Understanding Malaysian Public Opinion on Suicide through Sentiment Analysis and Topic Modeling of Reddit Posts

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ABSTRACT

Suicide is a global public health concern, with the World Health Organization (WHO) identifying it as the second leading cause of death among individuals aged from 15 to 29 years. In Malaysia, recent statistics indicate a 10% increase in suicide cases in 2023 compared to the previous year. Online forums, such as Reddit, have become platforms for sharing opinions on this matter. Extracting and automatically analyzing these discussions can provide valuable insights into public opinion concerning this issue. While the existing research primarily focuses on identifying suicidal ideation from posts, the work on discerning public opinion remains limited. This study scraped opinion posts on suicide from the Malaysian Reddit community. Sentiment Analysis (SA) was conducted using a lexicon-based sentiment analyzer and topic modeling was performed by deploying Latent Dirichlet Allocation (LDA). The analysis revealed the following insights: (1) predominantly negative sentiments were detected in the opinions, both overall and within identified topics and (2) topic modeling indicated two distinctive topics reflecting the different perspectives and concerns of the Muslim and non-Muslim communities. Specifically, the overall SA revealed that 58% of the posts were negative, 10% were neutral, and 32% were positive. Within the identified topics, the Muslim community expressed a notably higher percentage of negative sentiments at 64%, compared to the 50% found in the non-Muslim community. These findings offer evidence-based insights into public opinion regarding suicide in Malaysia, contributing to the understanding of societal perspectives on this critical issue.

Keywords-suicide opinions; Reddit; latent Dirichlet allocation; sentiment analysis; social media analytics

I. INTRODUCTION

Suicide constitutes a paramount public health issue globally. Statistics show that more than 700,000 people commit suicide every year. It is the fourth leading cause of death among young people aged 15-29 years old [1]. It is also reported that for every suicide case documented, there are more people intending to commit suicide. Therefore, it is agreed that identifying people who are at suicide risk in the general population needs to be given utmost attention. Hence, most research in the area of suicide prevention focuses on the identification of suicide ideation from individuals. Suicide prevention efforts require coordination and collaboration among multiple parties [1], which is one of the challenges that have not been fully addressed by previous studies related to the public opinion on suicide. Due to a lack of knowledge regarding suicide criticality as a public health issue and the taboo nature of an open suicide discussion in many communities, suicide prevention faces many challenges in such matters and often does not receive enough attention from the community.

Malaysia is ranked fourth among the Southeast Asian nations regarding its high suicide rate [1]. There were 1,087 suicide cases in 2023 in Malaysia as opposed to the 981 incidents recorded in 2022, constituting a 10% increase [2]. The Malaysian Ministry of Health has put forward several initiatives to mitigate this issue, such as establishing the

National Mental Health Crisis helpline operated by the ministry's counseling officers, The Mental Health and Psychosocial Support Services (MHPSS), which consists of health personnel trained in providing mental health screening services, and the Malaysia Suicide Awareness Voice of Hope (MySAVE) program, which is a multidisciplinary initiative aimed at preventing suicide by providing the frontline staff in law enforcement, fire and rescue, the Civil Defense Force, and the Malaysian Maritime Enforcement Agency with the appropriate training on how to deal with suicidal behavior [2]. Despite these efforts, the Malaysian public still has poor awareness and empathy regarding this issue. According to [3], Malaysian stakeholders have little knowledge of safe reporting practices related to suicide. Authors in [3] stressed that the dangerous messaging phenomenon taking place nowadays has a harmful effect on individuals who have experienced a suicidal behavior and, subsequently, on the mental health professionals who treat them by worsening the former's sorrow and trauma reactions.

Over the last few years, social media platforms have gained popularity as communication tools for numerous individuals. Platforms like Facebook, Twitter, and Reddit forums offer a rich source of data that can be potentially used to assess public opinion on suicide. Various studies utilize Malaysian social media data, including Twitter [4-8], Facebook posts [9], and Reddit posts [10], to address issues like mental health, depression, and suicide. While Twitter is often preferred due to its popularity, its 280-character limit can hinder detailed expression on suicide-related topics. In contrast, Reddit allows for up to 40,000 characters, enabling users to provide more comprehensive insights, which is beneficial for understanding complex issues like suicidal thoughts [11]. In terms of detection focus, the majority of research concentrated on the detection of general mental health issues [8-10] and depression [4, 5, 12], with a couple of studies focusing on suicide-related contents [6-7]. For instance, authors in [5, 7-9] particularly focused on the impact of Covid-19 on mental health.

Among the studies centering on suicide-related content, authors in [7] analyzed tweets and performed geospatial analysis, revealing the spatial distribution of sentiments across Malaysian regions. Key themes, involving government criticism, suicide awareness, and expressions of suicidal feelings were identified employing content analysis, and the Valence Aware Dictionary and sentiment Reasoner (VADER) sentiment analysis tools. Authors in [6] explored Machine Learning (ML) to identify suicidal ideation in social media posts, analyzing tweets to extract features related to mental disorders, such as fear, sadness, and negative sentiments, often linked to suicidal statements. They highlighted the importance of sentiment analysis and feature extraction from microblogs to detect mental distress. However, these studies did not combine sentiment analysis and topic modeling specifically to gauge public opinions on suicide-related social media content. Authors in [9] conducted a hybrid SA combining lexicon-based and ML approaches to detect mental health trends on tweets during the COVID-19 pandemic. They also applied LDA for topic modeling. This integration allowed them to explore specific mental health topics and assess the sentiments tied to these discussions. However, their work focused on general mental health topics from tweets and not on suicide-related content. Other related works on SA are [13, 14]. Studies on topic modeling were performed in [15, 16]. Authors in [15] worked on Deep-Learning-based Cryptanalysis through topic modeling, while authors in [16] performed topic modeling using LDA on hospital Facebook posts.

As social media reflect public opinions on sensitive subjects, like suicide, understanding these views is vital for shaping mental health interventions and suicide prevention policies. This study fills that gap by analyzing suicide discussions on the Malaysian Reddit forum. It applied VADER for SA and LDA for topic modeling. The analysis revealed predominantly negative sentiments and two distinct topics. The current results differ from those in [10], where more positive sentiments were found in mental health discussions while following similar methods. These insights can guide authorities in assessing public attitude toward this issue and understand why suicide remains stigmatizing.

II. METHOD

This study focuses on VADER-based SA and LDA-based topic modeling to analyze Reddit posts about opinions on suicide. VADER is well-suited for SA of social media content due to its ability to capture nuanced sentiment expressions. VADER combines a sentiment lexicon with rule-based adjustments to handle context, making it efficient for informal text like social media. In contrast, Linguistic Inquiry and Word Count (LIWC) covers a wide range of emotional and cognitive categories but lacks VADER's contextual rules. General Inquirer (GI) provides a lexicon with various categorizations, including sentiment, but is more complex and less sentiment-focused [17]. Meanwhile, LDA helps identify underlying topics within these discussions. LDA, introduced in [18], is a flexible generative probabilistic model for discrete data like text data. It assumes that both words and topics in a document are exchangeable, simplifying its structure and making it comparable to dimensionality reduction methods like Latent Semantic Indexing (LSI). However, unlike LSI, LDA is based on a proper probabilistic model, which renders it more suitable for handling text data [18]. When combined, these methods offer a comprehensive approach to understanding the complex emotional and thematic dimensions of public discourse on suicide. The study was implemented in 4 phases, as shown in Figure 1. Each phase is explained in detail below.

1) Data Acquisition and Preprocessing

The data for this study were scrapped from Reddit posts. Reddit was favored over other social media platforms because it allows for longer posts, up to 40,000 characters, offering more detailed insights into users' perspectives. Its high level of anonymity also encourages users to express suicidal thoughts without experiencing any fear of being stigmatized. Additionally, Reddit has specialized communities, such as subreddits r/malaysia, which provide regional data and are further validated by active moderation to ensure content relevance [11]. The Malaysian Reddit Forum has over 793,000 members. A post from 6th September 2023 requested members to share their opinions on suicide [19]. This particular post was chosen because it is a direct question asked to the whole r/malaysia Reddit community to express their perspective on suicide, having attracted 278 comments. The scrapping was done using Simplescapper, a browser extension that allows users to extract content from any website and turn it into structured data. To scrape a Reddit forum using SimpleScraper, first, the SimpleScraper extension should be installed and navigation to the desired subreddit should be performed. Once activated, elements for extraction, such as post titles, authors, upvotes, and timestamps can be selected. The scraper also supports pagination, allowing data collection from multiple pages. After scraping, the collected data can be exported in formats, like Comma Separated Values (CSV) or Javascript Object Notation (JSON), for analysis. This resulted in 417 rows of comments, which include the 278 comments mentioned earlier with the rest being replies to these comments. The 417 comments were then stored in CSV format, which is a plain text file that stores data by delimiting data entries with commas.

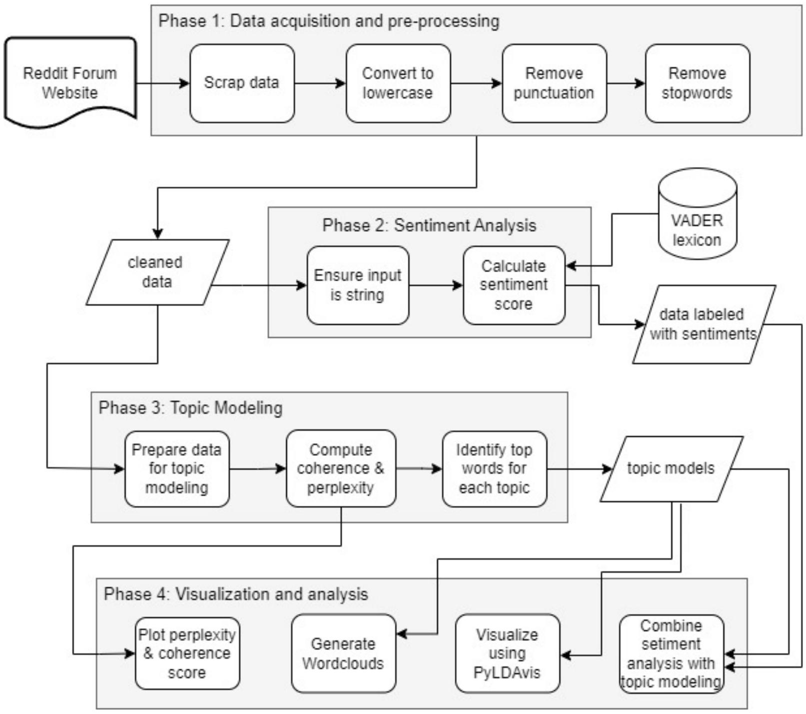


Fig. 1. The proposed method.

The data pre-processing involved a series of steps to clean the data in the CSV file that contained noise, such as duplication, missing values, and type mismatch. The objective of the data-preprocessing step is to clean and prepare the data for SA and topic modeling. At this stage, the data were converted into lowercase, punctuation and stop-words were removed. Stop-words are words that are commonly used, such as "the", "is", "are" etc., which are insignificant and should be filtered out before processing natural language text. The output of this phase is the cleaned data, which can be then input to the next phase.

2) Sentiment Analysis

The objective of this phase is to determine the sentiments, positive, negative, or neutral, of each text entry. This phase puts into service the VADER lexicon for analyzing the sentiments in the text. The process first checks if the input is a string and then calculates sentiment scores (positive, negative, neutral), and a combined compound score, adopting VADER's polarity scoring method. Polarity scoring in VADER assigns a sentiment score to each word utilizing its lexicon, tailored to capture the emotional intensity of commonly used online language. The model produces four scores: positive, negative, neutral, and compound. It also considers factors, like punctuation, capitalization, and intensifiers, such as "very", which can enhance the sentiment score, providing a deeper insight into the text's emotional tone. Table I presents an example of VADER's polarity scoring for a specific sentence.

TABLE I. EXAMPLE OF VADER'S POLARITY SCORING FOR A SENTENCE

Item	Example
Sentence	"I feel hopeless and don't see the point of living anymore"
Individual words and its scores given by VADER	Hopeless (-2.0), don't (-1.5), point (0), living (1.2), anymore (-0.8)
Overall VADER score for the sentence	Positive (0), Negative (-3,8), Neutral (0.1), Compound (-0.78).

For the example sentence portrayed in Table I, words such as "hopeless" (-2.0), "don't" (-1.5), and "anymore" (-0.8) are given negative scores, but the overall negative score is -3.8, as calculated by VADER's internal logic and adjustments, rather than just a direct sum of the negative scores. The compound score (-0.78), which is a normalized score between -1 (most extreme negative) and +1 (most extreme positive), is used to categorize the sentiment. Based on the compound score, the text is categorized as positive if the score is 0.05 or higher, negative if the score is -0.05 or lower, or neutral if the score falls between -0.05 and 0.05. This process effectively labels each text entry in the dataset as positive, negative, or neutral, allowing for further analysis of the sentiment distribution across the dataset. For instance, positive texts might include comments, like "There was this guy, a very kind person", whereas negative texts could include comments, like "Or people might say that's so stupid just work harder", and neutral texts might be more balanced, such as "It's okay, everyone processes trauma differently."

3) Topic Modeling

The objective of this phase is to identify the topics that were discussed within the text data. Three steps are involved in this phase including preparing the data for topic modeling, computing coherence and perplexity scores, and identifying the top words for each topic. At the first step, the cleaned data from phase one are tokenized. Tokenization is the process of breaking sentences into individual words. This step also involves creating a list of unique words and their frequency (number of occurrences). This list will be used to train the LDA. At the second step, the LDA model will be trained utilizing the generated list of different numbers of topics (k). The present study started the seed of k from 2 and proceeded with an increment of 2 until reaching $k = 18$. For each iteration, the perplexity and coherence scores were calculated. Perplexity score computes the inverse log-likelihood of the testing dataset, i.e. the unobserved documents. Perplexity score is calculated by:

$$perplexity(D) = exp\left\{-\frac{\sum_{d \in D} \log P(w_d)}{\sum_{d \in D} N_d}\right\} \quad (1)$$

where $\sum_{d \in D} \log P(w_d)$ is the sum of the log probabilities of the words across all comments and $\sum_{d \in D} N_d$ is the total number of words across all comments. The perplexity score provides a measure of how well the LDA model predicts the set of words in the Reddit comments. A lower perplexity score indicates a better predictive model. Next, the coherence score is calculated by:

$$\mathrm{coherence(V)} = \frac{1}{|\mathrm{T}|}\sum_{\mathrm{t} \in \mathrm{T}} \frac{1}{|\mathrm{W_t}|.(|\mathrm{W_t}|-1)} \sum_{(\mathrm{w_i},\mathrm{w_j} \in \mathrm{W_t}, \mathrm{i}<\mathrm{j})} \mathrm{NPMI}(\mathrm{w_i},\mathrm{w_j}) \quad (2)$$

where T is a set of topics, $\mathrm{W_t}$ is the set of words in topic *t,* $|\mathrm{W_t}|$ is the number of words in topic *t,* and $\mathrm{NPMI}(\mathrm{w_i},\mathrm{w_j})$ is the normalized pointwise mutual information for the word pair $(\mathrm{w_i},\mathrm{w_j})$. The NPMI-based coherence score incorporates normalization to ensure the coherence scores are comparable across different datasets and topic models. The computed coherence score helps in selecting the optimal number of topics by comparing coherence scores for different models, ensuring that the chosen model has topics that are semantically meaningful and coherent. It evaluates how coherent and interpretable the topics generated by the LDA model are. A higher coherence score indicates that the topics are more meaningful and consistent.

4) Visualization and Analysis

Phase 4 involves the visualization and analysis of the SA and topic modeling results. First, the coherence and the perplexity scores were plotted using a dual-axis graph to facilitate comparison and to identify the optimal number of topics, meaning the ones that have the highest coherence and the lowest perplexity score. Next, word clouds were generated for each topic to better visualize the 20 most significant words in every topic. This enhances the interpretability of the topic modeling result. The topic model was then interactively visualized using PyLDAvis. PyLDAvis is a Python library that helps visualize and interpret the results of the topic models. It provides further insights into the connections across themes, words, and comments. Finally, the topic modeling results are combined with the sentiment analysis results to visualize the sentiment distribution within each topic. This is achieved by assigning each text to its most probable topic and then plotting the sentiment distribution for each topic, providing a clear view of the sentiment trends within the identified topics.

III. RESULTS AND DISCUSSION

The results of the current study can be categorized into initial SA, topic modeling, and the sentiments for each topic.

1) Initial Sentiment Analysis Results

Figure 2 presents the distribution of sentiments across the dataset. It can be observed that the highest sentiments in the dataset are negative with 241 comments (58%), followed by positive with 132 comments (32%), and 43 neutral covering the 7% of the comments.

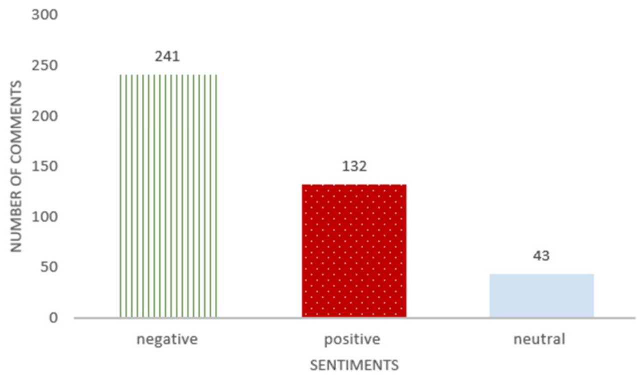


Fig. 2. Sentiment distribution in the posted comments.

This suggests an increase in negative comments related to suicide. Although sensitive topics often evoke negative sentiments, a study using similar data reported more positive sentiments [10]. This may be because the subreddits analyzed in [10] focused on social anxiety, OCD, grief support, and depression. The findings indicate that most mental health subreddits convey positive sentiments. In [20], a mix of positive and negative sentiments was observed in forums like r/anxiety and r/depression, where negative emotions coexisted with positive language, especially in discussions about recovery. Unlike the mental health-focused communities in [10, 20], this study's data come from the general public of r/malaysia, providing a broader view of the public opinion on suicide. This likely explains why sentiments in the present study are predominantly negative. The differences highlight the dynamic nature of online discussions around mental health, particularly suicide, and underscore the need for ongoing analysis to understand these trends. Further research could investigate why these discrepancies do exist, that is, whether due to changes in user behavior, data collection methods, or other factors.

2) Topic Modeling Results

The analysis of topic modeling involves evaluating how well different numbers of topics (k) fit the data. The scores of two key metrics, perplexity and coherence, were calculated, as elaborated in Section II. Figure 3 showcases the graph of the perplexity and coherence score plotted against the different number of topics.

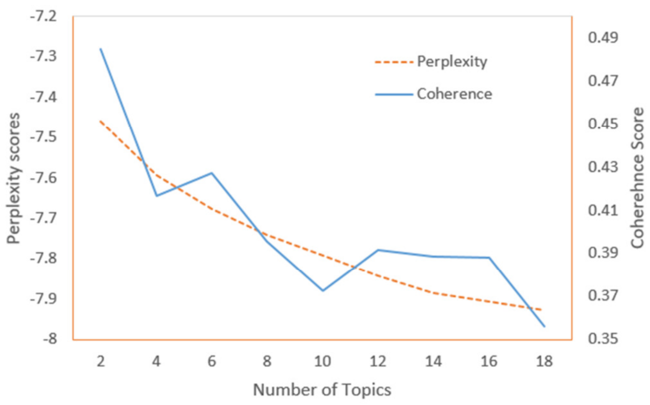
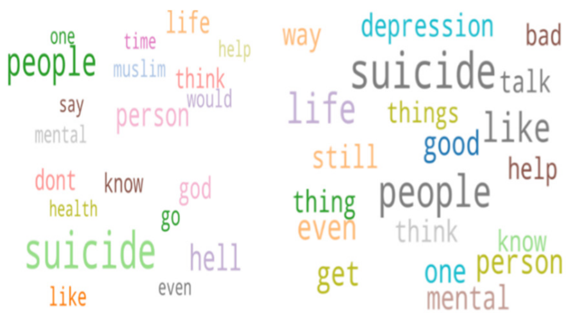


Fig. 3. Perplexity and coherence scores for different number of topics.

Perplexity measures how well a model predicts unseen data, with lower perplexity indicating better predictions. Coherence measures how well the words in a topic fit together, with higher coherence meaning more meaningful topics. In Figure 3, perplexity and coherence scores for topics ranging from 2 to 18 are plotted. Even though lower perplexity is desirable, higher coherence suggests more consistent topics. For this study's data, the highest coherence score, 0.48, occurs with 2 topics, indicating this is the optimal number for capturing key themes. Next, word clouds were drawn to visualize the top 20 words in each topic. Figure 4 shows the word cloud for topics 1 and 2.



(a) (b)

Fig. 4. Word cloud for (a) topic 1 and (b) topic 2.

As observed in Figure 4, there are common top words for both topics, such as "suicide," "people," "person," "like," "life," "mental," "think," "even," "one," "know," "help," etc. Interestingly, there are also top different words distinguishing the two topics. In topic 1, there are words such as "hell," "go," "muslim," "god," "time," and "health," whereas top words considered unique for topic 2 are words such as "depression," "bad," "good," "way," and "talk." The interpretation from the word cloud visualization is that topic 1 is inclined to the concept of religion, particularly relating to how the Muslims perceive suicide, which is perceived as a major sin and the person who commits suicide is considered that will go to hell. Topic 2, on the other hand, is inclined to a more non-religious perception, the non-Muslim one, of suicide, where the moral values of good and bad are discussed and depression is identified as the cause. This interpretation is data-driven, with terms, like "hell," "Muslim," and "God", in topic 1 suggesting a religious context, whereas topic 2 words, such as "depression" and "talk", point to a non-religious, mental health focus. This aligns with [21], suggesting that religion and culture influence perspectives on suicide. However, a qualitative study is needed to better understand how ethnicity and religion impact views on suicide. Although this study's findings suggest different community perspectives, alternatively these topics may also reflect broader societal discussions on mental health and morality beyond specific religious affiliations.

Further analysis was carried out on topic modeling results using PyLDAvis. PyLDAvis provides an overview of the model as well as details of the topics and the words in each topic. Figure 5 displays PyLDAvis overview results.

Fig. 5. PyLDAvis overview results.

Figure 5 illustrates topic clusters as circles, with size representing the statistical weight of each topic. The result demonstrates two main clusters related to suicide. The distance between the circles indicates that the topics are statistically distinct and different. This aligns with the earlier findings on perplexity vs. coherence scores and word clouds, suggesting that the two discussions stem from Muslim and non-Muslim community perspectives, as previously mentioned. Then, each topic was examined in detail by choosing each circle. Figure 6 presents the interface after selecting the first topic. As evidenced in Figure 6, there is a "relevance metric" (λ) slider, which can be adjusted to the scores of 0-1 to control how the words in the selected topic are sorted. Adjusting λ to values close to 0 highlights potentially rare but more exclusive terms for the selected topic. Larger λ values, closer to 1, highlight more frequently occurring terms in the document that might not be exclusive to the topic. Through experimentation with different λ values, it was found that λ = 0.3 was optimal for interpreting topic 1. Specifically, λ = 0.3 provides a balance, where words that are both frequent in topic 1 and relatively uncommon in other topics are highlighted.

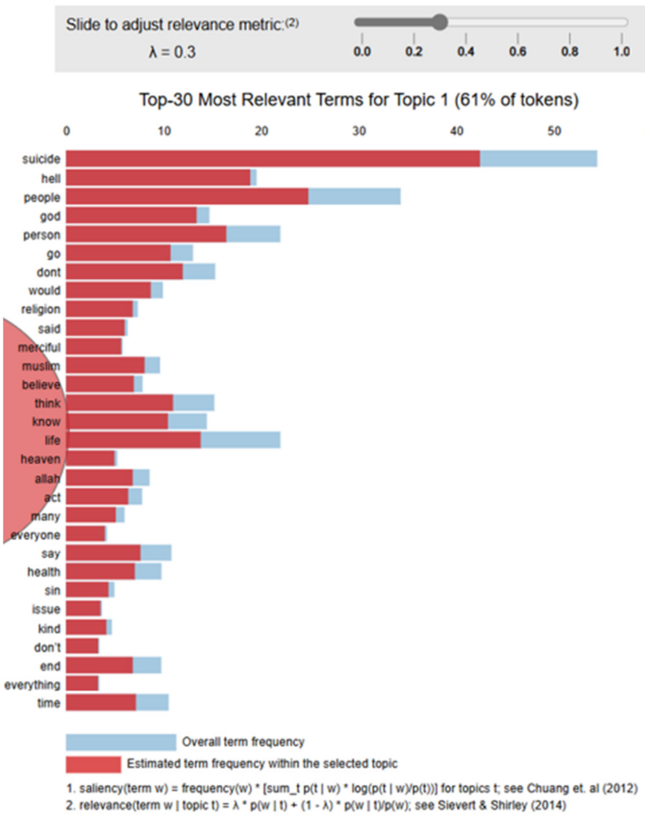


Fig. 6. PyLDAvis results for topic 1.

This value was chosen because it offers the clearest representation of the Topic 1 focus, emphasizing terms strongly associated with the Muslim community perspective. For instance, words, like "hell," "god," and "punishment", prominently appear, reflecting the topic's thematic relevance. In contrast, lower or higher λ values might either overly emphasize common words or obscure important topic-specific terms, leading to less interpretable results. Therefore, λ = 0.3 effectively captures the distinctive vocabulary of topic 1, enhancing the clarity and interpretability of the topic.

Figure 7 shows the interface after selecting the second topic. After experimenting with different relevance metric scores, it was found that λ=0.3 was also optimal for the interpretable results of topic 2. As can be seen from the red bars on the interface, topic 2 words are very much related to the non-Muslim community perspective, as words, such as "sad," "good," and "talk", seem to be better representations of this topic. The presence of specific words in both topics significantly informed authors' understanding. For topic 1, the prominence of terms, like "hell," "god," and "punishment", revealed a strong association with religious and moral discussions, most probably from a Muslim perspective, which aligned well with this study's expectations. The findings, according to which these terms were so central in this topic, constituted an insightful confirmation of this study's interpretations about the topic's focus. On the other hand, for topic 2, the appearance of words, such as "sad," "good," and "talk", initially seemed unexpected. Even though it was anticipated that this topic would reflect a different community perspective, the specific terms indicated a broader emotional and conversational content range.

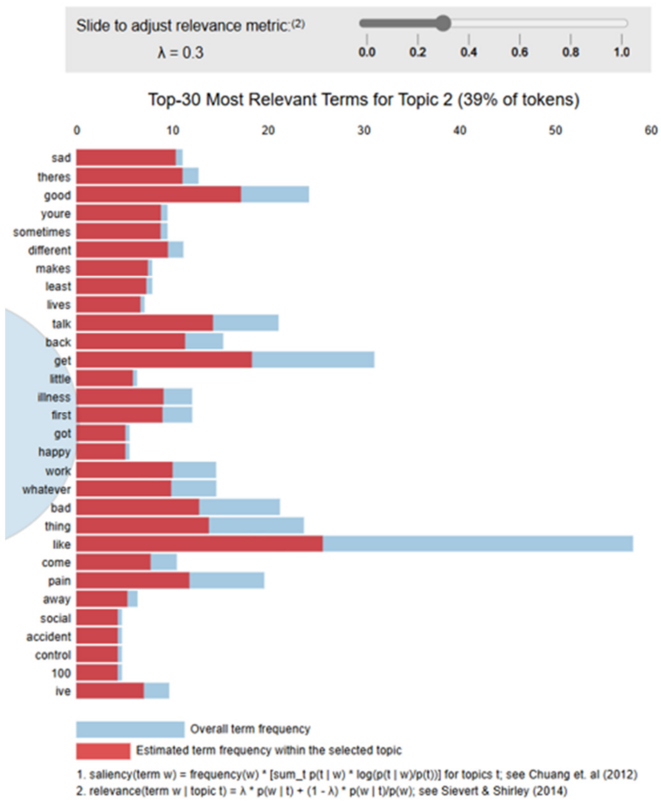


Fig. 7. PyLDAvis results for topic 2.

This unexpected finding stressed the need for a nuanced understanding of how different terms interact within the topics.

The $\lambda = 0.3$ value helped to discern these patterns by balancing the focus on frequent and distinctive terms, which enriched this study's interpretation of the topics' thematic content.

Next, the present study combined the SA results with topic modeling to examine the sentiments for each topic. Figure 8 demonstrates the sentiment results for each topic. As can be seen, the number of negatives is higher with 155 comments, 64%, for the first topic compared to the second topic with 85 comments (50%). This indicates that there are more negative perceptions from the Muslim community compared to the non-Muslim community. Based on these findings it can be concluded that, overall, the non-Muslim community is more open to the issue of suicide compared to the Muslim community, where this issue is relatively still considered a taboo.

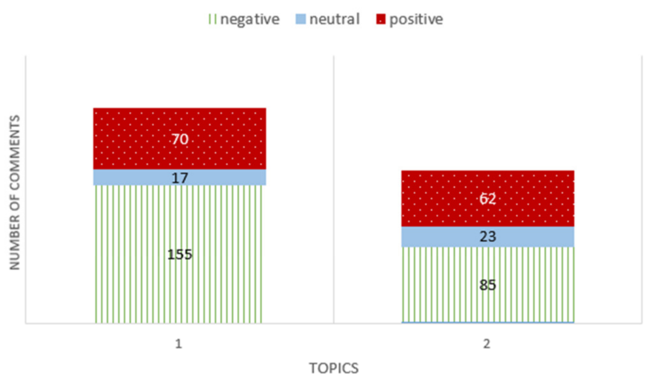


Fig. 8. Sentiment distribution for each topic.

IV. CONCLUSION

This study analyzed suicide-related opinions from Reddit posts using lexicon-based sentiment analysis and topic modeling. The findings revealed a general prevalence of negative sentiments, with two distinct topics emerging: one from the Muslim community and the other from the non-Muslim community. The Muslim community expressed more negative sentiments than the non-Muslim community. These results differ from those in [10], where predominantly positive sentiments were found in mental health communities on Reddit. Despite the different data sources, the contrasting emotional tone highlights the public sentiment on suicide, which is shaped by cultural and religious beliefs.

The findings provide valuable insights into the public sentiment and discourse on suicide, offering crucial information for promoting suicide-prevention efforts, public policies, and awareness campaigns. Monitoring online discussions is important to identify emerging issues. The obtained results stress two key points: initially, the public sentiment on suicide is shaped by cultural and religious beliefs; second, there is a need for policies and initiatives to prevent suicide, especially within the Muslim communities, where more negative sentiments were expressed. Raising awareness and fostering empathy is essential to support prevention efforts, helping to identify potential victims before tragedies occur.

Limitations of this study include the small sample size. However, the posts are considered reliable as they are dedicated to opinions on suicide and users are particularly focused on providing their honest opinions on suicide-related issues. Future research could explore other platforms and analytical techniques, as well as conducting longitudinal studies to track changes in sentiments over time.

In conclusion, ongoing research in this area is important as the role of social media in people's lives is becoming more crucial, especially in understanding and addressing sensitive issues, namely suicide and mental health. Data-driven insights, such as the one presented in this study, have various potential benefits to improve mental health support and interventions.

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