et al. [19] employed the LDA model to study the reasons behind COVID-19 vaccine hesitancy in Serbia. They found that the hesitant groups discussed concern over vaccine side effects, concern over vaccine effectiveness, concern over insufficiently tested vaccines, mistrust of authorities, and conspiracy theories.

ChatGPT has been shown to be efficient in various NLP tasks. It outperforms crowd workers and trained annotators in tasks such as relevance, stance, topics, and frame detection, with a zero-shot accuracy that exceeds crowd workers by about 25% [12]. Additionally, the per-annotation cost of ChatGPT is significantly lower than using platforms like MTurk, making it a more cost-effective option [28]. Rijcken et al. [24] highlight the potential of using ChatGPT to streamline the interpretation process of topic models and provide insights into the discrepancies and agreements between human and machine-generated interpretations. The findings suggest that ChatGPT can accurately describe topics and offer useful insights when prompted accurately. Some studies investigate the significant capability of ChatGPT in shaping public perceptions, patient education, and healthcare decision-making [5,7,20,27].

In this study, we investigate the potential efficiency of our proposed methodology in exploring social media sentiment trends at two levels: post content and X structure (user interactions). Additionally, we integrate topic modeling techniques, including LDA and BERTopic models, with ChatGPT to extract, model, and interpret topics of the large corpus of social media posts without reliance on domain experts. Moreover, we modify the methodology proposed in [24] for the topic modeling interpretation step to apply it to social media sentiments.

3 Methodology

The X data analysis provides valuable insights into the public's behavioral responses due to a wealth of data available for analysis. Figure 1 illustrates the architecture of the proposed methodology of the current study and consists of five main phases: data collecting, data preprocessing, sentiment analysis, network analysis, and topic modeling and interpretation using ChatGPT.

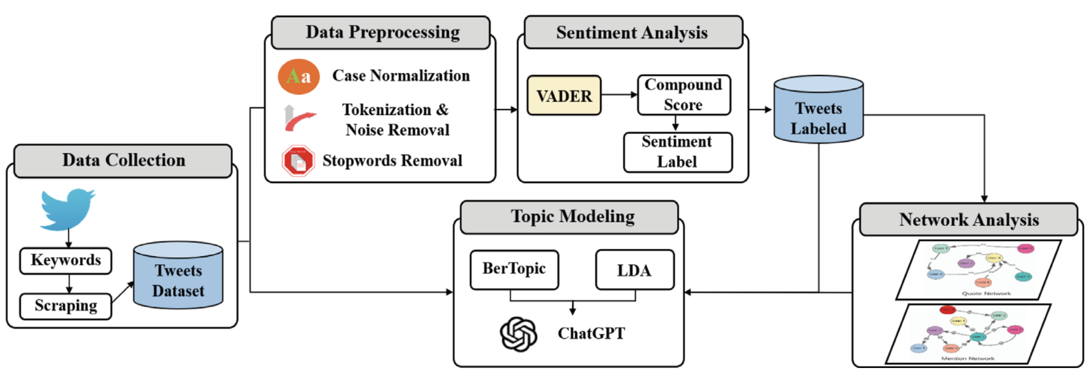

Fig. 1. Overview of the proposed methodology. We begin with the collection and preprocessing of X data. Then, sentiment analysis is applied to generate labeled data followed by the construction of networks and network analysis. Finally, a topic modeling methodology is proposed, leveraging the integration of ChatGPT and BERTopic.

3.1 Data Collection

We collected English-language posts from the USA regarding children's vaccines in two phases using the snscrape scraper tools for our case study. The initial phase involved posts on children's vaccines in the year before the pandemic, from January 1^{st}, 2019, to December 31^{st}, 2019. The second phase comprised posts related to the same topic in the year following the pandemic, ranging from January 1^{st}, 2021, to December 31^{st}, 2021. The posts were collected based on case-insensitive keywords combined with the vaccine, including singular and plural of (child, kid, son, daughter, boy, and girl). We collected a total of $694,637$ posts from $280,568$ users related to children's vaccines. The majority of posts were from 2021 set with a total of $596,154$ (86%) posted by $248,772$ users and only 14% with a total of $98,483$ posted in 2019 from $45,808$ users.

3.2 Data Preprocessing

Several common text mining techniques have been utilized to extract useful information from text, including converting letters to lowercase, removing unnecessary words, and stemming. We perform data cleaning by removing irrelevant content such as reposts, mentions, URLs, and hashtags. We also remove punctuation, square brackets, numbers, and new lines and convert text to lowercase to ensure consistency. Additionally, we remove stop words that do not add significant value to the analysis, such as "the," "and," and "a," but we retain negative words such as "against," "no," "not," and "don't" since they have a significant role in sentiment meaning. Furthermore, we apply stemming and lemmatization techniques to reduce words to their root forms, thereby enhancing the efficiency of text analysis. The purpose of these preprocessing steps was to help transform raw X data into a cleaner and more structured format essential for effective analysis and decision-making.

3.3 Sentiment Analysis

The objective of sentiment analysis based on utilizing NLP is to automatically extract attitudes, opinions, views, and emotions from various sources such as text, speech, posts, and database sources [9]. One way to perform sentiment analysis is through lexicon-based approaches, which rely on pre-built dictionaries that associate words with sentiment scores. The process of sentiment analysis involves categorizing opinions in text into distinct groups such as "positive," "negative," and "neutral." It is also referred to as subjectivity analysis, opinion mining, and appraisal extraction. For this study, the Valence Aware Dictionary for Sentiment Reasoning (VADER) lexicon approach [17] was applied to determine whether the sentiment is positive, neutral, or negative. According to lexicon-based approach review [3], the typical threshold values of VADER are as follows: positive sentiment is categorized when the compound score ≥ 0.05, while neutral sentiment falls within the range of -0.05 to 0.05. On the other hand, negative sentiment is identified when the compound score ≤ -0.05. Multiple thresholds are utilized to evaluate the robustness of our analysis, as shown in Fig. 2. We are concerned about strong positive and strong negative sentiments; however, the strong positive and strong negative threshold sets to yield more than 95% of neutral. Consequently, we utilize four thresholds for the VADER compound score to categorize the sentiments related to childhood vaccination hesitancy into positive, neutral, and negative as follows:

– **Threshold 1:** Positive $\geq$ 0.001; $-0.001 <$ Neutral < 0.001; Negative ≤ -0.001.
– **Threshold 2:** Positive $\geq$ 0.01; $-0.01 <$ Neutral < 0.01; Negative ≤ -0.01.
– **Threshold 3:** Positive $\geq$ 0.05; $-0.05 <$ Neutral < 0.05; Negative ≤ -0.05.
– **Threshold 4:** Positive $\geq$ 0.50; $-0.50 <$ Neutral < 0.50; Negative ≤ -0.50.

As a result, these techniques yield similar sentiment categories. Therefore, we utilize the VADER lexicon approach with standard threshold values to classify posts as positive, neutral, or negative based on the standard thresholds.

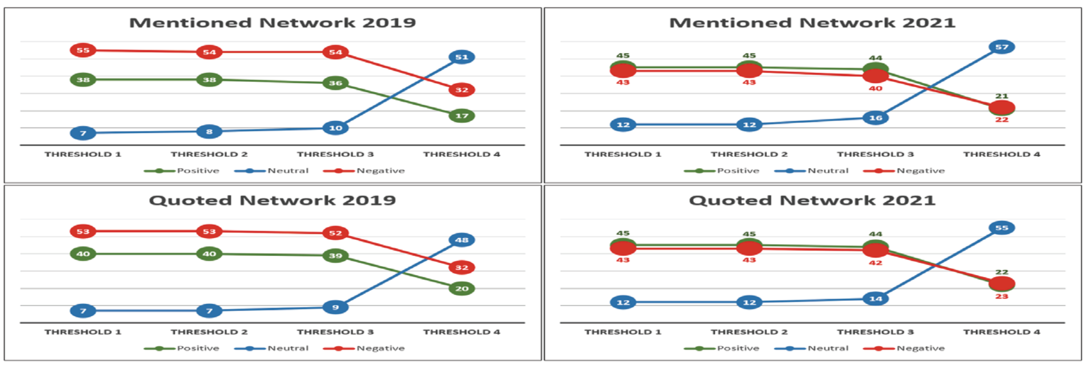

Fig. 2. Comparative sentiment distributions in Mentioned and Quoted Networks for 2019 and 2021. Colors indicate neutral (blue), positive (green), and negative (red) sentiments. Circled percentages represent the sentiment distribution corresponding to the respective threshold. (Color figure online)

3.4 Social Network Creation

We extract two distinct networks: the quoted network and the mentioned network. Quoted user refers to the user whose post is being quoted in another post. In contrast, the mentioned user is a user whose username is included in a post using the "@" symbol to tag or reference them. Let G be a quoted or mentioned network that consists of $G = (V, E)$, where $V = \{v_1, v_2, ..., v_n\}$ is the set of vertices and $E = \{e_1, e_2, ..., e_m\}$ is set of edges. We construct quoted network based on the $quotedUsername$ attribute. However, constructing the mentioned attribute was a challenge as our dataset did not include a mention attribute. To address this issue, we devise a method to scan the post content and append all mentioned users into a new data frame attribute named *mention*.

Based on the quoted and mentioned networks, all vertices $\{v_1, v_2, ..., v_n\}$ represented by X users. Each edge e is associated with a weight $\omega \subseteq \Omega$, where $\Omega \subseteq \mathbb{R}$ is a set of real numbers greater than or equal to 1. In addition, edge weight represents the strength of the connection between vertices (v, u). Here, vertices (v, u) are connected if both vertices (X users) engage in some social activities. The edge weight, $\omega =$ the number of social activities, where social media activities represent the number of quoted in the quoted network and the number of mentioned in the mentioned network. To ensure network accuracy, we exclude all self-relationships from both networks.

3.5 Topic Modeling

We generate topics from posts related to child vaccination hesitancy utilizing LDA and BERTopic. Since we have a large corpus dataset, we investigate the ability of ChatGPT to interpret the topics generated by the mentioned techniques. The LDA was implemented with the Gensim library in Python and trained on the Gensim dictionary that was created based on the tokenized documents. This algorithm required the number of topics to be setup by users. Therefore, we choose the number of topics to be 10 because generating an LDA model with limited topics results in ambiguous and unclear themes, while a large number of topics may lead to overfitting.

On the other hand, we leverage BERTopic, a more recent advancement in topic modeling that better captures the context of words and phrase relationships bidirectionally. We employ the sentence-transformers model "all-MiniLM-L6-v2" to create embeddings by converting the documents to numerical data. Since BERTopic is capable of generating topics for unsupervised text, we utilize it to generate topic themes for our unsupervised posts. Even though BERTopic is stable and accurate for short text, it generates hundreds of topics. Therefore, we extract the BERTopic model embedding and fit them to the Uniform Manifold Approximation and Projection (UMAP) approach to reduce dimensionality to prepare topics for plotting. UMAP is a technique for visualizing high-dimensional data in reduced dimensions while preserving the underlying structure. Additionally, we reduced the number of topics by setting the *nr_topic* parameter to "auto". This parameter iteratively decreases the number of topics by merging them whenever a pair of topics with a cosine similarity between c-TF-IDF vectors exceeds a minimum threshold of 0.90.

Despite the efficiency of LDA on topic modeling for larger documents, BERTopic performs more efficiently for short text such as posts [10,29]. Therefore, we compare the performance of LDA with ChatGPT against BERTopic with ChatGPT for topic modeling and interpretation of our posts. After generating the topics, we feed the extracted keywords in each topic from LDA and BERTopic to ChatGPT API, respectively, to assign a title and interpretation. To evaluate and compare the performances, we compute the coherence score between the WordCloud of the documents in each topic and its corresponding ChatGPT interpretation WordCloud. We consider both integrated LDA with

ChatGPT and BERTopic with ChatGPT. Equation 1 represents the coherence score or Jaccard similarity between two WordClouds:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \tag{1}$$

where A is the set of words in WordCloud (WordCloud_1) of original posts in a topic and B is the set of words in WordCloud (WordCloud_2) of interpretation of the topic generated by ChatGPT.

4 Results and Discussion

4.1 How Do People React Before and During Disruptive Events on Social Media?

We studied this research question by analyzing the sentiment on the X platform to characterize parental hesitancy toward child vaccination in the United States before and during the COVID-19 pandemic. Results presented at Fig. 3 show our estimate of daily sentiments about children's vaccines on X before and during the pandemic. The green line represents pro-vax (positive) sentiment over time, the blue line represents neutral sentiment, and the red line represents anti-vax (negative) sentiment. Our analysis revealed that parental hesitancy towards children's vaccines was higher in 2019 compared to 2021, as shown in Fig. 3. This finding provides evidence that public attitudes on X shifted slightly positively toward child vaccination during the COVID-19 pandemic.

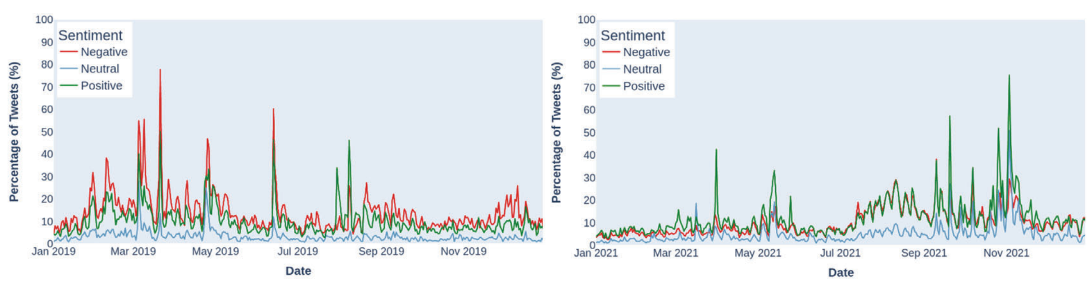

Fig. 3. Daily sentiments distribution about children's vaccines on X in year 2019 (left) and 2021 (right).

We hypothesized that parental hesitancy toward children's vaccines during the pandemic was higher than before the pandemic. However, the findings presented in Fig. 3 contradict our hypothesis and warrant further investigation. By linking this finding to the physical events, discourses on social media may influenced by the COVID-19 cases, death rate, and source of information.

4.2 How Does the Construction of Social Network Graphs Contribute to Understanding the Source of the Sentiment in Social Media?

To address this question, we analyze two types of social networks: the Quoted Network and the Mention Network to compare the interactions, information sources, and influencers' effects before and during the pandemic. These networks consist of nodes representing users and edges representing their interactions. Table 1 provides an overview of the extracted networks. The Mentioned Networks are larger than Quoted Networks since users can mention multiple accounts in one post while they quote a post from a single account in a single post.

Table 1. The overview of extracted networks before and during the pandemic

	Quoted Network		Mentioned Network	
	2019	2021	2019	2021
# of Nodes	7910	44516	56754	338635
# of Edges	6804	43542	102253	539150

Our analysis is focused on the most quoted X accounts, which could represent the most influential sources of information. We used network centrality measures of degree, eigenvector, and betweenness centrality to identify the most central accounts in the Quoted Network. We employ Gephi software (https://gephi.org) to illustrate the sources from which parents obtained information about children's vaccinations before and during the COVID-19 pandemic. Figure 4 and Table 2 demonstrate the sources of information prior to and during the pandemic.

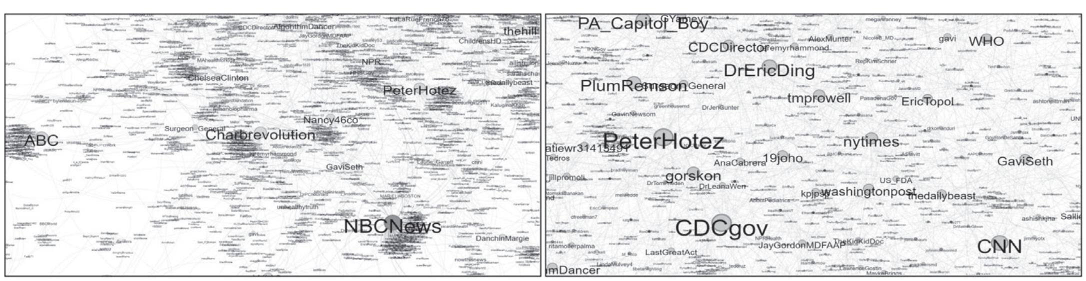

Fig. 4. Sources of information for childhood vaccination from quoted networks before the pandemic (left) and during the pandemic (right).

Table 2. Sources of information before and during the pandemic

Source of Information	2019	2021
News and Television Channels	34%	31%
Medical Doctors, Health Providers, Vaccine and Epidemiologist Scientists, and Vaccine Manufacturers	16%	29%
The Hill, Government Websites, & Politicians	11%	17%
Others	39%	23%

We found that individuals obtained information regarding childhood vaccinations before the pandemic (2019) mostly from television channels, vaccine scientists, The Hill, a leading political and policy news source, and others (unverified users and friends). In contrast, a year after the pandemic began (2021), users relied much more on news channels and reputable and verified sources such as medical doctors, health providers, vaccine and epidemiologist scientists, vaccine manufacturers, government websites, and The Hill.

4.3 Does the Proposed Methodology Enhance the Interpretability of Sentiment-Related Topics in Social Media?

Topic modeling was conducted utilizing both LDA and BERTopic methodologies, examining the discourse of parental hesitancy toward childhood vaccinations before and during the COVID-19 pandemic. Each approach has its strengths and generates a bag of words representing a topic. However, these keywords required human involvement to interpret the topic from the generated bag of words. Therefore, we explore the potential effectiveness of ChatGPT in interpreting the topics without the involvement of a domain expert. To obtain valuable results from ChatGPT, it was necessary to be explicit and specific in our prompts. Therefore, we used ChatGPT in multiple rounds (R) as follows:

- **R1:** What is the perfect topic title of topic keywords (KEYWORDS)?
- **R2:** Can you explain the likely Interpretation of topic keywords (KEYWORDS)?
- **R3:** What is the short topic title of topic keywords (KEYWORDS)?
- **R4:** What is the suggested short topic title of topic keywords (KEYWORDS)?
- **R5:** What is the suggested topic title of topic keywords (KEYWORDS)?
- **R6:** According to the keywords (KEYWORDS):
  - **a)** What is the likely topic title?
  - **b)** What is the likely interpretation of the topic?

After engineering multiple prompts as described above, we found that combining two questions, as in R6, yields a more effective interpretation of the topics among all rounds based on the coherence score. Figure 5 shows a sample output of our proposed methodology, which gives more explanation of the topic instead of showing a bag of words. Moreover, Table 3 explains the topic interpretation of discussion related to childhood vaccination in Mentioned and Quoted Networks before and during the COVID-19 pandemic applying our methodology.

Topic : The likely topic title could be "The Importance of HPV Vaccination for Girls to Prevent Cervical Cancers"

Keywords: [hpv, cancer, cervical, cancers, daughter, girls, sexually, vaccine, hpvvaccine, prevent]

Interpretation: The likely interpretation of the topic is that it discusses the significance of the HPV vaccine in preventing cervical cancers, particularly in girls. It may cover the relationship between HPV and cervical cancers, the benefits of vaccination, the target population for vaccination, and the overall impact of the HPV vaccine on reducing the incidence of cervical cancers.

Fig. 5. Sample of topic modeling interpretation using BERTopic with ChatGPT

Table 3 includes topics surrounding the correlation between autism and vaccines, along with debates on vaccination in the years 2019 and 2021. A detailed examination of posts within each identified topic for these two years indicates a prevailing negative and pessimistic sentiment among anti-vaccine parents regarding childhood vaccination pre-COVID-19 pandemic. In contrast, pro-vaccine advocates posit that having a child with autism is preferable to having a dead child.

We have found that integrating the topic modeling approach and ChatGPT results in useful and clear interpretations of the topics without involving humans. We evaluated ChatGPT's efficiency in interpreting topics based on the coherence score between the WordCloud of the original posts and its corresponding ChatGPT-generated interpretation of WordCloud for each topic, including LDA and BERTopic.

The results of the coherence score shown in Table 4 are based on Eq. 1, and they provide evidence that integrating BERTopic with the ChatGPT approach performs better than using LDA with ChatGPT for interpreting topics discussed on social media. This finding is consistent with a prior study [10] that confirmed that BERTopic yielded better performance in topic modeling for social media data than LDA. Presented below are samples of posts representative of each topic during the specified period. Notably, some topics appeared in 2019 and 2021, but discussions shifted from negative in 2019 to positive in 2021. For example, the posts belonging to the topic "The Link Between Vaccine and Autism" appeared as negative in 2019 and positive in 2021.

Table 3. Topic modeling and interpretation for positive and negative discussions before and during the COVID-19 pandemic in Mentioned and Quoted Networks

Positive Topics (Mentioned 2019)	Negative Topics (Mentioned 2019)
T1: Chickenpox: When and How it is Contracted	**T1:** The Link Between Vaccines and Autism
T2: Recommendations and Importance of Getting Flu Shots during Influenza Season	**T2:** The Impact of Injuries and Vaccines on Children
T3: HPV Vaccine for Cervical Cancer in Girls: Protecting Your Daughter from Sexually Transmitted Infections	**T3:** Refusing Mandatory HPV Vaccination
Positive Topics (Mentioned 2021**)**	**Negative Topics (Mentioned** 2021**)**
T1: The Link Between Vaccines and Autism	**T1:** Comparing the Danger of Influenza and COVID-19
T2: The Importance of Vaccinating Children against COVID-19 for School Attendance	**T2:** Concerns about COVID vaccination for children
T3: The Impact of the Influenza Season and the Importance of Yearly Nasal Shots	**T3:** The Polio Vaccine and its Impact
Positive Topics (Quoted Net 2019**)**	**Negative Topics (Quoted Net** 2019**)**
T1: Safety Concerns and Parental Decisions Regarding Child Vaccination	**T1:** The Link Between Vaccines and Autism
T2: The Importance of Vaccinations in Saving Lives and Preventing Measles and Polio	**T2:** Antivaxxers and their stance on vaccines for kids
T3: The Importance of Vaccinating Kids Against the Flu	**T3:** The Ridiculous Way Schools Make Students Suffer with MMR Requirements
Positive Topics (Quoted Net 2021**)**	**Negative Topics (Quoted Net** 2021**)**
T1: Importance and Safety of Vaccination in Preventing the Spread of Diseases Among Children	**T1:** The Debate between Vaccination and Anti-Vaxxers
T2: Pfizer's FDA Approval for COVID-19 Vaccine in Kids	**T2:** Pfizer's FDA Approval for COVID-19 Vaccine in Kids
T3: Impact of Delta Variant on Vaccinated and Unvaccinated Kids	**T3:** Impact of Delta Variant on Vaccinated and Unvaccinated Kids

- **The Link Between Vaccine and Autism** (2019)
  - *My old pharmacy manager truly believed that vaccines caused autism and wouldn't give them to his kids. He would push them constantly on pharmacy customers because part of his bonus was tied to how many vaccines the pharmacy gave a year*
- **The Link Between Vaccine and Autism** (2021)

Table 4. The evaluation of (LDA+ChatGPT) and (BERTopic+ChatGPT)

LDA + ChatGPT		BERTopic + ChatGPT	
Topic	Coherence	Topic	Coherence
Topic 1	0.0816	Topic 1	0.5873
Topic 2	0.0638	Topic 2	0.1012
Topic 3	0.1097	Topic 3	0.2784
Topic 4	0.0824	Topic 4	0.1801
Topic 5	0.2103	Topic 5	0.4631
Topic 6	0.0180	Topic 6	0.3315
Topic 7	0.1036	Topic 7	0.2010
Topic 8	0.3055	Topic 8	0.1960
Topic 9	0.0733	Topic 9	0.2101
Topic 10	0.0941	Topic 10	0.3780

- *@thehill Good. Not only is there NO EVIDENCE of a link between vaccines & autism - if you would rather your kid, or other people, die bc of a false belief that your child might be autistic then you're a horrible person. If autism is worse than death to you, I feel bad for your kids*

The above insights and findings illustrate the potential efficiency benefits of integrating BERTopic with ChatGPT in interpreting social media topics with reduced cost efficiency and time for a large corpus without human involvement.

Several challenges have accompanied this study, each presenting unique hurdles that require careful consideration. One of the primary difficulties arises from the structure of our dataset, complicating the extraction of Mentioned and Quoted Networks. Furthermore, integrating topic modeling techniques such as LDA and BERTopic with ChatGPT, specifically BERTopic and ChatGPT, presents a complex task. This integration aims to enhance the capacity to extract, model, and interpret topics of a large corpus seamlessly without relying on expert knowledge.

5 Conclusion

Our study proposed a framework for comprehensive analysis of social media sentiments based on sentiment analysis, social network graph extraction, and topic modeling and interpretation, and using ChatGPT for integrating topic modeling approaches. We found that categorizing sentiment into positive and negative, extracting Mentioned and Quoted Networks, and integrating BERTopic with ChatGPT contributed efficiently to providing valuable insights into social media sentiments. Furthermore, integrating topic modeling with ChatGPT would provide efficient insights and interpretations for topics in a large corpus that is more costly to employ domain experts. Despite the valuable information gained from

ChatGPT, LLMs may generate hallucinations and potential biases. In future work, domain experts and ChatGPT could be employed and integrated for semi-supervised topic interpretation. This approach may increase the performance and accuracy of LLMs for topic interpretation.

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